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TV advertising spillovers and demand for private labels: the case of carbonated soft drinks

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The expansion of private labels, or store brands, has transformed consumer choice sets and competition in retail markets, prompting manufacturers to fight back with renewed pricing and product and promotion strategies to forestall further private label expansion. This article examines the spillover effects of television advertising on brand-level consumer demand for carbonated soft drinks (CSDs), including private labels, using a random coefficients logit model with household purchasing and advertising viewing Nielsen data. As in previous work, we find that although brand spillover effects significantly increase demand for CSD brands in the same company and undermine demand facing other manufacturers' CSD brands, surprisingly, there are *positive* spillover effects on the demand for private label brands. This indicates that brand advertising is persuasive with respect to manufacturers' brands but complementary with respect to private labels. Further results show that eliminating television advertising for CSDs would lower aggregate CSD sales as consumers migrate to other beverages, although private labels stand to gain, particularly Wal-Mart brands.

Keywords: advertising; private labels; demand; competition; sodas; carbonated soft drinks

JEL Classification: D12; L66; Q18; I18

I. Introduction

Private labels (PLs), also known as store brands, have captured nearly a quarter of the product volume and a fifth of the dollars spent at US supermarkets (Private Label Manufacturers Association, 2014) and have made inroads in other types of retail outlets in the US and Europe (Ezrachi, 2010). Although manufacturer brands have fought the expansion of PLs through renewed pricing, promotion and product quality, advertising, as traditionally used by manufacturers, can play a role in recapturing market shares

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by building brand equity and reinforcing consumers' loyalty (Simon and Sullivan, 1993; Bagwell, 2007). Much of the work on PLs has focused on their effects on consumer brand choices (Bonfrer and Chintagunta, 2004; Geyskens *et al.*, 2010), the manufacturer brands' response to PL expansion (Cohen and Cotterill, 2011; Nasser *et al.*, 2013) and/or the effects of PLs on retailer market power (Steiner, 2004; Meza and Sudhir, 2010).

The preponderant empirical evidence on advertising spillover effects is that when competitors advertise more, firms will sell less (Erdem and Sun, 2002; Balachander and Ghose, 2003; Nakata, 2011; Rutz and Bucklin, 2011). An exception is the recent study by Anderson and Simester (2013), which, based on a field experiment on competitors' advertising impact on a PL apparel retailer, found positive spillover effects on sales of PLs.[1] In this study, we examine the impacts of manufacturing brand advertising on the demand for brands within the same company as well as brands owned by competitors, including manufacturing and PL brands. In spite of their importance, studies on the effects of manufacturers' advertising on PLs are lacking and apparently not well understood. If there are indeed spillover effects, as documented across manufacturer brands by previous work, then knowing the extent and direction of the effects on PLs would be helpful in understanding the nature of nonprice competition between PLs and manufacturer brands.

This article uses the carbonated soft drink (CSD) market as a case study to examine the effects of manufacturer brand advertising on the demand for PLs. The CSD market provides a good case study for several reasons. First, because CSD products operate in a mature market, advertising should play a persuasive rather than an informative role, allowing for accurately measuring the effects of advertising on demand for brands within the same company as well as competitors, including PL brands. Second, manufacturer CSD brands are heavily advertised on television (TV) in the US, while PL CSDs are not, allowing for isolating the effects of spillovers.[2] Last, by virtue of being a high-calorie staple in the American diet, CSDs have been scrutinized in terms of their contribution to the obesity epidemic.[3] Governments are considering a variety of policy solutions, including banning advertisements for so-called unhealthy beverages.[4]

This article contributes to the advertising debate by examining the spillover effects of manufacturer brand-level TV advertising on competitor brands and, particularly, on PL CSDs. We specify a demand model in the random coefficient discrete-choice framework of Berry, Levinsohn and Pakes (1995; henceforth BLP) and Nevo (2000), aimed at market-level estimation with product and consumer heterogeneity. This framework defines products in terms of their characteristics and solves the problems of dimensionality, consumer heterogeneity and endogeneity of product prices. Advertising of CSDs is modelled as goodwill and enters the demand model as product characteristics. Using the demand estimates and assuming Bertrand–Nash pricing, we calculate the new equilibrium pricings and simulate the predicted market shares of all branded and PLs CSDs without advertising, which further assesses the spillover effect of TV advertising on PLs.

We find that although brand advertising increases demand for the originating brand, as expected, company-wide advertising spillover effects are nearly as important. Not surprisingly, advertising by competitors undermines demand for a particular manufacturer's CSD brand. Surprisingly, however, manufacturer advertising spillover effects on the demand for PL brands are *positive*, increasing their demand, particularly for Wal-Mart brands. The net effect is to lift the aggregate demand for the entire CSD category. Consistent with the latter, simulation results indicate that *elimination* of manufacturer

[1] Karray and Martín-Herrán (2008) theoretically show that the spillover effects of manufacturer advertising can lift the demand for the entire category, including PLs, based on an assumed positive spillover parameter for both manufacturer and store umbrella advertising. Here we assume that the PLs are not advertised and that any umbrella store advertising has no effects on the products sold, as in Parker and Soberman (2004).

[2] In 2011, the Coca-Cola Company, PepsiCo and Dr. Pepper spent \$267 million, \$154 million and \$104 million, respectively, on advertising, on which the nonalcoholic beverage industry spends an average of \$2 billion per year.

[3] According to Zmuda (2011), in 2010, the average American drank approximately 50 gallons of CSDs per year.

[4] Beverage companies pledged to decrease targeting youth on television and radio and in print media as part of the Children's Food and Beverage Advertising Initiative (CFBAI) in 2006 (Better Business Bureau, 2014). However, there has been concern that this voluntary agreement is not working well, and the government has considered stepping in to implement more stringent regulation in the US.

advertising would lower market shares for all sodas collectively in the nonalcoholic beverage market as consumers migrate to other beverages, although the market shares of PLs either stay the same or increase, particularly Wal-Mart brands. Ultimately, these results shed light on how PLs compete in mature markets based on how advertising influences consumer choices.

The rest of the article is organized as follows. Section II briefly describes the PLs in the CSD industry. Section III presents the model. Section IV summarizes the data used. We discuss the estimation results in Section V, and Section VI concludes.

II. PLs in the CSD Industry

In 2012, CSDs accounted for approximately 60% of the total US refreshment beverages volume with roughly 44 gallons consumed per capita (Beverage Digest, 2013). Although per capita consumption of CSDs has continued to slowly decline since at least 2004, it remains the main beverage in the American diet.[5] The US market has been traditionally dominated by two companies: Coca-Cola and PepsiCo, which account for approximately 70% of CSD sales, with Dr. Pepper accounting for 17% of CSD sales, and PLs (and some rather smaller companies) accounting for the remaining 13% (Beverage Digest, 2013). However, the last decade has seen an expansion of PL brands, particularly between 2007 and 2009 in the midst of the recession (Scott-Thomas, 2014). As shown in Table 1, the market share of PL regular and diet CSDs sold by Wal-Mart and leading local supermarket chains alone exceed the market shares of Dr. Pepper for regular and diet CSDs.

The expansion of PLs in the CSD and other industries has provided added leverage to retailers in terms of marketing and pricing decisions. PL CSDs are generally cheaper due to lack of advertising and marketing expenses. As such, retailers are able to market PL goods for much less than they have to pay for comparable branded CSDs. Nationally, PL CSDs have grown in the last decade but their presence is larger at Wal-Mart, surpassing supermarket chains and other retailers for whom PLs constitute a significant percentage of their total sales and retailing strategy.

By virtue of being the largest retailer and retail grocery outlet in the US and in the world, Wal-Mart store brands, such as *Equate* in healthcare products and *Great Value* in CSDs, are among the fastest growing segments in PLs (Neff, 2009). Unlike supermarket chains, Wal-Mart operates nationally. Since 2009, the three leading US CSD companies have fought back with aggressive advertising, pricing and introduction of new products such as Cherry Coke and personalized labels. However, by selling their own label products, retailers compete with upstream brand suppliers on prices and by controlling shelf space. From the consumer side, many customers who have switched to relatively recent food retail formats, such as Wal-Mart Supercenters, might be more price-sensitive and less loyal to the manufacturer brands (Cleary and Lopez, 2014). In sum, an assessment of advertising spillover effects by manufacturing brands on PLs in the CSD industry requires a model that captures both the oligopolistic nature of this market and product differentiation conveyed by product characteristics and advertising.

III. Model

A natural way to model consumer demand for differentiated CSDs is to follow the BLP model, which involves a random coefficient logit model to capture consumer choices in the context of product and consumer characteristics. In the BLP model (summarized here for expository purposes), the consumer, in choosing a CSD brand from among competing products, maximizes utility, driven by the brand characteristics as well as his/her own. Assume there are a total number of G companies (e.g. PepsiCo Inc., The Coca-Cola Company, Dr. Pepper or a PL company) that own soft drink products under different brand names. Use $j = 1,\ldots J$ to denote a CSD product. Use $j = 0$ to denote the general outside product in the beverage market.

The conditional indirect utility of consumer i from purchasing CSD product j which belongs to company g in market m is represented by

[5] In Europe, the share of CSDs ranks well below tea, bottled water, coffee, milk and beer, and continues to increase mainly due to increased consumption in Western Europe (Beverage Digest, 2013).

Table 1. Summary of CSD brand characteristics

Company/brand	Price $/ 12 oz	Market share (%)	Weekly GRP	Calories per 12 oz	Sugar g/12 oz	Sodium mg/ 12 oz	Caffeine mg/ 12 oz
Coca-Cola							
Coke Regular	0.358	2.47	111.2	140	39	50	35
Coke Diet	0.370	1.99	72.6	0	0	40	47
Coke Zero	0.409	0.29	77.2	0	0	40	35
Sprite Regular	0.376	0.56	56.8	144	38	70	0
Fanta Regular	0.392	0.19	14.5	160	44	55	0
Pepsi							
Pepsi Regular	0.316	2.25	114.6	150	41	30	38
Pepsi Diet	0.341	1.57	66.8	0	0	35	35
Mountain Dew Regular	0.368	0.51	74.5	170	46	65	54
Mountain Dew Diet	0.343	0.19	57.6	0	0	50	54
Mountain Dew Code Red Reg.	0.331	0.07	36.6	150	39	38	0
Sierra Mist Regular	0.358	0.28	15.5	165	45	105	54
Sierra Mist Free Diet	0.258	0.24	23.8	0	0	38	0
Dr. Pepper							
Dr. Pepper Regular	0.371	0.53	135.9	150	40	55	42
Dr. Pepper Diet	0.379	0.49	58.8	0	0	55	42
Sunkist Regular	0.365	0.19	13.4	190	50	70	40
7 Up Regular	0.326	0.25	121.5	140	38	40	0
7 Up Diet	0.316	0.19	11.7	0	0	65	0
Diet Rite Pure Zero Diet	0.266	0.09	2.3	0	0	0	0
Wal-Mart							
Wal-Mart PL Regular	0.262	0.25	0.0	155	42	53	23
Wal-Mart PL Diet	0.268	0.27	0.0	0	0	40	31
Other chain							
Top other PL Regular	0.304	0.56	0.0	160	43	52	27
Top other PL Diet	0.339	0.39	0.0	0	0	44	34

Notes: Results are averages over five designated market areas (New York, Atlanta, Washington DC, Seattle and Detroit) in the 2006–2008 period. The results for 'other chain' PLs are averages for the regular and diet categories for the top chain supermarkets across DMAs and time periods.

$$u_{ijm} = \alpha_i p_{jm} + Z_j' \beta_i + \gamma_{1i} Ad_{jm} + \gamma_{2i} \sum_{k \neq j, k \in g} Ad_{km} + \gamma_{3i} \sum_{h \neq j, h \notin g} Ad_{hm} + \xi_{jm} + \epsilon_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm} \tag{1}$$

where p_{jm} is the price of CSD brand j in market m and Z_j is the nutritional characteristics of product j, including sugar, sodium and caffeine content. Ad_{jm} is the advertising goodwill of CSD j in market m, which captures the brand j's own advertising effects. Ad_{km} is the advertising goodwill of CSD k that belongs to the same company as j. For example, Coke Regular (j) and Coke Diet (k) are considered to be two different CSD products, but they both belong to the Coca-Cola Company (g). It is reasonable to believe that when Coke Regular starts an advertising campaign, the spillover effect will also benefit other brands within the company (e.g. Coke Diet or Coke Zero). Ad_{hm} is the advertising goodwill of CSD h from rival companies in market m, which will capture the competitive effect of advertising.

The indirect utility can be decomposed into three parts: a mean utility term δ_j, which is common to all consumers; a brand-specific and consumer-specific deviation from that mean, μ_{ij}, which includes interactions between consumer and product characteristics; and idiosyncratic tastes, where ϵ_{ijm} is a mean zero stochastic term distributed independently and identically as a type I extreme value distribution.

Let $X_j = (p_j, Z_j, Ad_{jm}, \sum_{k \neq j, k \in g}, Ad_{km}, \sum_{h \neq j, h \notin g} Ad_{hm})$ and $\theta = (\alpha, \beta, \gamma_1, \gamma_2, \gamma_3)$ where the mean utility $\delta_{jm} = X_j^{'}\theta + \xi_{jm}$ includes a vector X_j of all characteristics relevant to consumers of CSDs 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 variables, where Ω is a matrix of coefficients that measure how taste characteristics vary across households and Σ is a scaling matrix. The unobserved household characteristics V_i are assumed to have a standard multivariate normal distribution.

To complete the model and to define the market (and, hence, market shares), an outside good is included to give the consumer the possibility not to buy any of the brands included in the choice set. A consumer purchases a unit of a brand in the set or the outside good. The probability that consumer i purchases a unit of brand j in market m is

$$s_{ijm} = \frac{\exp\left(\delta_{jm} + \mu_{ijm}\right)}{1 + \sum_{r=1}^{J} \exp(\delta_{rm} + \mu_{irm})} \tag{2}$$

Aggregating over consumers, the market share of the jth brand corresponds to the probability that the jth brand is chosen in market m, given by

$$s_{jm}(p, x, \theta) = \int I\left\{\left(D_{im}, v_i, \epsilon_{ijm}\right) : U_{ijm} \geq U_{ikm} \forall k = 0, \ldots, J\right\} dH(D) dG(v) dF(\epsilon) \tag{3}$$

where θ is a vector of consumer taste parameters; $k = 0$ denotes the outside good; and $H(D)$, $G(v)$ and $F(\epsilon)$ are cumulative density functions for the indicated variables, assumed to be independent from each other. The price elasticities of the market shares for individual brands are given by

$$\eta_{ijm} = \frac{\partial s_{jm}}{\partial p_{km}} \cdot \frac{p_{km}}{s_{jm}} = \begin{cases} \dfrac{p_{jm}}{s_{jm} \int \alpha_i s_{ijm}\left(1 - s_{ijm}\right) dH(D) dG(v)}, & \text{for } j = k \\[2ex] \dfrac{-p_{km}}{s_{jm} \int \alpha_i s_{ijm} s_{ikm} dH(D) dG(v)}, & \text{otherwise} \end{cases} \tag{4}$$

where each consumer has a different price elasticity for each individual brand and α_i denotes an individual's price coefficient.

The direct effect (conventional: without including spillovers) of advertising on brand-level demand is measured by

$$\in_{jkm} = \frac{\partial s_{jm}}{\partial Ad_{km}} \cdot \frac{Ad_{km}}{s_{jm}} \begin{cases} > 0 \text{ for } j = k \\ < 0 \text{ for } j \neq k \end{cases} \tag{5}$$

where Ad_{km} measures advertising for brand k in market m. Note that Equation 5 only captures brand cannibalization effects. However, when a CSD product j changes its advertising level, it has two levels of effects on other brands, if we considered the spillover effects as well as the cannibalism effects.

The spillover effects of brand advertising are given by

$$\in_{jkm} = \frac{\partial s_{km}}{\partial \sum_{f \neq k,} Ad_{fm}} \cdot \frac{\partial \sum_{f \neq k,} Ad_{fm}}{\partial A_{djm}} \cdot \frac{Ad_{jm}}{s_{km}} \begin{cases} > 0 \text{ for} f \in g \\ \lesseqgtr 0 \text{ for} f \in g \end{cases} \tag{6}$$

First, consider the spillover effects on other brands $(f \in g)$ within the same company g. For CSD k, the increase of CSD j's advertising level will increase the total advertising levels of the whole company, which will in turn positively affect the demand for CSD k not just negatively through market cannibalization, as indicated by the direct effect. For brands in the same company, the ultimate effect of brand advertising on demand for other brands is indeterminate, depending on the strength of the negative cannibalization effect in Equation 5 relative to the positive company spillover effect in Equation 6. Thus, ignoring spillover effects would lead to negatively biased advertising effect estimates.

Second, consider the competitive effects on other brands $(f \notin g)$ belonging to a company other than g. The spillover has two components. One is enhancing the within-company effects from CSD brand j, which would further accentuate the negative effects of brand cannibalization on rival brands. The other is that an increase of CSD *j*'s advertising level may increase the total advertising levels of CSD *k*'s rival companies, which may have mixed effects on the demand of CSD *k* as all rival companies react. For competing CSD manufacturing brands, the net effect that includes spillover effects is expected to enhance the cannibalism effects. As an example, when Coke Regular increases advertising, it will have a direct negative effect on Coke Diet, but this effect will be mitigated, if not reversed, by the positive indirect effect on all Coca-Cola brands. For competitors such as Dr. Pepper or PepsiCo brands, both direct and indirect spillover effects are negative.

For PLs, since they commonly do not advertise on TV, as other manufacturers react to brand *j*'s advertising and are generally perceived as a basic CSD, there is a potential that PLs free-ride on the advertising of other companies to the extent that total advertising increases the demand for the category. That is, if brand advertising acts as a complementary good rather than a competitive one, as in Anderson and Simester (2013), then the possibility of positive spillovers dominating the cannibalism effects may apply to PLs.

IV. Data and Estimation

The data set used combines two Nielsen data sets: advertising and household (Homescan) panel data, both obtained from the Zwick Center for Food and Resource Policy at the University of Connecticut. The advertising data set contains brand-level information on weekly advertising expenditures and weekly gross rating points (GRPs) of national (cable, network and syndicated) and local (spot) TV networks in five designated market areas (DMAs) from 2006 to 2008.[6] The DMAs are New York, Atlanta, Washington DC, Seattle and Detroit.

The household panel data track 13 985 households and cover CSD weekly purchase records from grocery stores, drug stores, vending machines and online shopping sites in the same five DMAs. This data set contains information on product characteristics (e.g. flavour, packaging), marketing (e.g. unit price and in-store displays) and location and time of each purchase. The CSD purchase data were aggregated from the household to the DMA level. In addition, both CSD purchase and advertising data were aggregated from weekly to monthly observations. Combining these two data sets directly links brand-level advertising exposure to brand-level purchases. The market in this article is defined as a combination of month and DMA. The potential market size was defined as the combined per capita consumption (in volume, $total\ vol_t$) of CSDs plus the outside good (e.g. juices, water and milk) times population. The total potential consumption is calculated as the per capita consumption of all beverages times the population of the market *t*. Then market shares for product *j* in market *t* are defined as $\frac{vol_{jt}}{total\ vol_t}$.

Product characteristics in the estimating sample include price, nutritional characteristics, CSD company and TV advertising. Price is the average unit price for all CSD purchases (e.g. sizes, alternative outlets). Based on previous studies (e.g. Lopez and Fantuzzi, 2012), sugar, sodium and caffeine content are key nutritional indicators that affect CSD choices. Although whether a household watched a particular brand advertisement in a given month is not observed by the econometrician, at the market level this should not pose a problem.

Following Dubé *et al.* (2005), advertising is modelled as goodwill in order to capture the carryover effects of advertising's impact on demand. Advertising goodwill is derived in a distributed lag form, where the subscript for market *m* is eliminated for simplicity:

$$Ad_{jt} = \sum_{k=0}^{K} \lambda^k \psi(A_{j,t-k}) \tag{7}$$

where $\psi(\cdot)$ is a nonlinear advertising goodwill production function, A_{jt} represents GRP for a particular CSD brand, $\lambda \epsilon (0, 1)$ is a geometric decay factor and *t* and *k* denote time periods. In our model, advertising goodwill enters the utility function directly. Following Dubé *et al.* (2005), we use six lags and an advertising decay parameter of 0.68, and the

[6] A GRP measures the frequency of viewing a particular advertisement times the percentage of people reached over a specific time period. For example, if 10% of all households in a DMA watched a commercial five times during a week, then this specific commercial has a GRP of 50 during that week.

following function is applied before applying the decay factor:

$$\psi\left(A_{j,k-t}\right) = \log\left(1 + A_{j,k-t}\right), \text{if } A_{j,k-t} > 0; 0, \text{otherwise} \quad (8)$$

Note that since we have six monthly lags and 35 months of data, the first six observations are excluded in order to compute goodwill measures, resulting in 29 monthly observations in the estimating sample. In addition, prior to estimation, both advertising GRPs and nutritional characteristics were scaled between 0 and 1.

Company-wide spillovers from brand advertising were computed by aggregating the stocks of goodwill for other brands belonging to the same company and included in the estimating model. For competitors' advertising, the GRPs of all CSDs of all other companies were aggregated. Cannibalizing or business-stealing effects of advertising across brands and competitors were estimated in the econometric model through the cross-advertising elasticities of demand.

Table 1 lists the summary CSD brand characteristics of the sodas included in the sample. The estimating sample contains 3190 market-level observations based on 29 monthly periods (July 2006 to November 2008), 22 brands of CSDs and 5 DMA markets. In Table 1, the nutrition characteristics for PL brands under 'other chain' are averaged out over the corresponding regular or diet supermarket PLs in the data set.

Price is potentially endogenous since retail price effects depend on observed and unobserved product and consumer characteristics, and variation in these can induce variation in prices. Thus, the mean choice utility parameters are identified through the BLP-type market-level macro-moments using a complete set of instrumental variables. These include production input-cost variables (price and lag price of high fructose corn syrup), an advertising price index, a 2008 Olympics dummy for Coca-Cola products and Hausman-type price and advertising goodwill instruments (Hausman, 1994).[7] In addition, we use a set of optimal instruments to help identify random coefficients and increase estimation efficiency (Chamberlain, 1987; Berry *et al.*, 1999; Reynaert and Verboven, 2014). For the purpose of this article, and for simplicity and tractability, we do not include sociodemographic characteristics and treat deviations from the mean parameters as idiosyncratic random errors. We test for the validity of instrumental variables with a first-stage F-test and a Hansen J test. We conducted all estimations with the TOMLAB Optimization Environment in Matlab. The estimation approach builds upon the Mathematical Program with Equilibrium Constraints method, which has been demonstrated to avoid several numerical problems in optimization (Knittel and Metaxoglu, 2008; Dubé *et al.*, 2012). The results are presented in the following section.

V. Empirical Results

Demand results

Table 2 shows the coefficients estimation results. Overall, the results seem plausible in terms of signs and expected coefficients. Several specification tests were conducted. The first-stage F-statistics and Hansen J test results indicate that the instrumental variables are valid instruments and relatively strong, alleviating concerns with endogeneity of price. The Hansen J statistic indicates that the model failed to reject the null hypothesis of zero expected moments, lending credibility to the model specification.

Nearly all key parameter estimates in Table 2 are statistically significant at the 5% level. As expected, consumers have a negative and strong valuation of price and a positive and significant valuation of own-brand advertising. However, consumers also have a strong and positive valuation of company advertising when choosing a brand of CSD. In fact, the magnitude of the coefficient is nearly 70% (1.339/1.927) larger than the coefficient for own-brand advertising goodwill. This underscores the importance of company advertising as it would 'lift all boats' of brands in the company's portfolio through pay-off beyond the single brand being advertised. On the other hand, competitors' advertising has a negative effect on demand for other manufacturers' brand CSDs. Surprisingly, the effect is *positive* and statistically significant (at the 5% level) on the demand for Wal-Mart PL sodas, and positive but statistically insignificant (at the 10% level) on the demand for leading supermarket chain PL sodas. The coefficient of the goodwill spillover on supermarket PLs is about half of that for Wal-Mart.

[7] The advertising price index is calculated at the DMA level by dividing total expenditures on TV advertising by total units, as defined by the Kantar Media Company.

Table 2. Demand estimation results

	Mean utility		Unobservables	
Variable	Mean	SE	Mean	SE
Price	−11.045**	(4.692)	5.208	(4.161)
Own-brand goodwill	1.927***	(0.637)	2.329	(1.489)
Goodwill of brands in a same firm	1.339*	(0.718)	5.445***	(0.997)
Coca-Cola	1.188***	(0.445)	5.042**	(1.956)
PepsiCo	0.706***	(0.266)	−1.915*	(0.992)
Wal-Mart PLs	−3.363**	(1.403)	4.656***	(1.146)
Other chain PLs	0.506	(1.123)	2.894***	(0.737)
Goodwill other firms * Coca-Cola	−0.629**	(0.274)	−2.651	(2.323)
Goodwill other firms * PepsiCo	−0.281*	(0.149)	−0.192	(1.318)
Goodwill other firms * Wal-Mart PLs	0.421**	(0.175)	2.054	(2.867)
Goodwill other firms * other chain PLs	0.068	(0.143)	8.456***	(2.694)
Sugar	0.609**	(0.271)	−4.369***	(0.860)
Sodium	−7.537***	(1.882)	−6.406***	(1.357)
Caffeine	1.328***	(0.137)	−1.378***	(0.523)
Atlanta	−1.714**	(0.781)	3.099***	(0.745)
Washington DC	−3.045**	(1.459)	−6.225***	(2.107)
Seattle	−0.006	(0.580)	−1.499	(0.973)
Detroit	−0.286	(0.184)	0.546	(1.257)
Constant	−4.968***	(0.639)	−0.680	(0.881)
Observations		3190		
First-state F statistic		15.941		
p-value		0.000		
Hansen J statistic		21.623		
p-value		0.249		

Notes: Robust SE in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Firm baseline: Dr. Pepper; DMA baseline: New York.

Thus, PL sodas, even though they are not advertised on TV, benefit from an umbrella effect on the demand for CSDs generated by advertising for manufacturer brands. In fact, using the Dr. Pepper Company as a benchmark, PepsiCo and Coca-Cola brands are the most negatively affected by competitors' advertising, while Wal-Mart PLs benefit from it.

The results for company fixed effects show that relative to Dr. Pepper brands, consumers have a higher intrinsic valuation of Coca-Cola and PepsiCo brands and a lower valuation of Wal-Mart PL brands, regardless of product characteristics or advertising. Further econometric results show that consumers have, on average, a positive valuation of sugar and caffeine content and a negative valuation of sodium content. From the nutritional standpoint of excess consumption of sugar in the American diet and its designation as unhealthy (not to mention the corollary calories), the positive coefficient might reflect preferences for what is perceived as an average preference for flavour over nutritional or obesity concerns.

The estimated own-price elasticities (averaged across DMAs and time periods) are shown in Table 3. All own-price elasticities of demand were negative and all cross-price elasticities positive. The magnitude of the own-price elasticities ranges from −1.826 for Wal-Mart Regular to nearly −2.302 for Dr. Pepper Regular. The own-price elasticities for PLs (only Wal-Mart's shown in Table 3) were the lowest. The magnitudes of the manufacturer brand own-price elasticities are consistent with previously estimated elasticities of CSD demand using scanner data.[8] The cross-price

[8] For example, Zhen *et al.* (2011), using product categories rather than brand-level elasticities, report them in the −1 to −2 range for sugar-sweetened beverages, while Dubé (2004) reports them in the −2 to −3.5 range for specific sizes and brands of CSDs. Andreyeva *et al.* (2010) report elasticities for 14 soft drinks having a mean of −0.79 and a range of −0.13 to −3.18 at various levels of category aggregation, while Dhar *et al.* (2005) report them between −2.7 and −4.4, and, on the high side, Chan (2006) reports own-price elasticities for CSDs at the household level between −5 and −11.

Table 3. Sample of price elasticities of demand for CSDs

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr. Pepper Regular	Dr. Pepper Diet	Wal-Mart PL Regular	Wal-Mart PL Diet
Coke Regular	−2.191	0.053	0.053	0.054	0.053	0.053	0.053	0.051
Coke Diet	0.041	−2.178	0.040	0.041	0.043	0.044	0.044	0.045
Pepsi Regular	0.045	0.044	−2.072	0.050	0.043	0.040	0.039	0.042
Pepsi Diet	0.031	0.031	0.034	−2.120	0.028	0.027	0.026	0.027
Dr. Pepper Regular	0.012	0.012	0.011	0.011	−2.302	0.014	0.013	0.014
Dr. Pepper Diet	0.010	0.010	0.008	0.009	0.011	−2.248	0.011	0.011
Wal-Mart PL Regular	0.005	0.005	0.004	0.004	0.006	0.006	−1.826	0.006
Wal-Mart PL Diet	0.006	0.006	0.005	0.005	0.007	0.007	0.007	−1.954

elasticities in Table 3 illustrate that brand choices are more responsive to changes in the price of the leading brands (e.g. Coke Regular) than the other way around. In addition, brand choices are more responsive to changes in the price of the same type of soda (regular or diet) than across types. Although consumers' choices of a particular CSD are sensitive to changes in the price of that CSD, the cross-price elasticities are relatively very low. This attests to a strong degree of brand loyalty when it comes to substitution across brands based on price changes alone.

The top panel of Table 4 contains the direct effects of brand advertising on brand-level demand for a sample of CSDs stipulated in Equation 5 without including spillover effects, as done in much of the previous literature. With one exception (Dr. Pepper Regular), all own-advertising elasticities indicate inelastic responsiveness to brand advertising increases, *ceteris paribus*. Note that, in general, there is a greater degree of consumer responsiveness to advertising regular sodas than to advertising diet ones. All *direct* cross-advertising elasticities are negative as they reflect business-stealing effects (or cannibalization) for brands in the same company or business-stealing effects for brands in competing companies. One thing to notice is that relative to own-brand advertising elasticities, the cross-advertising elasticities are quite small.

Table 4 also contains the elasticities of demand with respect to brand advertising that *include* the spillover as well as direct effects of brand advertising

Table 4. Sample of advertising elasticities of demand for CSDs

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr. Pepper Regular	Dr. Pepper Diet	Wal-Mart PL Regular	Wal-Mart PL Diet
Direct effects								
Coke Regular	0.7982	−0.0193	−0.0195	−0.0196	−0.0192	−0.0194	−0.0192	−0.0187
Coke Diet	−0.0086	0.4532	−0.0084	−0.0086	−0.0090	−0.0092	−0.0091	−0.0093
Pepsi Regular	−0.0173	−0.0167	0.7893	−0.0191	−0.0163	−0.0151	−0.0150	−0.0160
Pepsi Diet	−0.0056	−0.0055	−0.0061	0.3805	−0.0051	−0.0049	−0.0046	−0.0048
Dr. Pepper Regular	−0.0063	−0.0066	−0.0060	−0.0058	1.2158	−0.0072	−0.0070	−0.0073
Dr. Pepper Diet	−0.0017	−0.0018	−0.0015	−0.0015	−0.0019	0.3997	−0.0019	−0.0019
Including spillover effects								
Coke Regular	0.6990	0.5048	−0.1822	−0.1827	−0.0659	−0.0602	0.1210	0.1157
Coke Diet	0.2901	0.3971	−0.0984	−0.0982	−0.0326	−0.0340	0.0684	0.0654
Pepsi Regular	−0.3152	−0.3138	0.6980	0.5093	−0.0488	−0.0496	0.1345	0.1286
Pepsi Diet	−0.1448	−0.1447	0.2499	0.3366	−0.0195	−0.0190	0.0644	0.0684
Dr. Pepper Regular	−0.3984	−0.3959	−0.1765	−0.1745	1.1033	0.8542	0.2711	0.2592
Dr. Pepper Diet	−0.1301	−0.1301	−0.0570	−0.0574	0.2791	0.3629	0.0891	0.0923

Note: Since the rows for Wal-Mart brands (or any PLs) were zero as they did not advertise on television, those rows were omitted from this table.

(bottom panel).[9] Our results provide strong support for the prevalence of positive spillover effects of brand advertising on other brands belonging to the same company as the positive spillover effects dominate the negative direct effects across brands. That is, the company spillover effects results are positive and dominant for all brands within the same company. Thus, advertising takes on the form of a quasi-public good for brands within the same company. Table 4 also shows that including spillover effects leads to larger cross-advertising elasticities relative to the elasticities without spillover effects. However, the response of demand for PLs to advertising of manufacturer brands is positive and of significant magnitude, indicating that PLs benefit from TV advertising by competitors. This may be explained by the fact that consumers become more aware of PL brands as aggregate TV advertising expands the global demand for CSDs. It is also interesting to note that the positive spillover effect on Wal-Mart PLs is the strongest for Dr. Pepper brands and that, overall, the spillovers are stronger for regular versus diet sodas.

Figure 1, taking Wal-Mart CSDs sold in New York as an example, provides an insight as to why the demand for PL brands increases with advertising of manufacturer brands. TV advertising for Coke and Pepsi Regular, particularly advertising for Pepsi Regular, is strongly correlated with physical sales of Wal-Mart's CSD (Great Value) Regular. Dr. Pepper Regular advertising GRPs, however, are not as closely correlated with Wal-Mart sales of their regular CSD. Although the correlations of advertising GRPs by the leading brands and Wal-Mart sales are paradoxical, our econometric results also confirmed very strong positive spillover effects from manufacturer brand advertising goodwill to PL CSD demand.

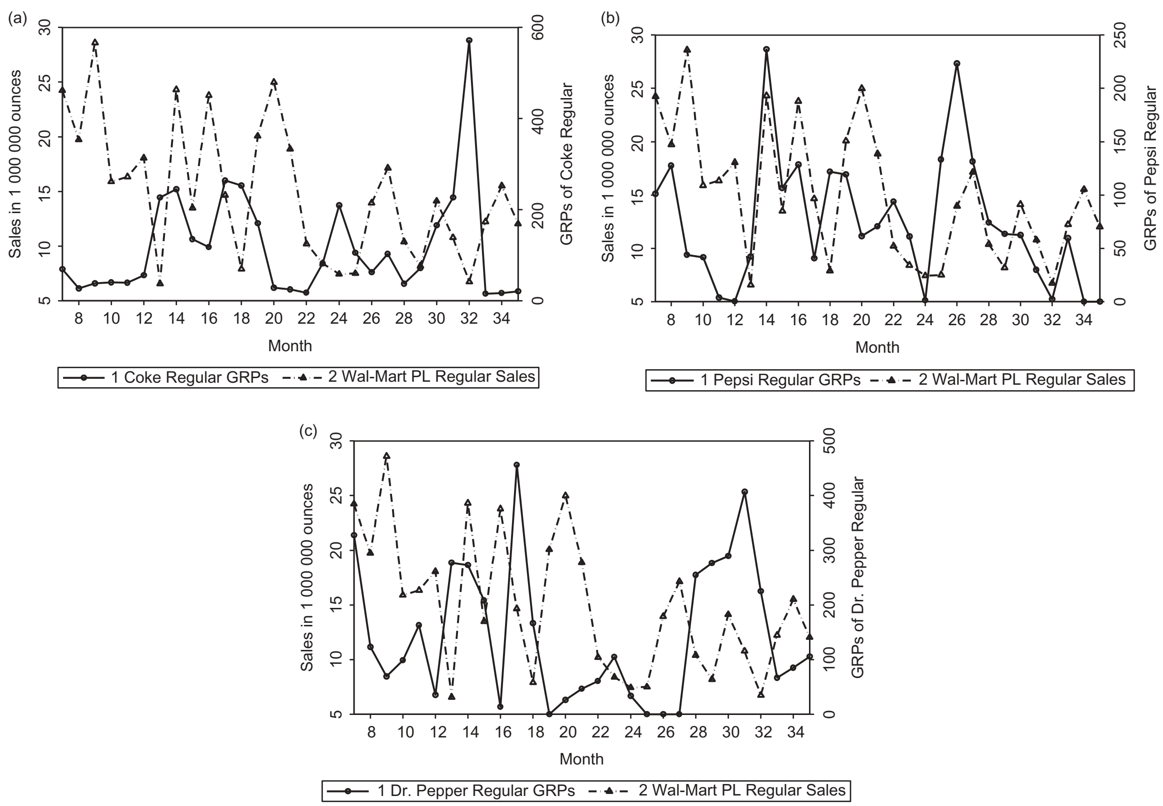

Fig. 1. TV advertising and Wal-Mart volume sales in New York. (a) Coke Regular advertising GRPs and Wal-Mart sales; (b) Pepsi Regular advertising GRPs and Wal-Mart sales; (c) Dr. Pepper Regular advertising GRPs and Wal-Mart sales

[9] Note that these elasticities do not represent economic returns to advertising in any way but only how consumer purchases respond to increases in brand advertising exposure.

Simulation results

Previous results confirm the positive spillover effects of brand advertising on PLs. In this section, using the demand estimates, we conducted two counterfactual experiments to examine how consumers' consumption of CSDs, especially PLs, might be affected without TV advertising (e.g. if a government advertising ban resulted in zero advertising for all CSD products).

Table 5 illustrates the effects of eliminating all TV CSD advertising on manufacturer and PL market shares. Doing so would lead to a general decline in the market shares of all sodas totalled and consumers switching to the outside good. The outside shares of alternative choices (e.g. fruit juice, bottled water, milk) go up from 86.72% to 89.54% when all CSD brands stop advertising. Thus, from a competition standpoint, the strong opposition of the industry to any kind of advertising regulation is consistent with these results. Overall, such a policy would wipe out the competitive advantage of Coca-Cola and PepsiCo brands and level competition with PLs whose market shares would stay the same or increase.[10] The results are consistent with the findings of Erdem *et al.* (2008), who used data on detergents, in that advertising raises the level of demand rather than decreasing the price elasticity of demand (i.e. it steepens the demand curve).[11] When only Coke and Pepsi advertising is set to zero, the main effect is to redistribute market shares towards Dr. Pepper and PLs, with the outside beverage shares remaining approximately the same by very slightly increasing to 86.81% (from 86.72%).

Table 5. Estimated market shares under alternative advertising scenarios

Company/brand	S0: current practice	S1: all GRP = 0	S2: Coke and Pepsi GRP = 0
Coca-Cola			
Coke Regular	2.36	1.81	1.32
Coke Diet	1.86	1.1	1.03
Coke Zero	0.35	0.24	0.22
Sprite Regular	0.51	0.41	0.35
Fanta Regular	0.17	0.1	0.1
PepsiCo			
Pepsi Regular	2.12	1.64	1.48
Pepsi Diet	1.42	1.08	0.79
Mountain Dew Regular	0.8	0.73	0.59
Mountain Dew Diet	0.3	0.27	0.2
Mountain Dew Code Red Regular	0.09	0.1	0.06
Sierra Mist Regular	0.22	0.24	0.21
Sierra Mist Free Diet	0.15	0.22	0.13
Dr. Pepper			
Dr. Pepper Regular	0.52	0.34	1.25
Dr. Pepper Diet	0.42	0.14	1.11
7 Up Regular	0.18	0.13	0.76
7 Up Diet	0.17	0.08	0.84
Sunkist Regular	0.21	0.22	0.95
Diet Rite Pure Zero Diet	0.09	0.11	0.32
Wal-Mart PLS			
Wal-Mart Regular	0.28	0.28	0.33
Wal-Mart Diet	0.29	0.36	0.37
Other chain PLS			
Top other chain Regular	0.44	0.49	0.4
Top other chain Diet	0.33	0.36	0.37
Outside shares	86.72	89.54	86.81

[10] So do a couple of manufacturer brands such as Sunkist Regular and Sierra Mist Free Diet.
[11] Our results also showed minimal effects on the price elasticities of demand when setting GRPs to zero.

VI. Concluding Remarks

This article estimates the demand for CSDs in five US cities using the BLP discrete choice model and combining household purchase and TV advertising data. The empirical analysis addresses potential endogeneity of prices, models advertising as goodwill stocks and considers company and competitors' spillover effects of advertising. The demand results are used to estimate price and advertising elasticities and the impact of alternative advertising strategies on leading company and PL market shares.

The estimated own- and cross-price elasticities at the CSD brand level indicate that consumers are strongly brand-loyal to their preferred CSD, particularly to the Coca-Cola Company products. TV brand advertising has a significant and strong effect in increasing demand, as do the spillover effects from brand advertising on other brands sold by the same company. At the same time, competitors' advertising has a negative effect on demand for manufacturer brands of CSDs with the surprising exception for PLs: the demand for PL CSDs increases with increases in TV advertising exposure to manufacturer brands. Thus, although TV advertising is effective for competition among manufacturing brands of Coca-Cola, PepsiCo and Dr. Pepper, it is counterproductive in competing against PL brands.

Simulation results indicate that eliminating TV advertising of CSDs, as suggested by advocacy groups focusing on public health and obesity, would result in a broad decline of market shares of CSDs generally with respect to competing beverages such as juices, milk and water. However, PLs stand to gain market shares, particularly Wal-Mart brands. PLs free-ride on TV advertising for manufacturing brands through spillover effects, as they would also from eliminating CSD advertising, as some health advocate propose, due to weakening brand value.

However, the results of this article should be interpreted with caution as the scope of the analysis did not fully account for possible substitutions of other forms of advertising (e.g. social media, which are increasingly being used by CSD companies). While our results provide a first-order approximation to the spillover effects of TV advertising using the CSD industry as a case study, further research is needed to assess the full extent of these effects in other industries where PLs are more prominent, such as the fluid milk market and pharmaceutical products. In addition, CSD companies, since the late 1990s when CSD consumption began to decline, have already made substantial investments in order to capture some of the top leading brands, such as Dasani (Coca-Cola) and Aquafina (PepsiCo), and are increasingly introducing new CSD products. The model and the results outlined here can provide a segue to further studies in other industries, and incorporation of emerging online media technologies and word of mouth among consumers constitutes a promising avenue of further inquiry to better assess broader media advertising spillover effects on consumer demand for CSDs and other products.

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