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Market Power in the Carbonated Soft Drink Industry

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Introduction

The rich content of scanner data enables the estimation of structural econometric models to be used to investigate market power and analyze policy. Recent advances in structural approaches to empirical market power analysis combines estimated demand functions with game-theoretic models of a particular industry to estimate its competitive nature. However, economic and econometric theory are often silent on the specific econometric estimators that should be employed. Each one having similar, but differing restrictions on the assumptions of the underlying sample from which the data is collected. As a result, the objective of this study is to empirically compare several different estimators of a supply model, and look at the differences each one implies with respect to the nature of the competitive game the carbonated soft drink (CSD) market plays.

Econometric Model of the CSD Market

We model the CSD market using a structural model of consumer, retailer, and producer behavior. This method ensures that our empirical results are consistent with theoretical expectations of firm behavior at all stages of the supply side. On the demand side we model consumer's discrete purchasing choices using a random parameter nested logit model. Because CSDs are a highly differentiated food product a discrete choice framework is appropriate (Jain, Vilcassim, and Chintagunta 1994; and Nevo, 2001). A random coefficient model captures unobserved household heterogeneity, while also controlling for other exogenous factors that may influence a household's brand decisions.

On the supply side we assume Bertrand-Nash competition among both producers and retailers (Draganska and Klapper 2007). We parameterize deviations from the maintained equilibrium to test both the direction and degree of diversion from Bertrand competition (Villas-Boas and Zhao 2005; Draganska and Klapper 2007). By parameterizing deviations from Bertrand-Nash (Villas-Boas and Zhao, 2005), we test for the presence of market power among either wholesalers or retailers.

Estimation

Demand:

There are several complications to address when estimating the demand and supply models. The share equation cannot be estimated using ordinary least squares because prices are likely to be correlated with elements in the error term. Promotional activities, in-store merchandising, and other strategies cause price and market share to be jointly endogenous, making our estimates biased (Villas-Boas and Winer, 1999). We therefore use simulated maximum likelihood (SML) estimation following Petrin and Train (2010) to estimate the demand model. In general, we use a control function approach whose econometric foundation is found in the sample-selection models of Heckman (1978) and Hausman (1978). The idea of the control function approach is to derive a proxy variable that conditions on the part of the endogenous price variable, thus making the remaining variation in the price variable independent of the error term. Then the standard simulated maximum likelihood approach will be consistent.

Specifically, we regress the endogenous variable, price, against a set of instrumental variables (which are detailed below) via OLS and obtain the residuals. The residuals from this regression are independent of the original error term and when added to the utility specification condition out any possible correlation between the endogenous price variable and the error term. The full model, including the control function, is then estimated using SML.

Supply:

In estimating the supply model, we use several different estimators to investigate the difference in the competitive nature implications from each. Given the retail and wholesale margins are likely to be endogenous we require a single equation instrumental variable (IV) estimator. Specifically, we estimate the supply function using 2SLS, LIML, and GMM. For comparison purposes with an inconsistent estimator, we also use OLS. 2SLS is a natural choice for an estimator because the model is linear, and the consistency of the estimator in the presence of endogenous variables is well understood (Theil 1953, and Basmann, 1957). However, the LIML estimator has been shown to have less bias in finite samples, but, due to its lack of finite moments, tends to have a wider sampling distribution (Davidson and MacKinnon, 2004). Both of these estimators, along with OLS, are members of the k-class estimators (Theil, 1961). Finally, we use the GMM estimator because it is the most general estimator and is by far the most widely used in current applications of market power estimation (Hansen, 1982).

For both the supply and demand models we use chose our set of IV following Berto Villas-Boas (2007) and Draganska and Klapper (2007) whose identification strategy is well accepted in the literature.

Data Description

The empirical estimation requires CSD retail level sales data. Consequently, this study uses Nielsen research group's Scantrack data, which measures weekly retail sales for 52 weeks in 2005. The data consist of dollar sales, unit volume (ounces), promotion attributes, and product specific identifiers. The Scantrack data features weekly sales information at the UPC level for participating retailers in 52 markets. Covering all 52 markets would have been intractable so we focus on the 5 largest markets: Chicago, IL; Los Angeles, CA; New York, NY; Atlanta, GA; and Philadelphia, PA. This sample of markets provides a wide variety of supermarkets representative of most retail outlets and prices. In total we have 143 retailers yielding 163,593 observations.

There are a large number of products available in the CSD category -- too large to model in a tractable way and obtain reliable estimates of each products' mark-up. Therefore, we choose thirty three brands that were common among all markets and retailers with the highest market share.

Results

Table: Supply Side Estimation Results.

Variable	OLS		LIML		2SLS		GMM	
	Estimate	t-ratio.	Estimate	t-ratio.	Estimate	t-ratio.	Estimate	t-ratio.
ϕ – Retail Bertrand Deviation	0.0000	-0.44	-7.2489	-0.81	-0.1181*	-3.81	-0.1341*	-5.08
θ – Wholesale Bertrand Deviation	0.0121*	5.20	18.9530	0.73	3.0856*	7.70	3.5014*	10.13
Electricity	0.0000	-0.74	0.0146	0.30	-0.2756*	-4.90	-0.1584*	-9.93
HFCS	0.0052*	17.94	-0.0512	-0.34	0.7462*	5.01	0.5089*	10.03
Sugar	0.0028*	10.11	-0.0318	-0.23	0.4908*	5.19	0.3823*	10.05
Gasoline	0.0002*	2.08	0.0217	0.32	0.3028*	4.56	0.0657*	9.13
A & W	-0.1256*	-28.97	-1.4822	-0.56	-0.2748*	-5.17	-0.4726*	-9.66
Barq's	-0.0070*	-5.06	-0.2586	-0.36	0.0007	0.03	-0.1757*	-8.19
Canada Dry	-0.0108*	-7.66	-0.4507	-0.53	-0.0170	-0.78	-0.1954*	-8.93
Coca-Cola Cherry	-0.0160*	-11.03	-0.7245	-0.64	-0.0819*	-3.48	-0.2684*	-10.79
Coca-Cola Caffeine Free	-0.0352*	-20.81	-0.0956	-0.12	-0.0410	-1.70	-0.2193*	-9.25
Coca-Cola	-0.0643*	-38.55	-0.2749	-0.34	-0.0444	-1.83	-0.2193*	-9.60
Private Label	-0.1148*	-59.30	-1.5426	-0.73	-0.3042*	-8.58	-0.5074*	-14.01
Dr. Pepper Caffeine Free	-0.0774*	-52.24	-0.7166	-0.69	-0.1152*	-5.05	-0.2979*	-12.68
Dr. Pepper	-0.1086*	-63.37	-0.5550	-0.58	-0.1100*	-4.51	-0.2877*	-12.21
Fanta	-0.1208*	-59.78	-4.8418	-0.83	-0.3977*	-9.18	-0.6127*	-14.36
:								
J-Statistic	-		75,871.06		1,582.44		2,809.29	
$T \cdot R_{\{err\}}^2$	-		30.647		1,158.05		2,208.11	
Hausman statistic	-		0.68		81.7886		166.643	
Overidentifying test stat.	-		28.731		-		-	

* Indicates significance at the 95% level.

Dependent variable: Price.

HFCS - High Fructose Corn Syrup price.

: - For space's sake the rest were omitted, but they were similar to those shown.

In this model, the conduct parameters are interpreted as measuring the extent of deviation from the maintained competitive nature assumed, on the part of either retailers (ϕ), or wholesalers (θ) (Villas-Boas and Zhao, 2005; Draganska and Klapper, 2007). In the retail case an estimated value of $\phi > 1$ implies retailers, on average, price CSDs more cooperatively than Bertrand-Nash would predict, while $\phi < 1$ suggests retailers price them more competitively. Upstream wholesale deviations are interpreted in the same way. Finally, we note that if $\phi = \theta = 0$, then retailers and wholesalers, respectively, do not take advantage of the differentiated nature of their products and price as purely competitive sellers would.

- The results of the four estimators taken together imply that retailers in general price CSDs at (OLS and LIML) or below (2SLS and GMM) their costs.
 - While these results are somewhat counterintuitive, if we take into consideration the myriad of product categories within the food retailing environment it may be profitable for retailers to price one category at or below cost to attract new customers to the store (e.g. loss leader pricing).
- The results of the four different estimators suggest that manufacturers price CSDs above purely competitive levels. However, the magnitude differs significantly among estimators.
 - First, the OLS estimator suggests wholesalers price their brands only slightly above competitive levels. Given the endogeneity of the margin variables, the OLS parameter estimates are likely biased downward.
 - Second, the parameter estimate from the LIML estimator implies wholesalers price their products significantly more cooperatively than Bertrand-Nash competition. The fact that the parameter is not statistically different from zero is not surprising given the LIML estimator tends to have a wider sampling distribution (Davidson and MacKinnon, 2004).
 - Finally, the 2SLS and GMM estimates, both having similar parameter estimates, implies that wholesalers price their brands significantly more cooperative than Bertrand-Nash competition. Given that the industry is dominated by two suppliers, this is not a surprising result.

Conclusions

The OLS and LIML estimators suggest retailers price CSDs at their respective prices, while the 2SLS and GMM estimators suggest retailers are pricing the category below cost. These results are consistent with previous research that investigates the competitive nature of the food retailing market and suggest retailers price specific categories at or below cost as a mean of expanding overall store sales (Hess and Gerstner, 1987; Hosken and Reiffen, 2001; and Richards, 2007).

On the wholesale side, the magnitude of the conduct parameter from the LIML estimator suggests wholesalers price their products significantly more cooperatively than Bertrand-Nash would imply. Though, due to the wide sampling distribution of the LIML estimator, the hypothesis that the parameter is statistically different from zero is not rejected. Finally, the results of the 2SLS and GMM estimates agree that wholesalers are in fact pricing their products significantly more cooperatively than Bertrand-Nash would suggest. Given the competitive nature of the retailing environment, wholesalers are likely taking advantage of retailer's dependence on CSD price promotions to capture inflated wholesale margins and excess profit. On the other hand, this may be because wholesalers compete for market share through venues other than price competition, such as new product introductions and advertising. The specific nature of wholesalers inflated prices is a matter for future research.