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On the Endogeneity of Retail Markups in an Equilibrium Analysis: A Control-Function Approach

Vardges Hovhannisyan, Kyle W. Stiegert, and Marin Bozic

The endogeneity of retail markups arises due to the correlation between the markups and unobserved costs in the retail pricing equation. This correlation may be a result of unobserved product quality affecting both price and markups. Despite inconsistency resulting from markup endogeneity, it has long been ignored in the equilibrium analysis of retail behavior. We account for retail markup endogeneity using a control-function approach in which controls are derived from empirical evidence in the marketing literature. Furthermore, we adopt three test procedures to evaluate this endogeneity and apply our method in an econometric analysis of retail market behavior in the marketing of yogurt in the United States. The results provide strong statistical evidence for the fact that markup endogeneity has been overlooked, resulting in upward bias in retail markups.

Key words: benefit function, conjectural variation, control function, retail conduct, retail markup endogeneity

Introduction

Empirical studies of market competition comprise both full and limited information approaches. In a full information analysis, various competition scenarios are tested based on the estimation of a full system of supply and demand equations (Yang, Chen, and Allenby, 2003). Alternatively, the limited information or reduced-form approach remains agnostic as to the market structure, provided the difficulty of representing institutional features of industries in simple behavioral equations, and infers firm market power potential based on estimates of demand elasticity (Chintagunta, Dubé, and Goh, 2005). The price endogeneity that is inherent in these reduced-form models has usually been addressed through the instrumental variables technique. Recent studies offer a fixed effects method (Berry, Levinsohn, and Pakes, 1995) or a control function approach (Villas-Boas and Winer, 1999; Petrin and Train, 2010) to account for price endogeneity resulting from the impact of unobserved brand characteristics (UBC) on price. On the other hand, the virtue of the equilibrium analysis (i.e., full information) is that it accounts for both types of price endogeneity (i.e., simultaneity and UBC correlation with price) by explicitly modeling firm pricing decisions (Chintagunta, Dubé, and Goh, 2005).

An important issue that remains unaddressed in an equilibrium analysis is the endogeneity of firm markups stemming from a variety of sources. For example, this may be a result of unobserved product quality both because product attributes are costly to provide and because higher quality may translate into higher markups and profitability (Rose, 1990). In another example, manufacturer

Vardges Hovhannisyan is a research associate in the Department of Applied Economics at the University of Minnesota, Kyle W. Stiegert is a professor in the Department of Agricultural and Applied Economics at the University of Wisconsin-Madison, and Marin Bozic is an assistant professor in the Department of Applied Economics at the University of Minnesota.
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advertising, which remains largely unaccounted for in empirical studies because of limited data, can both raise costs and induce large markups through brand loyalty (Bagwell, 2007). This violates the assumption of independence between retail markups and the unobservable determinants of retail price, thus leading to inconsistent parameter estimates and, ultimately, erroneous policy implications. Nevertheless, previous literature has ignored retail markup endogeneity because of limited data (see for example Genesove and Mullin, 1998; Hyde and Perloff, 1998; Hovhannisyan and Gould, 2012).

We offer a control function approach to address the endogeneity of retail markups. The method relies on additional variables to condition out the variation in the unobserved factors that is not independent of markups in the retail pricing equation. Given the lack of theoretical models on the determinants of retail markups, we use empirical evidence from the marketing literature to build our controls. In addition, we adopt three test procedures to evaluate retail markup endogeneity.

We illustrate our method in an econometric analysis of retail market conduct in the marketing of yogurt in the United States. Retail competition in dairy products remains a policy-relevant area of research in the light of rising retail concentration and has drawn increased government scrutiny (U. S. Department of Justice, 2010). Our empirical framework builds on a benefit function-based model of inverse demand and retail pricing equations with the latter derived via the conjectural variations (CV) approach.[1] The analysis is conducted on product-level weekly scanner data from the Information Resources Incorporated (IRI) covering 2006. We consider five IRI cities with varying degrees of retail concentration. Our findings provide strong statistical evidence for the endogeneity of retail markup. Ignoring this endogeneity results in upward bias in the Lerner Index estimates of retail market power. This finding would equivalently lead to a downward bias in the implied marginal cost estimates.

Methodology

An Inverse Demand Function

We revisit the Luenberger (1992) benefit-function approach to representing consumer preferences. More specifically, we use an inverse demand specification offered by Baggio and Chavas (2009) given its similarity to the Inverse AIDS of Eales and Unnevehr (1994).[2]

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

where $x \in R_+^N$ is a consumption bundle, p_i is the price for product i, N is the number of products, and α_i, α_{ik}, β_i, amd γ_i are parameters. Additionally, $\alpha(x)$, $\beta(x)$, and $\gamma(x)$ are quantity indices specified below:

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

where $\alpha_{ik} = \alpha_{ki}\ \forall\ i \neq k$.

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

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

[1] The CV parameter reflects a firm's perception of aggregate rival response to a unitary change in its own decision variable and essentially represents market competition (Bowley, 1924).

[2] Nevertheless, this demand specification offers more flexible utility effects relative to the Inverse AIDS model.

Let $g \in R^N_+ (g \neq 0)$ denote a reference bundle. Economic theory provides the following restrictions on the model:

$$\sum_{k=1}^{N} \alpha_k g_k = 1; \tag{5}$$

$$\sum_{k=1}^{N} \alpha_{ik} g_k = 0,\ i = 1,\ \ldots,\ N; \tag{6}$$

$$\sum_{k=1}^{N} \beta_k g_k = 0; \tag{7}$$

$$\sum_{k=1}^{N} \gamma_k g_k = 0. \tag{8}$$

We can also account for seasonal (μ_j) and space effects (δ_{jr}) via the extension of equation (2):

$$\alpha(x_{rt}) = \alpha_0 + \mu_j t + \sum_{j=1}^{N} \alpha_{jrt} x_{jrt} + \sum_{r=2}^{R} \sum_{j=1}^{N} \delta_{jr} D_r x_{jrt} + 0.5 \sum_{j=1}^{N} \sum_{k=1}^{N} \alpha_{jk} x_j x_k, \tag{9}$$

where t represents a time variable and D_r is a dummy variable denoting region r.

Substituting equation (9) into equation (1) yields our empirical specification of the inverse consumer demand:[3]

$$p_{jrt}(x) = \alpha_{j0} + \mu_j t + \sum_{r=2}^{R} \sum_{j=1}^{N} \delta_{jr} D_r + \sum_{k=1}^{N} \alpha_{jk} x_{krt} - \beta_j \alpha(x) - \gamma_j \frac{\alpha(x)^2}{\beta(x)},\ j = 1,\ \ldots,\ N. \tag{10}$$

Discrete choice models represent an alternative approach to modeling demand for differentiated products. Two of the most important reasons that motivate the use of these models are the relative ease with which they handle a large number of differentiated products without leading to parameter proliferation and their ability to account for consumer heterogeneity. On the other hand, neoclassical demand models like the one used in our study allow a closer link to consumer theory, provided that these models are explicitly derived from theory. Additionally, while the discrete choice demand models can only accommodate closely related varieties of one product (e.g., different yogurt varieties, based on brand, flavor, fat content), the neoclassical demand models can handle systems of different products, such as milk, butter, and yogurt. Finally, discrete choice demand models suffer from an arbitrary strong assumption of unit purchase, which may be appropriate for durable goods or products such as automobiles, but this assumption carries less intuitive appeal when applied to nondurables such as yogurt.

Retail Pricing Equations

To derive retail pricing equations, we consider a market with a handful of firms characterized by the following objective function:

$$\pi(x) = Max_x \left(\sum_{i=1}^{N} x_{irt} (p_{irt}(x) - c_{irt}) \right),\ \forall\, r = 1,\ \ldots,\ R,\ t = 1,\ \ldots,\ T, \tag{11}$$

where π denotes retail profit and c_{irt} represents marginal cost for product i in region r at time t.

[3] To preserve space, we skip the details concerning the derivation of the inverse demand model. See Baggio and Chavas (2009) for an excellent review of the benefit function approach to modeling demand.

Retail profit maximizing conditions derived from equation (11) represent competitive scenarios extending from perfect competition to a cartel (Hyde and Perloff, 1998):

$$p_{jrt} + \lambda_j \sum_{k=1}^{N} \frac{\partial p_{krt}}{\partial x_{jrt}} x_{krt} - c_{jrt} = 0,\ j = 1,\ \ldots,\ N,\ r = 1,\ \ldots,\ R,\ t = 1,\ \ldots,\ T, \tag{12}$$

where λ_j is a CV parameter, and $\left[p_{jrt} + \lambda_j \sum_{k=1}^{N} \frac{\partial p_{krt}}{\partial x_{jrt}} x_{krt}\right]$ is the "effective" marginal revenue associated with product j in region r at time t.

The CV parameter reflects a firm's nonzero conjecture about the aggregate rival response to a unitary change in its own decision variable (Bowley, 1924). With proper specification, the CV approach can be used to gauge competition without prior knowledge of institutional settings of industries. An important caveat is that the CV parameters are consistent if they represent a conjectural variations equilibrium (Corts, 1999). Additionally, inherently static CV parameters cannot be used to model dynamic firm interactions. However, numerous studies validate the precision of the CV method using fine cost data (see for example Genesove and Mullin, 1998). Furthermore, based on their finding of the CV method outperforming a menu of benchmark models, Dhar et al. (2005) recommend the former approach when no clear alternative is available. Finally, dynamics can be incorporated into the CV method under the assumption of bounded rationality (Dixon and Somma, 2003).

Our empirical equilibrium framework comprises the following retail pricing equations obtained via the substitution of the inverse demand slopes (i.e., $\frac{\partial p_{krt}}{\partial x_{jrt}}$) into equation (12):[4]

$$\begin{aligned} p_{jrt} \quad = \quad & c_{jrt} - \lambda_j \sum_k \Bigg\{ \alpha_{ij} + \beta_k \left(\alpha_j + \sum_k \alpha_{jk} x_{jkt} \right) - \\ & \frac{\gamma_k \alpha(x)}{\beta(x)} \left[2 \left(\alpha_j + \sum_k \alpha_{jk} x_{jkt} \right) - \beta_j \alpha(x) \right] \Bigg\} x_{irt} + e_{jrt}, \\ & \forall\, i, j = 1,\ \ldots,\ N,\ r = 1,\ \ldots,\ R,\ t = 1,\ \ldots,\ T \end{aligned} \tag{13}$$

where e_{jrt} is the stochastic component in equation (13).

The full structural model consists of consumer and retail behavioral equations given by equations (10) and (13) along with theoretical restrictions in equations (5)–(8).[5] As shown by Hyde and Perloff (1998), all the structural parameters including λ_j are identified.

Endogeneity in Retail Markups

In the following discussion, we illustrate the endogeneity of retail markups in an equilibrium framework and offer some potential sources of this endogeneity using the empirical evidence from marketing literature. Let p^w_{jrt} represent the wholesale price that retailers pay for product j in region r at time t and c^e_{jrt}, MK^e_{jrt}, and p^e_{jrt} denote retail marginal cost, markup, and price, respectively. Consider the following retail pricing equation presented in a general form (Yang, Chen, and Allenby, 2003):

$$p^e_{jrt} = p^w_{jrt} + c^e_{jrt} + MK^e_{jrt}. \tag{14}$$

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[4] The details concerning the derivation of the retail pricing equations in equation (13) can be found in Hovhannisyan and Bozic (2013).

[5] Incorporation of time and space variables gives rise to two additional restrictions (i.e., $\sum_{k=1}^{N} \mu_k g_k = 0$ and $\sum_{k=1}^{N} \delta_{kr} g_k = 0,\ r = 2,\ \ldots,\ R$) that need to be imposed on the demand system.

In a given empirical setting, wholesale price (p^w_{jrt}) and retail marginal cost (c^e_{jrt}) are only partially observed, given that fine cost data are rarely available. Therefore, the common approach in the empirical literature has been to use consumer demand estimates to infer retail market conduct (Aguirregabiria and Nevo, 2010). Specifically, retail markup is modeled using price sensitivities, while the wholesale price (p^w_{jrt}) and retail marginal cost (c^e_{jrt}) are represented by brand-specific function of cost shifters (Hyde and Perloff, 1998; Yang, Chen, and Allenby, 2003):[6]

$$p^w_{jrt} + c^e_{jrt} = Z^T_{jrt}\delta + \eta_{jrt}, \tag{15}$$

where Z_{jrt} are various wholesale and retail-level cost shifters with the associated parameter vector δ and η_{jrt} is the supply side error term.

Substitution of equation (15) into equation (14) results in the following stochastic retail pricing equation typically used in empirical studies of retail market behavior:[7]

$$p^e_{jrt} = Z^T_{jrt}\delta + MK^e_{jrt} + \eta_{jrt}. \tag{16}$$

Correlation in equation (16) between the retail markups (MK^e_{jrt}) and the error term (η_{jrt}) may arise because unobserved retail and wholesale marginal costs affect both retail price (p^e_{jrt}) and markups (MK^e_{jrt}), thus entering both MK^e_{jrt} and η_{jrt}. This may be driven by product quality that the researcher cannot typically fully observe, both because product attributes are costly to provide and the fact that retailers take quality into consideration when making markup decisions. For example, Rose (1990) finds that higher quality is associated with higher markups and profitability in an empirical study of airline pricing. Manufacturer advertising, which remains largely unaccounted for in empirical studies, is another omitted variable that both raises costs and induces large markups through brand loyalty (Bagwell, 2007).[8] This violates the assumption of independence between the retail markups and the error term, thus leading to inconsistent parameter estimates.

To get a sense of the size and the direction of the bias in markups, we abstract from demand and consider a single pricing equation. Let the correct specification for the retail pricing equation be as follows:[9]

$$p_j = b_1 + b_2 Z_{j2} + b_3 Z_{j3} + b_4 Z_{j4} + \varepsilon_j, \tag{17}$$

where Z_{j3} and Z_{j4} are some cost shifters, Z_{j2} is an analog of weighted sum of price sensitivities (i.e., $\sum_i [\partial p_i/\partial x_j] x_i$) and b_2 represents the Lerner Index as measured by λ.

In practice, marginal cost data are scarce; therefore, assume that instead of equation (17) we estimate the following equation:

$$p_j = b_1 + b_2 Z_{j2} + b_3 Z_{j3} + \varepsilon^*_j, \tag{18}$$

where $\varepsilon^*_j = b_4 Z_{j4} + \varepsilon_j$.

With the assumption $E[\varepsilon_i] = 0$, the OLS estimate for b_2 is: $E[\hat{b_2}] = b2 + b_4\phi_{42}$. Here $\phi_{42} = \frac{\rho_{42} - \rho_{32}\rho_{43}}{(1-\rho^2_{32})}\sqrt{\frac{V_4}{V_2}}$ is the regression coefficient for Z_{j4} in the auxiliary regression of the excluded

[6] In the CV approach, for example, the elasticity-adjusted retail markups are represented by $\lambda_j \sum_k (\partial p_{krt}/\partial x_{jrt}) x_{krt}$, as illustrated in equation (12), with $(\partial p_{krt}/\partial x_{jrt})$ denoting price sensitivities underlying consumer demand.

[7] To relate this general setting to our structural retail pricing equations in equation (13), note that $c_{jrt} = Z^T_{jrt}\delta$, $p_{jrt} = p^e_{jrt}$, and $MK^e_{jrt} = \lambda_j \sum_k \left\{ \alpha_{ij} + \beta_k \left(\alpha_j + \sum_k \alpha_{jk} x_{jkt}\right) - \frac{\gamma_k \alpha(x)}{\beta(x)} \left[2\left(\alpha_j + \sum_k \alpha_{jk} x_{jkt}\right) - \beta_j \alpha(x)\right] \right\} x_{irt}$.

[8] We acknowledge that the impact of manufacturer promotion on retail markups is not unequivocal and has been shown to depend on a host of other factors, such as the type of a good (e.g., convenience vs. nonconvenience). Furthermore, Ailawadi and Harlam (2004) show that advertising affects retail markups for national brand and store brand products differently (i.e., it suppresses retail margin for national brands while increasing that for store brands). In a related study, Lal and Narasimhan (1996) find a negative relationship between manufacturer advertising and retail markups. However, here the major point is that manufacturer-level unobservable actions affect both retail price and retail markups, thus setting up endogeneity of retail markups.

[9] Here we omit r and t in the variable subscripts for simplicity.

variable Z_4 on the included variables Z_2 and Z_3 and ρ and V represent the correlation coefficient and variance between the respective variables. Thus, the size of the bias depends on the magnitude of the excluded coefficient, b_4; the correlation between the included and excluded variables; ρ_{42}, ρ_{43}, and ρ_{32}; and variances of Z_2 and Z_4 (i.e., V_2 and V_4). Similarly, we have no guidance as to the direction of the endogeneity bias in the retail markups, which depends on the sign of b_4 and those of the respective variables determining ϕ_{42}.

The Control Function Approach to Retail Markup Endogeneity

As illustrated above, the estimated impact of the included factors (e.g., MK^e_{jrt}) on prices (p^e_{jrt}) represents not only the effect of this included factor but also the effect of unobserved factors (e.g., unobserved components in p^w_{jrt} and c^e_{jrt}) that are correlated with MK^e_{jrt}. This violates the assumption of independence between the retail markups and the unobservable determinants of retail price, resulting in inconsistent parameter estimates and, ultimately, erroneous policy implications. Importantly, the unobserved product quality and unobserved promotions in equation (16) cannot be fully accounted for via brand fixed effects, provided that the latter only capture observed and unobserved brand-specific effects that are constant over time. This still leaves open the possibility of the econometric error that remains in η to reflect the changes in the omitted variables.

This article offers a control function approach for addressing the endogeneity of retail markups in the equilibrium analyses of retail market performance. The method relies on additional variables that are used to condition out the variation in the unobserved factor in the retail pricing equation that is not independent of the retail markups. Given the lack of theoretical models on the determinants of retail markups, we use the empirical evidence found in marketing literature to build our controls. Specifically, brand equity emerges as a key determinant of retail markups and profitability through its effects on consumer perceptions. Branding and retail image together are important drivers of store choice and loyalty (Ailawadi and Keller, 2004). Connor and Peterson (1992) find that advertising intensity and retail market concentration are also important determinants of retail markups. Moreover, Steiner (1973, 1978, 1993) and Lal and Narasimhan (1996) show that manufacturer brand promotion influences retail markups by making the promoted products more identifiable (Steiner, 1973, 1978, 1993; Lal and Narasimhan, 1996). Finally, Ailawadi and Harlam (2004) construct an empirical model of retail markups using category-level estimates of market penetration, product depth, perceived store-brand quality, advertising and promotion. Based on the results from these studies and the fact that many of these determinants remain unobserved to the researcher in a typical empirical setting, we posit that the retail markup MK^e_{jrt} is a function of brand (B_j) and market fixed effects (G_r) and an unobserved term (ξ_{jrt}):

$$MK^e_{jrt} = f(B_j, G_r, \xi_{jrt}). \tag{19}$$

With our inclusion of brand fixed effects (B_j), we capture time- and market-invariant effects of product brands, which is basically brand equity (Villas-Boas, 2007). In addition, by using market fixed effects (G_r), our goal is to control for city-specific characteristics, such as market structure. Our use of the city fixed effects, rather than direct estimates of Herfindahl Index for market concentration, sidesteps potential issues related to this endogenous construct (see for example Evans, Froeb, and Werden, 1993). Finally, we are not able to account for these effects in equation (19) because of limited data on brand advertising, retail promotions, market penetration, product depth, and product quality as perceived by consumers.

The key to the control function approach is that η_{jrt} is independent of MK_{jrt} conditional on ξ_{jrt} (Villas-Boas and Winer, 1999; Petrin and Train, 2010).[10] As shown by Imbens and Newey (2009), it suffices to condition on any one-to-one function of ξ_{jrt}. Therefore, we decompose η_{jrt} into the part

[10] $E[\eta_{jrt}|MK^e_{jrt}, \xi_{jrt}] = 0 \;\forall\; j = 1, \ldots, N,\; r = 1, \ldots, R,\; t = 1, \ldots, T.$

that can be represented by ξ_{jrt} and the residual as follows:

$$\eta_{jrt} = \psi_j^T \xi_{jrt} + t_{jrt}. \tag{20}$$

We consider the control function case, when MK_{jrt}^e is additive in its observed (B_j, G_r) and unobserved covariates (ξ_{jrt}), and assume the latter variables are independent (see for example Ailawadi and Harlam, 2004; Petrin and Train, 2010). This allows us to recover the controls (ξ_{jrt}) via the OLS as follows: $\xi_{jrt} = MK_{jrt}^e - [Q_{jr}^T Q_{jr}]^{-1} Q_{jr}^T MK_{jrt}^e Q_{jr}$, where $Q_{jr} = [B_j, G_r]$. These controls are incorporated into the retail pricing equation (16) to condition out the part of the unobserved costs that are correlated with the retail markups:

$$p_{jrt}^e = Z_{jrt}^T \delta + MK_{jrt}^e + \psi_j^T \xi_{jrt} + t_{jrt}. \tag{21}$$

All of the structural parameters, including ψ_j, are estimated in our simultaneous system of supply and demand equations. This is unlike a typical use of the control function in a limited information setting, where estimation is carried out in two stages. Specifically, the controls are obtained in the first stage via the regression of prices on some observed costs, which are subsequently used in the demand function to control for the effects of UBCs on product price.

Test Procedures for the Retail Markup Endogeneity

We adopt two test procedures, which have been widely used in applied demand analyses, to evaluate retail markup endogeneity. As an additional test, we employ an adjusted likelihood ratio test that provides more robust results in small samples.

The first procedure offers a direct but somewhat ad hoc approach similar to the one suggested by Villas-Boas and Winer (1999) and Blundell and Robin (2000). Specifically, the finding of statistically significant coefficients for controls in the retail pricing equations is interpreted as evidence of endogeneity in retail markups, given that unexplained variation in the markups covaries with price.

The Durbin-Wu-Hausman test statistic (DWH) constitutes an alternative approach (LaFrance, 1993). Essentially, it provides a statistical estimate of the difference between two sets of parameters from models with exogenous and endogenous markups. In this setting, the null hypothesis maintains that parameter estimates are consistent without controlling for markup endogeneity, while the alternative hypothesis points to endogenous markups. With Ψ_{EX} and Ψ_{EN} denoting vectors of parameter estimates from the models with exogenous and endogenous markups, the DWH test statistic is specified below:

$$H = (\Phi_{EX} - \Phi_{EN})^T [Var(\Phi_{EX}) - Var(\Phi_{EN})]^{-1} (\Phi_{EX} - \Phi_{EN}). \tag{22}$$

Asymptotically, H follows a $\chi^2(h)$ distribution, with h denoting the number of endogenous variables in the model.

Finally, we use the Bewley likelihood-ratio test (LR_B) to evaluate the gain in the explanatory power of the more general model (Bewley, 1986). The respective test statistic is specified as $LR_B = 2(LL^U - LL^R)(EN - p^U/EN)$, where $LL^{U,R}$ are the log-likelihood values from the unrestricted and restricted models, respectively, E is the number of equations estimated, N is the sample size, p^U is the number of parameters under the more general structure, and the degrees of freedom equal the number of additional parameters in the unrestricted model.

An important advantage of LR_B over the traditional likelihood ratio test is its adjustment for small sample size, which has the promise of more robust results. As with the DWH test, rejecting the null hypothesis provides statistical evidence for markup endogeneity.

An Application to the U.S. Yogurt Industry

We apply our method in an econometric analysis of retail market power in the marketing of yogurt. We conduct the analysis based on the IRI weekly product-level data on yogurt sales and unit

Table 1. Summary Statistics

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

Source: Information Resource Incorporated (2006).

values in the United States in 2006. Our choice of product reflects important implications about retail empowerment for dairy consumers, processors, and dairy farm operators. We use five U.S. Midwestern areas with varying degrees of retail concentration.[11]

Given the vast variety of yogurt varieties, we aggregate products into three types—plain, fruit-flavored, and other-flavored—which are allowed to vary across brands and cities (Bonanno, 2013). U.S. yogurt manufacturing resembles an oligopoly, with two leading producers accounting for over 60% total market share (Villas-Boas, 2007). Therefore, we consider the two major manufacturer brands—national brand 1 (NB1) and national brand 2 (NB2)—and store brands (SB). This results in 780 observations used in the analysis (i.e., three yogurt brands in five cities over a period of fifty-two weeks).

Table 1 presents descriptive statistics for the main variables in the analysis. SB yogurt has a relatively much lower mean aggregate market share (7.0%) relative to NB1 (49.6%) and NB2 yogurts (43.3%). This is in stark contrast to the fluid milk market, where SBs account for over 70% of the total market share. It can also be observed that NB2 yogurts are the most expensive across all types (42.2, 43.5, and 45.9 cents per 4-ounce cup for the plain, fruit-flavored and other-flavored yogurt, respectively), followed by the NB1 (34.4, 38.9, and 43.3 cents), and SB yogurts (26.4, 26.7, and 28.2 cents).[12]

Following the standard practice in this line of literature, we specify as a linear function of manufacturer and retail cost shifters (see for example Hyde and Perloff, 1998):

$$(23) \qquad c^e_{jrt} = q_{0j} + q_{1j}Milk_{jt} + q_{2j}Wage_{rt},\ \forall\ j = 1, \ldots, N,\ r = 1, \ldots, R,\ t = 1, \ldots, T,$$

where $Milk_{jt}$ is the wholesale milk price from the states where the yogurt manufacturing plants are located and $Wage_{rt}$ is the retail wage in region r at time t.[13]

The CV parameter λ is key to the analysis of market power. Therefore, we allow for the possibility of λ varying across brands and over time (Hovhannisyan and Bozic, 2013):

$$(24) \qquad \lambda_j = \lambda_{1j} + \sum_{k=2}^{N} \lambda_{jk} I_j + \left(\phi_{1j} + \sum_{k=2}^{N} \phi_{jk} I_j\right) \times t,\ j = 1, \ldots, N,$$

where $(\lambda_{1j} + \phi_{1j})$ is the CV parameter for the reference brand in period one (i.e., $\lambda_{11} + \phi_{11}$, $\lambda_{12} + \phi_{12}$, and $\lambda_{13} + \phi_{13}$ are the respective CV parameters for NB1 plain, fruit-, and other-flavored yogurt in period 1), I_j is a dummy variable for brand, and λ_{jk} and ϕ_{jk} capture the markup variation across

[11] The largest three retail chains in these cities accounted for 49% to 78% of total market share.

[12] We acknowledge that prices may reflect other attributes—such as container size or organic—that remain unaccounted for in our application in part because of limited data.

[13] Milk price data are available online at http://future.aae.wisc.edu/data/monthly_values/by_area/6?

Table 2. Demand Model Diagnostics

Hypothesis	LR_B	df	p-value
(a) No nonlinear utility effects (i.e., $\gamma_i = 0,\ \forall\ i = 1,\ \ldots,\ N$)	2,531	3	<0.01
(b) No space effects (i.e., $\delta_{ir} = 0,\ \forall\ i = 1,\ \ldots,\ N,\ r = 1,\ \ldots,\ R$)	5,785	9	<0.01
(c) No seasonal effects $\mu_i = 0,\ \forall\ i = 1,\ \ldots,\ N$)	1,478	3	<0.01

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

brands and over time, respectively, for a given yogurt type.[14] Finally, identification of the structural parameters relies on both temporal (i.e., fifty-two weeks) and spatial variation (i.e., five cities).

Empirical Results

We use the GAUSSX module of the GAUSS software system to estimate both the demand system and the full structural model. We omit a demand equation to avoid singularity of the variance-covariance matrix. The parameter estimates from this excluded equation are recovered from the theoretical restrictions imposed on the demand system.

Table 2 presents the demand model diagnostics test results. Using LR_B, we first test for nonlinear utility effects (i.e., $\gamma_k = 0,\ \forall\ k = 1,\ \ldots,\ N$). The corresponding p-value (< 0.01) for the χ^2 test provides strong statistical evidence for the quadratic utility effects in the inverse demand system. We also find major differences in the consumption of yogurt across the cities in our sample (i.e., $\delta_{kr} \neq 0,\ \forall\ k = 1,\ \ldots,\ N,\ r = 1,\ \ldots,\ R$). Finally, yogurt consumption appears to follow a seasonal pattern (i.e., $\mu_k \neq 0,\ \forall\ k = 1,\ \ldots,\ N$).

A total of sixty structural parameter estimates from the full model were obtained via the full information maximum likelihood (FIML) that accounts for the true nature of simultaneity between the prices and quantities. Following Hyde and Perloff (1998) and Hovhannisyan and Gould (2012), we impose the restrictions of $\lambda \in [0,1]$ as suggested by economic theory.

Estimation results from the more general model that accounts for the endogeneity of retail markups are presented in tables A1 and A2.[15] The model provides a good fit of the data with a majority of parameter estimates statistically significant at standard significance levels (i.e., p-value associated with statistic of overall significance < 0.01).

Retail Markup Endogeneity Test Results

We performed the three test procedures presented above to evaluate retail markup endogeneity. All three test outcomes provide strong statistical evidence for retail markup endogeneity. Specifically, we find that the coefficients for the controls (i.e., ψ_j) in equation (21) are statistically significant at 1% significance level. Furthermore, our DWH test statistic value of 3,239 (the respective p-value < 0.01) indicates that the two sets of parameter estimates are statistically significantly different under the more general model and the model with exogenous markups. Finally, the LR_B test statistic is estimated at 4,836 (p-value < 0.01) implying that the estimated two models are statistically significantly different. Consequently, ignoring the retail markup endogeneity biases not only the supply-side parameter estimates but also those of the demand equations (Yang, Chen, and Allenby, 2003).

We use the estimates for λ_{jk} and ϕ_{jk} to calculate the elasticity adjusted Lerner Index estimates across yogurt brands and types via equation (24). These Lerner Index estimates from models with both exogenous and endogenous markups are presented in table 3. In line with the signs of the coefficients for controls (i.e., $\psi_1 = 0.277,\ \psi_2 = 0.318, \psi_3 = 0.324$) in equation (21), we find that ignoring markup endogeneity leads to upward bias in retail markups. This finding is consistent

[14] $j = 1,\ \ldots,\ 3$ indicates plain, other-flavored, and fruit-flavored yogurts, respectively, and $k = 2,3$ denotes NB2 and SB, respectively.

[15] Results from the model with exogenous markups are available upon request.

Table 3. Elasticity-Adjusted Lerner Index Estimates across Yogurt Brands and Types

	Exogenous Retail Markups		
Yogurt	**NB1**	**NB2**	**SB**
Plain	30.7***	16.0***	13.5***
Fruit flavor	15.4***	13.7***	10.4***
Other flavor	66.4***	51.0***	37.5***
	Endogenous Retail Markups		
Yogurt	**NB1**	**NB2**	**SB**
Plain	11.0***	6.7***	2.9***
Fruit flavor	12.7***	10.4***	7.6***
Other flavor	36.6***	28.5***	19.5***

Notes: Triple asterisks (***) indicate statistical significance at the 1% level.

with unobserved yogurt quality affecting marginal costs and markups. Alternatively, this may be a result of manufacturer advertising, which both raises costs and induces large markups through brand loyalty.

The Lerner Index estimates in the restricted model range from 10.4% to 66.4%, which concurs with the findings from di Giacomo (2008), Bonanno (2013), and similar studies. di Giacomo (2008), for example, finds strikingly high retail markups that extend from 43.1% to 74.9% in the sample period. Importantly, none of these studies control for unobserved product quality, which may be the driving force behind the unusually high estimates for retail markups.

An interesting pattern emerging in table 3 is that retailers charge the highest markups for all types of NB1 yogurt, followed by NB2 and SB yogurts. It therefore appears that SB yogurt is not as important a tool as NB yogurt from the retail profitability perspective, given its uniformly low markups across the types and very low market share relative to the NB yogurts. This finding is in accord with the results from Ailawadi (2001), Bonanno (2013), and similar studies, which find that consumer preferences for NB yogurts remain strong relative to the SBs. It is worth noting, nevertheless, that this is unlike many other industries, where successful SBs have become an important leverage for retailers against both rival chains and upstream players (see for example Bergès-Sennou, 2006; Barsky et al., 2003; Steiner, 2004). Another pattern is that retail markups for other-flavored yogurts exceed those for fruit-flavored and plain yogurts. Finally, the finding of the huge variability in markups across brands and types is consistent with the category profit maximization on the part of retailers (Vilcassim and Chintagunta, 1995). An important implication of the present study is that ignoring potential endogeneity of retail markups results in inconsistent demand and marginal cost parameter estimates and ultimately erroneous policy implications.

Conclusions

The endogeneity of retail markups arises due to the correlation between markups and unobserved costs in the retail pricing equation. This may be a result of unobserved product quality affecting both price and markups. Despite inconsistency resulting from markup endogeneity, it has long been ignored in the equilibrium analysis of retail behavior.

We account for retail markup endogeneity via the control function approach, in which controls are derived based on empirical evidence in the marketing literature. Furthermore, we offer three test procedures to evaluate markup endogeneity. We apply our method in an econometric analysis of retail market behavior in the marketing of yogurt in the United States. Our empirical framework builds on the recent developments in the empirical IO literature and offers the benefits of structural analysis. Specifically, we employ a benefit function-based inverse demand model with the respective retail pricing equations derived via the conjectural variations approach.

The results provide strong statistical evidence for markup endogeneity overlooking which results in upward bias in retail markups. Furthermore, retailers appear to be exploiting strong consumer preferences for national brand yogurt, while store brands remain relatively less important from a retail profitability perspective.

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Appendix

Table A1. Parameter Estimates from the Inverse Demand Model

Parameter	Estimate	SE	Parameter	Estimate	SE
α_1	0.345***	0.040	β_1	0.000	0.000
α_2	0.340***	0.000	β_2	0.003***	0.000
α_3	0.314***	0.001	β_3	−0.003***	0.000
γ_1	0.006***	0.000	μ_1	0.001**	0.000
γ_2	−0.002***	0.000	μ_2	−0.010***	0.004
γ_3	−0.003***	0.000	μ_3	0.009***	0.004
α_{11}	−0.007	0.000	δ_{22}	−0.008***	0.000
α_{12}	0.001	0.000	δ_{23}	−0.007***	0.000
α_{13}	−0.005	0.000	δ_{24}	−0.005***	0.000
α_{22}	0.239	0.000	δ_{25}	−0.012***	0.001
α_{23}	−0.250***	0.000	δ_{32}	−0.001**	0.001
α_{33}	0.255***	0.000	δ_{33}	−0.001**	0.001
δ_{12}	0.009***	0.000	δ_{34}	−0.001**	0.000
δ_{13}	0.008***	0.000	δ_{35}	−0.002**	0.001
δ_{14}	0.006	0.021			
δ_{15}	0.013	0.037			

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.

Table A2. Parameter Estimates from Retail Pricing Equations

Marginal Cost Function

Parameter	Estimate	SE	Parameter	Estimate	SE
q_{01}	0.425***	0.001	q_{13}	0.002***	0.000
q_{02}	0.272***	0.003	q_{21}	−0.450***	0.011
q_{03}	0.303***	0.004	q_{22}	0.388***	0.018
q_{11}	0.000***	0.000	q_{23}	0.062**	0.029
q_{12}	−0.002***	0.000			

CV Parameter Estimates

Parameter	Estimate	SE	Parameter	Estimate	SE
λ_{11}	0.099***	0.023	ϕ_{11}	0.041	0.038
λ_{12}	−0.162***	0.019	ϕ_{12}	0.134***	0.037
λ_{13}	−0.248***	0.042	ϕ_{13}	0.023	0.074
λ_{21}	0.579***	0.013	ϕ_{21}	−0.854***	0.051
λ_{22}	−0.444***	0.017	ϕ_{22}	0.812***	0.041
λ_{23}	−1.048***	0.048	ϕ_{23}	2.144***	0.191
λ_{31}	0.221***	0.006	ϕ_{31}	−0.378***	0.022
λ_{32}	−0.144***	0.008	ϕ_{32}	0.307***	0.019
λ_{33}	−0.381***	0.016	ϕ_{33}	0.911***	0.081

Estimates for Markup Endogeneity Controls

Parameter	Estimate	SE	Parameter	Estimate	SE
ψ_1	0.277***	0.028	ψ_3	0.324***	0.032
ψ_2	0.318***	0.030			

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.