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# ON ENDOGENEITY OF RETAIL MARKET POWER IN AN EQUILIBRIUM ANALYSIS: A CONTROL FUNCTION APPROACH

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# ON ENDOGENEITY OF RETAIL MARKET POWER IN AN EQUILIBRIUM ANALYSIS: A CONTROL FUNCTION APPROACH

## Abstract

The endogeneity of retail market power arises in the retail pricing equation due to the correlation between margins and unobserved cost components. Nevertheless, it has long been ignored in the equilibrium analysis of retail behavior.

We address the issue via a control function approach in a new conceptual framework with consumer preferences represented by a benefit function. We further offer three test procedures to evaluate the endogeneity of retail market power.

The empirical value of the model is illustrated in an application to the US yogurt industry. Outcomes from endogeneity tests provide strong evidence for market power endogeneity. Moreover, ignoring the issue results in downward bias in retail market power.

Keywords: Market power endogeneity, control function, conjectural variation, retail conduct, benefit function.

## 1 Introduction

Literature on brand-level demand and market power studies comprises both full and limited information approaches. In the full information analysis, the researcher specifies certain structures for firm competition and estimates supply and demand simultaneously (Yang 2003). The limited information or reduced-form approach, on the other hand, remains agnostic as to the structure of the

supply side of the market, provided the difficulty of representing important institutional features of many industries in simple behavioral equations (Chintagunta et al. 2005).

An increasing number of studies using the reduced-form address price endogeneity via the instrumental variables technique; which accounts for endogeneity stemming from the simultaneous nature of price and quantity/market share. Nevertheless, the possible impact of unobserved brand characteristics (UBC) on price has largely been ignored in this line of literature until recently. Berry, Levinsohn and Pakes (1995) address this issue through a fixed effects method that works best with market-level data. More recently, Petrin and Train (2002) proposed a control function approach to control for UBC impact on price that relieves data requirements and is simple to implement. The virtue of studies based on equilibrium analysis (i.e., full information), on the contrary, is that they account for both types of price endogeneity (i.e., simultaneity, UBC correlation with price) by explicitly incorporating a firm pricing equation into the system (Chintagunta et al. 2005).

An important issue that remains unaddressed in an equilibrium analysis is the potential endogeneity of firm markup/market power.<sup>1</sup> This may result from omitted cost components in the firm pricing equations, such as those relating to various promotional activities at both the manufacturer (e.g., brand advertising) and retail level (e.g., point of purchase displays, discount coupons). For example, Steiner (1973, 1978, 1993) documents the impact of advertising on manufacturer and retail margins in a series of empirical studies, while Lal and Narasimhan (1996) develop a game-theoretical model to illustrate this relationship. Therefore, to the extent that wholesale and retail marginal cost components remain unaccounted for in firm pricing equations, markup is endogenous. This may bias estimates relating not only to markup but also coefficients for

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<sup>1</sup>Throughout the paper we use market power, margins and markups interchangeably.

cost components and the demand parameter estimates.

Despite the importance of the matter, previous literature ignored the issue due in part to limited data (see for example, Genesove and Mullin (1995), Hyde and Perloff (1998); Hovhannisyan and Gould (2012)). Furthermore, the fixed effects approach that could be used to capture the impact of unobservable factors that remain constant over time (e.g., brand equity) still leaves the possibility of markups being correlated with the changes in the unobserved cost component.

We address the markup endogeneity in a new conceptual framework using a control function approach (Villas-Boas and Winer 1999; Petrin and Train 2003). The model builds upon an inverse demand system derived from the benefit function (Luenberger 1992; Baggio and Chavas 2009) that allows for a linear relationship between prices, marginal costs and markups. It should be mentioned that linearity is crucial for the applicability of the control function approach. In addition, we suggest three test procedures that can be used to evaluate markup endogeneity.

To derive retail pricing functions, we utilize the conjectural variation approach (CV). Firm conduct is assumed constant in this setting and reflects how responsive prices are to variations in demand elasticities. Unlike many other similar studies [see for example Hyde and Perloff 1998; Dhar, Chavas and Cotterill 2005], we also model the potential dynamics in demand.

The CV approach has been used extensively in the NEIO literature. Essentially, it provides a measure of the degree of market competition via estimation of a conduct parameter. The latter reflects a firm's non-zero "conjecture" about the aggregate response of rivals to the changes in its strategic variable (Bowley 1924). The primary criticisms of the CV approach are that the key parameter estimates do not provide information about the market structure and that the underlying dynamics associated with CV response functions cannot be esti-

mated in static oligopoly models (Corts 1999). Nevertheless, the precision of the CV approach has been validated in an empirical study by Genesove and Mullin (1998) using historical data on the sugar refining industry that contain detailed firm-level marginal cost information. Dhar, Chavas and Cotterill (2005), and Wang, Stiegert, and Dhar (2010), on the other hand, found that the CV model provided a superior fit of the data, compared to all other benchmark equilibrium models tested. As for dynamics, Friedman and Mezzetti (2002), Dixon and Somma (2003) showed that the CV parameters can be used to represent steady-state equilibrium in dynamic games under bounded rationality.

We illustrate the empirical value of our model in an application to the US yogurt industry at the retail level. Investigating the competitive condition of the US food system remains a critical and policy relevant area of research given the rising concentration of food retailers and the increasing market share of store brands (SB). Both have the potential to alter important dimensions in the food system including food pricing and accessibility, product variety and quality, and the performance of food retailers, manufacturers and farmers (Martinez 2007). The analysis builds upon product-level scanner data from Information Resources Incorporated (IRI). We consider an IRI city-market given its high level of retail concentration. Our findings provide strong evidence for retail market power endogeneity. Furthermore, ignoring the issue results in a downward bias in retail market power estimates.

The rest of the paper is organized as follows. Section 2 offers an overview of the methodology that forms the basis for the analysis. Section 3 presents an application of our structural framework along with a brief discussion of some major findings. Section 4 concludes. The details concerning the derivation of retail pricing equations are provided in the Appendix.

## 2 Methodology

In this section we develop a theoretical model of equilibrium analysis that can be used to examine the performance of food industries. The methodology follows more recent developments in the NEIO literature and offers the benefits of structural analysis. The choice of the demand model is of key importance in this type of analysis since modeling of the firm market behavior relies heavily on the consumer preferences being correctly represented. Early work relied on ad hoc linear inverse demand specifications motivated in part by empirical convenience [see for example, Just and Chern 1980; Bresnahan 1982; Lau 1982]. More recent studies embrace demand models that are explicitly derived from economic theory and accommodate product differentiation. One notable example is Hyde and Perloff (1998) where the Linear Approximate Almost Ideal Demand System (LA/AIDS) of Deaton and Muellbauer (1980) is used to examine retail conduct in Australian meat markets. Hovhannisyan and Gould (2012) extended this analytical framework by incorporating the Generalized Quadratic AIDS demand (Bollino 1987; Banks, Blundell and Lewbel 1997) to study retail competition in the marketing of fluid milk in the US.

We build a theoretical framework using an inverse neoclassical demand. This simplifies the development of retail behavioral equations while retaining the advantage of consumer demand being based on economic theory. More specifically, we revisit the Luenberger (1992) benefit function approach to derive the consumer demand functions. Despite its advantages, this approach has not been widely exploited (McLaren and Wong 2009). Following Baggio and Chavas (2009), we parametrize the benefit function and use the duality results to obtain the respective uncompensated demand equations. Unlike many other similar studies, we also model the potential dynamics in demand.<sup>2</sup>

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<sup>2</sup> See for example Hyde and Perloff (1998), Dhar, Chavas and Cotterill (2005).

## 2.1 Demand

Let  $x \in R_+^N$  denote the actual consumption bundle and  $g \in R_+^N (g \neq 0)$  be some reference bundle. The inverse demand specification underlying our model is provided by Baggio and Chavas (2009) and is presented below:<sup>3</sup>

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

where  $p_i$  is the price for product  $i$ , and  $\alpha_i, \alpha_{ik}, \beta_i, \gamma_i$  are parameters. Additionally,  $\alpha(x), \beta(x), \gamma(x)$  are quantity indices as specified below:

$$\alpha(x) = \alpha_0 + \sum_{k=1}^N \alpha_k x_k + .5 \sum_{i=1}^N \sum_{k=1}^N \alpha_{ik} x_i x_k \quad (2)$$

with  $\alpha_{ik} = \alpha_{ki}, \forall i \neq k$ , implied by the Young's theorem

$$\beta(x) = \exp \left( \sum_{k=1}^N \beta_k x_k \right) \quad (3)$$

$$\gamma(x) = \sum_{k=1}^N \gamma_k x_k \quad (4)$$

Theoretical restrictions that are imposed on the system are as follows:

$$\sum_{k=1}^N \alpha_k g_k = 1 \quad (5)$$

$$\sum_{k=1}^N \alpha_{ik} g_k = 0, \quad i = 1, \dots, N \quad (6)$$

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<sup>3</sup> For further details concerning the derivation of the inverse Marshallian demand functions see Luenberger (1992, 1995); Baggio and Chavas 2009; and Chavas and Baggio 2010, and references therein.



$$\sum_{k=1}^N \beta_k g_k = 0 \quad (7)$$

$$\sum_{k=1}^N \gamma_k g_k = 0 \quad (8)$$

Dynamics is an important issue that needs to be addressed in consumer demand analysis. Two important factors behind the potential inter-temporal linkages between utilities from different periods are consumer loyalty and variety seeking. Therefore, we incorporate dynamics into the model through the quantity effect  $\alpha_{krt}$  in (1) as follows:

$$\alpha_{it} = \alpha_{i0} + \mu_i t + \theta_i t^2 + \sum_{k=1}^N \alpha_{ikL} x_{k,t-1} + \alpha_{iL} p_{i,t-1} \quad (9)$$

where  $t$  is the time variable,  $x_{ikL,t-1}$  represents one period lagged quantity, and  $p_{i,t-1}$  is one period lagged prices.

Substituting (9) into (1) yields our empirical specification of the inverse consumer demand which is presented in a stochastic form:

$$p_{it}(x) = \alpha_{i0} + \mu_i t + \theta_i t^2 + \sum_{k=1}^N \alpha_{ikL} x_{k,t-1} + \alpha_{iL} p_{i,t-1}$$

$$+ \sum_{k=1}^N \alpha_{ik} x_{kt} - \beta_i \alpha(x) - \gamma_i \frac{\alpha(x)^2}{\beta(x)} + e_{it}, \forall i = 1, \dots, N, t = 1, \dots, T \quad (10)$$

where  $e_{it}$  is a stochastic component of the equation (10) with  $E[e_{it}] = 0$ .

The introduction of this new set of variables into the system yields additional theoretical restrictions. Specifically, the translation property implies that the weighted sum of the respective parameters (i.e.  $\alpha_{k0}, \mu_k, \theta_k, \alpha_{kmL}, \alpha_{kL}$ ) equals zero, where the weights are given by  $g$ .

We complete our review of the demand side by a discussion concerning the choice of a reference bundle  $g$ . The normal practice in the literature has been the use of a reference bundle in the form of  $g = (0, \dots, 1, \dots, 0)^T$  (i.e. reference is made with respect to only one good under study). Whereas this choice of  $g$  has been motivated by empirical convenience in the applied welfare analysis, our use of a structural framework requires a  $g$  that guarantees non-constant prices for all products.<sup>4</sup>

Nevertheless, it should be mentioned that the choice of  $g$  may vary depending on the specific problem at hand. Section 3 of this article presents  $g$  that is used in the empirical analysis.

## 2.2 Supply

To derive firm supply relations, consider a market with a handful of firms characterized by the following objective function:

$$\pi(x) = \text{Max}_x \left[ \sum_{i=1}^N x_i (p_i(x) - m_i) \right] \quad (11)$$

where  $m_i$  is the marginal cost for product  $i$  that is assumed exogenous and independent of scale.<sup>5</sup>

Market equilibrium is characterized by the following firm optimality relations

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<sup>4</sup> For example, Baggio and Chavas (2009) use a reference bundle of the form  $g = (1, 0, \dots, 0)^T$ , which leads to the price of the first good being a vector of ones in the result of price normalization. Due to this reason and the singularity of the variance-covariance matrix, they exclude demand for the first good from the estimation. Our inclusion of the supply side into the estimation, on the other hand, requires that all prices be variable.

<sup>5</sup> This has been a standard assumption in this line of literature.

that embrace a range of competitive scenarios (Hyde and Perloff 1998):

$$p_j + \lambda_j \sum_{k=1}^N \frac{\partial p_k}{\partial x_j} x_k = m_j, \quad j = 1, \dots, N \quad (12)$$

where  $p_j + \lambda_j \sum_{k=1}^N \frac{\partial p_k}{\partial x_j} x_k$  is the “effective” marginal revenue associated with product  $j$ , and  $\lambda_j$  represents the CV parameter.

As maintained by many game theorists, not all the possible values of the CV parameter find support from economic theory. In addition, being static in nature, the CV parameter may not be an appropriate way to represent competition in dynamic environments (Perloff, Karp and Golan 2007). The early NEIO literature offered an alternative interpretation of  $\lambda$  viewing it as a price over marginal cost markup adjusted by the elasticity of demand, i.e.  $\lambda = -L\varepsilon = -\left(\frac{p-MC}{p}\right) \left(\frac{\partial p}{\partial Q} \frac{Q}{p}\right)$ . Corts (1999) critiqued this definition of the CV parameter arguing that the latter is unbiased only if it is a result of the CV equilibrium.

In the face of these challenges, our use of the CV approach relies upon the assumption of bounded rationality that underlies works by Friedman and Mezzetti (2002), Dixon and Somma (2003) and other similar studies that validate this approach, as discussed above.

The empirical counterparts of the retail pricing functions in (12) are developed next. For that purpose, we derive the price sensitivities (i.e.  $\frac{\partial p_j}{\partial x_i}$ ) using the inverse demand specification in (10) and substitute them into (12). This yields us the following retail pricing equations that are linear in marginal cost and markup:

$$p_j = m_j - \lambda_j \sum_{i=1}^N \left\{ \alpha_{ij} + \beta_j (\alpha_i + \sum_t \alpha_{it} x_t) - \right.$$

$$\frac{\gamma_j \alpha(x)}{\beta(x)} \left[ 2 \left( \alpha_j + \sum_t \alpha_{jt} x_t \right) - \beta_j \alpha(x) \right] \} x_i \quad (13)$$

Subsection 5.2 in the Appendix provides the details concerning the derivation of (13).

As will be explained below, the assumption of marginal cost  $m_j$  being a linear function of wholesale and retail-level cost components is critical for addressing retail markup endogeneity via the control function approach.

Our full model comprises a system of behavioral equations given by (10) and (13) that describe consumer behavior and retail market conduct, respectively, and restrictions from economic theory as presented in (5)-(8).<sup>6</sup>

Finally, as can be seen from the system, all the structural parameters including  $\lambda_i$  are identified.

## 2.3 Endogeneity of Retail Market Power

### 2.3.1 A Control Function Approach to Retail Market Power Endogeneity

In this section, we present a more detailed discussion concerning our argument for markup endogeneity, as well as the approach we propose to address the problem.

Let retail and wholesale marginal costs and markups be represented by  $c_{ri}$ ,  $c_{wi}$  and  $MK_{ri}$ ,  $MK_{wi}$ , respectively. Consider the retail pricing equation provided below:

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<sup>6</sup> As discussed above, with the inclusion of time, lagged price and quantity variables we need to consider several additional restrictions (i.e. the weighted sum of parameters associated with these new variables is set equal to zero, where the weight is given by  $g$ ).

$$p_i = c_{ri} + MK_{ri} \quad (14)$$

where the retail marginal cost comprises the wholesale marginal cost and markup components, i.e.  $c_{ri} = c_{wi} + MK_{wi}$ .

Typically, a researcher only partially observes both  $c_r$  and  $c_w$  and relies on consumer demand estimates to infer  $MK_r$  (Aguirregabiria and Nevo 2010). Specifically, the retail marginal costs are normally represented by a brand-specific linear function of cost shifters (Hyde and Perloff 1998; Yang et al. 2003) as provided below:

$$c_{ri} = Z_i^T \delta_j + \eta_i \quad (15)$$

where  $Z_i$  are wholesale and retail level cost shifters and  $\eta_i$  represents the unobservable supply shifters.

Substituting (15) into (14) gives rise to the supply function used in a typical empirical application (see for example, Hovhannisyan and Gould 2012):

$$p_i = Z_i^T \delta_j + MK_{ri} + \eta_i \quad (16)$$

Given limited data, the manufacturer brand advertising and various weekly promotional activities at the retail level find their reflection in  $\eta_i$ . To the extent that these unobservable components of the pricing equation ( $\eta_i$ ) affect retail markup ( $MK_{ri}$ ), the latter is endogenous. Marketing literature offers ample evidence on brand promotion having an important impact on both manufacturer and retail markups, therefore providing empirical support for markup endogeneity in equilibrium analysis (see for example Steiner (1973, 1978, 1993); Lal and Narasimhan 1996).

To get a sense of the size and direction of the bias in the market power, we

consider a single pricing equation abstracting from consumer demand. Specifically, we assume that the correct specification for the retail pricing equation is a linear function of wholesale and retail level cost shifters  $Z_{i2}$  and  $Z_{i3}$ , respectively, as provided below:

$$p_i = b_1 + b_2 Z_{i2} + b_3 Z_{i3} + b_4 Z_{i4} + \epsilon_i \quad (17)$$

We further assume that, given our limited data, we estimate the following misspecified model:

$$p_i = b_1 + b_2 Z_{i2} + b_3 Z_{i3} + \epsilon_i^* \quad (18)$$

where  $\epsilon_i^* = b_4 Z_{i4} + \epsilon_i$ .

With  $E[\epsilon_i] = 0$ , we get the following OLS estimate for  $b_2$ :  $E[\hat{b}_2] = b_2 + b_4 g_{42}$  where  $g_{42} = \frac{r_{42} - r_{32} r_{43}}{(1 - r_{32}^2)} \sqrt{\frac{V_4}{V_2}}$  is the regression coefficient on  $Z_4$  in the auxiliary regression of the excluded variable  $Z_4$  on the included variables  $Z_2$  and  $Z_3$ , and  $r$  and  $V$  represent the respective correlation coefficient and variance, respectively. Thus, the size of the bias depends on the magnitude of an excluded coefficient,  $b_4$ , the correlation between the included and excluded variables,  $r_{42}$ ,  $r_{43}$  and the included variables  $r_{32}$  and variances of  $Z_2$  and  $Z_4$ . Therefore, we have no guidance as to the direction and magnitude of the markup bias caused by the excluded cost components in the pricing equation.

To resolve the markup endogeneity resulting from its potential correlation with unobserved shifters in the retail pricing function, we employ a control function approach offered by Villas-Boas and Winer (1999), Petrin and Train (2003). Specifically, we regress the markups on brand fixed effects and use the residuals from these regressions to condition out the part of the unobserved cost components that are correlated with retail markups:

$$p_{it} = Z_{it}^T \delta_j + MK_{ri} + \psi_i^T \xi_{it} + \nu_{it} \quad (19)$$

where  $\eta_i = \psi_i^T \xi + \nu_i$ ,  $\xi_i = MK_{ri} - [B_i^T B_i]^{-1} B_i^T MK_{ri}$  with  $B_i$  representing a matrix of brand fixed effects and  $\xi_i$  is the residual from the regression of markups on the brand fixed effects.

Unlike a typical use of the control function in a limited information setting, where prices are regressed on cost components in the first stage and the residuals from this regression are used in demand to control for unobserved brand characteristic impacts on price, our use of the simultaneous system of supply and demand in a full information/equilibrium framework requires that we estimate all structural parameters in one stage.

### 2.3.2 Test Procedure for Market Power Endogeneity

Retail market power endogeneity in an equilibrium framework is of central importance in the present study. Therefore, we adopt two test procedures that have been used in the consumer demand literature to evaluate markup endogeneity. Moreover, we employ an adjusted likelihood ratio test that accounts for small sample size.

The first procedure offers a direct, but somewhat ad hoc, approach developed by Villas-Boas and Winer (1999) and Blundell and Robin (2000). This essentially underlies the idea of a control function approach to address endogeneity in a limited information setting. More specifically, controls in the form of residuals from the regression of an endogenous variable (i.e., price) on a set of exogenous variables (i.e., exogenous supply shifters) are used in demand functions to control for price endogeneity resulting from UBCs. In our full information framework, as presented above, the endogenous variable of interest is the retail markup and brand fixed effects are used as exogenous shifters. We

interpret the finding of significant parameter estimates for the controls in the firm pricing equations as an evidence of market power endogeneity, given that unexplained variation in the markups co-varies with price.

An alternative approach suggested by LaFrance (1993) builds upon the Durbin-Wu-Hausman test statistic (DWH) that tests for consistency of parameter estimates. Essentially, it measures the difference between the parameter estimates from a model ignoring endogeneity and the one addressing the issue. In this setting, the null hypothesis maintains that parameter estimates are consistent without controlling for markup endogeneity, while the alternative hypothesis points to markups being endogenous.

With  $\Phi_{EX}$ ,  $\Phi_{EN}$  denoting vectors of parameter estimates from the models that control for and ignore endogeneity, respectively, the DWH test statistic is specified below:

$$H = (\Phi_{EX} - \Phi_{EN}) [\text{var}(\Phi_{EX}) - \text{var}(\Phi_{EN})]^{-1} (\Phi_{EX} - \Phi_{EN}) \quad (20)$$

It can be shown that  $H$  follows  $\chi^2(h)$  distribution asymptotically with  $h$  denoting the number of endogenous variables in the model.

Finally, we use the Bewley likelihood ratio test ( $LLR_B$ ) to evaluate whether the model treating markup endogeneity provides significant improvement in explanatory power over the standard model (Bewley 1986). The respective test statistic for ( $LLR_B$ ) is given by  $LR_B = 2 (LL^U - LL^R) (EN - p^U/EN)$ , where  $LL^{U,R}$  are the log likelihood values from the unrestricted and restricted demand models, respectively,  $E$  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  $LLR_B$  over the traditional likelihood ratio test is that it adjusts for small sample size. As with the DWH test, rejec-



tion of the null hypothesis implies that market power is endogenous.

### 3 An Application to the US Yogurt Industry

We illustrate the empirical value of our structural model in an application to the US yogurt industry. More specifically, we examine the competition in the retail sector of the yogurt industry using weekly product-level data on yogurt sale and unit values from the IRI. Yogurt is the fourth biggest dairy category at the retail level with yogurt characteristics being important demand drivers (Villas-Boas 2007).<sup>7</sup> These facts, combined with a recent effort on the part of the USDA and Department of Justice (DOJ) to better understand competition in dairy markets, motivate our choice of yogurt (US DOJ 2011).

We use a US Midwestern metropolitan area as the basis for our analysis. The market examined has a high level of retail concentration, with the three largest retail chains accounting for 72.3 % of total sales in 2001. Furthermore, all major retailers in this city remained active in the entire study period.<sup>8</sup> This features make the chosen market an interesting setting to test the relationship between market structure and retail performance.

Manufacturer brands considered include national brand 1 (NB1), national brand 2 (NB2), and store brand (SB). The sample period covers 2001 through 2006. Defining products in this way results in a total number of observations equaling 936 (312 (i.e., 6x52) observations for a given brand).

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<sup>7</sup> As illustrated in Baggio and Chavas (2009), the benefit function is an appropriate model for settings where demand is largely driven by the product attributes

<sup>8</sup> Due to confidentiality restrictions, we are not allowed to disclose the manufacturer and retailer identities.

Given the vast variety of yogurt products, we follow Bonnano (2012) and aggregate products into three groups, i.e. white, fruit-flavored, and other-flavored. Analysis is carried out at the brand-level provided that yogurt manufacturing in the US resembles an oligopoly with two leading producers enjoying over 60 % of total yogurt sales domestically (Villas-Boas 2007). Store brands, on the other hand, are believed to have become an important competitive tool for retailers against rival chains and wholesalers (Steiner 2004). Unfortunately, we are not able to incorporate fat content into the product definition due to data limitation.<sup>9</sup>

Table 1 presents the descriptive statistics on the main variables used in the analysis. It can be seen that NB1 yogurt enjoys higher mean aggregate market share (49.6 %) relative to NB2 (43.3 %), and SB yogurts (7.0 %). Meanwhile, NB2 yogurt is, on average, the most expensive option (42.2, 45.9, and 43.5 cents per 4 ounce cup, for the white, fruit flavored and other flavored yogurt, respectively), followed by the NB1 (34.4, 43.3 and 38.9 cents), and SB products (26.4, 28.2 and 26.7 cents). It should be mentioned that yogurt prices may be reflective of other attributes that cannot be accounted for in this application, given our aggregation method.<sup>10</sup> Furthermore, the empirical distribution of the container size may be another important factor underlying yogurt prices that is omitted from the analysis.

An important consideration in applications using the benefit function is the choice of the reference bundle  $g$ . Following previous studies, we assume the

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<sup>9</sup> Not all store brands in question carry white, fruit flavored and other flavored yogurts, with different fat contents each week.

<sup>10</sup> In fact, many important yogurt characteristics (such as organic) are either unobserved or only partially observed in our IRI dataset.

reference bundle contains only private goods that are constant across consumers. Nevertheless, we include more than one product in  $g$  for the reasons discussed earlier. To be more specific, we construct our reference bundle in a way that the benefit function reflects consumer willingness to pay for a marginal increase in each product, i.e.  $g = (1, 1, 1)$ .<sup>11</sup> As discussed in Baggio and Chavas (2009), the inverse Marshallian demands are then obtained by deflating the sample unit values by a factor of  $\sum_i p_i g_i$ .

Another important demand related issue is that 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 demand systems, one equation must be omitted to avoid singularity of the variance-covariance matrix. The parameter estimates from this excluded equation are recovered from the theoretical restrictions.

Finally, we need to address the choice of the  $m_j$  functional form. A standard assumption in the literature is to assume that marginal cost is a linear function of manufacturer and retail cost components. As discussed above, this is required for the applicability of the control function approach.

$$m_{jt} = f_j + s_j M_{jt} + h_j W_t, \forall j = 1, \dots, N, t = 1, \dots, T_1 \quad (21)$$

where  $M_{jt}$  represents wholesale milk price for the states where the respective manufacturer plants are located, and  $W_t$  is retail-level wage.<sup>12</sup>

<sup>11</sup> Unlike the previous studies, we cannot use  $g = (1, 0, 0)$ , as it results in the price for the first product to be a vector of ones. While the demand equation for this product is dropped from the system for singularity, the respective supply equation cannot be estimated with a constant price vector.

<sup>12</sup> Milk price data are available at: [http://future.aae.wisc.edu/data/monthly\\_values/by\\_area/6?](http://future.aae.wisc.edu/data/monthly_values/by_area/6?)

In this application we use fluid grade milk prices, given that other milk prices do not provide cross-sectional variation (e.g. federal order class prices). For similar reasons, Villas-Boas (2007) also uses the fluid grade milk price to instrument yogurt prices in the US. Ideally, (21) should also include a cost component that varies across the NB and SB yogurts and reflects the variation across wholesale/manufacturer-level markups (for example, advertising costs that NB manufacturers and food retailers incur promoting their yogurt brands). Nevertheless, researchers rarely observe this kind of fine data providing brand-level variation on the cost side. Despite this reality, our use of the control function method accounts for all brand-level unobservables in the retail pricing functions, both those that are constant, and those that vary over time.

The estimates of conduct parameters  $\lambda_i$  are of key importance in the analysis. We model this measure in a way that allows for variation across the brands considered. Specifically, the brand specific CV measures are modeled as given below:

$$\lambda_i = \lambda_{i1} + \sum_{j=2}^n \lambda_{ij} brand_j, \quad i = 1, \dots, 3 \quad (22)$$

where  $\lambda_{i1}$  is the CV parameter for the reference brand of yogurt (i.e.,  $\lambda_{11}$ ,  $\lambda_{21}$ ,  $\lambda_{31}$  are the respective parameters for NB1 plain, other flavored and fruit yogurt),  $brand_j$  is an indicator variable that is one for observations corresponding to the brand  $j$ , and is zero otherwise, and  $\lambda_{ij}$  represents the difference between the brands for the  $i$  type of yogurt (for example,  $(\lambda_{11} + \lambda_{12})$  and  $(\lambda_{11} + \lambda_{13})$  are the respective NB2 and SB parameters for plain yogurt).<sup>13</sup>

Finally, identification of the structural parameters relies upon temporal variation. As already discussed, the demand shifters include lagged quantity and

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<sup>13</sup> $i = 1, 2, 3$  indicates plain, other flavored and fruit flavored yogurts, respectively, and  $j = 2, 3$  reflects NB2 and SB, respectively.

price variables exogenous to the unobserved supply shifters. In addition, we use the milk price as a wholesale-level supply shifter assuming the latter is exogenous to the unobserved demand shifters.

### 3.1 Empirical Results

We use the GAUSSX module of the GAUSS software system to estimate the system of equations. More specifically, we use Newton-Raphsen and Gauss-Newton algorithms assuming that stochastic components in the system of equations are serially uncorrelated, meanwhile allowing for contemporaneous correlation across the equations. Dynamics in consumer demand for yogurt are captured through incorporation of lagged quantities of all products and lagged own price into the respective demand functions.

Table 2 presents the joint demand test results. Using  $LLR_B$ , we first test for nonlinear utility effects (i.e.,  $\gamma_i = 0$ ). The corresponding p-value (0.00) for the  $\chi^2$  test indicates that quadratic utility effects may be present in the inverse demand functions. We further find that dynamic effects (i.e.,  $\alpha_{kmL} = 0$ ) are important factors affecting yogurt demand (i.e., p-value is 0.00). Finally, time (i.e.,  $\mu_k = 0$ ) is found to be statistically significant while square effect (i.e.,  $\theta_k = 0$ ) is insignificant at the standard levels of significance. Therefore, we use this demand specification and the respective retail pricing equations in further empirical analysis.

A total of 51 structural parameter estimates from the full model were obtained via the full information maximum likelihood (FIML). Following Hyde and Perloff (1998), Hovhannisyan and Gould (2012), we impose the restrictions of  $\lambda_i \in [0, 1]$  as suggested by economic theory. 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. It further controls for the UBC impact on yogurt price and quantity (Yang et al. 2003). Therefore, the FIML procedure yields unbiased and consistent parameter estimates [see Dhar, Chavas and Cotterill (2005) for more on the benefits of using the FIML estimation procedure].<sup>14</sup> Furthermore, we use a control function approach to account for the potential endogeneity of retail markups.

Estimation results are presented in Tables A.1 and A.2. The model shows a good fit to the data with most parameter estimates being statistically significant at 5 % and lower levels of significance. Furthermore, the p-value for the  $\chi^2$  statistic of overall significance is less than 0.01. Importantly, most of the supply and demand shifters are statistically significant; which is important from the identification perspective.

#### *Results of Retail Markup Endogeneity Tests*

We performed three tests for retail markup endogeneity as described in 2.3.2. The first one is based on the t-values for coefficients of the controls used in the retail pricing equations, i.e.  $\psi_i, i = 1, 2, 3$ . Specifically, we find that all three coefficients are statistically significant at one percent significance level (associated p-values are zero) and are close to one in magnitude. As for the DWH test, the respective test statistic is 3,749 with the p-value being zero. This implies that the null hypothesis of exogenous markups may be strongly rejected. Finally, we find similar results from the  $LLR_B$  test (test statistic value is 4,195 with zero p-value). Summarizing the results from all three test procedures, we find a strong evidence for retail markup endogeneity. Consequently, ignoring markup endogeneity biases not only markups in retail pricing equations, but also the coefficients for cost components demand equations.

We make use of  $\lambda_{i1}, \lambda_{ij}, \forall i = 1, 2, 3, \forall j = 2, 3$  estimates to compute the

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<sup>14</sup>As shown in Hayashi (2003, p. 482), the FIML is also superior to the instrumental variable approach.

estimates for the elasticity adjusted Lerner Index which are subsequently used to obtain the Lerner Index parameter estimates across brands and yogurt types (i.e.,  $L = -\lambda/\varepsilon$  with  $L = (p - m)/p$ ) with the latter evaluated at the sample mean data points. In addition, we bootstrap the standard errors for Lerner Index estimates assuming the ratio  $\lambda/\varepsilon$  is defined and using the following formula:  $var(L) = E[\lambda^2/\varepsilon^2] - [E[\lambda/\varepsilon]]^2$ .

As shown in Table 3, the majority of Lerner Index estimates are statistically significant except for white yogurt. Moreover, retailers are found to charge higher markups for fruit flavored yogurts relative to those with other flavors. An important finding to note is that there is a great deal of heterogeneity in markups across yogurt brands. This is in line with findings from Vilcassim and Chintagunta (1995); which finds that category profit maximizing implies different markups across yogurt brands. Finally, retail market power for SB lags behind that for NB2 yogurts and varies from 6.5 % to 10.6 %.

We also estimate the model without controlling for markup endogeneity and compute the respective markups across brands and yogurt types. All of these estimates are found to be close to zero. Therefore, it appears that accounting for the unobservable manufacturer and retail cost components in the retail pricing equation has a favorable impact on both retail price and markup. This finding is consistent with microeconomics theory and the results from several empirical studies (see for example, Ferguson (1982), Pindyck and Rubinfeld (1989)) where advertising is argued to affect market power favorably through increased product differentiation that results in higher retail prices and margins. In a series of studies on non-durable goods, on the contrary, Steiner (1978, 1984, 1993) shows that manufacturer promotional activities may lead to diminishing retail margins due to the following reasons. First, heavily advertised brands are more “identifiable” from the consumer perspective and serve as a benchmark for across

retail price comparisons. Therefore, it may be in the retailer's best interest to keep prices for these items relatively low. Furthermore, well-promoted brands are normally more sought-after on the market which gives manufacturers more leverage to raise wholesale prices.

An important implication of the present study is that ignoring potential endogeneity of retail markups in equilibrium studies may result in unreliable market power estimates. More specifically, retailers have been found to be almost perfectly competitive in the previous literature that relies on the assumption of exogenous retail market power (see for example, Gollop and Roberts 1979; Appelbaum 1982; Roberts 1984; Genesove and Mullin 1998; Hyde and Perloff 1998; Hovhannisyan and Gould 2012). More importantly, ignoring market power endogeneity, when unobservable wholesale and retail cost components do in fact co-vary with retail markups, biases not only the estimates of marginal cost function, but may also contaminate the demand side parameter estimates (Chintagunta et al. 2005) leading to erroneous policy implications.

## 4 Conclusions

This article provides a theoretical framework that can be used to examine retail market performance in an equilibrium analysis. The methodology follows more recent developments in the NEIO literature and offers the benefits of structural analysis. We employ an inverse demand model derived from the benefit function and develop the retail pricing equations using the CV approach. We also allow for potential dynamics in the demand that may result from inter-temporal linkages between utilities from different periods.

We maintain that retail market power is endogenous in a full information framework provided that manufacturer and retail unobservable promotional activities are correlated with retail margins. To account for both constant and



time varying unobservables, we propose a control function approach. Finally, we suggest test procedures that can be used to evaluate market power endogeneity.

The empirical value of our model is illustrated in an application to the US yogurt industry. Our findings provide strong empirical support for retail market power endogeneity. Furthermore, we find that ignoring the issue may result in a downward bias in retail market power. For comparison, a huge body of literature assuming exogenous margins reports almost perfect retail competition.

One feature of this study that may be restrictive in certain environments is that the supplier relations are of a static nature, while dynamics may be present due to both fundamental and strategic reasons. Given the empirical difficulties associated with dynamic supply analysis, it remains to be pursued in our future research efforts.

Table 1. Summary Statistics

	Price (Cents/ 4ounces)				Quantity (4 ounces x 1000)				Share (%)
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean
NB1									49.6
White	34.4	2.6	29.2	41.4	25.0	3.0	17.6	33.4	
Other flavored	38.9	3.0	28.4	47.8	40.2	7.5	19.4	59.9	
Fruit	43.3	3.7	30.1	52.8	146.5	32.5	57.9	230.9	
NB2									43.3
White	42.2	3.9	28.5	52.4	45.8	14.1	22.6	93.0	
Other flavored	43.5	3.4	35.5	55.5	40.2	10.2	18.0	73.4	
Fruit	45.9	3.0	37.8	51.9	87.6	21.7	39.3	164.4	
SB									7.0
White	26.4	2.0	19.7	33.2	4.0	2.0	0.4	9.2	
Other flavored	26.7	2.3	20.1	33.8	7.4	3.1	0.9	17.2	
Fruit	28.2	2.8	20.4	34.5	34.8	12.2	7.2	73.7	

Source: Authors' calculations based on IRI Infoscan data, 2001-06.

Table 2. Model Diagnostics

Hypothesis	Restrictions	$LLR_B$	df.	p-value
(a) No nonlinear utility effects (i.e., $\gamma_i = 0, \forall i = 1, \dots, n$ )	3	3,964	3	<0.01
(b) No quantity dynamics (i.e., $\alpha_{kmL} = 0$ )	9	18,557	9	<0.01
(c) No time effect (i.e., $\mu_k = 0$ )	3	11,808	3	<0.01
(d) No time square effect (i.e., $\theta_k = 0$ )	3	5.4	3	0.15

Table 3. Retail Lerner Index ( $\frac{p-c}{c}$ ) Estimates for Yogurt Types (%)

	NB1	NB2	SB
White	2.8	16.4	9.1
Other flavored	3.4***	18.4 ***	6.5*
Fruit flavored	21.3***	18.6 ***	10.6 ***

Note: \*\*\* - 1%, \*\* - 5%, \* - 10% level of significance.

## 5 Appendix

### 5.1 Tables

Table A.1. Estimation Results for Consumer Demand Parameters

Parameter	Estimate	SE	Parameter	Estimate	SE
$\alpha_1$	0.366***	0.149	$\alpha_{1L}$	-0.174	0.259
$\alpha_2$	0.279***	0.003	$\alpha_{2L}$	0.171***	0.009
$\alpha_3$	0.355***	0.001	$\alpha_{3L}$	0.003	0.002
$\gamma_1$	0.006***	0.007	$\alpha_{11}$	-0.013***	0.004
$\gamma_2$	-0.002***	0.001	$\alpha_{12}$	0.009***	0.001
$\gamma_3$	-0.004***	0.001	$\alpha_{13}$	0.004***	0.001
$\alpha_{11L}$	0.574***	0.096	$\alpha_{22}$	-0.015***	0.001
$\alpha_{12L}$	-0.509***	0.111	$\alpha_{23}$	0.006***	0.001
$\alpha_{13L}$	-0.065	0.278	$\alpha_{33}$	-0.011***	0.001
$\alpha_{21L}$	-0.012***	0.002	$\beta_1$	-0.023	0.017
$\alpha_{22L}$	0.020***	0.002	$\beta_2$	0.004	0.004
$\alpha_{23L}$	-0.008***	0.002	$\beta_3$	0.018***	0.003
$\alpha_{31L}$	0.005***	0.001	$\mu_1$	0.001	0.005

$\alpha_{32L}$	-0.003***	<i>0.001</i>	$\mu_2$	-0.001***	<i>0.000</i>
$\alpha_{33L}$	-0.002	<i>0.003</i>	$\mu_3$	0.001***	<i>0.000</i>

Note: \*\*\* - 1%, \*\* - 5%, \* - 10% level of significance.

Table A.2. Estimation Results for Retail Pricing Equation Parameters

Marginal cost function			CV Parameters		
Parameter	Estimate	SE	Parameter	Estimate	SE
$f_1$	0.288***	<i>0.005</i>	$\lambda_{11}$	0.045	<i>0.106</i>
$f_2$	0.369***	<i>0.004</i>	$\lambda_{12}$	0.024*	<i>0.012</i>
$f_3$	0.343***	<i>0.003</i>	$\lambda_{13}$	0.874	<i>1.057</i>
$s_1$	0.056***	<i>0.005</i>	$\lambda_{21}$	0.706***	<i>0.180</i>
$s_2$	-0.041***	<i>0.005</i>	$\lambda_{22}$	0.294	<i>0.313</i>
$s_3$	-0.015***	<i>0.002</i>	$\lambda_{23}$	0.294	<i>1.036</i>
$h_1$	0.107***	<i>0.033</i>	$\lambda_{31}$	0.671***	<i>0.195</i>
$h_2$	-0.219***	<i>0.025</i>	$\lambda_{32}$	-0.570***	<i>0.188</i>
$h_3$	0.111***	<i>0.018</i>	$\lambda_{33}$	0.329	<i>1.102</i>
Estimates of Controls for Markup Endogeneity					
$\psi_1$	0.966***	<i>0.039</i>	$\psi_3$	1.008***	<i>0.004</i>
$\psi_2$	1.001***	<i>0.001</i>			

Note: \*\*\* - 1%, \*\* - 5%, \* - 10% level of significance.

## 5.2 Derivation of Retail Pricing Equations

To derive the supplier functions we need to derive the price sensitivities from the demand function (10) and substitute them into firm optimality conditions in (12). Differentiating both sides of (10) yields the following:

$$\frac{\partial p_j}{\partial x_i} = \frac{\partial (\sum_t \alpha_{jt} x_j)}{\partial x_i} + \beta_j \frac{\partial \alpha(x)}{\partial x_i} - \gamma_j \left[ \frac{\partial (\alpha(x)^2 / \beta(x))}{\partial x_i} \right] \quad (23)$$

where

$$\frac{\partial (\sum_t \alpha_{jt} x_j)}{\partial x_i} = \alpha_{ij} \quad (24)$$

$$\frac{\partial \alpha(x)}{\partial x_i} = \alpha_i + \sum_t \alpha_{it} x_t \quad (25)$$

$$\frac{\partial (\alpha(x)^2 / \beta(x))}{\partial x_i} = \frac{\partial \alpha(x)^2}{\partial x_i} \beta(x)^{-1} + \alpha(x)^2 \frac{\partial \beta(x)^{-1}}{\partial x_i} \quad (26)$$

and

$$\frac{\partial \alpha(x)^2}{\partial x_i} = 2\alpha(x) \frac{\partial \alpha(x)}{\partial x_i} \quad (27)$$

with  $\frac{\partial \alpha(x)}{\partial x_i}$  defined as in (25).

$$\frac{\partial \beta(x)^{-1}}{\partial x_i} = (-1)\beta(x)^{-2} \frac{\partial \beta(x)}{\partial x_i} = -\beta(x)^{-2} \exp\left(\sum_{k=1}^N \beta_k x_k\right) \beta_i = -\beta(x)^{-1} \beta_i \quad (28)$$

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

Substitution of all the derivatives in the respective order yields the price sensitivities:

$$\frac{\partial p_j}{\partial x_i} = \alpha_{ij} + \beta_j \left( \alpha_i + \sum_t \alpha_{it} x_t \right) - \frac{\gamma_j \alpha(x)}{\beta(x)} \left[ 2 \left( \alpha_i + \sum_t \alpha_{it} x_t \right) - \beta_i \alpha(x) \right] \quad (29)$$

Finally we substitute (29) into (12) to obtain supply functions:

$$p_i = mc_i(x_i) - \lambda_i \sum_{j=1}^N \left\{ \alpha_{ij} + \beta_j \left( \alpha_i + \sum_t \alpha_{it} x_t \right) - \frac{\gamma_j \alpha(x)}{\beta(x)} \left[ 2 \left( \alpha_i + \sum_t \alpha_{it} x_t \right) - \beta_i \alpha(x) \right] \right\} x_j \quad (30)$$

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