Structural Model of Retail Market Power: The U.S. Milk Industry

Vardges Hovhannisyan* and Brian W. Gould*

*Department of Agricultural and Applied Economics
University of Wisconsin-Madison
Email: hovhannisyan@wisc.edu and bwgould@wisc.edu
Phone: (608) 698-4325


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Structural Model of Retail Market Power: The U.S. Milk Industry

Vardges Hovhannisyan¹* and Brian W. Gould²

Abstract

The objective of our research is to investigate retailer market conduct in the sale of beverage milk using a structural model of consumer behavior and retailer optimality conditions that embrace a range of competitive scenarios. The study is based on an aggregate level analysis of retailer behavior with milk quantity used as a strategic variable.

We contribute to the literature by employing a Generalized Quadratic Almost Ideal Demand System (GQAIDS) to model milk demand. Furthermore, we derive the retailer optimality conditions that incorporate the slopes of inverse GQAIDS demand curves for the products under study. Lastly, we apply this generalized structural model to study the retailer behavior in marketing national brand (NB) and private label (PL) milk.

The market in question is rather concentrated at the downstream level; however we believe that the retailer behavior is most consistent with a competitive atmosphere. Moreover, the results support the conjecture that retailers mainly use the leading NB milk to assure some store traffic while utilizing PL brands for rent extraction.

Keywords: GQAIDS demand, structural model, national brand, private label milk

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

* Corresponding author (hovhannisyan@wisc.edu)
1. Introduction

The retail competitive landscape in the U.S. has been undergoing significant changes in recent years. This is reflected in food marketing system becoming increasingly concentrated in downstream channels for the most part, with retailers having their market share increased from 16 to 36 percent over the past three decades (U.S. Government Accountability Office). Despite potential gains from the economies of scale, some fear that rising retail concentration might translate into an exercise of market power on the retail end. Furthermore, retailers have been offering a wide range of increasingly differentiated products in an attempt to shift the demand for their offerings outward or, perhaps rotate the demand curve to make it more inelastic (Martinez, 2007). Finally, with the emergence of some strong store brands/private labels (PL) major retailers have become more flexible not only in their dealings with national brand manufacturers, but against their rival chains on the horizontal landscape as well (Berges-Sennou et al., 2003).

In theory, the above factors may reinforce each other in empowering the retailers. Whether this translates into an exercise of market power, however, remains more of an empirical question that needs to be studied in certain contexts and for specific products. We choose to study retailer conduct in milk marketing given the implications of retail empowerment for final consumers and food producers/farmers as well. The importance of the matter is exemplified by the joint hearings in 2010 initiated on the part of the USDA and the Department of Justice with the aim of gaining a clear understanding of the competitive atmosphere in the U.S. dairy industry.

The objective of this study is to investigate the retailer market conduct using a structural model of consumer and retailer market behavior. More specifically, we rely on a neoclassical demand system to model consumer behavior; meanwhile allowing the retailer optimality conditions to embrace a range of competitive scenarios extending from perfect competition to the
retail cartel. These structural models were first developed to study markets for homogeneous goods and laid the ground for New Empirical Industrial Organization (NEIO) literature (see for example Bresnahan, 1982; Lau, 1982). This approach is in line with conjectural variation analysis and, in principle, can be applied to a differentiated goods market. Conjectural variation or conduct parameter represents the collective response of the competitor firms to a unitary change in the own quantity produced, as perceived by a given firm (Bowley, 1924). With proper specification, these parameters allow modeling various oligopoly scenarios and represent the degree of competitiveness in the market (Dixit, 1986). Unlike the Structure-Conduct-Performance approach, whose primary concern was accounting for the sources of market power based on an assumption that some measures of market power were readily available (mainly from accounting data), the NEIO estimates market power. The underlying reason for modeling market power is that firm marginal cost functions are rarely observable as opposed to retail prices, while some of the cost components may be used to infer price over marginal cost markups (Perloff et al., 2007).

Hyde and Perloff (1998) extend the early structural framework to embrace differentiated products, based on a Linear Approximate Almost Ideal Demand System (LA/AIDS) specification of demand and corresponding retailer optimality conditions. While an important early contribution to the NEIO literature and driven mostly by computational ease, the use of the LA/AIDS is restrictive in several ways. First of all, it ignores a potential pre-committed demand component (that is insensitive to variations in economic factors) and may result in unreliable demand parameter estimates whenever the pre-committed demand is present. Secondly, it assumes a linear relationship between the budget shares and logarithm of total expenditures, which is not guaranteed in empirical applications (Banks et al., 1997).
We contribute to the literature by employing a Generalized Quadratic Almost Ideal Demand System (GQAIDS) to model milk demand. This addresses potential issues discussed earlier that relate to the use of restrictive demand models. Furthermore, we derive the retailer optimality conditions that incorporate the slopes of inverse GQAIDS demand curves for the products under study. Lastly, we apply this generalized structural model to study the retailer behavior in marketing national brand (NB) and private label (PL) milk.

The market in question is rather concentrated at the downstream level, however we receive that the retailer behavior is most consistent with a competitive atmosphere. Moreover, the results support the conjecture that retailers use leading NB milk to assure store traffic while utilizing the PL brands for rent extraction.

The remainder of the study is organized as follows. Section two discusses the methodological background of the paper by presenting the GQAIDS demand model and corresponding retailer optimality conditions. Section three offers a brief description of the product-level data used for the aggregate-level analysis. Empirical results from the generalized structural model are presented next. The final section concludes. Lastly, optimality conditions underlying the behavioral underpinnings of retailers are derived in the Appendix.

2. Methodology

In this manuscript we study the market conduct of major retail chains in a Midwestern U.S. city using weekly product-level data on milk disappearance. We employ a structural framework with certain behavioral assumptions underlying milk supply and demand. Specifically, milk demand is modeled via a neoclassical demand system and supply equations represent retailer optimal decisions. Our methodological contribution is that we generalize the milk demand using the GQAIDS specification and derive the respective retailer optimality
conditions which include the slopes of inverse GQAIDS demands for a variety of milk types included in this analysis.

The Structure of Milk Demand

Milk demand is modeled via the GQAIDS demand specification. This extends the previous literature which relied upon the LA/AIDS model of demand to explore the retailer market behavior (Hyde and Perloff, 1998). The rationale for using the GQAIDS model is that it offers the most flexibility and generality of nested AIDS models. More specifically, the results from the more restrictive demand models will be biased if the pre-committed component of demand is not accounted for, or alternatively, if the milk budget shares are restricted to be linearly related to the logarithm of total expenditure.

Price independent generalized logarithmic (PIGLOG) preferences underlie the GQAIDS model of demand, which allows for modeling a potential pre-committed component of demand.\(^3\) In addition, the expenditure share Engel curves are allowed to depend on the quadratic logarithm of income (Deaton and Muellbauer, 1980; Bollino, 1987; Banks et al., 1997). Consumer behavior in this framework is described by the following indirect utility function (V):\(^4\)

\[
\ln V = \left[ \frac{\ln(s) - \ln(P)}{b(p)} \right]^{-1} + \lambda(p) \]

Where \(s = m - \sum_{i=1}^{n} t_i p_i\) is the supernumerary expenditure, \(m\) is the total expenditure on a group of products under study, \(\sum_{i=1}^{n} t_i p_i\) is defined as the pre-committed expenditure, with \(t_i\)

\(^3\) This is the part of demand insensitive to variation in economic variables, i.e. income own and related prices

\(^4\) The utility function must be specified in stochastic terms in order for the Roy’s identity to yield the error terms (i.e. the unobservable and prices must interact)
parameterizing the pre-committed demand of the product i. In addition, ln (P) and b(p) are the translog and Cobb-Douglass price aggregator functions, respectively, with

\[
\ln(P) = \alpha + \sum_{j=1}^{n} \alpha_j \ln(p_j) + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) \ln(p_i) \quad \text{and} \quad b(p) = \prod_{k=1}^{n} p_k^{\beta_k} = e^{\exp \left( \sum_{i=1}^{n} \beta_i \ln(p_i) \right)}.
\]

Here \( p_j \) is the price of the \( j^{th} \) commodity, and \( \alpha, \gamma, \beta \) are parameters.

Aggregation, homogeneity and symmetry restrictions stemming from consumer theory are represented by

\[
\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \beta_i = 0, \quad \sum_{i=1}^{n} \lambda_i = 0, \quad \sum_{j=1}^{n} \gamma_{ij} = 0, \quad \text{and} \quad \gamma_{ij} = \gamma_{ji} \quad \forall \ j \neq i,
\]

respectively.

Uncompensated budget share equations are then obtained via Roy’s identity:

\[
w_i = \frac{t_i p_i}{m} + \frac{s}{m} \left\{ \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) + \beta_i \ln \left( \frac{s}{P} \right) + \frac{\lambda_i}{b(p)} \left[ \ln \left( \frac{s}{P} \right) \right]^2 \right\}
\]

Consumer demographic characteristics \( (D_j) \) may be incorporated into (2) via demographic translating of the pre-committed quantities as follows (Pollak and Wales, 1981):

\[
t_i = t_{i0} + \sum_{j=1}^{d} t_{ij} D_j
\]

An important benefit of the Generalized AIDS models as opposed to the AIDS demand is that demographic translating assures invariance of elasticity estimates to the scale of data (Alston et al., 2001).

Uncompensated \((\epsilon_{ij}^M)\) and expenditure elasticity \((\xi_i)\) estimates are computed via the respective formulas associated with GQAIDS demand (Hovhannisyan and Gould, 2011):
\[
\xi_i = \left\{ \frac{t_i p_i}{m} + \sum_{k=1}^{n} \frac{1_k p_k}{m} \left\{ a_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) + \beta_i \ln \left( \frac{s}{p} \right) + \frac{1_j}{b(p)} \left[ \ln \left( \frac{s}{p} \right) \right]^2 + \beta_j + \frac{2 \lambda_i}{b(p)} \left( \ln(s) - P \right) \right\} \right\} \frac{1}{w_i} + 1 \quad (4)
\]

\[
e_{ij} = \frac{1}{w_i} \left\{ \frac{t_i p_i \delta_{ij}}{m} + \frac{t_j p_j}{m} \left\{ a_i + \sum_{k=1}^{n} \gamma_{ik} \ln(p_k) + \beta_i \ln \left( \frac{s}{p} \right) + \frac{1_i}{b(p)} \left[ \ln \left( \frac{s}{p} \right) \right]^2 + \beta_j + \frac{2 \lambda_i}{b(p)} \left( \ln(s) - P \right) \right\} \right\} - \frac{\lambda_i \beta_j}{e} \sum_k \beta_k \ln(p_k) \left[ \ln \left( \frac{s}{p} \right) \right]^2 - 2 \frac{\lambda_k}{b(p)} \left\{ \frac{t_i p_i \ln(s)}{s} + \frac{t_j p_j}{s} \right\} + \ln(s) \left\{ a_j + \sum_{k=1}^{n} \gamma_{jk} \ln(p_k) \right\} + 2 P \left\{ a_j + \sum_{k=1}^{n} \gamma_{jk} \ln(p_k) \right\} \delta_{ij} \quad (5)
\]

Where \( \delta_{ij} \) is the Kronecker delta.

\textit{Retailer Optimality Conditions}

The retail sector is rather concentrated in the market under study, therefore we allow for a range of possible equilibria in an oligopolistic environment with the perfect competition and retail cartel being two extreme scenarios.\(^5\) This is performed by equating respective retailer effective marginal revenues and marginal cost functions as follows (Bresnahan, 1982; Hyde and Perloff, 1998):

\[
p_i + \lambda_i \sum_{j=1}^{n} \frac{\partial p_j}{\partial q_i} q_j = m c_i(q_i) \quad (6)
\]

Where \( m c_i(q_i) \) represents the retailer marginal cost function\(^6\), and \( \lambda_i \in [0, 1] \) measures the level of competition in a given retail market. The latter is also known as a conjectural variation or conduct parameter in the spirit of the NEIO literature, which represents a given firm’s perception of its competitive surrounding. More specifically, the conjectural variation parameter represents the aggregate response of the rivals to a unitary change in a firm’s control variable as perceived by the latter (Bowley, 1924). With proper specification these parameters allow for modeling

\(^5\) The equilibrium concept here is assumed to be Nash in quantities (i.e., Cournot).

\(^6\) Retailers are assumed to have an identical marginal cost function, which allows for studying retailer market conduct at an aggregate-level.
various oligopoly scenarios and represent the degree of competitiveness in the market (Dixit, 1986). A value of zero implies perfect competition, while a value of one signifies a cartel functioning on a horizontal competitive landscape. Infinitely many oligopolistic scenarios fall between these two polar cases.

From a game theoretic perspective, however only certain values of \( \lambda \) can be substantiated by meaningful economic theories, namely Bertrand, Cournot, and collusion. Therefore, some studies refrain from game-theoretic interpretation of \( \lambda \), and model it as a gap between price and marginal cost that can be used to obtain the Lerner index of price over marginal cost markup.

\[
L_i = \frac{p_i - m_i}{p_i} = -\frac{\lambda Q_i p'(q_i)}{p_i} = -\frac{\lambda}{\epsilon} \tag{7}
\]

This interpretation of \( \lambda \) is also not immune to criticism. Particularly, it is argued that \( \lambda \) estimates are unbiased if it is modeled to represent behavior resulting from conjectural variations in equilibrium (Corts, 1998).

The structural model of retailer market behavior is then represented by a system of equations (2), (6), and theoretical restrictions from the neoclassical demand model. However, to have an estimable system of behavioral equations we need to specify a marginal cost function, and obtain the slopes of the inverse demand curves, i.e. \( \frac{\partial p_j}{\partial q_i} \). Following Hyde and Perloff (1998), we adopt constant marginal cost structure that is determined by wholesale milk price \( v_i \), and retail wages \( w \):

\[
m_i c_i(q_i) = a + b v_i + d w \tag{8}
\]

An important assumption underlying the optimality conditions is that retailers carry all the products covered in this study. We derive \( \frac{\partial p_j}{\partial q_i} \) for the GQAIDS demand model and respective supplier optimality conditions as provided below (see Appendix for derivation):
\[ p_i = m c_i \left[ 1 - \lambda_i \left( (E_i - q_i)^{-1} q_i + \sum_{j \neq i} (E_j)^{-1} q_j \right) \right]^{-1} \]  

(9)

Where \( E_j = t_j \left( \delta_{ij} \cdot Q \right) + s \left[ -\frac{\gamma_{ij}}{p_j} - \beta_j \left( t_j + \frac{A_j}{s} + \frac{\lambda_i}{p_j} \ln \left( \frac{s}{p_j} \right) \right) \right] \left( \beta_j \ln \left( \frac{s}{p_j} \right) + \frac{2A_j + 2t_j}{s} \right) \left( -\delta_{ij} q_i \right) \)

\[ Q = a_j + \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) + \beta_j \ln \left( \frac{s}{p_j} \right) + \frac{\lambda_i}{b(p)} \left[ \ln \left( \frac{s}{p_j} \right) \right]^2 \]

\[ A_j = a_j + \sum_{k} \gamma_{jk} \ln p_k \]

We apply the generalized structural model of retailer market power to the milk market in a Midwestern U.S. city-market.

3. Data

The choice of the market is justified by the high level of retail concentration throughout the period under study. Specifically, three major retail chains accounted for over 60% of the total market share in our study market. This makes it an interesting setting for testing the relationship between the market concentration and the retailer behavior, provided that Wall-Mart had a small presence in the entire period in question (less than 5% total market share).

The product-level weekly data from 2001 to 2006 on milk purchase volumes and respective value of sales are provided by the Information Resources Incorporated (IRI). We define three groups of products, namely milk by a leading NB manufacturer, the fringe NB manufacturers collectively, and PL milk. We observe that all the retailers carry both the leading and fringe NB milk in our data, which does not hold for PL milk.

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7 The biggest player alone was responsible for around 35% of the total market share (Market Scope, various years).

8 We observe that all the retailers carry both the leading and fringe NB milk in our data, which does not hold for PL milk.
however, that the IRI dataset only covers two of the three leading retail chains in the IRI city in analysis. Aggregating products across retailers results in 312 observations (six years, each comprising 52 weeks).

An important assumption underlying the analysis is that various store brands are identical; which allows us to aggregate PL milk across retailers. However, this may be an abstraction from the reality provided that store brands may well be perceived as distinct products by some consumers (even though certain PL brands of milk may have been produced by the same manufacturer).

Table 1 Weekly descriptive statistics for products defined

<table>
<thead>
<tr>
<th>Product/Variable</th>
<th>Quantity (1000* Pints)</th>
<th>Price (Cents/pints)</th>
<th>Market share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S. D.</td>
<td>Mean</td>
</tr>
<tr>
<td>Leading NB</td>
<td>51.1</td>
<td>10.5</td>
<td>44.3</td>
</tr>
<tr>
<td>Private Label</td>
<td>780.2</td>
<td>175.6</td>
<td>31.4</td>
</tr>
<tr>
<td>Fringe NB</td>
<td>34.8</td>
<td>13.0</td>
<td>58.7</td>
</tr>
</tbody>
</table>

Source: Information Resources Incorporated, years 2001-06.

It is worth noting that PLs are the most prevalent milk/products in the market (Table 1). Specifically, they comprise about 85% of the total market share, with the remaining share accruing to milk by different NB manufacturers. This makes PL milk an important strategic tool for retailers, given that store brands are immune to inter and intra-brand competition (Steiner, 2004). Meanwhile, the PL milk constitutes the cheapest option (31.4 cents per pint) followed by milk by fringe NB (58.7 cents) and leading NB (44.3 cents). Because of aggregation, the difference in container sizes may be just one factor accounting for price differentials. Another important factor that we observe in data is that the fringe NB mostly offered specialty products, such as organic and lactose free milk.
The IRI dataset was supplemented by data on retailer cost components, namely a proxy for wholesale level milk prices (Announced Class I Coop prices) and average wages for employees from the market in question.\textsuperscript{9}

4. Empirical results

For estimation of our empirical model we use the GAUSSX module of the GAUSS software system. We include a system of GQAIDS demand equations given by (2) with respective theoretical restrictions of aggregation, homogeneity, and symmetry, and retailer optimality conditions represented by equations in (9). On the account of adding-up restriction, one demand equation was excluded from estimation to avoid overidentification. The parameter estimates for the omitted equation are obtained from the theoretical restrictions imposed on the model.

The estimates of 24 structural parameters, including the \( \lambda \)'s are estimated via the BHHH algorithm (Table 2). The model provides an extremely good fit to the data as all parameter estimates were found to be statistically significant (except for the \( \lambda \) for the leading NB milk) at the one percent level of significance (only \( b_2 \) is significant at five percent level). This result is highly supported by an overall goodness of fit test.\textsuperscript{10}

Therefore, it appears that the GQAIDS model is the correct demand specification, provided that the estimates of pre-committed demand components and those of parameters representing the effect of quadratic logarithmic expenditures are statistically significant.

\textsuperscript{9} Data on wages were collected from the official website of BLS, and the Announced Class I Coop prices came from the Dairy Markets website (AAE Department, UW-Madison)

\textsuperscript{10} Test statistic value is 1999.4 and the critical \( \chi^2 \) with 24 degrees of freedom is 42.9 (at the 99 % confidence level)
Alternatively, we could perform a likelihood ratio tests for pre-committed demand, using estimates from the GQAIDS and GAIDS, and those from GQAIDS and QAIDS for quadratic logarithmic expenditures. Thus, the results from the previous research studies may not be very reliable from this perspective, and whenever possible, the most general formulation of the nested AIDS models must be used.

The estimates of $\lambda_1, \lambda_2, \lambda_3$ parameters are of central importance in this study, as they delineate the retailer market conduct for the milk products. The estimate for milk by a leading NB (i.e., $\lambda_1$) is insignificant both economically and statistically. On the other hand, retailers seemed to have received economic profits from the PLs and milk by fringe NB, since $\lambda_2, \lambda_3$ are statistically significant. However, the latter are rather small in value, indicating that the nature of the retail competition on the horizontal landscape has been most consistent with the perfect competition scenario. Anecdotal evidence suggests that despite a small presence of Wall-Mart supercenters in the market, its entry heralded an era of intense competition among the two major retail chains.

We also present uncompensated and expenditure elasticity estimates (Table 3). The vast majority of these estimates are statistically significant, and all of these measures are consistent with consumer theory. Own price elasticity for the PL milk is almost unitary elastic (-1.08), with those for both types of NB milk being rather elastic (-1.44 and -1.97, respectively). It is worth noting that milk by the fringe NB manufacturers is mostly specialty milk, such as organic and lactose free. As shown by other studies, consumers are most price-sensitive towards these products.\footnote{See for example Hovhannisyan and Stiegert (2011), where the analysis is conducted at a disaggregate level.} This speaks to the fact that retailers may have more latitude in charging higher markups for PL milk as opposed to the NB milk. In fact, at the bottom of Table 2 we evidence
the highest markup, as measured by the Lerner Index, accruing to the PL milk (3.41 %), which is followed by the fringe NB milk (3.13 %) and the leading NB milk manufacturer (zero markup). One interpretation of the estimated values of λ’s is that retail chains may use some leading NB milk to assure certain level of store traffic, while PL milk are used to extract rents from the customers (especially given the huge market share of the PL milk). This is in line with an extensive literature, according to which retailers may use the PLs strategically both vertically and against their rival chains, given that PLs are immune to inter and intra-brand competition (Berges-Sennou et al., 2003; Steiner, 2004).

Another interesting finding that emerges is that the leading NB and fringe NB milk are important substitutes based on the cross-price effects, and while the PL milk demand is rather sensitive to the leading NB milk prices, the demand for the latter is completely unresponsive to variations in the PL milk price. This maybe due to the fact that retailers maintain PL milk price at a reasonably low level so that even for a given rise in the PL price NB milk is still an expensive substitute.

5. Conclusions

The objective of this manuscript is to investigate the retailer market conduct in the U.S. milk market using a structural model of consumer behavior and retailer optimality conditions that embrace a range of competitive scenarios. The study is based on an aggregate level analysis with the retailer equilibrium behavior assumed to be Cournot-Nash in milk quantity.

We contribute to the literature by employing a Generalized Quadratic Almost Ideal Demand System (GQAIDS) to model milk demand. Furthermore, we derive the retailer optimality conditions that incorporate the slopes of inverse GQAIDS demand curves for the
products under study. Lastly, we apply this generalized structural model to study the retailer behavior in marketing national brand (NB) and private label (PL) milk.

The market in question is rather concentrated at the downstream level, however we receive that the retailer behavior is most consistent with a competitive atmosphere. Moreover, the results support the conjecture that retailers mainly use the leading NB milk to assure some store traffic while utilizing PL brands for rent extraction.

The importance of the current study can not be underestimated. It offers an understanding of retailer market conduct with no access to very detailed data and brand-level analysis. It also brings in more information as opposed to studies treating milk as a homogeneous good, provided that retailers may be using PL and NB products differently.

Literature


Dairy Markets Data, Department of Agricultural and Applied Economics, University of Wisconsin-Madison (http://future.aae.wisc.edu/tab/prices.html)


U.S. Government Accountability Office, “U.S. Agriculture: Retail food prices grew faster than the prices farmers received for agricultural commodities, but economic research has not established that concentration has affected these trends.” GAO-09-746R June 30, 2009.
Table 2 Estimation results and Lerner Indices across products

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Estimate</th>
<th>S. E.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demand model</strong></td>
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<tr>
<td>( t_1 )</td>
<td>0.033**</td>
<td>0.006</td>
</tr>
<tr>
<td>( t_2 )</td>
<td>-3.783**</td>
<td>0.131</td>
</tr>
<tr>
<td>( t_3 )</td>
<td>0.005**</td>
<td>0.001</td>
</tr>
<tr>
<td>( z_1 )</td>
<td>0.032**</td>
<td>0.001</td>
</tr>
<tr>
<td>( z_2 )</td>
<td>-0.009**</td>
<td>0.000</td>
</tr>
<tr>
<td>( z_3 )</td>
<td>-0.023**</td>
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</tr>
<tr>
<td>( a_1 )</td>
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</tr>
<tr>
<td>( a_2 )</td>
<td>1.253**</td>
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</tr>
<tr>
<td>( a_3 )</td>
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<td>( \gamma_{11} )</td>
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</tr>
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<td>( \gamma_{12} )</td>
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</tr>
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<td>( \gamma_{13} )</td>
<td>0.045**</td>
<td>0.003</td>
</tr>
<tr>
<td>( \gamma_{22} )</td>
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</tr>
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<td>( \gamma_{23} )</td>
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<td>( \gamma_{33} )</td>
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<table>
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<tr>
<td>( a_1 )</td>
<td>2.181**</td>
<td>0.096</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>-9.221**</td>
<td>1.888</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>13.557**</td>
<td>1.080</td>
</tr>
<tr>
<td>( b_1 )</td>
<td>0.005**</td>
<td>0.002</td>
</tr>
<tr>
<td>( b_2 )</td>
<td>0.074*</td>
<td>0.039</td>
</tr>
<tr>
<td>( b_3 )</td>
<td>0.057**</td>
<td>0.009</td>
</tr>
<tr>
<td>( d_1 )</td>
<td>-0.103**</td>
<td>0.005</td>
</tr>
<tr>
<td>( d_2 )</td>
<td>0.455**</td>
<td>0.115</td>
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<tr>
<td>( d_3 )</td>
<td>-0.820**</td>
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<table>
<thead>
<tr>
<th><strong>Market power</strong></th>
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<tbody>
<tr>
<td>( \lambda_1 )</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>0.037**</td>
<td>0.002</td>
</tr>
<tr>
<td>( \lambda_3 )</td>
<td>0.062**</td>
<td>0.003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Lerner Index (%)</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading NB milk</td>
<td>0</td>
</tr>
<tr>
<td>PL milk</td>
<td>3.41</td>
</tr>
<tr>
<td>Fringe NB milk</td>
<td>3.13</td>
</tr>
</tbody>
</table>

Note: The symbols ***, **, and * denote statistical significance at 1, 5, and 10 % level of significance, respectively. Standard errors appear in italic. The bottom part represents the own-price elasticity adjusted Lerner Index Estimates.
Table 3 Structural Model Uncompensated and Expenditure Elasticity Estimates

<table>
<thead>
<tr>
<th>Product</th>
<th>Leading NB</th>
<th>Private Label</th>
<th>Fringe NB</th>
<th>Expenditure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leading NB</td>
<td>-1.442***</td>
<td>0.268*</td>
<td>0.324*</td>
<td>0.850***</td>
</tr>
<tr>
<td></td>
<td>0.235</td>
<td>0.162</td>
<td>0.186</td>
<td>0.089</td>
</tr>
<tr>
<td>Private Label</td>
<td>0.012</td>
<td>-1.080***</td>
<td>0.051***</td>
<td>1.017***</td>
</tr>
<tr>
<td></td>
<td>0.012</td>
<td>0.009</td>
<td>0.006</td>
<td>0.005</td>
</tr>
<tr>
<td>Fringe NB</td>
<td>0.354***</td>
<td>0.652</td>
<td>-1.975***</td>
<td>0.969</td>
</tr>
<tr>
<td></td>
<td>0.143</td>
<td>1.054</td>
<td>0.277</td>
<td>1.166</td>
</tr>
</tbody>
</table>

Note: The symbols ***, **, and * denote statistical significance at 1, 5, and 10 % level of significance, respectively. Standard errors appear in italic. The last column represents the expenditure elasticity estimates.

Appendix

To obtain the retailer optimality conditions, first we derive the slopes of inverse GQAIDS demand curves, i.e. \( \frac{\partial p_j}{\partial q_i} \), \( \forall \ i, j = 1, 2, 3 \), and plug them in (6). For that purpose, we differentiate both sides of (2) and set them equal to each other.

\[
\frac{\partial \text{LHS}}{\partial p_j} = \frac{\partial \text{RHS}}{\partial p_j} = \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) + \beta_j \ln\left(\frac{s}{p_j}\right) + \frac{\lambda_{ij}}{b(p)} \left[ \ln\left(\frac{s}{p_j}\right) \right]^2 + \frac{s}{m} \frac{\partial Q}{\partial p_j}
\]  

Where \( Q = a_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_j) + \beta_j \ln\left(\frac{s}{p_j}\right) + \frac{\lambda_{ij}}{b(p)} \left[ \ln\left(\frac{s}{p_j}\right) \right]^2 \)  

\( (R_1) \)

\( \frac{\partial \left(\frac{t_i p_j}{m}\right)}{\partial p_j} = \delta_{ij} \frac{t_i}{m} \), with \( \delta_{ij} \) denoting the Kronecker delta

\( (R_2) \)

\[
\frac{\partial \left(\frac{s}{m}\right)}{\partial p_j} = \frac{1}{m} \left( \frac{s}{p_j} \right) = \frac{1}{m} \left( \frac{m - \sum_{j=1}^{n} t_j p_j}{p_j} \right) = \frac{t_j}{m}
\]

\( (R_3) \)

\[
\frac{\partial Q_i}{\partial p_j} = \gamma_{ij} + \beta_j \ln\left(\frac{s}{p_j}\right) + \frac{\lambda_{ij}}{b(p)} \left[ \ln\left(\frac{s}{p_j}\right) \right]^2 + \frac{s}{m} \frac{\partial Q}{\partial p_j}
\]

\( (R_4) \)
\[
\frac{\partial \ln (s/p)}{\partial p_j} = \frac{\partial \ln s}{\partial p_j} - \frac{\partial \ln p}{\partial p_j} = \frac{\partial \ln (m - \sum r_i p_r)}{\partial p_j} - \frac{1}{p_j} A_j = -\frac{t_j}{s} - \frac{1}{p_j} A_j
\]

with \( A_j = a_j + \sum r_i \gamma_j \ln p_j \)

\[
\frac{\partial}{\partial p_j} \left( \frac{z_i}{b(p)} \left[ \frac{\ln \left( \frac{s}{p} \right)}{2} \right] \right) = \frac{\partial}{\partial p_j} \left( \frac{z_i}{b(p)} \right)^2 \frac{\partial b(p)}{\partial p_j}^{-1} + \frac{\partial}{\partial p_j} \left[ \frac{\ln \left( \frac{s}{p} \right)}{2} \right]^{\frac{1}{2}}
\]

\[
\frac{\partial}{\partial p_j} \left[ \frac{\ln \left( \frac{s}{p} \right)}{2} \right] = \frac{\partial}{\partial p_j} \left( \frac{\ln s}{2} \right) - 2 \frac{\partial (\ln s \ln p)}{\partial p_j} - \frac{\partial (\ln p)^2}{\partial p_j}
\]

\[
\frac{\partial}{\partial p_j} \ln s = 2 \ln s \frac{\partial \ln (m - \sum r_i p_r)}{\partial p_j} - \frac{2 t_j \ln s}{s}
\]

\[
\frac{\partial}{\partial p_j} \ln p = \frac{\partial \ln s}{\partial p_j} + \frac{\partial \ln p}{\partial p_j} = \frac{\partial \ln s}{\partial p_j} + \frac{\ln s}{p_j} A_j, \text{ with } A_j \text{ as in (9)}
\]

\[
\frac{\partial}{\partial p_j} (\ln p)^2 = 2 \ln p \frac{\partial \ln p}{\partial p_j} = \frac{2 \ln p}{p_j} A_j, \text{ with } A_j \text{ as in (9)}
\]

Plugging all the derivatives back into the derivative of the RHS in the right order we get:

\[
\frac{\partial \text{RHS}_i}{\partial p_j} = \frac{t_j}{m} (\delta_{ij} - Q) + \frac{s}{m} \left[ \frac{\gamma_{ij}}{s} - \beta_i \left( \frac{t_j}{s} + \frac{A_j}{p_j} \right) - \frac{\beta_i}{b(p)} \ln \left( \frac{s}{p} \right) \left( \beta_i \ln \left( \frac{s}{p} \right) + \frac{2A_j}{p_j} + \frac{2t_j}{s} \right) \right]
\]

Specifically, in the case where \( i=j \), after some rearrangements and using the fact that \( p_i = \frac{m w_i}{q_i} \), we get:

\[
\frac{\partial \text{RHS}_i}{\partial p_i} = \frac{t_i}{m} (1 - Q) + \frac{s}{m} \left[ \frac{\beta_i t_i}{s} - \frac{\lambda_i}{b(p)} \ln \left( \frac{s}{p} \right) \left( \beta_i \ln \left( \frac{s}{p} \right) + \frac{2t_i}{s} \right) \right] + \frac{q_i s}{w_i m} \left[ \gamma_{ii} - A_i \left( \beta_i + \frac{2z_i}{b(p)} \ln \left( \frac{s}{p} \right) \right) \right]
\]
Equating the derivatives of both sides gives us the following:

\[
\frac{1}{m} \left( \delta_{ij} q_i + \frac{\partial q_i}{\partial p_j} \right) = -\frac{t_j}{m} (\delta_{ij} - Q) + \frac{s}{m} \left[ \frac{\gamma_{ij}}{p_j} - \beta_i \left( \frac{t_j}{s} + \frac{A_j}{p_j} \right) - \lambda_i \ln \left( \frac{s}{P} \right) \left( \beta_i \ln \left( \frac{s}{P} \right) + \frac{2A_j}{p_j} + \frac{2t_j}{s} \right) \right]
\]

After rearranging we get:

\[
\frac{\partial q_i}{\partial p_j} = -t_j (\delta_{ij} - Q) + s \left[ \frac{\gamma_{ij}}{p_j} - \beta_i \left( \frac{t_j}{s} + \frac{A_j}{p_j} \right) - \lambda_i \ln \left( \frac{s}{P} \right) \left( \beta_i \ln \left( \frac{s}{P} \right) + \frac{2A_j}{p_j} + \frac{2t_j}{s} \right) \right]^{-1}\delta_{ij} q_i
\]

Similarly, \( E_i \) is the right hand side of \((11)\) divided by \(m\). Thus, the slopes of inverse GQAIDS demands are given below:

\[
\frac{\partial p_j}{\partial q_i} = p_i^{-1} E_j^{-1}
\]

Finally, after plugging the slopes of inverse demands back into the retailer optimality conditions, the latter take the following form:

\[
p_i = m c_i \left[ 1 - \lambda_i \left( (E_i - q_i)^{-1} q_i + \sum_{j \neq i} (E_j)^{-1} q_j \right) \right]^{-1}
\]