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A Benefit-Function Approach to Studying Market Power: An Application to the U.S. Yogurt Market

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This article provides a structural framework for studying the market performance of various food industries. It revisits the benefit-function approach to modeling demand and extends its application to the empirical industrial-organization literature. We illustrate the empirical value of our model in an econometric analysis of competitive conditions in the retail market for branded yogurt. The results show that retailers are engaged in imperfect competition. Furthermore, national brand yogurt remains an important tool for retail profitability.

Key words: benefit function, conjectural variation, market performance, retail competition, yogurt

Introduction

The U.S. food-marketing system has undergone significant structural changes over the past several decades. Two notable trends have been the rising concentration of food retailers and the increasing market share of store brands (SB). In retail food sector, the four largest grocery chains have seen their market share increase from 16% in 1982 to 36% in 2005. Both trends have the potential to alter aspects of the food system, including food pricing and accessibility, product variety and quality, and the performance of food retailers, manufacturers, and farmers (Martinez, 2007). Understanding the competitive condition of the U.S. food system remains a critical and policy-relevant area of research, as illustrated by recent USDA-DOJ joint hearings with agricultural stakeholders to better understand competition in certain agricultural markets (U. S. Department of Justice, 2012).

This article develops a structural framework to examine the performance of various food industries. We build upon the recent developments in the new empirical industrial organization (NEIO) literature and emphasize the benefits of structural analysis, including the ability to quantify firms' market behavior in the absence of marginal cost data. The choice of demand model is of key importance in this type of analysis, since modeling a firm's market behavior relies on correct representation of consumer preferences. Early work (e.g., Just and Chern, 1980; Bresnahan, 1982; Lau, 1982) relied on ad hoc linear demand specifications motivated by empirical convenience. More recent studies have tended to use demand models explicitly derived from economic theory. One notable example is Hyde and Perloff (1998), who used the Linear Approximate Almost Ideal Demand System (LA/AIDS) developed by Deaton and Muellbauer (1980) to model competition in multiple industries. Hovhannisyan and Gould (2012) extended this analytical framework by incorporating the Generalized Quadratic AIDS demand specification that relieves important restrictions underlying the LA/AIDS model (Bollino, 1987; Banks, Blundell, and Lewbel, 1997). Recently in applied IO research there has been an increase in the popularity of discrete-choice demand models, such as logit specification (see Werden and Froeb, 1994). Of particular interest is the random coefficient logit demand model, which allows for product differentiation and consumer heterogeneity (Berry, 1994, 1995).

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Unlike these past studies, we use an inverse demand system to build our structural framework. Inverse demand functions have been popular in applied demand analysis for perishables, such as agricultural commodities. The empirical appeal of this approach stems from prices being treated endogenously. This is especially valuable in research environments where a lack of access to detailed cost data makes the instrumental-variable approach infeasible (Nevo, 1998). Quantities, on the other hand, are assumed exogenous to the system. Given the natural lags in agricultural production responses, this assumption may not be very restrictive in the context of agricultural products (Barten and Bettendorf, 1989; Eales and Unnevehr, 1994). Finally, our use of inverse rather than quantity demand systems appreciably simplifies the derivation of supply functions and makes the analysis empirically more tractable.[1]

We revisit the Luenberger (1992) benefit-function approach to modeling inverse demand functions. This is a relatively new method in applied demand analysis. Despite the advantages it offers in welfare analyses, this approach has not been widely exploited (McLaren and Wong, 2009). We extend the application of the benefit-function approach to empirical industrial organization studies by utilizing the conjectural variations (CV) approach to derive firm behavioral equations with the underlying price sensitivities obtained from this specification of demand.

We illustrate the empirical value of our structural framework in an econometric analysis of retail performance in the U.S. yogurt industry. The analysis is based on product-level scanner data from the Information Resources Incorporated (IRI). We consider five IRI city markets characterized by varying degrees of retail concentration. Our findings suggest that retail-market conduct is far from perfectly competitive in the marketing of yogurt. Moreover, retailers appear to be exploiting strong consumer preferences for national brand (NB) yogurt.

Methodology

The benefit-function approach to modeling demand is subsequently used to develop a structural framework for firms' market behavior.

A Benefit-Function-Based Demand Model

We adopt the benefit-function approach to modeling demand first developed by Luenberger (1992) and use the particular specification for the benefit function provided by Baggio and Chavas (2009).[2]

Let $x \in \mathbb{R}^N_+$ denote the actual consumption bundle and $g \in \mathbb{R}^N_+$ be a reference bundle. Luenberger (1992) defines the benefit function as

$$(1) \qquad B(x,u;g) = \max_b \{b : U(x - bg) \geq u, x \geq bg\},$$

where $U(x)$ is a utility function representing consumer preferences and $B(x,u;g)$ measures the maximum number of units of the reference bundle $g(x)$ that consumers are willing to trade to move from the reference utility u to bundle x.

With the assumption of a unit price, the benefit function can be interpreted as a measure of consumer willingness to pay for bundle x in terms of g. Its partial derivative, $(\partial B/\partial x)$, reflects marginal willingness to pay for x, provided that $B(x,u;g)$ is differentiable in x.[3]

Using duality results, we derive the following "Luenberger" adjusted prices, which are equivalent to compensated inverse demand functions. We use these prices to obtain empirically

[1] Direct demand systems require the price sensitivities that underlie supply functions to be inverted. This adds complexity to the derivation of the latter relations and estimation of the structural model (see Hovhannisyan and Gould, 2012). Using inverse demand systems, on the other hand, obviates the need for inversion, resulting in simpler supply formulations.

[2] This demand specification is somewhat similar to the Inverse AIDS of Eales and Unnevehr (1994); however it offers more flexible utility effects.

[3] From this point, we suppress the argument g in the benefit function B for simplicity.

tractable demand equations (Luenberger, 1992, 1995):

$$P_j^L(x,u) = \frac{\partial B}{\partial x_j}, \tag{2}$$

where the Luenberger price, P_j^L, reflects the marginal benefit of x_j.

Our empirical demand system builds on the parametric specification offered by Baggio and Chavas (2009), motivated in part by its flexibility and convenience in empirical analyses:

$$B(x,u) = \alpha(x) - \frac{u\beta(x)}{1-u\gamma(x)}, \tag{3}$$

where $\alpha(x)$, $\beta(x)$, and $\gamma(x)$ are some quantity indices satisfying the restrictions $\beta(x) > 0$, $[1-u\gamma(x)] > 0$:

$$\alpha(x) = \alpha_0 + \sum_{k=1}^{N} \alpha_k x_k + 0.5 \sum_{i=1}^{N} \sum_{k=1}^{N} \alpha_{ik} x_i x_k, \tag{4}$$

where $\alpha_{ki} = \alpha_{ik}, \forall\, i \neq k$. According to the Young's theorem,

$$\beta(x) = \exp\left(\sum_{k=1}^{N} \beta_k x_k\right); \tag{5}$$

$$\gamma(x) = \sum_{k=1}^{N} \gamma_k x_k. \tag{6}$$

Combining equations (2) and (3) yields the following Luenberger price equations:

$$p^L(x,u) = \frac{\partial \alpha}{\partial x} - \frac{\partial \beta}{\partial x}\left[\frac{u}{1-u\gamma(x)}\right] - \frac{\partial \gamma}{\partial x}\left[\frac{\beta(x)u^2}{[1-u\gamma(x)]^2}\right]. \tag{7}$$

The Marshallian counterpart of the compensated inverse demand system in equation (7) can be obtained via duality relationships:[4]

$$p^{**}(x,u) = \frac{\partial \alpha}{\partial x} - \frac{\partial \beta}{\partial x}\frac{\alpha(x)}{\beta(x)} - \frac{\partial \gamma}{\partial x}\frac{\alpha(x)^2}{\beta(x)}, \tag{8}$$

where $p^{**}(x,u) = \frac{p^*(x)}{\kappa(x,g)}$, $p^*(x)$ represents actual prices, and $\kappa(x,g)$ is a proportionality factor satisfying $\kappa(x,g) = p^*(x)^T g$.

Finally, substitution of indices (4)–(6) into equation 8 results in the following demand system and theoretical restrictions used in the empirical analysis:

$$p_i(x) = \alpha_i + \sum_{k+1}^{N} \alpha_{ik} x_k - \beta_i \alpha(x) - \gamma_i \frac{\alpha(x)^2}{\beta(x)},\ i = 1, \ldots, N; \tag{9}$$

$$\sum_{k=1}^{N} \alpha_k g_k = 1; \tag{10}$$

[4] To preserve space, we skip further details concerning the derivation of the demand function. See Baggio and Chavas (2009) for an excellent exposition of the benefit-function approach to modeling demand, along with a discussion of its basic properties.

(11) $$\sum_{k=1}^{N} \alpha_{ik} g_k = 0,\ i = 1, \ldots, N;$$

(12) $$\sum_{k=1}^{N} \beta_k g_k = 0;$$

(13) $$\sum_{k=1}^{N} \gamma_k g_k = 0.$$

To account for spatial heterogeneity we transform equation (4) as

(14) $$\alpha(x_{rt}) = \alpha_0 + \sum_{k=1}^{N} \alpha_{krt} x_{krt} + \sum_{r=1}^{R} \sum_{i=1}^{N} \delta_{ir} D_r x_{irt} + 0.5 \sum_{i=1}^{N} \sum_{k=1}^{N} \alpha_{ik} x_{jrt} x_{krt},$$

where D_r is a space fixed effect with an associated parameter δ_{ir}. Similarly, seasonality effects can be modeled with the inclusion of $\sum_{s=1}^{S} \tau_{iS} I_S x_i$, where I_S represents a seasonality variable.

We further model lagged effects through transformation of α_{krt} in equation (14), which accounts for potential lags in the effects of price and quantity variables:

(15) $$\alpha_{krt} = \alpha_{k0} + \mu_{kt} t + \theta_k t^2 + \sum_{m=1}^{N} \alpha_{kmL} x_{mr,t-1} + \alpha_{kL} p_{kr,t-1},$$

where $x_{kmL,t-1}$ and $p_{kr,t-1}$ represent one-period lagged quantities and prices. The introduction of these new variables into the system creates an additional restriction of the weighted sum of the respective parameters (i.e., α_{k0}, μ_k, θ_k, α_{KmL}, α_{kL}) equaling zero, with weights given by g.

Concerning the choice of the reference bundle g, normal practice has been to use $g = (0, \ldots, 1, \ldots, 0)^T$ (i.e., reference is made with respect to only one good under study). Our choice of g is motivated by empirical convenience in applied demand analysis, and we use a structural framework requiring a that guarantees nonconstant prices for all products.[5] Nevertheless, it should be mentioned that the choice of g may be problem-specific.

Supply

To develop supply functions, we model a range of possible equilibrium outcomes obtained by equating firm marginal revenue and marginal cost. Marginal revenue is derived via the CV approach, using price sensitivity relations from our inverse demand system (Hyde and Perloff, 1998). The CV parameter measures the degree of competition via a firm's "conjecture" on the aggregate rival response to a unitary change in its own strategic variable (Bowley, 1924). Despite the profound impact of this method on the NEIO literature, it has been plagued with several issues. The primary criticism has been that the CV parameter does not reflect market structure and that the dynamic effects underlying the CV response functions cannot be estimated using static oligopoly models (Corts, 1999). On the contrary, Genesove and Mullin (1998) validated the precision of the CV model using historical data on the sugar-refining industry that contain detailed firm-level marginal cost information.

The menu approach, which builds on discrete-choice demand models, forms the basis for the most recent NEIO studies (e.g., Berry, 1995; Villas-Boas, 2007; Cohen and Cotterill, 2011). This

[5] For example, Baggio and Chavas (2009) use a reference bundle of the form $g = (0, \ldots, 1, \ldots, 0)^T$, which leads to the price of the first good being a vector of ones in the result of the price normalization. For this reason and the singularity of the variance-covariance matrix, they exclude the demand for the first good from the estimation. Our inclusion of the supply side, on the other hand, requires that all prices be variable.

method compares various supply scenarios—each corresponding to some game-theoretic type of firm interaction—and selects the one providing the best fit of the data. Despite its benefits, this approach requires knowledge of the institutional setting of industries, and the supply scenarios considered are not typically exhaustive. The CV approach, on the other hand, allows for a wide range of scenarios without imposing ad hoc game-theoretical structures. Moreover, CV has been the preferred model in many empirical studies. Dhar et al. (2005) (U.S. soft drink industry) and Wang, Stiegert, and Dhar (2010) (U.S. butter and margarine market) found that the CV model provided a superior fit of the data compared to all other benchmark models tested.[6] Finally, under certain assumptions, the CV approach is flexible enough to embrace dynamics in studies of competition Friedman and Mezzetti (2002); Dixon and Somma (2003); Kutlu and Sickles (2012).

Derivation of Supply Equations

Consider a market with a handful of firms that are characterized by the following profit function:

$$\pi(x) = Max_x \left[\sum_{i=1}^{n} x_i (p_i(x) - MC_i) \right], \tag{16}$$

where x_i is the quantity, $p_i(x)$ is the price, and MC_i is the marginal cost for product i.

The market equilibrium conditions obtained via the CV approach are

$$p_i + \lambda_i \sum_{j=1}^{N} \frac{\partial p_j}{\partial x_i} x_j = MC_i(x_i), \tag{17}$$

where $p_i + \lambda_i \sum_{j=1}^{N} \frac{\partial p_j}{\partial x_i} x_j$ is the "effective" marginal revenue for product i and λ_i represents the respective CV parameter.

Our inclusion of the price sensitivities for all products in equation (17) (i.e., $\sum_{j=1}^{N} \frac{\partial p_j}{\partial x_i} x_j$ instead of $\frac{\partial p_i}{\partial x_i} x_i$) reflects our assumption that all firms carry all N products under consideration. By definition, the CV parameter is given by $\lambda_i = (1+v)$, where $v = \frac{\partial X_{-i}}{\partial x_i}(X_{-i} \sum_{j \neq i} x_j)$. Economic theory provides guidance as to the possible values of λ. Specifically, $\lambda = 1$ is indicative of the monopoly market power, $\lambda = 0$ reflects a perfectly competitive market, and $\lambda = 1/n$ resembles Cournot competition, where n is the number of firms in the market. In this study, we interpret λ as an elasticity-adjusted Lerner Index; that is, $\lambda = -L\varepsilon = -\left(\frac{p-MC}{p}\right)\left(\frac{\partial p}{\partial Q}\frac{Q}{p}\right)$.

To develop supply functions, we derive price sensitivities $(\partial_j/\partial x_i)$ using the demand specification in equation (9) and substitute them into equilibrium conditions given by equation (17). Specifically, differentiating both sides of equation (9) yields

$$\frac{\partial p_j}{\partial x_i} = \frac{\partial(\sum_t \alpha_{jt} x_j)}{\partial x_i} - \beta_j \frac{\partial \alpha(x)}{\partial x_i} - \gamma_j \left[\frac{\partial(\alpha(x)^2/\beta(x))}{\partial x_i} \right], \tag{18}$$

where

$$\frac{\partial(\sum_t \alpha_{jt} x_j)}{\partial x_i} = \alpha_{ij}; \tag{19}$$

$$\frac{\partial \alpha(x)}{\partial x_i} = \alpha_i + \sum_t \alpha_{it} x_t; \tag{20}$$

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[6] Based on their results, Dhar et al. (2005) recommend using the CV approach in situations where there is no clear alternative.

$$\frac{\partial\left(\alpha(x)^2/\beta(x)\right)}{\partial x_i}=\frac{\partial\alpha(x)^2}{\partial x_i}\beta(x)^{-1}+\alpha(x)^2\frac{\partial\beta(x)^{-1}}{\partial x_i}; \tag{21}$$

$$\frac{\partial\alpha(x)^2}{\partial x_i}=2\alpha(x)\frac{\partial\alpha(x)}{\partial x_i}. \tag{22}$$

Equation (20) provides the term $\frac{\partial\alpha(x)}{\partial x_i}$.

$$\frac{\partial\beta(x)^{-1}}{\partial x_i}=(-1)\beta(x)^{-2}\frac{\partial\beta(x)}{\partial x_i}=-\beta(x)^{-2}\exp\left(\sum_{k=1}^{N}\beta_k x_k\right)\beta_i=-\beta(x)^{-1}\beta_i, \tag{23}$$

where use is made of the relationship $\beta(x)=\exp\left(\sum_{k=1}^{N}\beta_k x_k\right)$.

Substituting equations (19)–(23) into equation (18) yields price sensitivities:

$$\frac{\partial p_j}{\partial x_i}=\alpha_{ij}-\beta_j\left(\alpha_i+\sum_i\alpha_{it}x_t\right)-\frac{\gamma_j\alpha(x)}{\beta(x)}\left[2\left(\alpha_i+\sum_t\alpha_{it}x_t\right)-\beta_i\alpha(x)\right]. \tag{24}$$

Finally, our supply equations are obtained by substituting equation (24) into equation (17):

$$\begin{aligned} p_i \quad = \quad & MC_i(x_i)-\lambda_i\sum_{j=1}^{N}\left\{\alpha_{ij}-\beta_j\left(\alpha_i+\sum_t\alpha_{it}x_t\right)-\right. \\ & \left.\frac{\gamma_j\alpha(x)}{\beta(x)}\left[2\left(\alpha_i+\sum_t\alpha_{it}x_t\right)-\beta_i\alpha(x)\right]\right\}x_j. \end{aligned} \tag{25}$$

The question remains as to how we specify the marginal cost function in equation (25), $MC(x_i)$, which may also be case specific. For example, Hyde and Perloff (1998) use a linear functional form in wholesale and retail-level cost components. Our full model comprises a system of equations (9), (25), and the respective theoretical restrictions given by equations (10)–(13).[7]

An Application to the U.S. Yogurt Industry

We illustrate the empirical value of our structural framework in an econometric analysis of U.S. retail competition in the marketing of yogurt. The study is based on weekly product-level IRI data on yogurt sales and unit values from 2001 to 2006. Our product choice is driven by increased interest from the USDA and DOJ to gain insight into competition in U.S. dairy markets (U. S. Department of Justice, 2012).[8] Yogurt is the fourth largest dairy category at the retail level, and yogurt characteristics being important demand drivers (Villas-Boas, 2007).

We use five U.S. metropolitan areas as the basis for the analysis. Three of these markets stand out, with relatively high levels of retail concentration. Total market share of the three largest chains ranged from 72.3% to 87.4 % in 2001. The other two markets had relatively moderate concentration (50.2% and 54.1% in 2001). These facts create an interesting setting in which to observe the relationship between market structure and retail market power. Given the sample period of six years, we have a total of 1,560 observations (5 cities, each with 312 observations).[9]

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[7] With the inclusion of time, regional, and lagged price and quantity variables, we must consider several additional restrictions. The weighted sum of parameters associated with these new variables is set equal to 0, where the weight is given by g.

[8] Due to confidentiality, we are not allowed to disclose the manufacturer and retailer identities.

[9] We do not explicitly model the relationship between market structure and firm behavior.

Table 1. Summary Statistics

					Variation (%)	
Price (cents/4 ounces)	**Mean**	**SD**	**Min**	**Max**	**City**	**Week**
NB1 skim	36.9	3.7	19.9	46.7	9.7	10.1
NB1 fat	43.9	4.0	22.7	53.2	8.4	9.0
NB2 skim	41.8	4.8	24.5	53.1	10.3	11.6
NB2 fat	47.7	4.4	31.1	60.1	8.2	9.2
SB skim	26.9	3.2	16.2	35.1	10.3	12.1
SB fat	28.0	3.2	17.6	41.4	10.4	11.4
Quantity ($10,000 \times 4$ ounces)						
NB1 skim	3.8	4.1	0.1	19.6	105.8	107.5
NB1 fat	3.7	3.8	0.1	17.1	102.8	103.8
NB2 skim	3.8	4.4	0.2	21.2	114.7	114.5
NB2 fat	2.4	2.1	0.1	10.2	87.1	87.2
SB skim	1.1	0.9	0.1	6.2	79.3	84.3
SB fat	1.1	0.9	0.1	6.0	78.1	81.1
Brand market share (%)						
NB1	43.1	10.5	17.5	68.2	–	–
NB2	42.7	9.2	25.8	73.5	–	–
SB	14.2	11.2	2.2	50.2	–	–

Source: IRI, Years 2001–06.

The U.S. yogurt industry resembles an oligopoly at the manufacturing level, with the two largest producers accounting for 60% of total market share (Villas-Boas, 2007). For this reason, we perform a brand-level analysis and define products as a combination of brand—national brand one (NB1), national brand two (NB2), and store brand (SB)—and fat content (skim and whole).[10]

Table 1 presents descriptive statistics for the main variables. Specifically, NB1 had higher total market share (43.1%, on average) relative to NB2 (42.7%) and SB (14.2%). Additionally, NB2 yogurts are, on average, the most expensive options (41.8 and 47.7 cents per four-ounce cup, for the respective fat contents), followed by the NB1 (36.9 and 43.9 cents), and SB (26.9 and 28.0 cents). Nonfat varieties are less expensive across all brands.[11] Much of the variation in both price and quantity comes from temporal variation. Quantities also manifest tremendous variation across cities.

An important consideration in applications using the benefit function is the choice of reference bundle g Following previous studies, we assume the reference bundle contains only private goods that are constant across consumers. We also construct a nonzero reference bundle for reasons discussed previously. We use a bundle containing a unit of each product. Luenberger price functions in this context are then interpreted as consumer willingness to pay for additional units of each product in the sample.[12]

Another important demand-related issue is that the imposition of theoretical restrictions results in a singular variance-covariance matrix. That is, the application of the normalization rule $\sum_i p_i g_i = 1$ to the adjusted price functions $p_i^L = f(x_i;\Gamma) + e_i$ results in $\sum_i f(x_i;\Gamma) g_i = 1$ and $\sum_i e_i g_i = 0$. Therefore, when estimating the demand system, one equation must be omitted to avoid singularity of the

[10] We acknowledge that SBs are manufactured by NB producers, as well as by large retail chains that run their own manufacturing plants. However, here it is the potential strategic use of the different brands by large retail chains that drives our product definitions (Hovhannisyan and Gould, 2012, use similar product definitions).

[11] Yogurt prices may also be reflective of other attributes that cannot be accounted for in this application, given our aggregation method and data limitations.

[12] We also estimated the model with the underlying g differing in its elements, such as the one containing sample averages. Our choice of a unitary g in the analysis reflects its superior fit to the data.

variance-covariance matrix. The parameter values from this excluded equation are recovered from the theoretical restrictions.

To model our marginal cost function, we borrow the linear specification from Hyde and Perloff (1998):

$$MC_i(x_i) = f_i + s_i V_i + h_i W, \tag{26}$$

where V_i represents milk price, and W is retail wage. In this application, we use fluid-grade milk prices from states where the respective manufacturing plants are located.[13] Ideally, equation (26) should also include a cost component that varies across brands and reflects variation across wholesale- and manufacturer-level markups (for example, advertising costs that NB manufacturers and food retailers incur in promoting their brands). However, researchers rarely have access to fine data that provide brand-level cost variation. Therefore, the only identifying variation in the supply and demand equations in our empirical setting is due to exogenous factors, such as milk price and wage.

CV parameters (λ_i) are of key importance in the analysis. Therefore, we allow this parameter to vary not only across cities but also over time:

$$\lambda_{ij} = \lambda_{i1} + \varphi_{ij} D_j + \phi_{ij} D_j t,\ i = 1, \ldots, 6;\ j = 1, \ldots, 5, \tag{27}$$

where λ_{ij} is the CV parameter for product i in market j (λ_{i1} is the parameter for product i in the reference market), φ_{ij} accounts for the city effect, and ϕ_i represents the time effect (t is a time variable).

Finally, the identification of structural parameters is based on both the temporal and cross-sectional variation of variables. Specifically, the demand shifters include city effects, as well as lagged quantity and price variables that are exogenous to the unobserved supply shifters (i.e., obviously lagged variables are predetermined, while the regional dummies are not likely to be correlated with the supply unobservables, provided that yogurt plants are outside these regions). In addition, we use the marketing cooperative-level milk price as a supply shifter, assuming the latter is exogenous to unobserved demand shifters (for example, public mood for yogurt).

Empirical Results

We use the GAUSSX module of the GAUSS software system to estimate our model. We allow for contemporaneous correlation across equations and assume the stochastic components are serially uncorrelated.

The choice of the demand specification may have a tremendous effect on structural parameter estimates. Therefore, we perform several demand-specification tests using the Bewley likelihood ratio test (LR_B) given by $LR_B = 2(LL^U - LL^R)(En - p^U/En)$ (Bewley, 1986). Here $LL^{U,R}$ is the log-likelihood value from the unrestricted and restricted demand models, E is the number of equations estimated, n is the sample size, p^U is the number of parameters in the unrestricted model, and the degrees of freedom equals the number of additional parameters in the unrestricted model. An important advantage of LR_B over the traditional likelihood-ratio test is that no asymptotic assumptions are needed for the model selection.

Table 2 presents the joint demand test results. First, we test for nonlinear utility effects, $\gamma_i = 0$. The corresponding p-value (< 0.01) for the χ^2 test indicates that quadratic utility effects are present in the inverse demand functions. Using this specification, we find that regional heterogeneity, $\delta_{ir} = 0$, as well as lagged quantity, $\alpha_{kmL} = 0$, and price effects, $\alpha_{kL} = 0$, are important considerations with regards to yogurt demand (p-value < 0.01). Furthermore, we find that seasonality, $\tau_{is} = 0$, and nonlinear time effects, $\theta_k = 0$, only marginally affect yogurt demand. Therefore, we use this demand specification in the estimation of the full model.

[13] Milk price data are available at: http://future.aae.wisc.edu/data/monthly_values/by_area/5?tab=prices

Table 2. Model Diagnostics

Demand Models	Hypothesis	Restrictions	LLR_B	df.	p-value
Model 1	$\gamma_i = 0$	5	58.8	5	< 0.01
Model 2	$\alpha_{kmL} = 0$	35	1205.2	35	< 0.01
	$\delta_{ir} = 0$	11	174.2	11	< 0.01
	$\alpha_{kL} = 0$	6	2200.0	6	< 0.01
	$\tau_{si} = 0$	18	24.3	18	14.5
	$\theta_k = 0$	6	8.5	6	0.24

Notes: The LR_B test statistic is distributed χ^2.

We obtained 177 structural-parameter estimates from the full model using the full information maximum likelihood (FIML) procedure. Following Hyde and Perloff (1998) and Hovhannisyan and Gould (2012), we impose the restrictions of $\lambda_i \in [0,1]$. The advantage of the FIML procedure over the seemingly unrelated regressions, the limited information maximum likelihood, or other similar estimation procedures is that the former accounts for the true nature of simultaneity between the supply and demand equations. Therefore, the FIML procedure yields unbiased and consistent parameter estimates (see Dhar et al., 2005, for more on the benefits of using the FIML estimation procedure).[14]

Estimation results are presented in tables 3, A1 and A2. The model provides a good fit of the data, and most parameter estimates are statistically significant at 5% or lower levels. Furthermore, the χ^2 statistic of overall significance has an associated p-value of < 0.01. Importantly, most of the supply and demand shifters are statistically significant; which is important from the identification perspective.

Next, we use equation (27) to evaluate the elasticity-adjusted Lerner Index estimates, $\lambda = -L\varepsilon = -\left(\frac{p-MC}{p}\right)\left(\frac{\partial p}{\partial Q}\frac{Q}{p}\right)$, using λ_{i1}, φ_{ij}, and ϕ_{ij} estimates at the mean of city dummy and time variables. To compute the standard errors for λ_{ij}, $\forall\, i = 1,\ldots,N,\ j = 1,\ldots,J$ we use the delta method, which takes the sample covariance between λ_{i1}, φ_{ij}, and ϕ_{ij} into account. As illustrated in table 4, all but one Lerner Index estimate is statistically significant at the 1% level.

There is a great deal of heterogeneity in markups across the yogurt brands. Retailers appear to have charged the highest margins on NB2 skim yogurt. These markups vary from 5.5% in city 5 to 12.5% in city 3. For whole yogurt, NB1 was the source of the highest markups, which ranged from 5.8% in city 5 to 11.1% in city 3. SB yogurt was not found to be as important a source of retail profitability, given its markup range from 0% to 4.4% in cities 5 and 3 and the fact that the SB yogurt market share remains low relative to its NB counterparts (i.e., 14.2% SB market share versus 42.7% for NB2 and 43.1% for NB1). This is in contrast to the fluid milk market, where empirical evidence suggests a more important role for SB from the retailer perspective (Hovhannisyan and Stiegert, 2011). Our finding that retail markups vary across brands is consistent with retailers maximizing category profit (Vilcassim and Chintagunta, 1995).

Retail market power also showed considerable variability across cities in our sample. For example, NB margins were the highest in city 3 (from 6.5% to 12.5%) and the lowest in city 5 (3.3% to 5.8%). The same pattern was found for SB yogurt (0% to 3.1% in city 5 versus 4.4% to 4.7% in city 3). Market power increases in retail concentration, provided that cities 1–3 have more concentrated retail sectors relative to cities 4 and 5. While designing the study in a way that allows for variation in concentration may enhance the identification, a word of caution is necessary. An increase in market power cannot be attributed to higher concentration, provided that we do not explicitly model the relationship between market structure and firm behavior. Therefore, it may well be that market power is driven by other factors excluded from this study.

In a study of vertical interactions between yogurt manufacturers and retailers, Villas-Boas (2007) reports that a median retail margin of 21.1% in a supply scenario provides the best fit of the data.

[14] As shown in Hayashi (2000), FIML is also superior to the instrumental variable approach.

Table 3. Marginal Cost Parameter Estimates

Parameter	Estimate	SE	Parameter	Estimate	SE
λ_{11}	0.002	0.003	λ_{41}	0.001	0.002
φ_{12}	−0.003	0.014	φ_{42}	0.001	0.005
φ_{13}	0.024***	0.012	φ_{43}	0.025***	0.005
φ_{14}	−0.016***	0.007	φ_{44}	0.000	0.006
φ_{15}	−0.016	0.011	φ_{45}	−0.011**	0.005
ϕ_{11}	0.015***	0.005	ϕ_{41}	0.012***	0.004
ϕ_{12}	−0.036	0.033	ϕ_{42}	−0.031***	0.015
ϕ_{13}	−0.048*	0.024	ϕ_{43}	−0.034***	0.011
ϕ_{14}	0.004	0.015	ϕ_{44}	−0.020	0.013
ϕ_{15}	0.031	0.039	ϕ_{45}	−0.004	0.008
λ_{21}	0.004	0.003	λ_{51}	−0.001	0.002
φ_{22}	0.003	0.007	φ_{52}	0.000	0.004
φ_{23}	0.043***	0.007	φ_{53}	0.028***	0.005
φ_{24}	−0.004	0.006	φ_{54}	0.000	0.005
φ_{25}	−0.016***	0.007	φ_{55}	−0.009	0.007
ϕ_{21}	0.020***	0.005	ϕ_{51}	0.007	0.005
ϕ_{22}	−0.056***	0.020	ϕ_{52}	−0.021**	0.011
ϕ_{23}	−0.060***	0.015	ϕ_{53}	−0.037***	0.009
ϕ_{24}	−0.026*	0.013	ϕ_{54}	−0.010	0.011
ϕ_{25}	−0.006	0.010	ϕ_{55}	−0.011	0.018
λ_{31}	0.005	0.003	λ_{61}	0.003**	0.001
φ_{32}	−0.003	0.013	φ_{62}	−0.002	0.004
φ_{33}	0.054***	0.012	φ_{63}	0.010***	0.004
φ_{34}	−0.018***	0.008	φ_{64}	−0.004	0.005
φ_{35}	−0.023***	0.011	φ_{65}	−0.002	0.006
ϕ_{31}	0.020***	0.007	ϕ_{61}	0.009***	0.004
ϕ_{32}	−0.061*	0.033	ϕ_{62}	−0.012	0.009
ϕ_{33}	−0.065***	0.026	ϕ_{63}	0.005	0.008
ϕ_{34}	−0.004	0.015	ϕ_{64}	−0.003	0.012
ϕ_{35}	0.017	0.020	ϕ_{65}	−0.012	0.015

Notes: λ_{i1} reflects the base city, and φ_{ij} and ϕ_{ij} are city and time effects. Triple, double and single asterisks (***,**,*) indicate statistical significance at the 1%, 5%, and 10% level.

Additionally, manufacturers are found to follow the marginal cost-pricing rule with a possibility of retailers channeling a share of their profits back to the manufacturers. In a similar study, di Giacomo (2008) finds strikingly high margins for Italian yogurt retailers that extend from 43.1% to 74.9%. In addition to country differences, it is also important to keep in mind the methodological distinctions of these applications with our structural framework (discrete versus continuous demand models and the CV versus menu approach to supply modeling) when comparing our study with the respective literature.

One important result emerging from this study is that SB may not be as important for retailers when it comes to marketing yogurt as opposed to other products (see Bergès-Sennou, 2006; Barsky et al., 2003; Steiner, 2004). Consumers continue to have strong preferences for NB yogurt and, therefore, a competitive NB assortment remains key to retail success (Ailawadi, 2001; Bonanno, 2013).

Table 4. Estimates of Elasticity Adjusted Lerner Indices

	NB1		NB2		SB	
	Skim	**Fat**	**Skim**	**Fat**	**Skim**	**Fat**
City 1	0.054***	0.072***	0.076***	0.042***	0.022***	0.034***
	(0.010)	(0.008)	(0.012)	(0.008)	(0.009)	(0.009)
City 2	0.050***	0.075***	0.073***	0.043***	0.022***	0.032***
	(0.010)	(0.009)	(0.012)	(0.008)	(0.010)	(0.010)
City 3	0.075***	0.111***	0.125***	0.065***	0.047***	0.044***
	(0.011)	(0.009)	(0.012)	(0.008)	(0.009)	(0.010)
City 4	0.039***	0.068***	0.059***	0.042***	0.022***	0.032***
	(0.010)	(0.009)	(0.013)	(0.008)	(0.010)	(0.010)
City 5	0.039***	0.058***	0.055***	0.033***	0.014	0.031***
	(0.011)	(0.009)	(0.013)	(0.008)	(0.010)	(0.010)

Notes: Triple, double and single asterisks (***,**,*) indicate statistical significance at the 1%, 5%, and 10% level. Numbers in parentheses are standard errors.

Conclusion

This article develops a structural framework that can be used to examine the performance of various food industries. The methodology follows the recent developments in the NEIO literature and offers the benefits of structural analysis. We employ an inverse demand system derived from the benefit function and use the CV approach to derive firm behavioral equations, with the underlying price sensitivities obtained from this specification of demand. Our major contribution is the extension of the application of the benefit-function approach to the empirical industrial organization studies. This method allows one to gauge competition without imposing ad hoc game-theoretical structures on a firm's market interactions. Furthermore, it is not data demanding and does not require knowledge of the institutional settings of industries.

We illustrate the empirical value of our structural model in an econometric analysis of retail-market performance in the U.S. yogurt industry. Using five IRI city markets with varying degrees of retail concentration in our sample, we find that retail-market conduct in yogurt marketing is far from perfectly competitive. Moreover, retailers appear to be exploiting strong consumer preferences for NB yogurt, whereas SB yogurt remains relatively less important from a retail profitability perspective. Finally, our findings with respect to retail margins indicate lower Lerner indices relative to previous research.

One aspect of our study that may be restrictive in certain environments is our abstraction from the true dynamics underlying both consumer demand and retail competition. Given the empirical difficulties associated with modeling dynamics, this remains to be pursued in future research.

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References

Ailawadi, K. L. "The Retail Power-Performance Conundrum: What Have We Learned?" *Journal of Retailing* 77(2001):299–318.

Baggio, M., and J. P. Chavas. "On the Consumer Value of Complementarity: A Benefit Function Approach." *American Journal of Agricultural Economics* 91(2009):489–502.

Banks, J., R. Blundell, and A. Lewbel. "Quadratic Engel Curves and Consumer Demand." *Review of Economics and Statistics* 79(1997):527–539.

Barsky, R., M. Bergen, S. Dutta, and D. Levy. "What Can the Price Gap between Branded and Private Label Products Tell Us about Markups?" NBER Working Paper No. w8426, 2003.

Barten, A. P., and L. J. Bettendorf. "Price Formation of Fish: An Application of an Inverse Demand System." *European Economic Review* 33(1989):1509–1525.

Bergès-Sennou, F. "Store Loyalty, Bargaining Power and the Private Label Production Issue." *European Review of Agricultural Economics* 33(2006):315–355.

Berry, S. T. "Estimating Discrete-Choice Models of Product Differentiation." *RAND Journal of Economics* 25(1994):242–262.

———. "Automobile Prices in Market Equilibrium." *Econometrica* 63(1995):841–890.

Bewley, R. *Allocation Models: Specification, Estimation, and Applications*. Cambridge, MA: Ballinger, 1986.

Bollino, C. A. "GAIDS: A Generalized Version of the Almost Ideal Demand System." *Economics Letters* 23(1987):199–202.

Bonanno, A. "Functional Foods as Differentiated Products: The Italian Yogurt Market." *European Review of Agricultural Economics* 40(2013):45–71.

Bowley, A. L. *The Mathematical Groundwork of Economics: An Introductory Treatise*. Oxford, UK: Oxford University Press, 1924.

Bresnahan, T. F. "The Oligopoly Solution Concept Is Identified." *Economics Letters* 10(1982):87–92.

Cohen, M. A., and R. W. Cotterill. "Assessing the Impact of Retailer Store Brand Presence on Manufacturer Brands in an Equilibrium Framework." *Journal of Industrial Economics* 59(2011):372–395.

Corts, K. S. "Conduct Parameters and the Measurement of Market Power." *Journal of Econometrics* 88(1999):227–250.

Deaton, A., and J. Muellbauer. "An Almost Ideal Demand System." *American Economic Review* 70(1980):312–326.

Dhar, T., J. P. Chavas, R. W. Cotterill, and B. W. Gould. "An Econometric Analysis of Brand-Level Strategic Pricing between Coca-Cola Company and PepsiCo." *Journal of Economics and Management Strategy* 14(2005):905–931.

di Giacomo, M. "GMM Estimation of a Structural Demand Model for Yogurt and the Effects of the Introduction of New Brands." *Empirical Economics* 34(2008):537–565.

Dixon, H. D., and E. Somma. "The Evolution of Consistent Conjectures." *Journal of Economic Behavior and Organization* 51(2003):523–536.

Eales, J. S., and L. J. Unnevehr. "The Inverse Almost Ideal Demand System." *European Economic Review* 38(1994):101–115.

Friedman, J. W., and C. Mezzetti. "Bounded Rationality, Dynamic Oligopoly, and Conjectural Variations." *Journal of Economic Behavior and Organization* 49(2002):287–306.

Genesove, D., and W. P. Mullin. "Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890-1914." *RAND Journal of Economics* 29(1998):355–377.

Hayashi, F. *Econometrics*. Princeton: Princeton University Press, 2000.

Hovhannisyan, V., and B. W. Gould. "A Structural Model of the Analysis of Retail Market Power: The Case of Fluid Milk." *American Journal of Agricultural Economics* 94(2012):67–79.

Hovhannisyan, V., and K. W. Stiegert. "Vertical Channel Analysis of the U.S. Milk Market." 2011. Paper presented at the annual meeting of the AAEA, Pittsburg PA. Available online at http://ageconsearch.umn.edu/bitstream/103631/2/Paper_1_AAEA2011.pdf.

Hyde, C. E., and J. M. Perloff. "Multimarket Market Power Estimation: The Australian Retail Meat Sector." *Applied Economics* 30(1998):1169–1176.

Just, R. E., and W. S. Chern. "Tomatoes, Technology, and Oligopsony." *Bell Journal of Economics* 11(1980):584–602.

Kutlu, L., and R. C. Sickles. "Estimation of Market Power in the Presence of Firm Level Inefficiencies." *Journal of Econometrics* 168(2012):141–155.

Lau, L. J. "On Identifying the Degree of Competitiveness from Industry Price and Output Data." *Economics Letters* 10(1982):93–99.

Luenberger, D. G. "Benefit Functions and Duality." *Journal of Mathematical Economics* 21(1992):461–481.

———. *Microeconomic Theory*. New York: Oxford University Press, 1995.

Martinez, S. "The U. S. Food Marketing System: Recent Developments, 1997-2006." Economic Research Report ERR-42, U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2007. Available online at http://www.ers.usda.gov/media/196925/err42_1_.pdf.

McLaren, K. R., and K. K. G. Wong. "The Benefit Function Approach to Modeling Price-Dependent Demand Systems: An Application of Duality Theory." *American Journal of Agricultural Economics* 91(2009):1110–1123.

Nevo, A. "Identification of the Oligopoly Solution Concept in a Differentiated Products Market." *Economics Letters* 59(1998):391–395.

Steiner, R. L. "The Nature and Benefits of National Brand/Private Label Competition." *Review of Industrial Organization* 24(2004):105–127.

U. S. Department of Justice. "Agriculture and Antitrust Enforcement Issues in Our 21st Century Economy." 2012. Available online at http://www.justice.gov/atr/public/workshops/ag2010/index.html.

Vilcassim, N. J., and P. K. Chintagunta. "Investigating Retailer Product Category Pricing from Household Scanner Panel Data." *Journal of Retailing* 71(1995):103–128.

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

Wang, S. S., K. W. Stiegert, and T. P. Dhar. "Strategic Pricing Behavior under Asset Value Maximization." *Canadian Journal of Agricultural Economics* 58(2010):151–170.

Werden, G. J., and L. M. Froeb. "The Effects of Mergers in Differentiated Products Industries: Logit Demand and Merger Policy." *Journal of Law, Economics, and Organization* 10(1994):407–426.

Appendix A

Table A1. Parameter Estimates from the Inverse Demand System

Parameter	Estimate	SE	Parameter	Estimate	SE
α_1	0.569***	0.083	δ_{63}	−0.001***	0.000
α_2	0.079***	0.002	α_{11L}	0.007*	0.004
α_3	0.098***	0.001	α_{12L}	−0.003	0.006
α_4	0.108***	0.002	α_{13L}	−0.001	0.004
α_5	0.072***	0.001	α_{14L}	−0.006	0.007
α_6	0.075***	0.001	α_{15L}	−0.006	0.006
α_{11}	−0.007	0.002	α_{16L}	0.002	0.002
α_{12}	0.000	0.001	α_{21L}	−0.003***	0.000
α_{13}	0.001***	0.001	α_{22L}	0.022***	0.001
α_{14}	0.006***	0.001	α_{23L}	−0.004***	0.001
α_{15}	0.000	0.001	α_{24L}	−0.006***	0.001
α_{16}	0.001	0.001	α_{25L}	−0.008***	0.002
α_{22}	−0.028***	0.001	α_{26L}	−0.002	0.002
α_{23}	0.004***	0.000	α_{31L}	−0.003***	0.000
α_{24}	0.007***	0.000	α_{32L}	−0.007***	0.001
α_{25}	0.007***	0.001	α_{33L}	0.013***	0.000
α_{26}	0.009***	0.000	α_{34L}	−0.007***	0.001
α_{33}	−0.018***	0.000	α_{35L}	0.001	0.002
α_{34}	0.004***	0.000	α_{36L}	−0.012***	0.002
α_{35}	0.004***	0.000	α_{41L}	−0.003***	0.000
α_{36}	0.006***	0.000	α_{42L}	−0.006***	0.001
α_{44}	−0.038***	0.001	α_{43L}	−0.004***	0.000
α_{45}	0.010***	0.001	α_{44L}	0.027***	0.001
α_{46}	0.011***	0.001	α_{45L}	−0.002	0.002
α_{55}	−0.040***	0.001	α_{46L}	−0.011***	0.002
α_{56}	0.018***	0.001	α_{51L}	0.000	0.000
α_{66}	−0.045***	0.001	α_{52L}	−0.003***	0.001
β_1	−0.008***	0.003	α_{53L}	−0.002***	0.001
β_2	−0.007***	0.002	α_{54L}	−0.005***	0.001
β_3	−0.016***	0.002	α_{55L}	0.026***	0.002
β_4	−0.001	0.002	α_{56L}	−0.008***	0.002
β_5	0.013***	0.002	α_{61L}	0.001***	0.000
β_6	0.019***	0.002	α_{62L}	−0.003***	0.001
γ_1	0.001***	0.000	α_{63L}	−0.002***	0.000
γ_2	−0.001**	0.000	α_{64L}	−0.003***	0.001
γ_3	−0.001***	0.000	α_{65L}	−0.011***	0.001
γ_4	0.001	0.000	α_{66L}	0.031***	0.002
γ_5	0.000	0.000	α_{1L}	−2.420***	0.342
γ_6	0.000	0.000	α_{2L}	0.576***	0.008
δ_{12}	0.000	0.009	α_{3L}	0.446***	0.007
δ_{13}	−0.002	0.007	α_{4L}	0.474***	0.010
δ_{22}	0.000	0.000	α_{5L}	0.465***	0.008
δ_{23}	0.001	0.000	α_{6L}	0.459	0.007
δ_{32}	0.000	0.000	μ_1	0.000	0.005
δ_{33}	0.000	0.000	μ_2	0.000	0.001

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Table A1. – continued from previous page

Parameter	Estimate	SE	Parameter	Estimate	SE
δ_{42}	0.001*	0.000	μ_3	−0.001	0.001
δ_{43}	0.001***	0.000	μ_4	−0.001*	0.000
δ_{52}	0.000	0.000	μ_5	0.001	0.001
δ_{53}	0.001	0.000	μ_6	0.001	0.001
δ_{62}	−0.002***	0.000			

Notes: Triple, double and single asterisks (***,**,*) indicate statistical significance at the 1%, 5%, and 10% level.

Table A2. Parameter Estimates from Supply Equations

Parameter	Estimate	SE	Parameter	Estimate	SE
f_1	0.163***	0.001	s_4	0.020***	0.005
f_2	0.182***	0.001	s_5	−0.003	0.004
f_3	0.174***	0.002	s_6	0.002	0.004
f_4	0.190***	0.002	h_1	0.000	0.007
f_5	0.145***	0.002	h_2	0.020***	0.005
f_6	0.145***	0.002	h_3	0.022	0.013
s_1	−0.016***	0.004	h_4	0.047***	0.011
s_2	0.015***	0.004	h_5	−0.045***	0.014
s_3	−0.018***	0.005	h_6	−0.042***	0.012

Notes: f_i is the intercept, and s_i and h_i are coefficients for milk and wage. Triple asterisks (***) indicate statistical significance at the 1% level.