Spillover Effects of TV Advertising: The Case of Carbonated Soft Drinks

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Abstract

This paper examines the spillover effects of television brand advertising on consumer demand for carbonated soft drinks using a nested logit model and household purchase and advertising data from nine U.S. cities over a three year period. Spillover effects are modeled using the conventional linear advertising production function with brand and company advertising, which assumes perfect substitution and constant returns to scale, and the results are compared to those attained via a constant elasticity of substitution (CES) model. Empirical results indicate that brand advertising spillover effects have a positive and significant impact on the demand for all brands belonging to the same company, highlighting the importance of accounting for spillover effects in demand models. The CES advertising production function outperforms the linear form, indicating decreasing returns to advertising goodwill and imperfect substitutes between brand advertising and company advertising.

Key words: advertising, demand, spillover, carbonated soft drinks, CES, Sodas
JEL Codes: C51, D12, L66, M37

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Introduction

Although advertising significantly affects consumer choices, relatively few studies include it in empirical demand studies of food and beverage products. Even when included, the demand for a particular brand is typically assumed to depend only on that brand's advertising (e.g., Nevo, 2001; Dubé, Hitsch and Manchanda, 2005). A few studies that include both brand advertising and spillover effects treat them as perfect substitutes (Tulin and Sun, 2002; Subramanian and Ghose, 2003) by using a linear form, which implies that advertising has a constant return to scale. Thus, if advertising for each brand is doubled, its effect on demand is doubled. However, Thomas (1989) reports evidence of advertising diseconomies of scale in the cigarette and soft drink industries. Thus, the consequences of ignoring or assuming perfect substitution between brand advertising and spillover effects are that it might lead to biased estimated parameters for advertising as well as other key parameters such as price responses, which may result in misleading policy conclusions or marketing strategies.

This paper uses the carbonated soft drinks (CSDs) industry as a case study. Several features make this industry a relevant and interesting case to examine advertising spillover effects. First, CSDs are the most heavily advertised beverage product in the United States. The advertising expenditure of Coca Cola Company was $267 million in 2010, competing with PepsiCo.' $154 million and a $104 million expenditure by Dr. Pepper (Zmuda, 2011). Second, CSD brands belonging to the same company can be clearly identified and spillover effects measured. Third, the major CSD manufacturers (Coca Cola, PepsiCo., and Dr Pepper) emphasize non-price competition such as advertising, highlighting the importance of appropriately modeling the effects of advertising on consumer choices. Fourth, given the link between CSD advertising, consumption and obesity, it is important to get a better understanding of advertising and its spillover effects.

With a dataset that includes brand-level advertising for 14 leading carbonated soft drinks in 9 designated market areas (DMAs), this paper contributes to the advertising literature by measuring and testing for the degree of advertising spillover effects among brands of CSDs by nesting brands' advertising and companies' advertising via a constant elasticity of substitution (CES) advertising production function. The results indicate that brand advertising spillover effects have a positive and significant impact on the demand for all brands belonging to the same company. Moreover, the CES model advertising function outperforms the linear form, rejecting the assumptions of perfect substitution and constant returns to scale. In addition, the CES results indicate decreasing returns to advertising goodwill and that brand and company advertising are imperfect substitutes.

Model

Consumers are assumed to choose a CSD companies (or an outside good) and then choose a specific brand within that company. Given our interest in advertising spillover effect, companies are regarded as "groups" or clusters of brands facing consumers. Following Berry (1994) and Kusuda (2011), the utility of consumer i from choosing one unit of product $j \in g$ ($g = 1,2, \dots G$ and denotes the groups or companies) is assumed to be:

$$U_{ij} = \delta_j + \zeta_{ig} + (1 - \sigma)\epsilon_{ij} \ , \tag{1}$$

where $\delta_j = X_j{}'\beta - \alpha P_j + \xi_j$ is the mean of the utility. X_j is a vector of observable product characteristics, P_j is the price of product j. ξ_j is the utility shocks that is observed by the consumer but not the researcher . The second component ζ_{ig} is common to all products in group g . ϵ_{ij} is an identically and independently distributed extreme value. Parameter σ is between zero and one, determining the within group correlation of utility levels. As σ approaches ones, the within group correlation of utility level goes to one, and as σ approaches zero, the within group correlation goes to zero. Based on Cardell (1991), $\zeta_{ig} + (1 - \sigma)\epsilon_{ij}$ is an extreme value random variable.

The market share of brand j in group g is given by

$$s_{j/g} = \frac{exp(\frac{\delta_j}{1-\sigma})}{\sum_{j \in g} exp(\frac{\delta_j}{1-\sigma})} \ , \tag{2}$$

and the probability of choosing one of the group g products (the group share) is

$$s_g = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}} \ , \tag{3}$$

where $D_g = \sum_{j \in g} exp\left(\frac{\delta_j}{1-\sigma}\right)$.

Thus, market share of brand j can be simply expressed as $s_j = s_{j/g} s_g$.

Normalizing the utility from the outside good to zero, the nested logit model (Berry, 1994) is

$$ln(s_{jt}) - ln\,(s_{0t}) = X_j{}'\beta - \alpha P_j + \sigma ln(s_{j/g,t}) + \xi_{jt}. \tag{4}$$

Advertising is introduced in this model as a product characteristic. Consider the effect of advertising as having two components. The first is brand advertising, which is modeled via a stock of goodwill as in Tulin and Sun (2002). Advertising goodwill GW_{jt} for CSD brand j in time period t is given by $GW_{jt} = \sum_{n=1}^{\infty} \lambda^n A_{j,t-n}$, where A_{jt} represents advertising for product j in time period t and λ is a decay parameter of advertising. The second component is the spillover effect across brands belonging to the same company, i.e. the sum of goodwill stocks of the other brands belongs to the same manufacturer, denoted as GW_{-jt} . Two forms of advertising function are considered: a linear form and a CES form. A linear form is given by $Ad_{jt} = \Phi GW_{jt} + \Psi GW_{-jt}$. Note that the spillover affects parameter $\Psi \geq 0$, where $\Psi = 0$ indicates no spillover effect. A CES advertising production function is given by

$$Ad_{jt} = (\Phi GW_{jt}{}^{\rho} + \Psi GW_{-jt}{}^{\rho})^{k/\rho}, \tag{5}$$

where $\rho = \frac{\gamma-1}{\gamma}$, γ being the elasticity of substitution. When $k = 1$ and $\rho = 1$, the CES advertising production function collapses to the linear form. k measures returns to scale, and when $k > 1$ or $k < 1$), advertising has corresponding increasing or decreasing return to scale. Incorporating (5) into (4), the estimating model becomes:

$$lns_{jt} - lns_{0t} = X_j{}'\beta - \alpha P_j + \left(\Phi g_{jt}{}^{\rho} + \Psi g_{-jt}{}^{\rho}\right)^{k/\rho} + \sigma ln(s_{j/g,t}) + \xi_{jt}\,. \tag{6}$$

Following Kusuda (2011), when brands j and l belongs to group g, the own and cross-price elasticity of demand of brand j are:

$$\eta_{jj} = \frac{-\alpha}{1-\sigma} P_j + \frac{\alpha}{1-\sigma} s_{l/g} P_j - \alpha\left(1 - s_g\right) s_{l/g} P_j\,, \tag{7}$$

$$\eta_{jl} = \frac{\alpha}{1-\sigma} s_{l/g} P_l - \alpha\left(1 - s_g\right) s_{l/g} P_l\,. \tag{8}$$

When brands j and l are not in the same nest, the cross-price elasticity is given by $\eta_{jl} = \alpha s_g s_{l/g} P_l$.

Data and Estimation

This paper combines two A.C. Nielsen datasets. One is the Homescan dataset depicting households' brand-level CSDs purchases in grocery stores, drug stores, vending machines, and online shopping sites in 9 designated market areas (DMAs) on a weekly basis from 2006 to 2008. The records of the Homescan dataset include product characteristics information (e.g., package size, name of brand), marketing information (e.g., unit price and promotion displays), location and time of each purchase, and demographic information about households that made the purchases. The other is the television dataset consisting of brand level advertising Gross Rating Points (GRPs) on national (cable, network and syndicated) and local (spot) television in the same DMAs. By combining these two datasets, one can directly link brand level advertising to brands and companies purchases of households. The market share is computed based on the potential market size, which is defined as combined per capita consumption (in volume) of the top 14 CSDs plus the outside good (juices, milk and other CSDs) times population for each period and DMA.

In the regression model, independent variables include price, nutritional characteristics, brand advertising, company advertising, within-group market share (in logarithmic form) and demand shifters such as seasonal dummies, DMA dummies and time trend. Advertising GRPs and nutritional characteristics are scaled between 0 and 1. Here product nutritional characteristics include sugar, sodium, caffeine contents (Lopez and Fantuzzi, 2012) as well as calories; a high collinearity exists between calories and sugar. We do not discard either one to avoid collinearity. First, from labeling perspective, sugar content mainly conveys how sweet the drink will taste, while the number of calories in boldface on the label reminds consumers of the drink's potential energy. Many researchers, such as Steiner (1979) and Clark (1998), show that the existence of innate sensory preferences for sweetness is genetically determined. On the other side, strategies such as launching new products with lower calories by the CSD companies show that consumers dislike calories. [1] Second, from the standpoint of modeling, omitting either one of them from the logistic model would result in risk estimates of one nutrient confounded by the other (Smith, Slattery and French, 1991),

[1] "The big three beverage companies are also endlessly tinkering with combinations of sweeteners and sugars to lower calories without altering taste. PepsiCo., for instance, introduced Pepsi Next, which uses a blend of sweeteners to deliver half the calories of a standard Pepsi." "Dr. Pepper's Snapple has gone even further with 10-calorie versions using a blend of artificial sweeteners and high-fructose corn syrup in many of its carbonated soft drinks." (The New York Times, May 15, 2012).

and an omitted variable bias. Third, low standard errors and highly significant estimators, if possible in this paper, indicate no Type II error happens due to collinearity.

Table 1 lists CSD brands and product attributes examined in this paper, including 14 brands belonging to three companies: Coca Cola, PepsiCo., and Dr. Pepper. In this paper, we use 9,576 market-level observations across 9 DMA markets (New York, Detroit, Boston, Washington D.C., Atlanta, Chicago, Houston, Los Angeles, and Seattle) over 76 consecutive bi-weeks (From February 2006 to December 2008).

Table 2 provides summary statistics of market share, price and advertising goodwill. The market share and price for a brand are the average across the 9 DMA markets over the 76 bi-weekly periods. Brand goodwill is advertising goodwill for one brand itself, which captures the carry-over effects of advertising's impact on demand. Company goodwill is aggregation of goodwill for the other brands under the same company. Goodwill is derived from GRPs. We use Clarke's (1976) decay parameter for advertising estimated at 0.6. [2]

Following Berry (1994), price and within-group market share are regarded as endogenous variables. As price is a function of marginal costs and a markup that reflects a deviation by the market, price should be correlated with the error term. Second, within group market share may be affected by the brand's market share, so it should not be treated as exogenous variable (Nevo, 2001; Kusuda, 2006). Third, advertising affects market shares and on the other side, company adjusts its advertising level based on the market share observed which lead to its endogeneity.

To eliminate potential biases due to endogeneity, a set of instrumental variables are used in identification procedure. Price of sugar and price of high fructose corn syrup (including one-period lag) are instruments for price. These variables are inputs in production. For the within-group market share, Berry (1994) suggests that characteristics of other firms in the group may be used as instruments. Kusuda (2011) uses the share of price within group and product characteristics of other firms in the group as instruments. Following Berry (1994) and Kusuda (2001), the first instrument for within-group market share is average

[2] Besides, Lambin's (1976) estimated depreciation-rates for brand advertising which vary widely across product groups but take an average of around 50% per year. Tchumtchoua and Cotterill (2010) report goodwill decay rate estimated with milk data is 0.556.

within-group market share over all other cities during all periods, which reflects average level of a brand's within-group share while uncorrelated with the error term. The second IV is ratio of price of one brand to average price of other brands within the same group. Here we use one-period lag of it as instrument to avoid potential correlation with error term. This instrument describes the price level of a brand within a group, which affects within-group market share but uncorrelated with the error term. For brand advertising, we use average level of advertising goodwill across all other cities as instrument.

With the instruments above, two-stage least squares (2SLS) method is applied for the linear advertising model and two-stage residual inclusion (2SRI) approach is used for the CES model. The 2SRI estimator has been shown to be better (consistent) than two-stage predictor substitution (2SPS) in nonlinear model (TerZa, Basu and Rathouz, 2007). The first stage F-stats and the Sargan's test are used to test whether the instrumental variables are valid and relatively strong. As for model specifications, the Vuong test (Vuong, 1989) is used to compare the linear form model and CES form model. In the estimation procedure, the term ${}^{k}/_{\rho}$ is replaced as one part, i.e. $\tau = {}^{k}/_{\rho}$. Parameter k are computed with estimated τ and ρ.

Empirical Results

Table 3 shows the estimation results from three model specifications: (1) excluding advertising in the demand model; (2) using a linear production function of brand advertising and company advertising; (3) using a CES function of brand advertising and company advertising. All the estimated coefficients are consistent with expected signs.

From the Sargan's test results and first stage F-stats, the instrumental variables are valid and relatively strong. The Durbin (1954) statistic validates that the three variables, price, own-adverting and within group share, are endogenous. Finally, the Vuong (1989) test indicates that the specification with CES goodwill production function outperforms the linear advertising form.

From Table 3, the spillover effect of advertising (0.826) from the CES model is higher than the own effect (0.184). One illustration is that since brands within a company is relatively highly homogenous and substituted, one brand may receive the spillovers from any one of the other brands under same company, the aggregation of which exceeds the own-effect. Another finding is the advertising function has a decreasing return to scale (with a scale of 0.246). This result, which coincides with Thomas (1989), may arise from two reasons. First, at high level of advertising, less responsive consumers are reached; second, an increasing number of messages must be sent in order to reach a consumer that has not yet been exposed to the advertising (Bagwell, 2005). The elasticity of substitution (1.039) indicates that modeling with a linear advertising form may be invalid because of an underlying perfect substitution assumption.

There are other two conclusions. First, the estimated within-group heterogeneity parameter is 0.909, indicating that the utility of consumers are highly correlated within a company. In addition, elasticities computed in the Tables 4, 5 and 6 indicate that incorporating spillover effects, especially with CES function form, leads to higher price elasticity of demand, which highlights the importance of model specification when one makes policy suggestions based on computed price elasticities.

Concluding Remarks

This paper estimates the spillover effects of television advertising using a nested logit demand model along with data on television advertising and purchases of carbonated soft drinks by nearly 14,000 households in nine U.S. cities over three years. An innovative feature of the analysis is the use of a CES advertising production function that considers both brand and company-wide spillover effects that allows for non-constants returns to advertising and partial substitution between brand and company advertising.

Empirical results confirm that spillover effects are quite significant in affecting demand for particular brands of sodas. Allowing for a non-linear advertising production function, such as CES, leads to better estimates of price and advertising responses than using the conventional linear function. Furthermore, brand and company advertising are found to be imperfect substitutes, and advertising is found to be subject to decreasing returns. Thus, to properly account for the impact of advertising on food and beverages, future studies should incorporate spillover effects, as brand advertising is the rising tide that lifts all boats in a company's product portfolio.

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Table 1: CSD Brands Attributes

Brand Name	Company	Sugar (g/12oz)	Sodium (mg/12oz)	Caffeine (mg/12oz)	Calories
Coke Classic Regular	Coca Cola	39	50	35	140
Coke Diet	Coca Cola	0	40	47	0
Sprite Regular	Coca Cola	38	70	0	144
Coke Zero Diet	Coca Cola	0	40	35	0
Pepsi Regular	PepsiCo.	41	30	38	150
Pepsi Diet	PepsiCo.	0	35	35	0
Mountain Dew Regular	PepsiCo.	46	65	54	170
Sierra Mist Regular	PepsiCo.	38	38	0	150
Mountain Dew Diet	PepsiCo.	38	38	0	150
Dr Pepper Regular	Dr Pepper	40	55	42	150
Dr Pepper Diet	Dr Pepper	0	55	42	0
Sunkist Regular	Dr Pepper	50	70	40	190
7 Up Regular	Dr Pepper	38	40	0	140
7 Up Diet	Dr Pepper	0	65	0	0

Table2: Summary Statistics for Price and Advertising

Brand Name	Company	Mkt. Share (%)	Price ($/12oz)	Own Goodwill	Others' Goodwill
Coke Classic Regular	Coca Cola	5.17	0.1585	0.3139	0.5680
Coke Diet	Coca Cola	4.54	0.1631	0.1718	0.7102
Sprite Regular	Coca Cola	1.14	0.1720	0.1795	0.7024
Coke Zero Diet	Coca Cola	0.74	0.1776	0.2167	0.6652
Pepsi Regular	PepsiCo.	4.56	0.1418	0.2969	0.5938
Pepsi Diet	PepsiCo.	3.11	0.1511	0.1584	0.7323
Mountain Dew Regular	PepsiCo.	1.54	0.1643	0.2200	0.6706
Sierra Mist Regular	PepsiCo.	0.59	0.1493	0.0819	0.8095
Mountain Dew Diet	PepsiCo.	0.55	0.1512	0.1336	0.7571
Dr Pepper Regular	Dr Pepper	1.49	0.1653	0.3064	0.4255
Dr Pepper Diet	Dr Pepper	1.06	0.1552	0.1141	0.6177
Sunkist Regular	Dr Pepper	0.63	0.1618	0.0335	0.6978
7 Up Regular	Dr Pepper	0.58	0.1482	0.2642	0.4680
7 Up Diet	Dr Pepper	0.46	0.1385	0.0139	0.6283

Note: Brand goodwill and company goodwill are calculated respectively via equation (5) with the GRPs of brand advertising and companie advertising, which are scaled between 0 and 1.

Table 3: Estimation Results of Different Specific Models

Specification Variables	No Advertising (1)	Linear Form (2)	CES Form (3)
Price	-1.638 (0.406)	-1.707 (0.411)	-2.161 (0.347)
Sugar	5.080 (0.636)	4.927 (0.662)	4.183 (0.611)
Calories	-5.095 (0.647)	-4.954 (0.672)	-4.288 (0.621)
Sodium	-0.916 (0.041)	-0.847 (0.042)	-0.505 (0.040)
Caffeine	0.313 (0.024)	0.288 (0.023)	0.140 (0.021)
Brand Advertising	----	0.287 (0.043)	0.184 (0.025)
Spillover Effect	----	0.288 (0.019)	0.826 (0.022)
Within-Group Market Share	0.874 (0.011)	0.882 (0.011)	0.909 (0.010)
Time Trend	0.007E-2 (0.004E-1)	0.003 (0.005E-1)	0.002 (0.004E-1)
Substitution Parameter ρ	----	----	0.038 (0.007)
Scale Parameter τ	----	----	6.530 (1.254)
Season Fixed Effects DMA	YES	YES	YES
Fixed Effects	YES	YES	YES
Elasticity of Substitution	----	----	1.039
Return to Scale	----	----	0.246
Observations	9443	9443	9443
First Stage F Stat.			
Price (p-value)	32.926 (0.00)	30.084 (0.00)	30.084 (0.00)
Within-Group Mk. Sh.(p-value)	1397.160 (0.00)	1157.250 (0.00)	1157.250 (0.00)
Advertising (p-value)	---	22858.000 (0.00)	22858.000 (0.00)
Sargan Stat.(p-value)	2.076 (0.56)	4.616 (0.20)	4.616 (0.20)
Durbin Score(p-value)	42.736 (0.00)	50.832 (0.00)	50.832 (0.00)
Vuong test (p-value)		23.375(0.00)	

Note: The robust standard errors are reported in the parentheses. Elasticity of Substitution and Return to Scale are computed based on Substitution Parameter ρ and Scale Parameter τ. The Vuong test results for model 3 vs. model 2 indicate that model 3 outperforms model 2 at the 1% significance level.

Table 4: Own- and Cross-Price Elasticities for Top14 CSD Brands (Model 1: No Advertising)

	Coke Class R.	Coke Diet	Sprite Regular	Coke Zero D.	Pepsi R.	Pepsi D.	Mountain Dew R.	Sierra Mist R.	Mountain Dew D.	Dr. Pepper R.	Dr. Pepper D.	Sunkist Regular	7 Up Regular	7 Up Diet
Coke Class R	-2.8294	1.6522	0.4296	0.2894	0.0234	0.0172	0.0093	0.0030	0.0029	0.0089	0.0060	0.0034	0.0030	0.0022
Coke Diet	1.8332	-3.1473	0.4296	0.2894	0.0234	0.0172	0.0093	0.0030	0.0029	0.0089	0.0060	0.0034	0.0030	0.0022
Sprite Regular	1.8332	1.6522	-4.6310	0.2894	0.0234	0.0172	0.0093	0.0030	0.0029	0.0089	0.0060	0.0034	0.0030	0.0022
Coke Zero D.	1.8332	1.6522	0.4296	-4.9362	0.0234	0.0172	0.0093	0.0030	0.0029	0.0089	0.0060	0.0034	0.0030	0.0022
Pepsi R.	0.0299	0.0270	0.0070	0.0047	-2.5601	1.1719	0.6448	0.1997	0.2060	0.0089	0.0060	0.0034	0.0030	0.0022
Pepsi D.	0.0299	0.0270	0.0070	0.0047	1.6106	-3.2743	0.6448	0.1997	0.2060	0.0089	0.0060	0.0034	0.0030	0.0022
Mountain Dew R.	0.0299	0.0270	0.0070	0.0047	1.6106	1.1719	-4.1905	0.1997	0.2060	0.0089	0.0060	0.0034	0.0030	0.0022
Sierra Mist R.	0.0299	0.0270	0.0070	0.0047	1.6106	1.1719	0.6448	-4.1934	0.2060	0.0089	0.0060	0.0034	0.0030	0.0022
Mountain Dew D.	0.0299	0.0270	0.0070	0.0047	1.6106	1.1719	0.6448	0.1997	-4.2434	0.0089	0.0060	0.0034	0.0030	0.0022
Dr. Pepper R.	0.0299	0.0270	0.0070	0.0047	0.0234	0.0172	0.0093	0.0030	0.0029	-3.4830	1.0206	0.6249	0.4896	0.4028
Dr. Pepper D.	0.0299	0.0270	0.0070	0.0047	0.0234	0.0172	0.0093	0.0030	0.0029	1.3798	-3.5460	0.6249	0.4896	0.4028
Sunkist Regular	0.0299	0.0270	0.0070	0.0047	0.0234	0.0172	0.0093	0.0030	0.0029	1.3798	1.0206	-4.1290	0.4896	0.4028
7 Up Regular	0.0299	0.0270	0.0070	0.0047	0.0234	0.0172	0.0093	0.0030	0.0029	1.3798	1.0206	0.6249	-3.8691	0.4028
7 Up Diet	0.0299	0.0270	0.0070	0.0047	0.0234	0.0172	0.0093	0.0030	0.0029	1.3798	1.0206	0.6249	0.4896	-3.6730

Table 5: Own- and Cross-Price Elasticities for Top14 CSD Brands (Model 2: Linear Form of Advertising)

	Coke Class R.	Coke Diet	Sprite Regular	Coke Zero D.	Pepsi R.	Pepsi D.	Mountain Dew R.	Sierra Mist R.	Mountain Dew D.	Dr. Pepper R.	Dr. Pepper D.	Sunkist Regular	7 Up Regular	7 Up Diet
Coke Class R	-3.1471	1.8641	0.4847	0.3265	0.0243	0.0180	0.0096	0.0031	0.0031	0.0093	0.0062	0.0035	0.0031	0.0023
Coke Diet	2.0684	-3.5044	0.4847	0.3265	0.0243	0.0180	0.0096	0.0031	0.0031	0.0093	0.0062	0.0035	0.0031	0.0023
Sprite Regular	2.0684	1.8641	-5.1759	0.3265	0.0243	0.0180	0.0096	0.0031	0.0031	0.0093	0.0062	0.0035	0.0031	0.0023
Coke Zero D.	2.0684	1.8641	0.4847	-5.5186	0.0243	0.0180	0.0096	0.0031	0.0031	0.0093	0.0062	0.0035	0.0031	0.0023
Pepsi R.	0.0311	0.0282	0.0073	0.0049	-2.8477	1.3223	0.7277	0.2253	0.2325	0.0093	0.0062	0.0035	0.0031	0.0023
Pepsi D.	0.0311	0.0282	0.0073	0.0049	1.8175	-3.6510	0.7277	0.2253	0.2325	0.0093	0.0062	0.0035	0.0031	0.0023
Mountain Dew R.	0.0311	0.0282	0.0073	0.0049	1.8175	1.3223	-4.6809	0.2253	0.2325	0.0093	0.0062	0.0035	0.0031	0.0023
Sierra Mist R.	0.0311	0.0282	0.0073	0.0049	1.8175	1.3223	0.7277	-4.6886	0.2325	0.0093	0.0062	0.0035	0.0031	0.0023
Mountain Dew D.	0.0311	0.0282	0.0073	0.0049	1.8175	1.3223	0.7277	0.2253	-4.7445	0.0093	0.0062	0.0035	0.0031	0.0023
Dr. Pepper R.	0.0311	0.0282	0.0073	0.0049	0.0243	0.0180	0.0096	0.0031	0.0031	-3.8814	1.1524	0.7057	0.5528	0.4549
Dr. Pepper D.	0.0311	0.0282	0.0073	0.0049	0.0243	0.0180	0.0096	0.0031	0.0031	1.5580	-3.9555	0.7057	0.5528	0.4549
Sunkist Regular	0.0311	0.0282	0.0073	0.0049	0.0243	0.0180	0.0096	0.0031	0.0031	1.5580	1.1524	-4.6119	0.5528	0.4549
7 Up Regular	0.0311	0.0282	0.0073	0.0049	0.0243	0.0180	0.0096	0.0031	0.0031	1.5580	1.1524	0.7057	-4.3226	0.4549
7 Up Diet	0.0311	0.0282	0.0073	0.0049	0.0243	0.0180	0.0096	0.0031	0.0031	1.5580	1.1524	0.7057	0.5528	-4.1042

Table 6: Own- and Cross-Price Elasticities for Top14 CSD Brands (Model 3: CES Form of Advertising)

	Coke Class R.	Coke Diet	Sprite Regular	Coke Zero D.	Pepsi R.	Pepsi D.	Mountain Dew R.	Sierra Mist R.	Mountain Dew D.	Dr. Pepper R.	Dr. Pepper D.	Sunkist Regular	7 Up Regular	7 Up Diet
Coke Class R	-5.0596	3.1298	0.8138	0.5482	0.0308	0.0228	0.0122	0.0040	0.0039	0.0117	0.0079	0.0044	0.0040	0.0029
Coke Diet	3.4728	-5.6529	0.8138	0.5482	0.0308	0.0228	0.0122	0.0040	0.0039	0.0117	0.0079	0.0044	0.0040	0.0029
Sprite Regular	3.4728	3.1298	-8.4468	0.5482	0.0308	0.0228	0.0122	0.0040	0.0039	0.0117	0.0079	0.0044	0.0040	0.0029
Coke Zero D.	3.4728	3.1298	0.8138	-9.0143	0.0308	0.0228	0.0122	0.0040	0.0039	0.0117	0.0079	0.0044	0.0040	0.0029
Pepsi R.	0.0394	0.0357	0.0093	0.0062	-4.5793	2.2210	1.2223	0.3784	0.3906	0.0117	0.0079	0.0044	0.0040	0.0029
Pepsi D.	0.0394	0.0357	0.0093	0.0062	3.0528	-5.9152	1.2223	0.3784	0.3906	0.0117	0.0079	0.0044	0.0040	0.0029
Mountain Dew R.	0.0394	0.0357	0.0093	0.0062	3.0528	2.2210	-7.6260	0.3784	0.3906	0.0117	0.0079	0.0044	0.0040	0.0029
Sierra Mist R.	0.0394	0.0357	0.0093	0.0062	3.0528	2.2210	1.2223	-7.6607	0.3906	0.0117	0.0079	0.0044	0.0040	0.0029
Mountain Dew D.	0.0394	0.0357	0.0093	0.0062	3.0528	2.2210	1.2223	0.3784	-7.7517	0.0117	0.0079	0.0044	0.0040	0.0029
Dr. Pepper R.	0.0394	0.0357	0.0093	0.0062	0.0308	0.0228	0.0122	0.0040	0.0039	-6.2769	1.9396	1.1879	0.9303	0.7656
Dr. Pepper D.	0.0394	0.0357	0.0093	0.0062	0.0308	0.0228	0.0122	0.0040	0.0039	2.6218	-6.4169	1.1879	0.9303	0.7656
Sunkist Regular	0.0394	0.0357	0.0093	0.0062	0.0308	0.0228	0.0122	0.0040	0.0039	2.6218	1.9396	-7.5116	0.9303	0.7656
7 Up Regular	0.0394	0.0357	0.0093	0.0062	0.0308	0.0228	0.0122	0.0040	0.0039	2.6218	1.9396	1.1879	-7.0458	0.7656
7 Up Diet	0.0394	0.0357	0.0093	0.0062	0.0308	0.0228	0.0122	0.0040	0.0039	2.6218	1.9396	1.1879	0.9303	-6.6929