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Spillover and Competitive Effects of Advertising in the Carbonated Soft Drink Market

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Abstract

This paper examines the spillover effects of television advertising on brand-level consumer demand for carbonated soft drinks (CSDs) and the competition consequences for manufacturers' and private label CSDs. Using a random coefficients logit model (BLP) with household purchasing and advertising viewing data from five U.S. cities, we find that although brand advertising is important in increasing demand as previous work confirms, company advertising spillovers are nearly as important. Not surprisingly, advertising by competitors undermines demand for a particular manufacturer's CSD brand but, surprisingly, there are positive spillover effects on the demand for private label brands. Further results show that eliminating all television advertising for CSDs would lower both brand and aggregate market shares (including private labels) as consumers migrate to other beverages. However, the dominant strategy is for leading companies to advertise to avoid losing revenues when competitors advertise or to increase revenues when they do not.

Key words: advertising, demand, competition, consumer behavior, sodas, carbonated soft drinks

JEL Codes: D12, L66, Q18, I18

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Spillover and Competition Effects of Advertising in the Carbonated Soft Drink Market

1. Introduction

Carbonated soft drinks (CSDs) are the leading beverage category in both consumption and advertising in the United States. According to Zmuda (2011), in 2010 the average American drank 45 gallons of CSDs per year, and the Coca-Cola Company, PepsiCo and Dr. Pepper spent $267 million, $154 million, and $104 million respectively on advertising, on which the non-alcoholic beverage industry spends an average of $2 billion per year. This study focuses on the effects of television advertising on demand in the U.S. carbonated soft drinks market and on demand spillovers and competition.

Understanding how advertising of CSDs impacts demand is important for two reasons. First, given the importance of demand spillover effects in brand advertising (Tulin and Sun, 2002; Subramanian and Ghose, 2003; Nakata, 2011; Rutz and Bucklin, 2011), understanding the full effects of advertising by a company and its competitors will more accurately measure advertising effects on demand and the ensuing implications for competition. Second, CSDs have been identified as the leading contributor of calories in the ongoing obesity epidemic. Thus, understanding how consumption is affected by advertising can serve as a basis for policies aimed at regulating advertising of CSDs as is done in other countries (e.g., France, Denmark, and Sweden).

Obesity, especially childhood obesity, is a growing problem. Governments are considering a variety of policy solutions, including banning advertisements of so-called unhealthy food and beverages. Large CSD consumption in particular is identified by obesity researchers as one of the key drivers of this problem as it significantly increases caloric intake per meal. CSDs being one of the most heavily advertised product categories, 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. 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 United States. In fact, the U.K. banned junk-food advertising to children in 2007, and various forms of advertising bans have existed in the province of Quebec, Canada, since 1980.

This article contributes to the advertising debate by examining the effects of brand-level television advertising on the brand, company, and competitors' demand for CSDs. We specify our 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.

Our dataset includes brand-level advertising for 18 leading manufacturer and four private label brands of CSDs in five designated market areas. A BLP model is estimated using the MPEC approach, and the spillover effects of advertising on both brand-level demand and market shares are computed. We find that although brand advertising increases demand as expected, company advertising spillover effects are nearly as important. Not surprisingly, advertising by competitors undermines demand for a particular manufacturer's CSD brand but, surprisingly, the spillover effects on the demand for private label brands are positive. Simulation results indicate that *elimination* of advertising would lower market shares for all sodas (including private labels) as consumers migrate to beverages outside the CSD brands considered, including water, milk and juices. Finally, it is shown that the dominant business strategy is for leading companies to advertise to either avoid losing revenue through unilateral elimination of advertising or because revenues are higher relative to a situation where no one advertises.

2. 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 heterogeneity. In the BLP model (summarized here for expository purposes), the consumer, in choosing a CSD brand 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, or Dr.Pepper.) that own soft drink products under different brand names. Use *j=1,...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

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

$$= \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}, \qquad (1)$$

where p_{jm} is the price of CSD *j* in market m; and Z_j is the nutritional characteristics of product *j* including calories, 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 of *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 $X_j = (p_{j,} Z_j, \ Ad_{jm}, \sum_{k\neq j,k\in g}, \ Ad_{km}, \sum_{h\neq j,h\notin g} Ad_{hm})$, where the mean utility $\delta_{jm} = X_j' \beta + \xi_{jm}$ includes a vector X_j of all characteristics of relevance 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 the 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

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

Aggregating over consumers, the market share of the j^{th} brand corresponds to the probability that the j^{th} brand is chosen in market *m*, given by

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

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:

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

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

The conventional effect of advertising on brand-level demand is measured by

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

where Ad_{km} measures advertising for brand *k* in market *m*. Note that (5) only captures the 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 and the competitive effects.

First, consider the spillover effects on other brands ($k \neq j$) 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 affect the demand of CSD *k*, not just through market cannibalizations:.

$$\epsilon_{jkm} = \frac{\partial s_{km}}{\partial \sum_{f \neq k, f \in g} Ad_{fm}} \cdot \frac{\partial \sum_{f \neq k, f \in g} Ad_{fm}}{\partial A_{jm}} \cdot \frac{Ad_{jm}}{S_{km}}. \tag{6}$$

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 (5) relative to the positive company spillover effect in (6). Thus, ignoring spillover effects would lead to negatively biased advertising effect estimates.

Second, consider the competitive effects on other brands ($h \neq j$) belonging to a different company other than g. For CSD *h*, the increase of CSD *j*'s advertising level will increase the total advertising levels of CSD *k*'s rival companies, which will further affect the demand of CSD *h*:.

$$\epsilon_{jhm} = \frac{\partial s_{hm}}{\partial \sum_{f \neq k, f \notin g} Ad_{fm}} \cdot \frac{\partial \sum_{f \neq k, f \notin g} Ad_{fm}}{\partial A_{jm}} . \frac{Ad_{jm}}{s_{hm}} . \qquad (7)$$

For brands in competing companies, the competitive effects accentuate the negative direct effect of brand cannibalization. Thus, ignoring the competitive effects would lead to underestimation of the effects of brand advertising by competitors. As an example, when Coke Regular increases advertising, it will have a direct negative effect on Diet Coke, 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 the direct and indirect spillover effects are negative.

Note that substitution patterns are not constrained by a priori segmentation of the market as in the multiple-stage budgeting approach. Also note that the commonly-used logit model delegates consumer heterogeneity to the error term, assumed to follow an i.i.d. Type I extreme value distribution, which would restrict substitution patterns by indicating that a consumer is more likely to switch to a brand with a larger market share (rather than one that is most similar).

3. Data and Estimation

The dataset used combines two Nielsen datasets: advertising and household (Homescan) panel data, both obtained from the Zwick Center for Food and Resource Policy (formerly the Food

Marketing Policy Center) 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 5 designated market areas (DMAs) from 2006 to 2008. The DMAs are: New York, Atlanta, Washington D.C., Seattle and Detroit. 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..

The household panel data tracks 13,985 households and covers CSD weekly purchase records from grocery stores, drug stores, vending machines, and online shopping sites in the same 5 DMAs. This dataset contains information on product characteristics (e.g., flavor, packaging), marketing (e.g., unit price and in-store displays), and location and time of each purchase. The CSD purchase data was aggregated from household to the DMA level. In addition, both the CSD purchase and advertising data were aggregated from weekly to monthly observations. Combining these two datasets directly links brand-level advertising exposure to brand-level purchases. The potential market size, used to compute market shares, was defined for each period and DMA as the combined per capita consumption (in volume) of CSDs plus the outside good (e.g., juices, water and milk) times population.

Product characteristics in the estimating sample include price, nutritional characteristics, and television 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 modeled as goodwill in order to capture the carry-over 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:

$$Ad_{jt} = \sum_{k=0}^{K} \lambda^k \, \psi(A_{j,t-k}), \tag{8}$$

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 following function is applied before applying the decay factor:

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

(9) Note that since we have six monthly lags and 35 months of data, the first six observations were 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 spillovers from 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 are estimated in the econometric model through the cross-advertising elasticities of demand.

Figure 1 illustrates the pattern of television advertising GRPs for the leading regular and diet sodas. The largest peak for Coke Regular (circa period 32) is the spike in advertising during the 2008 Olympics. The advertising for Coke Diet and Pepsi Diet follows a pulsating behavior between peaks and valleys (in fact, no advertising in some periods, particularly after period 23), which is a typical pattern of television advertising. The advertising GRP pattern for Coke Diet is not very different from Coke Regular's, whose variation is, however, more exaggerated. It is also interesting to note that, particularly in the regular sodas, Coke's and Pepsi's advertising coverages seem to respond to each other.

Table 1 lists the summary CSD brand characteristics of the sodas included in the sample. The estimating sample contains 3,190 market-level observations based on 29 monthly periods (July 2006 to November 2008), 22 brands of CSDs, and 5 DMA markets. The characteristics for the four private label brands are averaged out over the corresponding regular or diet Wal-Mart or other supermarket private label brands in the dataset.

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 product nutritional characteristics, production input-cost variables (price and lag price of high fructose corn syrup), an advertising price index, and Hausman-type price and goodwill instruments (Hausman, 1994). For the purpose of this article, for simplicity and tractability we do not include socio-demographic 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 (MPEC) method, which has been demonstrated to avoid several numerical problems in optimization (Dubé et al., 2013; Knittel and Metaxoglou, 2008). The results are presented in the following section.

4. Empirical Results

4.1 Demand Results

Table 2 shows the 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. Estimating the model under the assumptions of exogenous or endogenous advertising stocks did not lead to statistically different results, alleviating concerns about the endogeneity of advertising goodwill in this model. 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 GRP. However, consumers also have a positive valuation of company advertising when choosing a brand of CSD; in fact, the magnitude of the coefficient is nearly the same as for own brand GRP. 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 other manufacturers’ brand demand for CSDs. Surprisingly, the effect is positive and statistically significant (at the 10% level) on the demand for Wal-Mart private label sodas, and positive but statistically insignificant (at the 10% level) on the demand of leading supermarket chain private label sodas. The coefficient of the goodwill spillover on supermarket private label

CSDs is about half of the ones for Wal-Mart. Thus, private label sodas, even though they are not advertised on television, 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 private labels 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 private label 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 flavor over nutritional or obesity concerns.

All own-price elasticities of demand were negative and all cross-price elasticities positive for all models. The magnitude of the own-price elasticities in Table 3 range from a -1.85 for Wal-Mart Regular to nearly -2.36 for Dr. Pepper Diet. These magnitudes are consistent with previously estimated elasticities of CSD demand using scanner data: for example, Zhen et al. (2011), using product categories rather than brand-level elasticities, reports 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. Andreyeba et al. (2010) reports 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) reports 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.

The cross-price 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 results for partial (without spillover effects) own-advertising elasticities in Table 4 show inelastic responsiveness to brand GRP increases, *ceteris paribus.* Note that, in general, there is a greater degree of consumer responsiveness to advertising regular sodas than to advertising diet ones and that the responsiveness to brand advertising is generally higher for the leading brands, particularly Coke Regular, for which a 1% increase in advertising goodwill returns a 0.6% increase in demand with additional benefits to other Coca-Cola brands through spillover effects. However, the highest degree of responsiveness at the brand level is that for Dr. Pepper Regular with a GRP elasticity of 0.92. Incidentally, this is the most heavily advertised brand in the sample in terms of GRPs (see Table 1). Cross-advertising elasticities show a moderate degree of business-stealing effect or cannibalization within the same CSD company when advertising a particular brand. There is also asymmetry in responding to advertising: demand for Coca-Cola competitors' products is more sensitive to Coke's advertising than the other way around. Finally, one should also keep in mind two caveats in terms of interpreting GRP elasticities. First, these elasticities do not represent economic returns to advertising in any way but only how consumer purchases respond to increases in brand GRPs. Second, they do not include spillover effects to other brands in the same company or the effect it will have on competitors or their reaction.

Table 4 contains only the direct effects of brand advertising on brand-level demand stipulated in equation (5) as it ignores the spillover effects as done in much of the previous literature. As all cross-advertising elasticities are negative, 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 although the response to brand advertising is relatively strong for that brand, the cross-advertising elasticities are quite small, suggesting that competing brands are relatively shielded.

Table 5 contains the total elasticities of demand with respect to brand advertising that include the business direct effects as well as spillover effects of brand advertising. 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 in Table 4. 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. This has important implications for managers as it generates economies of advertising based on consumer response, which might be important, particularly within limited advertising budgets. Brand advertising spillover effects increase the productivity of brand advertising beyond product brand boundaries and suggest that advertising should be spread across all brands because “all boats rise” with brand advertising. However, as these effects are asymmetric, with spillover being greater from a company’s leading brands onto its secondary brands than the other way around (e.g., Coke Regular has a higher total advertising elasticity effect on Coke Diet than the other way around), the results suggest concentrating advertising on leading brands as the most effective way to energize the global demand for a company's portfolio of brands.

Table 5 also shows the total cross-elasticity of demand with respect to brand advertising. Taking into account aggregate competitors' advertising goodwill significantly accentuates the cross partial elasticities relative to the partial elasticities without spillover effects in Table 4. This implies that if spillover effects are not taken into account, one may underestimate the full effect of advertising by competitors. An interesting exception is the response of demand for private label CSDs to advertising of manufacturer brands. This response is positive and of a large magnitude, indicating that private labels benefit from television advertising by competitors. This may be explained by the fact that consumers become more aware of private label brands as aggregate television advertising expands the global demand for CSDs. Figure 2 provides an insight as to why the demand for Wal-Mart private label CSDs increases with advertising of manufacturer brands. Although TV advertising for Pepsi Regular is positively correlated with physical sales of that brand, as one would expect and our results confirm, Sales of Wal-Mart's Regular are even more closely correlated to Pepsi Regular's TV advertising than sales of Pepsi Regular itself (Figure 2). Although this correlation is paradoxical, our econometric results also confirmed very strong positive spillover effects from manufacturer brand advertising to private label CSD demand.

4.2 Simulations Results

We conducted policy simulations to examine how consumers' consumption of CSD might be affected by either absolute voluntary industry restrictions or government advertising bans. In particular, we assessed consumer consumption, firm revenues, mark up and market share changes of various brands of CSD under the counterfactual analysis of 4 different advertising scenarios: (1) All CSD firms stop advertising (GRP = 0) ; (2) All brands of top 2 firms, Coca-Cola and PepsiCo, stop advertising and all other CSD firms maintain current level of advertising (Coca-Cola GRP = 0 & PepsiCo GRP=0); (3) Only Coca-Cola brands do not advertise, PepsiCo and other firms continue current level of advertising (Coca-Cola GRP = 0); and (4) Only PepsiCo brands do not advertise, Coca-Cola and other firms continue current level of advertising (PepsiCo GRP =0). For these simulations, we paid special attentions to advertising strategies of Coca-Cola and PepsiCo since these two firms' market shares added together control over 70% of the CSD market and the main competition in the market is the head-to-head rivalry between them. For each scenario, we computed the simulated demand, price elasticity, market shares and firm revenues for each brand and firm.

Table 6 illustrates the counterfactual results in the four scenarios of own-price elasticities for all brands as well as outside shares. The results suggest that elimination of advertising would result in slightly higher price elasticities of demand. This result illustrates that advertising plays both a modest persuasive and an anti-competitive role, though persuasive advertising is associated with lower price elasticities of demand (Bagwell, 2007). An implication for price competition is that advertising, by virtue of resulting in lower price elasticities, allows firms to compete under wider price-cost margins. As a consequence, eliminating advertising would result in lower price-cost margins of demand under Nash-Bertrand competition.

Table 6 also illustrates the effects of eliminating all television CSD advertising on market shares. Doing so would also lead to a general decline in the market shares of all sodas 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 88.05% when all CSD brands stop advertising and to 87.22% when the top 2 players do not advertise. 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 private labels. If Coca-Cola unilaterally removes all TV advertising, then Pepsi Regular and Diet brands would become the market leaders by moderate margins. Similarly, if Pepsi stopped all advertising on TV, Regular Coke and Diet Coke would lead the market and both Coca-Cola and Dr. Pepper brands enjoy a market share growth. The simulation results are consistent with the findings of Erdem et al. (2008) using data on detergents in that advertising raises the level of demand, but unlike in Erdem et al., advertising decreases the price elasticity of demand (steepens the demand curve).

One thing worth noticing is the impact of advertising bans on private label products, whose advertising level is by default held as zero constantly. Presumably one might infer a market share increase for private label CSDs when all brands or leading brands of CSDs do not advertise, as such bans eliminate the advantages of branded products. Surprisingly, the market shares of private label CSDs offered by Wal-Mart and other top chains all go down dramatically when all firms or leading brands do not advertise. Such huge losses of market share suggest that private label CSDs, although they do not advertise and maintain a relatively weak position in the market, are benefitting from major brand CSD advertising, as the advertising of branded CSD products expands the overall market of CSDs.

Table 7 presents a payoff matrix from competition between Coca-Cola and PepsiCo under different advertising scenarios for the two leading companies. The payoffs are average monthly sales in a market. In this advertising game, each firm can choose either to advertise or not to advertise. The payoffs when both firms choose to advertise is generated from our data and all other payoffs are calculated through simulation scenarios 2, 3, and 4. From this simple 2×2

game, it is easy to conclude that advertising is a dominant strategy for both companies, and the Nash Equilibrium is achieved by both companies advertising.

5. Concluding Remarks

This paper estimates the demand for carbonated soft drinks (CSDs) in 5 U.S. cities using the BLP discrete choice model and combining household purchase and television 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 revenues.

The estimated own- and cross-price elasticities at the CSD brand level indicate that consumers are strongly brand-loyal to their preferred CSD. Television 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 private labels: the demand for private label CSDs increases with the increase in advertising by manufacturer brands.

Simulation results indicate that eliminating television advertising of CSDs would result in a broad decline of market shares of all sodas with respect to competing beverages such as juices, milk, and water. However, the dominant Nash equilibrium is for leading companies to advertise to avoid losing revenues to competitors or to increase revenues in a situation where no one advertises.

As the most heavily advertised beverage product on television and the most politically controversial in terms of health implications, the CSD industry is increasingly emphasizing social media as a promotion tool, which is not only potentially more influential but also more cost effective. Given that social media currently account for 22 percent of all time spent online in the U.S., how do social media websites, including Facebook, Twitter and You Tube, affect CSD consumption? It is certainly the case that the internet, whose effects on consumer demand and competition are still unknown, is an increasingly important substitute for television advertising. Extension of research to address this emerging issue is both a current shortcoming and a worthwhile avenue for further research.

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Table 1. Summary of CSD Brand Characteristics

Company/Brand	Price $/12 oz.	Market Share (%)	Weekly GRP	Calories per 12 oz.	Sugar g/12oz	Sodium mg/12oz	Caffeine mg/12oz
CocaCola							
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 Diet	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 Chain PL Regular	0.304	0.56	0.0	160	43	52	27
Top Other Chain PL Diet	0.339	0.39	0.0	0	0	44	34

Note: Results are averages over five designated market areas (New York, Atlanta, Washington D.C., Seattle, and Detroit) in the 2006-2008 period.

Table 2. Demand Estimation Results

	Mean Utility		Unobservables	
Variable	Mean	Standard Errors	Mean	Standard Errors
Price	-8.601***	(3.012)	8.181	(5.704)
Own Brand other Goodwill	1.458***	(0.209)	1.447	(2.629)
Goodwill of brands in a same firm	1.343***	(0.327)	0.224	(1.440)
CocaCola	1.154**	(0.524)	6.180**	(2.455)
Pepsi	0.711***	(0.239)	-1.076	(0.812)
Wal-Mart PLs	-0.280**	(0.112)	13.774**	(6.326)
Other Chain PLs	-0.814	(1.981)	-2.015	(1.861)
Goodwill other firms * CocaCola	-0.591**	(0.261)	4.829	(3.171)
Goodwill other firms * Pepsi	-0.675*	(0.382)	0.399	(3.450)
Goodwill other firms * Wal-Mart PLs	1.687*	(0.867)	-1.725	(1.859)
Goodwill other firms * Other Chain PLs	0.770	(1.047)	-0.284	(2.869)
Sugar	0.349**	(0.162)	1.686***	(0.657)
Sodium	-3.248***	(0.945)	1.161	(1.857)
Caffeine	1.287***	(0.219)	0.140	(0.829)
Atlanta	-0.358*	(0.204)	1.120	(1.234)
Washington DC	-1.630	(3.359)	3.123	(3.966)
Seattle	-2.374	(4.035)	2.880	(3.536)
Detroit	-4.682*	(2.596)	5.801*	(3.216)
Constant	-6.676***	(1.190)	1.434	(1.115)
Observations	3,190			
First State F Statistic	17.394			
P-value	0.000			
Hansen J Statistic	13.623			
p-value	0.478			

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

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	Mountain Dew Regular	Mountain Dew Diet	Wal-Mart PL Regular	Wal-Mart PL Diet
Coke Regular	-2.095	0.192	0.230	0.169	0.276	0.191	0.229	0.190	0.120	0.129
Coke Diet	0.164	-2.077	0.182	0.200	0.208	0.269	0.347	0.395	0.114	0.183
Pepsi Regular	0.192	0.178	-1.891	0.141	0.265	0.166	0.230	0.197	0.090	0.103
Pepsi Diet	0.099	0.137	0.099	-2.056	0.102	0.133	0.124	0.141	0.084	0.113
Dr Pepper Regular	0.071	0.062	0.082	0.045	-2.296	0.060	0.100	0.077	0.023	0.028
Dr Pepper Diet	0.035	0.058	0.037	0.042	0.044	-2.364	0.060	0.066	0.028	0.041
Mountain Dew Regular	0.074	0.131	0.089	0.069	0.125	0.104	-2.199	0.172	0.040	0.057
Mountain Dew Diet	0.021	0.052	0.027	0.027	0.034	0.040	0.060	-2.189	0.014	0.025
Wal-Mart PL Regular	0.060	0.067	0.054	0.072	0.045	0.074	0.062	0.061	-1.846	0.086
Wal-Mart PL Diet	0.052	0.086	0.049	0.077	0.043	0.088	0.071	0.089	0.069	-1.934

Table 4. Sample of Partial Advertising Elasticities of Demand for CSDs

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet	Mountain Dew Regular	Mountain Dew Diet	Wal-Mart PL Regular	Wal-Mart PL Diet
Coke Regular	0.604	-0.015	-0.015	-0.015	-0.014	-0.0147	-0.015	-0.015	-0.015	-0.014
Coke Diet	-0.006	0.343	-0.006	-0.006	-0.007	-0.0070	-0.007	-0.006	-0007	-0.007
Pepsi Regular	-0.013	-0.013	0.597	-0.014	-0.014	-0.0114	-0.013	-0.013	-0.011	-0.012
Pepsi Diet	-0.004	-0.004	-0.005	0.288	0.288	-0.0037	-0.005	-0.005	-0.003	-0.004
Dr Pepper Regular	-0.005	-0.005	-0.004	-0.004	0.920	-0.0054	-0.004	-0.004	-0.005	-0.005
Dr Pepper Diet	-0.001	-0.001	-0.001	-0.001	-0.001	0.3024	-0.001	-0.001	-0.001	-0.001
Mountain Dew Regular	-0.004	-0.004	-0.004	-0.005	-0.005	-0.0038	0.517	-0.005	-0.004	-0.004
Mountain Dew Diet	-0.001	-0.001	-0.001	-0.001	-0.001	-0.0009	-0.001	0.322	-0.001	-0.001
Wal-Mart PL Regular	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wal-Mart PL Diet	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 5. Sample of Advertising Elasticities of Demand for CSDs that Include Spillover Effects

Brand	Coke Regular	Coke Diet	Pepsi Regular	Pepsi Diet	Dr Pepper Regular	Dr Pepper Diet	Mountain Dew Regular	Mountain Dew Diet	Wal-Mart PL Regular	Wal-Mart PL Diet
Coke Regular	0.573	0.518	-0.338	-0.338	-0.0494	-0.050	-0.338	-0.337	0.665	0.665
Coke Diet	0.297	0.326	-0.188	-0.188	-0.0279	-0.028	-0.188	-0.191	0.376	0.376
Pepsi Regular	-0.297	-0.296	0.568	0.515	-0.0488	-0.050	0.517	0.514	0.658	0.657
Pepsi Diet	-0.138	-0.138	0.250	0.274	-0.0195	-0.019	0.250	0.253	0.322	0.321
Dr Pepper Regular	-0.366	-0.365	-0.419	-0.421	0.9065	0.854	-0.419	-0.420	1.085	1.080
Dr Pepper Diet	-0.120	-0.120	-0.138	-0.137	0.2831	0.299	-0.138	-0.138	0.356	0.355
Mountain Dew Regular	-0.239	-0.239	0.454	0.452	-0.0278	-0.025	0.491	0.451	0.574	0.573
Mountain Dew Diet	-0.145	-0.144	0.285	0.285	-0.0129	-0.016	0.285	0.306	0.364	0.363
Wal-Mart PL Regular	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Wal-Mart PL Diet	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6. Estimated Price Elasticities and Market Shares Under Alternative Advertising Scenarios

	Own Price Elasticities					Predicted Shares (%)				
Brand	S0: Current Price	S1: All GRP = 0	S2: Coke and Pepsi GRP=0	S3: Coke GRP=0	S4: Pepsi GRP=0	S0: Current Price	S1: All GRP=0	S2: Coke and Pepsi GRP=0	S3: Coke GRP =0	S4: Pepsi GRP=0
CocaCola										
Coke Regular	-1.706	-1.715	-1.717	-1.719	-1.706	2.36	1.88	1.75	1.67	2.37
Coke Diet	-1.696	-1.697	-1.703	-1.706	-1.691	1.86	1.80	1.46	1.35	2.14
Coke Zero Diet	-1.892	1.892	1.894	-1.894	-1.891	0.35	0.35	0.28	0.25	0.40
Sprite Regular	-1.966	-1.960	-1.962	-1.963	-1.955	0.51	0.71	0.64	0.60	0.86
Fanta Regular	-2.278	-2.271	-2.274	-2.274	-2.268	0.17	0.25	0.23	0.22	0.31
Pepsi										
Pepsi Regular	-1.613	-1. 617	-1.622	-1.591	-1.625	2.12	1.85	1.53	3.09	1.41
Pepsi Diet	-1.651	-1.652	-1.656	-1.635	-1.658	1.42	1.30	1.07	2.08	0.98
Mountain Dew Regular	-1.773	-1.771	-1.777	-1.765	-1.777	0.80	0.77	0.61	1.16	0.56
Mountain Dew Diet	-1.775	-1.775	-1.777	-1.771	-1.777	0.30	0.28	0.22	0.45	0.20
Mountain Dew Code Red Regular	-2.017	-2.017	-2.018	-2.017	-2.018	0.09	0.08	0.06	0.12	0.06
Sierra Mist Regular	-1.902	-1.901	-1.902	-1.894	-1.902	0.22	0.28	0.26	0.05	0.22
Sierra Mist Free Diet	-1.874	-1.872	-1.873	-1.867	-1.874	0.15	0.20	0.17	0.36	0.15
Dr. Pepper										
Dr. Pepper Regular	-1.793	-1.796	-1.782	-1.786	-1.782	0.52	0.31	0.92	0.70	0.90
Dr. Pepper Diet	-1.751	-1.754	-1.740	-1.745	-1.741	0.42	0.26	0.77	0.59	0.74
7 Up Regular	-1.878	-1.879	-1.873	1.875	-1.873	0.18	0.13	0.36	0.27	0.35
7 Up Diet	-1.842	-1.842	-1.837	-1.840	-1.837	0.17	0.13	0.34	0.25	0.33
Sunkist Regular	-2.118	-2.118	-2.098	-2.104	-2.099	0.21	0.23	0.72	0.54	0.70
Diet Rite Pure Zero Diet	-1.757	-1.756	-1.745	-1.750	-1.746	0.09	0.11	0.35	0.25	0.33
Wal-Mart										
Wal-Mart PL Regular	-1.422	-1.424	-1.424	-1.423	-1.423	0.28	0.18	0.20	0.22	0.23
Wal-Mart PL Diet	-1.521	-1.523	-1.523	-1.522	-1.522	0.29	0.18	0.21	0.23	0.24
Other Chain										
Top Other Chain PL Regular	-1.409	-1.409	-1.40-	-1.410	-1.409	0.44	0.38	0.36	0.32	0.39
Top Other Chain PL Diet	-1.822	-1.823	-1.823	-1.824	-1.823	0.33	0.26	0.26	0.25	0.29
Outside Shares	-		-		-	86.72	88.05	87.22	84.54	85.83

Table 7. Payoffs under Alternative Advertising Scenarios

		PepsiCo. adv	PepsiCo. no adv
CocaCola	adv	(8.8, 7.7)	(10.2, 5.4)
	no adv	(6.9, 11.7)	(7.3, 5.9)

Note: Payoff = Average Monthly Total Sales in a DMA (in $1000,000)

Figure 1. Advertising GRPs for Coke and Pepsi Leading Brands in New York

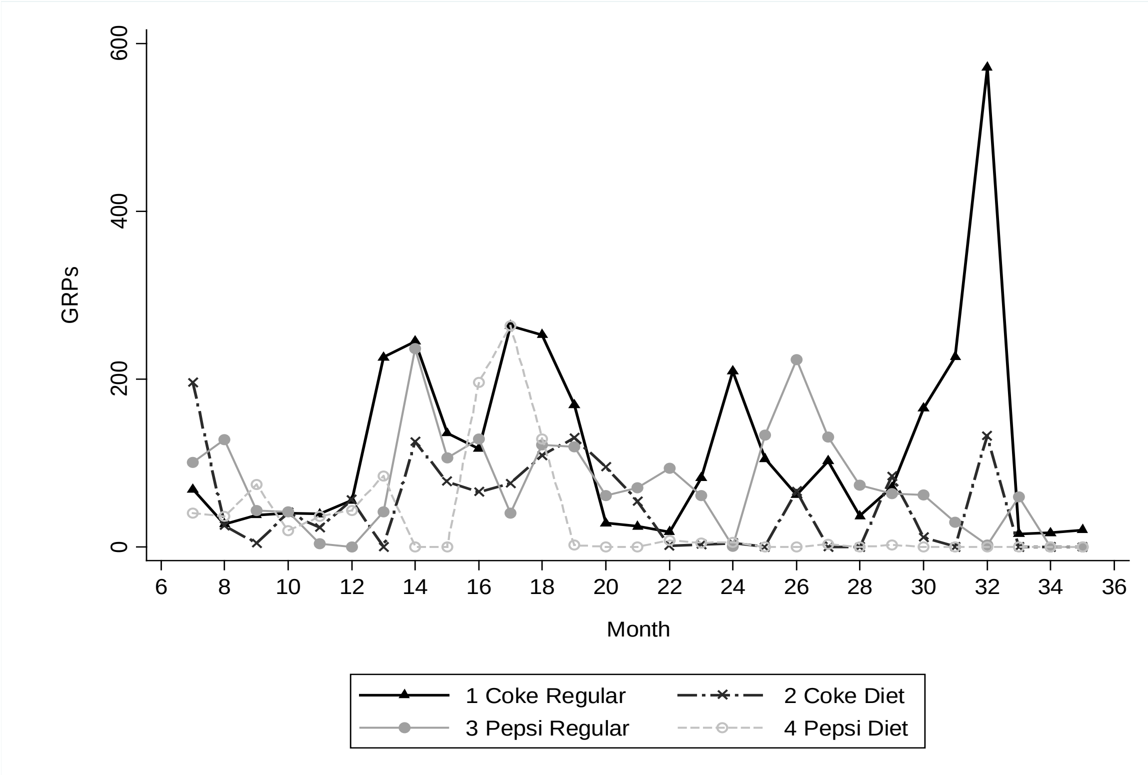

Figure 2. Pepsi Regular Advertising GRPs and Volume Sales of Pepsi Regular and Wal-Mart PL Regular in New York