Television Advertising and Soda Demand

Rigoberto A. Lopez, Yizao Liu, and Chen Zhu

University of Connecticut
Department of Agricultural and Resource Economics & Zwick Center for Food and Resource Policy
1376 Storrs Road, Unit 4021
Storrs, Connecticut 06269-4021
Phone: (860) 486-2836

rigoberto.lopez@uconn.edu, yizao.liu@uconn.ed, chen.2.zhu@uconn.edu

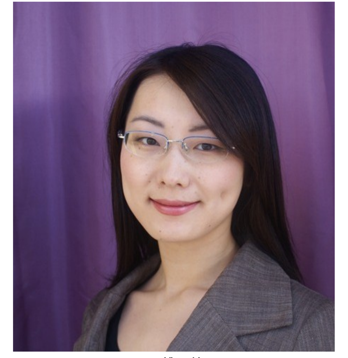
Poster prepared for presentation at the Agricultural & Applied Economics
Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012

Television Advertising and Soda Demand

Rigoberto A. Lopez, Yizao Liu, and Chen Zhu

Department of Agricultural and Resource Economics & Zwick Center for Food and Resource Policy

Rigoberto Lopez
Professor and Department Head
Director, Zwick Center for Food and Resource Policy



Yizao Liu
Associate Professor

Chen Zhu
Ph.D. Candidate

Introduction

The U.S. beverage industry spends $2 billion a year on advertising. Carbonated soft drinks (CSDs) are the leading beverage category in both consumption and advertising expenditures in the United States. In 2010, for example, the average American drank 45 gallons of CSDs and the Coca Cola, PepsiCo, and Dr. Pepper companies spent $267 million, $154 million, and $104 million, respectively.

Understanding how advertising of CSDs impacts demand is important for several reasons. First, sodas have been identified as the leading contributor of calories in the ongoing obesity epidemic. Second, ignoring or inaccurately measuring advertising might lead to biased estimates of consumer price and advertising responsiveness, resulting in misguided (taxation) price or advertising policies. Finally, the long-standing debate as to whether advertising is persuasive (shift preferences) or informative is an important basis for competition policy depending on how advertising affects demand.

The poster examines the effects of television advertising on consumer demand for carbonated soft drinks using a random coefficients logit model (BLP) with household and advertising data from seven U.S. cities over a three year period. In addition, it accounts for brand spillover effects and compares the implications of using the expenditures to measure advertising to using advertising coverage.

Objective

The main objective of the poster is to determine how impacts demand for CSDs and market shares. A corollary objective is to assess whether advertising plays a persuasive or an informative role in the CSD market.

Method

CSDs are differentiated products. We proceed by modeling the demand for CSDs in characteristics space and follow Berry, Levinsohn and Pakes (1995; herein BLP), which takes into account product and consumer heterogeneity using market level data and allows advertising to be treated as a product characteristic. The starting point is to segment an individual's utility from consuming CSDS into two additive components: the mean utility (common to all consumer in the market) and a deviation from that utility (unique to that individual).

Following BLP, let the indirect utility of consumer *i* from consuming one unit of CSD product *j* in market *m* be denoted by, $u_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}$,

where the mean utility $\delta_{jm} = X_j' \beta + \xi_{jm}$ includes a vector X_j of product characteristics, including advertising and product-specific market shocks ξ_{jm}. The utility deviations $\mu_{ijm} = X_j' (\Omega D_{im} + \Sigma V_i)$ depend on the vector D_{im} of household-specific demographic variables; Ω is a matrix of coefficients that measure how the taste characteristics vary across households; Σ is a scaling matrix; and V_i are unobserved household characteristics.

The relevant market is defined as the sum of consumption of CSDs in the choice set plus the consumption of outside beverage options. A consumer purchases a unit of a CSD brand in the set or an outside good. Letting the stochastic term ϵ_{ijm} follow an i.i.d. type I extreme value distribution, the probability that consumer *i* purchases a unit of brand *j* in market *m* is then given by

$$s_{ijm} = \frac{\exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{r=1}^{J} exp(\delta_{rm} + \mu_{irm})} .$$

where *r* = 1,…*J* denotes the CSD set in the model. Aggregating over consumers, the market share of the brand corresponds to the probability that a CSD is chosen in a given market. This allows us to use market level data to make inferences. From the resulting expression, the price and advertising elasticities at the market level are computed and counter-factual experiments are conducted.

Advertising goodwill is introduced as a product characteristic. Following Dubé et al. (2005), advertising in a given market is modeled via distributed lag model to capture the carry-over effects via a goodwill production function: $g_{jt} = \sum_{k=0}^{K} \lambda^k \psi(A_{jt-k})$, where $\psi(\cdot)$ is a nonlinear advertising goodwill production function, A_{jt} represents advertising levels for product *j, t* and *k* denote time periods, and, $\lambda \epsilon (0,1)$ is a geometric time decay factor.

Data and Estimation

To operationalize the model, we combine two A.C. Nielsen datasets:

(1) *Television advertising data* that contains brand-level information of weekly advertising expenditures and weekly Gross Rating Points (GRPs) of national (cable, network and syndicated television) and local (spot television) TV networks in 7 designated market areas (DMAs) from 2006 to 2008.

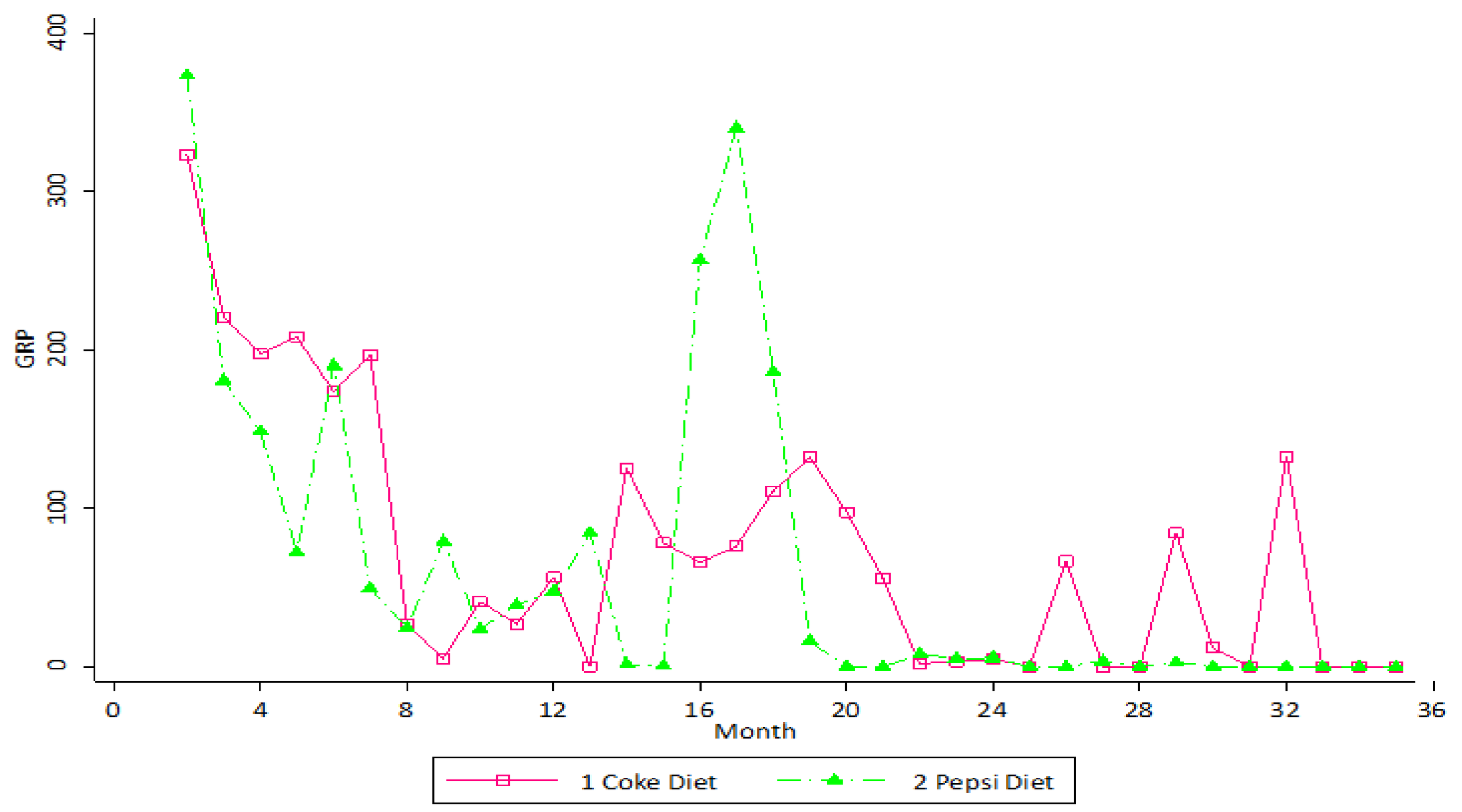
(2) *Household Purchase data* that tracks 13,985 households and covers their CSD purchase records made from grocery stores, drug stores, vending machines, and online shopping sites in 7 DMAs.

Observations from both datasets are aggregated to the monthly level. In addition, household data are aggregated to the market level, resulting in 4,060 observations, denoting 20 brands over 29 periods for seven DMAs.

Product characteristics (Table 1) include price, sugar, sodium, caffeine, and television advertising (GRP, for example in Figure 1) or expenditure goodwill). For simplicity, we do not use demographic information in this research and simply allow for idiosyncratic deviations from a mean market utility.

The potential market size, used to compute market shares and define the outside good share, was computed for each period and DMA as the per capita consumption of CSDs, juices, water and milk times population.

We tested for a complete set of instruments, used to address price endogeneity. We conducted all estimations with TOMLAB's Optimization Environment in Matlab (Dubé et al., 2012).



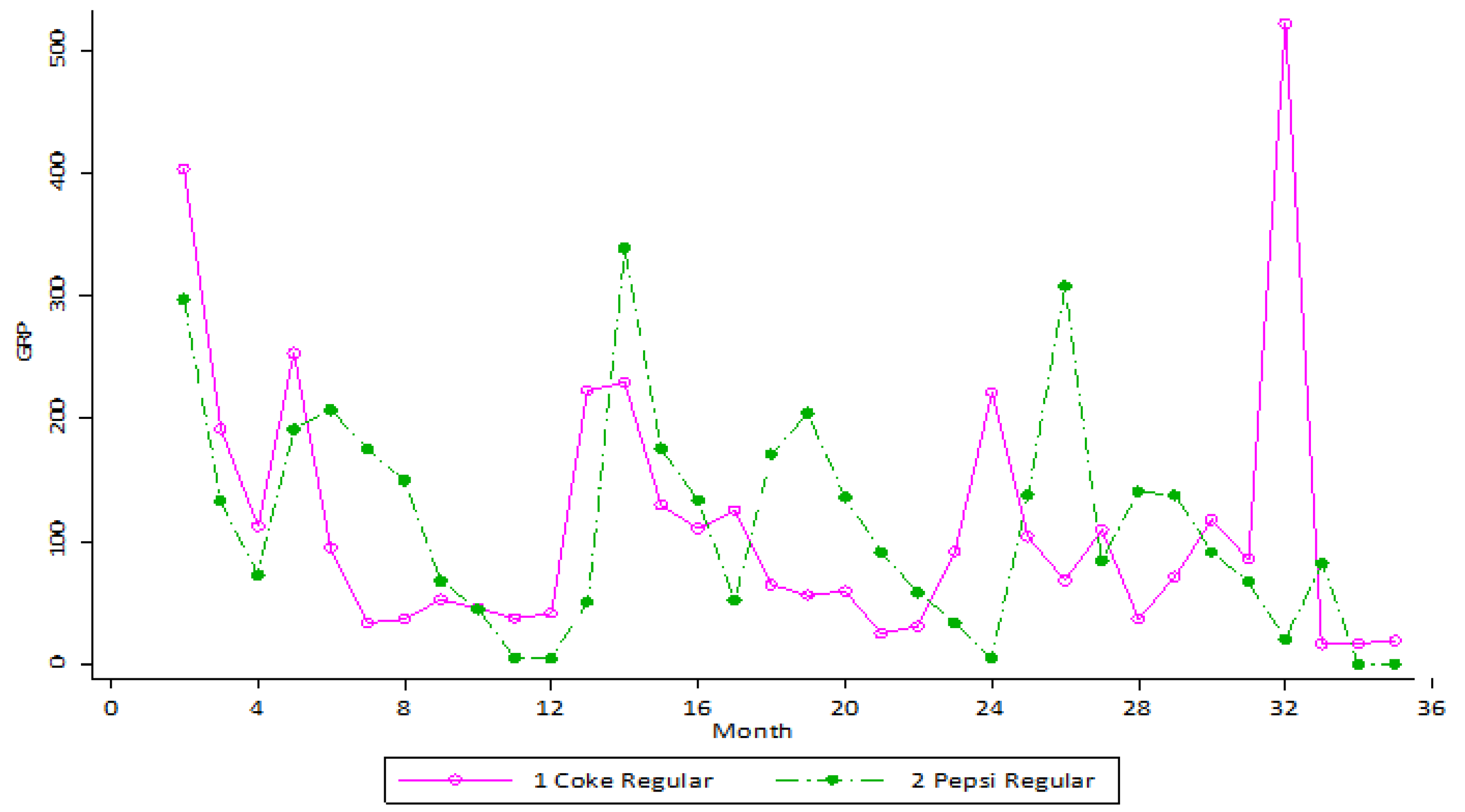


Table 1. CSD Brand Data Summary over Seven Designated Market Areas and 2006-2008

Company/Brand	Price $/12 oz.	Market Share (%)	Weekly GRP	Weekly Adv. Exp ($1,000)	Calories per 12 oz.	Sugar g/12oz	Sodium mg/12oz	Caffeine mg/12oz
Coca Cola								
Coke Classic Regular	0.3621	3.30	111.20	414.90	140	39	50	35
Coke Diet	0.3722	2.75	72.55	288.02	0	0	40	47
Sprite Regular	0.4057	0.70	56.84	91.17	144	38	70	0
Coke Zero Diet	0.4273	0.49	77.19	159.09	0	0	40	35
Fanta Regular	0.4310	0.21	14.47	8.20	160	44	55	0
Pepsi								
Pepsi Regular	0.3220	3.09	114.56	187.41	150	41	30	38
Pepsi Diet	0.3391	2.07	66.79	164.97	0	0	35	35
Mountain Dew Regular	0.3668	1.05	74.50	80.55	170	46	65	54
Sierra Mist Regular	0.3538	0.35	36.57	54.47	150	39	38	0
Mountain Dew Diet	0.3437	0.39	57.62	103.82	0	0	50	54
Mountain Dew Code Red Reg.	0.3447	0.11	15.51	21.20	165	45	105	54
Sierra Mist Free Diet	0.2721	0.20	23.81	31.40	0	0	38	0
Dr. Pepper								
Dr Pepper Regular	0.3782	0.81	135.92	195.46	150	40	55	42
Dr Pepper Diet	0.3810	0.59	58.80	108.38	0	0	55	42
Sunkist Regular	0.3693	0.41	13.36	29.28	190	50	70	40
7 Up Regular	0.3244	0.39	121.46	131.02	140	38	40	0
7 Up Diet	0.3084	0.32	11.71	8.94	0	0	65	0
Diet Rite Pure Zero Diet	0.2760	0.22	2.27	3.09	0	0	0	0
Private Label								
Private Label Regular	0.3006	1.98	0.00	0.00	155	42	53	23
Private Label Diet	0.3150	1.51	0.00	0.00	0	0	40	31

Table 2. Demand Estimation Results

*Note: Standard errors in parentheses. ***p<0.01, ** p<0.05, * p<0.1.*

Specification	Adv. Excluded		Expenditure Goodwill		GRP Goodwill	
Variable	Mean Parameters	Deviations	Mean Parameters	Deviations	Mean Parameters	Deviations
Price	-1.241** (0.558)	0.527*** (0.152)	-3.866*** (1.417)	0.387** (0.082)	-5.021*** (1.466)	5.761** (2.305)
Goodwill			1.066*** (0.282)	0.123*** (0.045)	2.074*** (0.562)	3.262* (1.749)
Spillover			0.162 (0.207)	0.111 (0.639)	0.790** (0.345)	0.171 (0.342)
Sugar	1.240*** (0.414)	0.086 (0.183)	1.189*** (0.260)	1.048** (0.467)	1.912** (0.840)	0.845*** (0.381)
Sodium	-2.836*** (0.745)	0.069 (0.638)	-3.095** (1.331)	0.003 (0.069)	-4.977*** 1.897)	0.143** (0.066)
Caffeine	2.922*** (0.691)	0.157** (0.077)	0.989*** (0.220)	4.709** (0.868)	1.475** (0.751)	9.757*** (3.484)
Intercept	-4.782*** (0.700)	0.060 (0.202)	-5.020** (2.514)	0.023 (0.026)	-4.325*** (1.079)	0.325 (1.701)
DMA Fixed Effects	Yes		Yes		Yes	
Month Fixed Effects	Yes		Yes		Yes	
Firm Fixed Effects	Yes		Yes		Yes	
Observations	4,060		4,060		4,060	
First Stage F Statistic	140.030		124.075		138.530	
p-value	0.000		0.000		0.0000	
Hansen J Statistic	1.036		0.898		0.705	
p-value	0.596		0.638		0.703	

The top ten soda brands in the U.S.

Table 3. Own Price and Advertising Elasticities of Demand for CSDs

Model Specification	Price Elasticities: ADV Excl.	Price Elasticities: GRP	Advertising Elasticities: GRP
Company/Brand			
Coca Cola			
Coke Classic Regular	-1.095	-2.095	9.032
Coke Diet	-1.131	-2.077	4.220
Coke Zero Diet	-1.329	-2.514	7.336
Sprite Regular	-1.257	-2.428	3.837
Fanta Regular	-1.331	-2.615	0.755
Pepsi			
Pepsi Regular	-0.979	-1.891	8.983
Pepsi Diet	-1.036	-2.056	3.876
Mountain Dew Regular	-1.136	-2.199	5.526
Mountain Dew Diet	-1.067	-2.189	4.425
Mountain Dew Code Red Reg.	-1.049	-2.208	0.414
Sierra Mist Regular	-1.105	-2.177	1.301
Sierra Mist Free Diet	-0.858	-1.743	1.422
Dr. Pepper			
Dr Pepper Regular	-1.164	-2.296	8.257
Dr Pepper Diet	-1.171	-2.364	4.581
7 Up Regular	-1.008	-2.002	5.854
7 Up Diet	-0.959	-1.929	0.889
Sunkist Regular	-1.158	-2.358	1.129
Diet Rite Pure Zero Diet	-0.853	-1.726	0.010
Private Label			
Private Label Regular	-0.922	-1.846	0.000
Private Label Diet	-0.971	-1.934	0.000

Table 4. Simulated Results under Alternative Advertising Scenarios

Brand	Own Price Elasticities: Base-line	Own Price Elasticities: All GRP = 0	Price-Cost Margins (%): Base-line	Price-Cost Margins (%): All GRP = 0	Predicted Shares (%): Base-line	Predicted Shares (%): All GRP = 0
Coca-Cola						
Coke Regular	-2.0946	-2.2654	0.4774	0.4414	2.40	0.56
Coke Diet	-2.0766	-2.2110	0.4816	0.4523	2.00	1.66
Coke Zero Diet	-2.5141	-2.5955	0.3978	0.3853	0.35	0.38
Sprite Regular	-2.4279	-2.4678	0.4119	0.4052	0.51	0.08
Fanta Regular	-2.6149	-2.8250	0.3824	0.3540	0.15	0.25
Pepsi						
Pepsi Regular	-1.8914	-1.9388	0.5287	0.5158	2.24	2.25
Pepsi Diet	-2.0561	-2.1333	0.4863	0.4688	1.51	0.56
Mountain Dew Regular	-2.1991	-2.1857	0.4547	0.4575	0.76	3.34
Mountain Dew Diet	-2.1891	-2.2060	0.4568	0.4533	0.28	1.10
Mountain Dew Code Red Regular	-2.2080	-2.2980	0.4529	0.4352	0.08	0.59
Sierra Mist Regular	-2.1773	-2.1786	0.4593	0.4590	0.25	0.39
Sierra Mist Free Diet	-1.7427	-1.7624	0.5738	0.5674	0.15	0.20
Dr. Pepper						
Dr Pepper Regular	-2.2956	-2.3231	0.4356	0.4305	0.59	0.97
Dr Pepper Diet	-2.3639	-2.3707	0.4230	0.4218	0.43	0.44
7 Up Regular	-2.0024	-2.0151	0.4994	0.4963	0.28	0.34
7 Up Diet	-1.9291	-1.9427	0.5184	0.5147	0.23	0.25
Sunkist Regular	-2.3579	-2.3441	0.4241	0.4266	0.29	0.51
Diet Rite Pure Zero Diet	-1.7258	-1.7985	0.5794	0.5560	0.16	1.18
Private Label						
Private Label Regular	-1.8458	-1.9163	0.5418	0.5218	1.44	0.23
Private Label Diet	-1.9345	-1.9419	0.5169	0.5150	1.10	0.32
Outside Share	-		-		84.79	84.40

Conclusions

How does advertising impact the demand for sodas?

- Television advertising *steepens* and *expands* the demand for CSDs (Table 2).
- Television advertising decreases the price elasticity of demand, indicating that advertising plays predominantly a persuasive, therefore anti-competitive, role in this market (Table 3).
- Eliminating advertising would increase the price elasticity of demand, lower mark ups and reduce the market shares across all brands of sodas as consumers migrate to the outside goods–e.g., water, juices, and milk (Table 4).

Important demand modeling implications emerge:

- Excluding advertising from demand models results in significantly lower estimated consumer responsiveness to prices, leading to biased results.
- Both own brand and company spillover effects have a strong effect in increasing demand for CSDs.
- Measuring advertising goodwill based on coverage (GRPs) outperforms measuring it based on advertising expenditures as conventionally done.

Finally, **the CSD industry is increasingly emphasizing social media, which is not only potentially more influential than television advertising but also more cost effective.** However, social media's impact on soda demand and competition is an unexplored avenue for further research.

Highlights

- Television advertising steepens and expands the demand for sodas as well as lowers the price elasticity of demand.
- Eliminating television advertising would result in a broad decline of price-cost margins and CSD shares of non-alcoholic beverage consumption in the United States.
- It is important to include television advertising in the demand specification for beverages, or any other differentiated product, to avoid biases of price impacts.

Contact

Rigoberto.Lopez@uconn.edu, Yizao.Liu@uconn.edu, Chen.2.Zhu@uconn.edu

860-486-2836

We gratefully acknowledge funding from the Zwick Center for Food and Resource Policy (formerly the Food Policy Marketing Center) at the University of Connecticut via USDA-NIFA-2010-34178-20766 and from the Storrs Agricultural Experiment Station.