Price Discrimination with Asymmetric Firms:
The Case of the U.S. Carbonated Soft Drinks Market

Yizao Liu

University of Connecticut
yizao.liu@uconn.edu

Shu Shen

University of California, Davis
shushen@ucdavis.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

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Yizao Liu
University of Connecticut
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Shu Shen
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May 31, 2012

PRELIMINARY AND INCOMPLETE

Abstract

This paper investigates the relationship between price discrimination and vertical product differentiation, using National Brands and Private Labels in the Carbonated Soft Drink market as a case study. We decompose prices difference into quantity discount and cost difference across packagings and recover marginal cost by a structural demand model of consumer preference and firm behavior. Our results suggest that in the carbonated soft drinks market, both national brands and private labels offers quantity discount to consumers: consumers pay lower unit prices when buying larger packed soft drinks. In addition, the price curvature parameter is lower for private labels, implying that the price schedule is more curved for private label soft drinks than national brands. This means in the CSD market, private labels have more ability to perform price discrimination, segment consumers, and generate high revenues, comparing to national brands. This result, to some extent, explains the growing market shares of private label soft drinks and the significant percentage of total sales from private labels goods for retailers, such as Wal-Mart and Target.

1 Introduction

The U.S. Carbonated Soft Drinks (CSD) Market is featured as a market with significant product differentiation, as well as a large degree of price discrimination. Specifically, although national brand soft drinks, such as Coke and Pepsi, are sold all over, private label soft drinks have become increasingly more accepted by the public. Retailers like Wal-Mart and Target have expanded their offerings of private label goods (Karp 2012). Many consumers now seriously consider private labels as acceptable alternatives to national brands.

On the other hand, soft drinks companies always offer a variety of bottle sizes and packing choices to consumers: ranging from a small 8 oz. can to a giant 3 liter bottle. The diversity in package sizes offers more price options to consumers. They could choose to purchase soft drinks in smaller packages which carry lower sticker prices but higher unit prices or to those in larger packages. Meanwhile, companies can choose the level of quantity discount so as to maximize their profit. For example, they need to set prices on larger packages lower to attract consumers to buy more, but still high enough to best exploit the "rich" or "addicted". In fact, facing the consecutive decline of American consumption of carbonated soft drinks, companies, not only national brands, but also retailers' private labels, are trying new bottle sizes and price schemes in an effort to boost deflating soda sales.

In this analysis, we empirically assess the relationship between vertical production differentiation (national brands vs. private labels) and price discrimination in the Carbonated Soft Drinks market. It is well known that price discrimination allows firms to increase their revenues above what may be obtained from uniform pricing, while product differentiation will relax competition between firms. However, less is known that how price competition would be complicated in a vertically differentiated market where all firms are able to price discriminate. This paper examines whether national brand firms and private label firms offer the same or different levels of price discrimination on a vertically differentiated market. The situation is even complicated by the facts that quantity discount is not the only reason that accounts for non-linearity in prices. Cost-side differences can also explain the differences: it is possible that economy of scale may lead to lower cost for larger package. By taking into account the cost related terms, we further investigate the characteristics of the different non-linear price schemes as differences are found to exist in the real data.

Some previous studies has focused on oligopolistic price discrimination in theoretical location models dealing with asymmetric firms while maintaining the assumption that firms can classify the consumers either into two groups or perfectly. Corts (1998) shows that in a duopoly model of vertical differentiation, price discrimination between two groups of consumers may intensify competition and leads to lower profits for both firms. Thisse and Vives (1988) developed a perfect price discrimination model and assume that one firm has a cost advantage over the other. They show that, in a dominant strategy equilibrium, both firms will choose to price discriminate. Liu and Serfes (2005) showed that if the cost of information for segmenting consumers is below a threshold, in a price discrimination model with two asymmetric (vertically differentiated) firms, the high quality firm are more inclined to practices price discrimination.

In the empirical lieterature, price discrimination in imperfectly competitive environments has been studied extensively. Many works have tested for the presence of second degree and third degree price discrimination in imperfectly competitive environments in various markets. An incomplete sample of papers and markets includes: Shepard (1991) for gasoline service stations, Cohen (2001) for paper towels, Crawford and Shum (2001) for cable television and Leslie (2004) for Broadway theaters. A few studies, focus on second degree price discrimination, have tried to address how competition affect the extent of price discrimination. Busse and Rysman (2005) examined the effect of competition on second degree price discrimination in Yellow Page advertising and found that competition increases the curvature of the price schedule. Borenstein and Rose (1994) examine price dispersion in the airline industry and there is greater variation in the fares paid on a given flight on routes with more competing airlines. Another trend in empirical studies try to endogeneize the optimal price schedule to recover the demand the cost structure of firm. Ivaldi and Marimort (1994) analyzed the Frence dairy market's demand for energy after solving a nonlinear pricing duopoly competition model under a specific functional structure. Miravete and Roller (2004) analyzed the early US cellular telephone industry and estimated structural parameters to evaluate the effect of competition. Perrigne and Vuong (2009) proposed a structural analysis of nonlinear pricing in yellow page advertising using a general demand and cost function then establish a nonparametric identification and estimation for the model.

To the best of our knowledge, the results from theoretical models with asymmetric firms are inconclusive and suggests a wide disparity. Further, there are no studies that examine directly how vertical product differentiation affects firm's ability to price discriminate.

In this paper, we address this issue with evidences on the second degree price discrimination in the carbonated soft drink market. We use a unique A.C. Nielsen home scanner data on soft drinks in 7 designated markets areas (DMA) to examine how product differentiation affects price discrimination. In particular, we use pricing and packaging data of various national brands and private labels from 7 markets during the year 2006-2008. The richness of the data allows us to capture price variation of soft drinks from brands, time, markets, packing, and product characteristics.

To recover the marginal cost for each brand/packaging, we first estimate a structural discrete choice model of consumer choices in the carbonated soft drink market, which capture the effect of multiple packing size. Using the demand estimates, we recover the marginal costs by assuming a Bertrand-Nash pricing competition of the firm side. We then specify a tractable functional form to describe the shape of the price schedule for soft drinks with different sizes. Use of the functional specification allows a variety of pricing schedule shape: linear pricing without price discrimination, quantity discount, and quantity premium.

Specifically, we are able to decompose the price into a mark-up term that allow price discrimination and a cost term. We then reduce our model to a linear panel data model where the price that a consumer pays at time t for a certain brand is proportional to the log total volume of a pack he purchased at time t. The estimates allow us to test how the price curvature estimates vary between national brands and private labels, after controlling for time, location, and costs for multiple packs.

Our results suggest that in the carbonated soft drinks market, both national brands and private labels offers quantity discount to consumers: consumers pay lower unit prices when buying larger packed soft drinks. In addition, we find that the price curvature parameter is lower for private labels, implying that the price schedule is more curved for private label soft drinks than national brands. This means in the CSD market, private labels have more ability to perform price discrimination, segment consumers, and generate high revenues, comparing to national brands. This result, to some extent, explains the growing market shares of private label soft drinks and the significant percentage of total sales from private labels goods for retailers, such as Wal-Mart and Target.

The rest of the paper is organized as follows. Section 2 provides empirical models and estimation.Section 3 describes the data. Section 4 presents results and discussion. Section 5 concludes.

2 Model

2.1 Price Schedule

The variation of prices of soft drink with different package can come from price discrimination, as well as cost differences. To better identify the difference from price discrimination, we decompose the price of the soft drink with a certain packaging into two part: a cost term and a markup term that reflect competition and price discrimination. In order to understand how product differentiation affects price discrimination, we first specify a tractable functional form to describe the shape of the price schedule:

$$p_{ij} = A_i q_j^{\beta_i} + C_{ij} = A_i q_j^{\beta_i} + q_j mc_{ij} \tag{1}$$

where p_{ij} is the price of brand i with packing size q_j and β_i is the measure of price curvature of brand i. C_{ij} is the total cost, and mc_{ij} is the marginal costs per oz of producing brand i with packing size j. Use of this functional specification allows a variety of pricing schedule shape: $\beta_i = 0$ denote linear pricing without price discrimination, $\beta_i < 1$ denote quantity discount and $\beta_i > 1$ represent quantity premium.

We estimate the log version of the above function. Take logs of both sides, we have

$$\log(p_{ij}) = \log(A_i) + \beta_i \log(q_i) + \lambda \log C_{ij} + \epsilon_{ij} \tag{2}$$

Our object is to find how price discrimination affected by vertical differentiation. Based on the above setting, we can now make it equivalent to test how the curvature measure β_i varies for high and low quality firms. If the effect of vertical product differentiation is to lower prices for larger volume purchase by a greater proportion, then β_i is lower for high quality firm. This change in price discrimination could be viewed as greater quantity discount for high quality firm. Formally, it is equivalent between testing for changes in the curvature of price schedule β_i and testing whether high or low price fall proportionally more.

We estimate the relationship between the shape of the price schedule and product quality by specifying:

$$\beta_i = \gamma_0 + \gamma_1 Private\ Label_i + v_i \tag{3}$$

here $PrivateLabel_i$ is a dummy variable which equals to 1 if the product is not a national brand product. Substituting to get

$$\log(p_{ij}) = \alpha_i + \gamma_0 \log(q_i) + \gamma_1 Private\ Label_i * \log(q_i) + v_i \log(q_i) + \lambda \log C_{ij} + \epsilon_{ij} \tag{4}$$

The parameter of interests is γ_i, which captures the effects of product quality on the curvature of the price schedule.

Estimation of equation 4 require knowledge of C_{ij} and further marginal costs mc_{ij}, which is usually unobserved by econometricians. Therefore, we empirically recover mc_{ij} of a brand i with size j through a discrete choice model, in which a consumer choose a product (a brand and a size of the brand), using a characteristics based approach, described in section 2.2.

2.2 Recovering Marginal Costs

2.2.1 Demand Estimation

In this section, we recover the marginal costs of a brand of soft drink i of size q_j by structural demand estimation. Following BLP(1995), the conditional indirect utility of consumer i from purchasing soda brand j is

$$u_{ij} = x_j\beta + \phi_1 size_j + \phi_2 pack_j + \xi_j - \alpha p_j + \epsilon_{ij} \tag{5}$$

where x_j is the vector of observed product characteristics common to the brand to which j belongs (i.e., calories, sodium, caffeine per oz); $size_j$ is a dummy variable that equals to 1 if the size of a single bottle/cans in the pack is greater than 12 oz ; $pack_j$ is a dummy variable that equals to 1 if there is more than 1 cans/bottles per package. ξ_j captures unobserved (to the econometricians) product characteristics; and p_j is unit price per oz. Package size and unit price are unique to each product while product characteristics are common across a given brand.

Assuming an iid type I extreme value distribution of ϵ_{ij} yields a closed form solution of the probability a consumer i choose product j:

$$Prob_{ij} = \frac{\exp(\delta_j)}{\sum_{j=0}^{J} exp(\delta_j)} \tag{6}$$

where $\delta_j = x_j\beta + \phi_1 size_j + \phi_2 pack_j + \xi_j - \alpha p_j$ is the mean utility of product j that is common to all consumers. Matching the predicted market share with data, We can solve for (β, ϕ) using GMM.Further, we can calculate the price elasticities using estimated parameters (β, ϕ),

2.2.2 Marginal Costs

Marginal costs usually cannot be observed directly. Therefore, we use the demand system that determines the market shares to infer marginal costs. We first partition the product space into S disjoint sets where $h \in k(s)$ is the set of products hold by firm s. Each firm chooses a set of unit-prices to maximize its total profits. Suppose the profits of firm s are

$$\Pi_s = \sum_{h \in k(s)} (p_h - mc_h) M * s_h \tag{7}$$

where s_h is the market share for brand h of firm s. M is the market size. For simplicity, assume firms compete in prices and the existence of a pure-strategy Bertrand-Nash equilibrium. Then the joint profit maximization of firm s with all brands is equal to profit maximization leads to the following first order condition for p_j where $j \in k(s)$

$$s_j + \left[\sum_{h \in k(s)} (p_h - mc_h) \frac{\partial s_h}{\partial p_j} \right] = 0. \tag{8}$$

We can further express the first order condition in vector forms as:

$$(-\Delta)(p - mc) + S = 0 \tag{9}$$

where $\Delta_{jr} = -\partial s_j / \partial p_r * I_{jr}$ and I_{jr} is an indicator variable equal to 1 if product j and r are sold by the same firm and zero otherwise. Therefore, the marginal costs for audit service j in market m could be recovered by:

$$\widehat{mc} = p - \left(\Delta^{-1} S\right), \tag{10}$$

where Δ can be calculated from demand estimation in the previous section. We now recovered the marginal costs mc that allows us to estimate equation 4

3 Data

The main data used in this analysis is a unique A.C. Nielson home scan data which records Carbonated Soft Drink purchases in 7 designated market areas (DMA) [1]. This dataset contains information on product characteristics (e.g. nutrition content and package), marketing (e.g. price and in-store displays), location, and time of each purchase. The richness of the data allows us to capture price and packaging variation of soft drinks from various national brand and private labels, time, markets, and product characteristics.

3.1 Demand Estimation

This demand analysis uses 18 major national brands of CSD and 2 private label products, which accounts for around 70% of the whole CSD market. Of these 18 national brands, 5 are owned by Coca Cola, 7 are owned by Pepsi, and 6 are owned by Dr.Pepper. We aggregate

[1] These markets are New York, Detroit, Washington DC, Atlanta, Chicago, Los Angeles, and Seattle.

all private label brands into 2 categories in the demand estimation to recover marginal costs: Private Label Regular CSD and Private Label Diet CSD, and ignore the stores difference between these private label brands. There are two reasons for this aggregation. First, the private label brands are usually owned grocery stores and therefore the number of total brands is very large while each of them has a small fraction of the market. Treating a specific private label brand individually will significantly increase the number of products in the demand estimation and impose a heavy computational burden. Second, the emphasis in the analysis is the competition and price discrimination between national brands and private label brands, not between private label brands. Specifically, we barely see two private labels appear in the same store and compete directly. Since the price and characteristics differences between private label brands are also marginal, we aggregate them into two categories in the demand estimation. However, in the second stage price schedule regression, we treat all private labels brands separately.

The packaging variation of soft drinks comes from two dimensions: large bottle/can size and multiple packaging. The soft drinks sold on the market have bottle sizes ranging from a small 8 oz can to a large 3 little bottle. It's possible that larger bottles/cans can be produced at lower unit costs. which leads to price differences. On the other hand, different packagings are also available for CSD. We can buy a single bottle/can from a vending machine and pay higher price per bottle/can, or alternatively, we can choose a 6-pack, a 12-pack or even 36-pack as a bundle and pay less unit price. The multi-pack packing will also account for the nonlinearity in prices since the inventory, transaction, or restocking costs are lower for larger packages. Table 1 gives an example of frequently observed packing and size options for CSDs in the data. Among them, the most frequently purchased pack is a single bottle/can soda and the 12-pack soda, while the most popular sizes offered are the 12oz can and the 67.6 oz (2-liter) bottle.

To capture the potential cost differences from both sides, we consider a product as a

Multipack (No. of bottle/can per pack)	Size (oz per bottle/can)
1	12
12	67.6
6	33.8
24	20
4	8
8	16.9
36	101.4
32	24
18	16
20	8.45

Table 1: The Most Frequently Observed CSD Package and Size

Size/Pack Combination	Multipack (No. of bottle/can per pack)	Size (oz per bottle/can)
1	1	small (8-12 oz)
2	6or8	small (8-12 oz)
3	12	small (8-12 oz)
4	24	small (8-12 oz)
5	32or36	small (8-12 oz)
6	1	middle (16.9-24 oz)
7	6or8	middle (16.9-24 oz)
8	12	middle (16.9-24 oz)
9	1	large (33.8-101.4 oz)

Table 2: Available Combinations of Package and Size

brand with a specific size and package in the demand estimation. Clearly, not every size has all multi-package options. In the demand estimation, we further classify the size offering of CSDs into three categories: small size, middle size, and large size. Table 2 provides all 9 available combinations of package and size offering for brands in the data. Large size bottles (33.8, 67.6, & 101.4 oz) are only sold in single bottle pack while small sizes can be purchased in single/can, 6-pack, or even 36-packs. With 20 brands of CSD, this gives us a total of 180 products per market [2].

Table 3 reports the summary statistics of nutrition content (calories, sugar, sodium and caffeine) as well as the average unit price and market shares for each brand. We also report the unit prices separately for different packaging and sizes (1-pack of small size, multi-pack of small size soda, 1-pack of middle/large size soda, multi-pack of middle/large size soda). In general, for national brands (i.e. Coca Cola, Pepsi, and Dr. Pepper), the unit prices are the lowest for multi-pack of middle/large size CSD. For 1-pack CSD, the middle/large size soda are also enjoying a lower unit prices than small size soda. Surprisingly, the unit costs for the multi-pack of small size is higher than 1-pack of small size, for almost all national brands CSD. For private label brands, however, the unit price are the highest for 1-pack of small size soda and lower for 1-pack of middle/large size soda. The prices for private labels are lower than those of the national brands, for package/size combinations.

[2] For example, the products here are 6-pack of small size Pepsi Regular, 1-pack of large size Dr.Pepper Regular, or 12-pack of middle size Private Label Diet

Brand	Market Share (%)	Calories	Sugar g/oz	Sodium mg/oz	Caffeine mg/oz	Price cent/ oz				
						Brand Mean	1-pack S Size	Multi-pack S Size	1-pack M/L Size	Multi-pack M/L Size
Coca Cola										
Coke Classic Regular	5.24	11.67	3.25	4.17	2.92	3.02	4.38	4.90	2.39	2.20
Coke Diet	4.37	0.00	0.00	3.33	3.92	3.10	5.17	4.70	2.22	2.33
Sprite Regular	1.00	12.00	3.17	5.83	0.00	3.38	4.58	5.38	2.35	2.36
Coke Zero Diet	0.77	0.00	0.00	3.33	2.92	3.56	4.76	5.64	2.24	2.22
Fanta Regular	0.33	13.33	3.67	4.58	0.00	3.59	4.10	4.82	2.24	0.00
Pepsi										
Pepsi Regular	4.91	12.50	3.42	2.50	3.17	2.68	4.25	4.68	2.03	1.94
Pepsi Diet	3.29	0.00	0.00	2.92	2.92	2.83	3.94	4.68	2.03	2.03
Mountain Dew Regular	1.67	14.17	3.83	5.42	4.50	3.06	4.58	4.87	2.08	2.00
Sierra Mist Regular	0.56	12.50	3.25	3.17	0.00	2.95	5.57	4.56	2.13	2.02
Mountain Dew Diet	0.62	0.00	0.00	4.17	4.50	2.86	4.98	4.94	1.99	1.91
Mountain Dew Code Red Reg.	0.17	13.75	3.75	8.75	4.50	2.87	2.95	4.34	2.26	2.06
Sierra Mist Free Diet	0.32	0.00	0.00	3.17	0.00	2.27	2.28	2.44	2.18	1.97
Dr. Pepper										
Dr Pepper Regular	1.29	12.50	3.33	4.58	3.50	3.15	4.34	5.12	2.17	2.21
Dr Pepper Diet	0.93	0.00	0.00	4.58	3.50	3.18	16.44	5.06	1.93	2.01
Sunkist Regular	0.65	15.83	4.17	5.83	3.33	3.08	4.25	5.02	2.20	2.06
7 Up Regular	0.62	11.67	3.17	3.33	0.00	2.70	4.17	4.69	2.08	2.45
7 Up Diet	0.50	0.00	0.00	5.42	0.00	2.57	4.28	4.72	2.13	2.37
Diet Rite Pure Zero Diet	0.35	0.00	0.00	0.00	0.00	2.30	11.73	2.44	1.95	2.15
Private Label										
Private Labels Regular	3.14	12.92	3.50	4.42	1.92	2.51	5.61	3.32	1.59	1.74
Private Labels Diet	2.40	0.00	0.00	3.33	2.58	2.63	6.55	3.43	1.54	1.93

Table 3: Summary Statistics by Brand, Package, and Size in Demand Estimation

	Price (cents/oz)					
	All		National Brands		Private Label Brands	
	Mean	Std	Mean	Std	Mean	Std
Total Price	224.36	277.31	268.11	324.26	163.90	177.73
Total Volume	94.69	100.29	105.29	113.93	80.04	75.19
Private Label	42%	0.49				

Table 4: Summary Statistics for the Total Price and Volume

3.2 Price Schedule Regression

In the price schedule regression, we take total price of the whole pack as the dependent variable, and the total volume as independent variable. For example, for a 12-pack of 12oz can Pepsi Regular, the total price (e.g. \$4) is the price paid the whole pack, the total volume sold is 144oz (12×12) and the unit price per oz is calculated accordingly (\$4/ 144). Table 4 present the mean total price and volume soda for a package of soda on market. On average, private labels are sold is smaller package/size with lower prices.

4 Results

4.1 Demand Estimation Results

Table 5 presents the estimated demand parameters described in Section 2.2.1.As expected, the price coefficient is -0.3609, which is negative and significant. Consumers have on average positive valuation of calories and caffeine content and negative valuation of sodium content. The positive coefficient of calories might reflect preferences of what is perceived as preference for flavor over nutritional or obesity concerns. To capture consumer's preference of packaging size, dummies variables Multi-pack and Middle/Large Size are also included and estimated to be positive and significant. This suggests that people prefer multi-packs with larger volume

Variable	Mean	Std	t-stat
Price	-0.3609	0.0079	-45.88
Calories	0.0185	0.0022	8.41
Sodium	-0.2217	0.0101	-21.93
Caffeine	0.1972	0.0080	24.63
Multi-Pack	0.0778	0.0370	2.1
Middle/Large Size	0.0970	0.0290	3.34
DMADum1	-0.2910	0.0484	-6.02
DMADum2	-0.5161	0.0471	-10.96
DMADum3	0.0577	0.0480	1.2
DMADum4	-0.4559	0.0472	-9.65
DMADum5	-0.4386	0.0461	-9.52
DMADum6	-0.0177	0.0476	-0.37
monthdum1	-0.1088	0.0588	-1.85
monthdum2	-0.1461	0.0588	-2.48
monthdum4	-0.0632	0.0583	-1.08
monthdum5	-0.0090	0.0582	-0.15
monthdum6	0.0201	0.0584	0.34
monthdum7	-0.0146	0.0514	-0.29
monthdum8	-0.0142	0.0514	-0.28
monthdum9	-0.1810	0.0517	-3.5
monthdum10	-0.0834	0.0516	-1.62
monthdum11	-0.0044	0.0518	-0.09

Table 5: Demand Estimates of Consumer Preferences in the CSD Market

of carbonated soft drinks in general. The time and DMA dummies are also included in the estimation.

To check how product characteristics and packing size affect marginal cost, we also regress the marginal costs for products as a function of the vector X^{cost} and the regression results are presented in Table 6. The coefficient of Multi-pack and Middle/Large size are both negative and significant. The cost parameters indicate that multi-pack is, on average, about \$ 0.56 per oz less expensive to produce, while a larger size of carbonated soft drinks is \$ 0.09 per oz cheaper to produce.

Variable	Mean	Std	t-stat
Calories	-0.0176	0.0008	-23.07
Sodium	0.1396	0.0035	39.88
Caffeine	-0.0164	0.0028	-5.9
Multi-Pack	-0.5651	0.0101	-55.96
Middle/Large Size	-0.0875	0.0100	-8.73
Raw Sugar Price	0.0118	0.0480	0.25
DMADum1	-0.0206	0.0168	-1.23
DMADum2	-0.0317	0.0163	-1.94
DMADum3	-0.0032	0.0167	-0.19
DMADum4	0.0012	0.0164	0.07
DMADum5	0.0109	0.0160	0.68
DMADum6	-0.0161	0.0165	-0.98
monthdum1	-0.0140	0.0204	-0.69
monthdum2	-0.0018	0.0204	-0.09
monthdum4	0.0006	0.0202	0.03
monthdum5	0.0023	0.0202	0.11
monthdum6	-0.0004	0.0206	-0.02
monthdum7	0.0021	0.0180	0.12
monthdum8	0.0001	0.0183	0
monthdum9	0.0040	0.0180	0.22
monthdum10	0.0008	0.0180	0.04
monthdum11	-0.0020	0.0180	-0.11
Constant	0.5229	0.0380	13.75

Table 6: Cost Parameters Estimates

Variable	Mean	Std	t-stat
Log Volume (γ_0)	0.5695	0.0103	55.28
Private * Log Volume (γ_1)	-0.0638	0.0033	-19.54
Log (Total Costs)	0.2186	0.0112	19.6
Diet * Log Volume	-0.0046	0.0027	-1.68
Year 2007 * Log Volume	-0.0108	0.0032	-3.33
Year 2006 * Log Volume	-0.0288	0.0033	-8.84
Cosntant	3.2345	0.0465	69.62
DMA Dummies	Yes		

Table 7: Price Schedule Estimates: The Effect Vertical Product Differentiation on Curvature

4.2 Price Schedule Regression

The key focus of this analysis is to check how the degree of price discrimination varies with vertical product differentiation. Therefore, γ_0 and γ_1 are of special interests. Table 7 reports estimates of γ_0 and γ_1. The coefficient on the Private Lable-volume interaction, γ_1 is precisely estimated at -0.0638. That is, β in Equation 2 is lower for private label products, implying that the price schedule is more curved for private label carbonated soft drinks in the market.

5 Conclusion

In this analysis, We assess the relationship between vertical production differentiation (national brands vs. private labels) and price discrimination in the Carbonated Soft Drinks market. Specifically, we use a unique A.C. Nielsen home scanner data on soft drinks in 7 designated markets areas (DMA) to examine how product differentiation affects the curvature of price schedule of National Brands and Private Label products.

Our results suggest that in the carbonated soft drinks market, both national brands and private labels offers quantity discount to consumers: consumers pay lower unit prices when buying larger packed soft drinks. In addition, we find that the price curvature parameter is lower for private labels, implying that the price schedule is more curved for private label soft drinks than national brands. This means in the CSD market, private labels have more ability to perform price discrimination, segment consumers, and generate high revenues, comparing to national brands. This result, to some extent, explains the growing market shares of private label soft drinks and the significant percentage of total sales from private labels goods for retailers, such as Wal-Mart and Target.

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