The Impact of Four Alternative Policies to Decrease Soda Consumption

Yizao Liu, Rigoberto A. Lopez, and Chen Zhu

We examine the impact of four policy options on consumption of carbonated soft drinks (CSDs) by estimating a random-coefficient discrete-choice model of demand. Policy simulations using demand estimates indicate that the impacts of banning television advertising, limiting container size, and limiting calories on total consumption would be similar—an estimated 15.40–15.75 percent reduction. However, limiting calories would have a significantly greater impact on consumption of regular CSDs (–28.89 percent) and on calories consumed from CSDs (–19.34 percent). A tax on calories was least effective in curtailing overall consumption and consumption of regular CSDs.

Key Words: advertising, carbonated soft drinks, consumer behavior, demand, obesity, policy, sodas, taxes

There is little debate on the negative health consequences of excessive consumption of sugar-sweetened carbonated soft drinks (CSDs). Of the identified causes of obesity and related health issues seen in the United States and elsewhere in recent years, such drinks constitute the main source of added calories in diets (Marriott et al. 2010, Johnson and Yon 2010) and thus are an important contributor. The nutritional and medical science elements associated with CSDs are well documented, but debate continues regarding how to effectively change consumers' behavior so that they make healthier beverage and food choices. We evaluate and quantitatively illustrate the potential impact of four policies aimed at decreasing consumption of CSDs.

Previous work on the economics of obesity policy related to CSDs has focused on imposition of taxes at the point of sale.[1] Overall, empirical evidence from

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[1] Most states exempt food from sales taxes; 32 apply sales taxes to soft drinks, including CSDs; only a handful of states apply excise taxes (Zheng, McLaughlin, and Kaiser 2013, Tax Foundation 2011).

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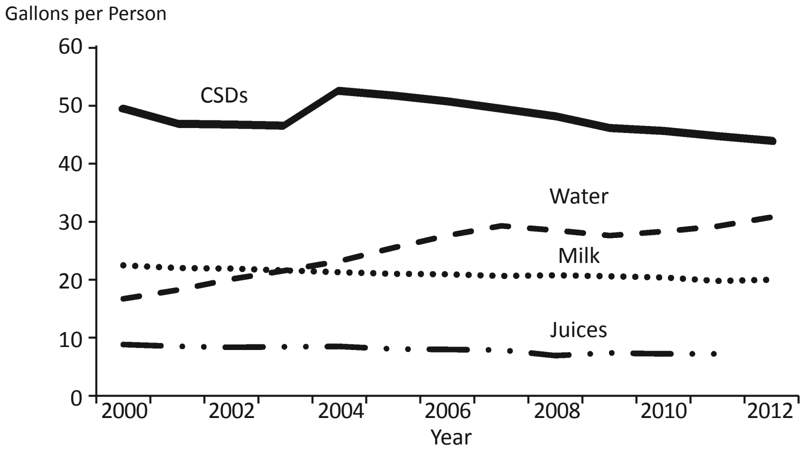

Figure 1. Trends in Consumption of Leading Nonalcoholic Beverages

Notes: Total per capita consumption of nonalcoholic beverages was approximately consistent at 158 gallons per year in this period. The graph does not indicate other beverages such as coffee, tea, or energy and sports drinks.

Source: 2000–2003 data are from the Economic Research Service, U.S. Department of Agriculture (2013). Data for 2004–2012 are from *Beverage Digest* (2013).

those studies has shown that such taxes can be effective generally in curbing consumption but quasi-ineffective in curbing obesity (Fletcher, Frisvold, and Tefft 2010, Marlow and Shiers 2010, Lopez and Fantuzzi 2012, Zheng, McLaughlin, and Kaiser 2013) unless the taxes are large and are mostly passed on to consumers. Arguments against using a tax to reduce CSD consumption include the large share of such a tax that falls on low-income consumers (Chen, Liu, and Binkley 2012), likely substitution of other sugar-sweetened beverages that replace the CSD calories (Finkelstein et al. 2013), and claims advanced by CSD companies and others that such taxes represent the government acting as food police (Lusk 2013).

Figure 1 presents trends in annual consumption of leading nonalcoholic beverages in the United States. Although per capita consumption of all CSDs has been declining since 2004, they remain the primary beverage consumed by Americans and the main source of their beverage calories. Interestingly, total beverage consumption has remained steady. Americans consume about 158 gallons of nonalcoholic beverages and 180 gallons of beverages overall per capita per year. The figure demonstrates that consumers have more often consumed bottled water as a replacement for CSDs in recent years.

Little research has been done on alternatives to a soda tax. One alternative is restriction of television advertising of CSDs, a policy used in the United Kingdom (since 2007) and in Quebec, Canada (see Dhar and Baylis 2011). In the United States, Coca-Cola Company and fifteen other food and beverage companies pledged in 2006 to alter child-directed advertising to encourage "healthier" dietary choices and healthy lifestyles through the Children's Food and Beverage Advertising Initiative (Better Business Bureau 2013). However, public health experts have questioned the effectiveness of the initiative because of its narrow definition of child-directed advertising (Harris et al. 2013). Another policy option is to reduce "package" sizes, which seems likely to reduce consumption of CSDs since experiments have shown that increasing beverage portion sizes significantly increases the total volume of beverage consumed annually (Flood, Roe, and Rolls 2006). Another policy alternative is to reduce the amount of sugar contained in sweetened CSDs to make them less attractive to sugar lovers.

In this study, we quantitatively illustrate the impact of four public policy instruments aimed at decreasing CSD consumption: (i) a ban on television advertising, (ii) a soda excise tax of one cent per ounce, which has been proposed in several states (Tax Foundation 2011), (iii) limiting calories in a 12-ounce CSD to 100, and (iv) banning large containers such as 2-liter bottles. Using a random-coefficient logit demand model and simulations of each policy alternative, we estimate the demand for CSDs with the Nielsen data sets and compare changes in CSD consumption generated by each policy. Modeling demand using product characteristics (including calories, television advertising, prices, and packaging) rather than the conventional product space allows for a counterfactual analysis of alteration of characteristics that are pertinent to the policy scenarios. We use the random-coefficient logit demand model described in Berry, Levinsohn, and Pakes (hereafter referred to as BLP) (1995), which examined products at a brand level using the characteristic space.[2] Our analysis has implications for issues of obesity and health generally, but our focus is on the direct impacts of the policies on consumption of CSDs.

Empirical Model

To simulate the effect of alternative policy options on CSD consumption, several steps are needed: estimating demand for CSDs, recovering the marginal cost of CSDs using demand estimates and horizontal Bertrand-Nash pricing, and simulating new market equilibria prices and market shares for each product based on the policy scenarios.

Following the approach in BLP, we model demand for CSDs using the characteristic space and define products in terms of their characteristics, which solves the problems of dimensionality, consumer heterogeneity, and endogeneity of product prices.[3] This model also offers a solution to the restrictive and implausible substitution patterns generated by classic discrete choice models such as a logit or nested logit approach.

We use $j = 1, \ldots, J$ to denote each CSD product and $j = 0$ to denote a general outside choice in the beverage market. We consider CSD products of the same brand contained in different sized packages as separate products (Dubé 2004). Therefore, the subscript j includes two dimensions of the product, brand and container size. For example, a 2-liter bottle and a 12-ounce can of Dr. Pepper are treated as separate products indexed by different values of j.

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[2] An alternative is to model demand based on the product space. However, when many products are involved, the classic product space approach suffers from dimensionality because the larger number of products greatly increases the number of parameters, which makes conventional demand estimation models intractable. In addition, demand for differentiated products also is affected by consumer heterogeneity.

[3] Although the BLP model is commonly used for counterfactual analysis and even for product elimination (Cohen 2008), it employs estimated parameters that capture marginal effects of banning advertising rather than total effects. Thus, the analysis should be interpreted with caution as it produces first-order approximations. Other methods, such as choice experiments and natural experiments (e.g., Dhar and Baylis 2011), that use controls and treatment effects for the with-policy and without-policy scenarios may prove to be more appropriate. Note, however, that our data set contains a significant number of zero-observation points for advertising exposure and, of course, dichotomous variables for container size. Consequently, our simulated policy scenarios use values that are within range of observed values in the sample.

In line with the model described in BLP, we specify the conditional indirect utility of consumer *i* from purchasing a CSD product or an outside product in market *m* as

$$(1) \quad u_{ijm} = \alpha_i p_{jm} + \mathbf{size}'_j \varphi_i + \gamma_i Ad_{jm} + \mathbf{x}'_j \beta_i + \xi_{jm} + \epsilon_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}$$

where p_{jm} is the unit price per ounce of CSD product *j* in market *m*; $\mathbf{x}_j$ is a vector of observed nutrition characteristics of brand *i* that include calories and percent quantity of sugar, sodium, and caffeine, which are the same for each product regardless of package size; and $\mathbf{size}_j$ is a vector of dummy variables that represents container sizes. In this study, we include three sizes: 12-ounce cans and 20-ounce and 2-liter plastic bottles. These dummy variables are used to account for consumers' preferences for a particular size of soft drink. ξ_{jm} captures unobserved fixed effects of products and ϵ_{ijm} is the idiosyncratic shock to unobserved utility.

Ad_{jm} represents advertising goodwill and captures the carryover effect of advertising's impact on demand for brand *j* in market *m* (Dubé, Hitsch, and Manchanda 2005). Specifically, advertising goodwill is derived in a distributed lag form in which the subscript for market *m* is eliminated for simplicity: $Ad_{jt} = \sum_{k=0}^{K} \lambda^k \psi(A_{j,t-k})$ where $\psi(\cdot)$ is a nonlinear advertising-goodwill production function. A_{jt} represents advertising exposure for a particular CSD brand, $\lambda \in (0,1)$ is a geometric decay factor, and *t* and *k* denote time periods.[4] Advertising goodwill enters the utility function directly.[5]

To capture the heterogeneous preference of consumers, let $\theta_i = (\alpha_i, \beta_i, \gamma_i, \varphi_i)$ denote a vector of consumer-specific coefficients that follows a normal distribution: $\theta_i = \theta + \sum v_i$, $v_i \sim N(0, I)$ where $\sum$ is a scaling matrix and the unobserved household characteristics, v_i, are assumed to have a standard multivariate normal distribution.

The indirect utility term, μ_{ijm}, in equation 1 can then be broken down into three parts: (i) a mean utility term, $\delta_{jm} = \alpha p_{jm} + \mathbf{size}'_j \varphi + \gamma Ad_{jm} + \mathbf{x}'_j \beta + \xi_{jm}$, that is common to all consumers; (ii) $u_{ijm} = (p_{jm}, \mathbf{size}_j, Ad_{jm}, \mathbf{x}_j) \times (\sum v_i)$, which denotes brand- and consumer-specific deviations from the mean utility given by interactions between consumer and product characteristics; and (iii) ϵ_{ijm}, a mean-zero stochastic term representing idiosyncratic tastes that is distributed independently and identically as a type I extreme value.

To complete the model and to define the market (and, hence, market shares), we include an outside good to provide the consumer with an opportunity to buy something other than a CSD product. The probability that consumer *i* will purchase a unit of brand *j* in market *m* is

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

By aggregating over consumers, we generate the market share of CSD product *j* in market *m*:

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[4] In the estimation, we use six lags in accord with the literature (see Dubé, Hitsch, and Manchanda 2005).

[5] The use of advertising as a goodwill stock is standard in the marketing literature. Goodwill stocks capture the dynamic effects of advertising by taking both cumulative effects and depreciation into account over time (Doganoglu and Kappler 2006).

$$s_{jm} = \int I\{(v_i, \epsilon_{ijm}) : U_{ijm} \geq U_{ikm} \quad \forall k = 0, \ldots, J\} dG(v) dF(\epsilon) \tag{3}$$

where v is a vector of v_i (consumer-specific deviations), ϵ is a vector of ϵ_{ijm}, and $G(v)$ and $F(\epsilon)$ are their cumulative density functions, which are assumed to be independent of each other. The own- and cross-price elasticities of the market share for each brand can be calculated as[6]

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

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

To attain equilibrium prices and market shares generated by each policy option, we assume that the CSD companies have sole market power in the marketing channel and thus set new retail prices in response to a change in policy.[7] Let multiproduct CSD company f produce a subset, $\mathcal{F}_f$, of $j = 1, \ldots, J$ CSD products. The profit of firm f is

$$\Pi_f = \sum_{j \in \mathcal{F}_f} (p_j - mc_j) \, M \, s_j(p) - C_f \tag{5}$$

where p_j is the price and mc_j is the marginal cost of product j. M denotes market size and C_f is the fixed production cost. $s_j(p)$ is the market share of product j, which depends on the price of each of the products in the market. Assuming the existence of a pure-strategy Bertrand-Nash equilibrium in prices, the price of product j produced by firm f must satisfy the first-order condition:

$$s_j(p) + \sum_{l \in \mathcal{F}_f} (p_l - mc_l) \frac{\partial s_l(p)}{\partial p_j} = 0 \quad j, l = 1, \ldots, J \tag{6}$$

where $s_j(p)$ is derived from equation 3 and

$$\frac{\partial s_l(p)}{\partial p_j}$$

is calculated from equation 4. In vector notation, marginal costs are recovered as

$$mc = p - \Omega^{-1} s(p) \tag{7}$$

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[6] Note that these elasticities correspond to standard quantity-based elasticities since market size (M) is assumed to be constant and quantities can be obtained by $q_{jm} = s_j M$. In support of this assumption, the total amount of per capita nonalcoholic beverages consumed by Americans has remained, to a large extent, fixed at approximately 158 gallons per year.

[7] The CSD market channel typically consists of companies at a national level and retailers at a local level. Because of the interest of policymakers in consumers' purchases of CSDs, we obtain equilibrium retail (rather than manufacturer) prices. Thus, as in Nevo (2001), the manufacturers set retail prices in our model. This approach is consistent with prior studies of pricing by CSD companies (Gasmi, Laffont, and Vuong 1992, Mariuzzo, Walsh, and Whelan 2003, Dhar et al. 2005).

where mc, p, and $s(p)$ are vectors of the marginal cost, price, and market share and Ω is a block diagonal matrix of equilibrium prices. In sum, we follow the approach of BLP for demand estimation and then assume Bertrand-Nash horizontal competition among CSD companies and compute equilibrium prices and market shares for each of the four policy scenarios that we compare to the benchmark scenario (the current situation) and to each other.

Data and Estimation

This analysis combines information from two Nielsen data sets. The Homescan data set obtained from Zwick Center for Food and Resource Policy at University of Connecticut contains information on product characteristics (unit prices, package sizes, and brand names) and the locations and dates of all purchases of the products examined in the study at a household level. The advertising data set contains brand-level information on CSD companies' weekly advertising expenditures and weekly gross rating points[8] for national ads (aired on cable, network, and syndicate outlets) and local (spot) television networks in seven designated market areas (DMAs)[9] for 2006, 2007, and 2008. We aggregated the weekly CSD purchase and advertising data to generate monthly observations. By combining the data sets, we could directly link brand-level advertising exposure to brand-level purchases. Product characteristics in the sample include price, nutrition content, and amount of television advertising. Previous studies (e.g., Lopez and Fantuzzi 2012) suggest that sugar, sodium, and caffeine content are key nutrition indicators that can affect consumers' CSD choices. We model advertising goodwill using the aggregated gross rating points for each brand.[10]

In this analysis, the market is defined by both the month and the DMA. The potential size of each market area per period, which is used to compute market shares, is both per capita consumption by volume of CSDs and the outside good (e.g., juices, water, and milk) combined and multiplied by the population of the DMA.

Table 1 presents summary statistics for the CSD products' characteristics across all periods, markets, and container sizes. There is an extremely high degree of correlation between calories and sugar since CSDs contain no other source of calories.

Table 2 presents a summary of average prices and market shares by package size. Note that 20-ounce bottles are three to four times more expensive per ounce than 12-ounce cans and 2-liter bottles.[11] In our sample, the aluminum can is the most popular of the three packages in terms of volume and market share, followed by 2-liter bottles.

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[8] Gross rating points are calculated by multiplying the number of times a particular advertisement is viewed over a specific period by the number of people reached by the ad during the same period. For example, if 10 percent of all households in a specific DMA watched a commercial five times during a week, the commercial has a GRP rating of 50 for that week.

[9] The DMAs included in our study are New York, Detroit, Washington D.C., Atlanta, Chicago, Los Angeles, and Seattle.

[10] Prior to estimation, both advertising goodwill and nutrition characteristics were scaled between 0 and 1 to facilitate the computational process.

[11] The price difference may seem surprising. A large number of bloggers have discussed the potential cause of the disparity, which occurs at all retail outlets, including Wal-Mart and Target. Some factors cited are convenience and the fact that 20-ounce bottles are often dispensed in vending machines. The summary statistics shown in Table 2 are consistent with this observation.

Table 1. CSD Brand Data Summary over Seven Designated Market Areas for 2006 through 2008

	Price	Market Share	Weekly Gross Rating	Calories	Sugar	Sodium	Caffeine
Company and Brand	dollars per 12 ounces	percent		per 12 ounces	grams per 12 ounces	mg per 12 ounces	mg per 12 ounces
Coca-Cola							
Coke regular	0.358	2.11	111.2	140	39	50	35
Coke diet	0.370	1.97	72.6	0	0	40	47
Coke Zero diet	0.409	0.31	77.2	0	0	40	35
Sprite regular	0.376	0.48	56.8	144	38	70	0
PepsiCo							
Pepsi regular	0.316	1.91	114.6	150	41	30	38
Pepsi diet	0.341	1.35	66.8	0	0	35	35
Mtn Dew regular	0.368	0.57	74.5	170	46	65	54
Mtn Dew diet	0.343	0.21	57.6	0	0	50	54
Dr. Pepper							
Dr. Pepper regular	0.371	0.73	135.9	150	40	55	42
Dr. Pepper diet	0.379	0.47	58.8	0	0	55	42
Sunkist regular	0.365	0.29	13.4	190	50	70	40
7•Up regular	0.326	0.31	121.5	140	38	40	0

Notes: For each product, we consider three container sizes (12-ounce cans, 20-ounce bottles, and 2-liter bottles) so there are 36 brand-size combinations. The designated market areas are New York, Detroit, Washington D.C., Chicago, Kansas City, Los Angeles, and Seattle.

Table 2. Summary Statistics by Container Size

Bottle Size	Price	Unit Price	Market Share
12-ounce can	\$0.022 per ounce	\$0.269	7.23%
20-ounce bottle	\$0.076 per ounce	\$1.515	0.26%
2-liter bottle	\$0.022 per ounce	\$1.497	2.90%

Price is potentially endogenous since retail price effects depend on observed and unobserved product and consumer characteristics and variations in those characteristics can induce variations in prices. Thus, mean choice-utility parameters are identified through the BLP-type market-level macro-moments using a complete set of instrumental variables. The instruments include products' nutrition characteristics, production input-cost variables (the price and lag price of high fructose corn syrup), an advertising price index, and Hausman-type price and goodwill instruments (Hausman 1994). We tested for the validity of the instrumental variables with a first-stage F-test and a Hansen J-test and report the results in Table 3. The tests indicated that the instrumental variables are valid and relatively strong, alleviating concern about potential price endogeneity. The Hansen J-statistic indicated that the null hypothesis of zero expected moments in the model was not rejected, a result that lends credibility to the model specification. We conducted all estimations in the TOMLAB optimization environment in Matlab. Our estimation approach builds on mathematical programming with equilibrium constraints, which eliminates several numerical problems in optimization (Dubé, Fox, and Su 2012, Knittel and Metaxoglou 2008).

Empirical Results

Demand Results

Table 3 shows the results of our estimations of demand. Overall, the results seem plausible in terms of signs and expected coefficients. Nearly all of the key parameter estimates are statistically significant at the 5 percent or lower level. As expected, consumers have a strong, negative valuation of price and a positive valuation of brand advertising. In addition, the standard deviations of the price and advertising coefficients are significant, suggesting that consumers' responses to changes in price are heterogeneous. The econometric

Table 3. Demand Estimation Results

	Parameters		Deviations	
Variable	Estimate	Standard Deviation	Estimate	Standard Deviation
Price	–5.971**	(2.974)	–5.201*	(2.814)
Advertising	1.914*	(1.033)	–2.740**	(1.170)
Calories	0.863**	(0.399)	2.579***	(0.527)
Sodium	–9.117***	(2.279)	3.247***	(0.962)
Caffeine	1.122***	(0.430)	–2.685***	(0.720)
Bottle size 20 ounces	–5.166***	(1.233)	2.867***	(0.903)
Bottle size 2 liters	–1.312***	(0.180)	–0.142	(1.132)
Coca-Cola	0.769**	(0.324)	1.195**	(0.581)
Pepsi	0.315	(0.258)	0.801*	(0.416)
Constant	–5.460***	(0.881)	–0.617	(0.501)
DMA fixed effects	Yes			
Month fixed effects	Yes			
Observations	5,580			
First-stage F statistic	12.498			
p-value	0.000			
Hansen J statistic	43.116			
p-value	0.381			

Notes: Standard errors are listed within parentheses. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.10$.

Benchmarks: Container size: 12-ounce can. CSD company: Dr. Pepper. DMA: Seattle. Month: December.

results show that consumers have, on average, a positive valuation of calories and caffeine content and a negative valuation of sodium content. From a nutrition standpoint, the positive coefficient for calories may reflect an average preference for flavor over nutrition concerns. Since sugar (whether sucrose or high fructose corn syrup) is the exclusive source of calories in CSDs, this positive consumer valuation (both at the mean utility and for unobservable consumer characteristics) is a concern given the link between sugar-sweetened beverages and obesity.

The estimated mean parameters for container size indicate that 20-ounce and 67-ounce (2-liter) bottles are valued less than 12-ounce cans. This may reflect a preference for the smaller aluminum containers, which are often perceived as better preserving carbonation and taste (Palmer 2009). It is important to recognize, however, the significantly different valuation of 2-liter bottles relative to 12-ounce and 20-ounce containers even after controlling for prices and advertising. Finally, the results for fixed effects for CSD company show that, relative to Dr. Pepper brands, consumers have a higher intrinsic valuation of Coca-Cola brands and are relatively indifferent to PepsiCo brands.

Table 4 presents own-price elasticities of demand by CSD brand and container size for sugar-sweetened (regular) and diet drinks. The elasticities are negative and elastic, ranging from –1.022 for 67-ounce (2-liter) diet Pepsi to –4.724 for 20-ounce regular Sunkist. It is interesting to note that demand for 20-ounce containers is the most price sensitive and that demand for 12-ounce cans is only moderately less price sensitive than demand for 2-liter bottles. The magnitudes of these estimated own-price elasticities are consistent with previous estimates of elasticities of CSD demand from models that used scanner data. For example, Zhen et al. (2011) used product categories rather than brand-level characteristics and reported elasticities in the –1 to –2 range for sugar-sweetened beverages. Dubé (2004) reported elasticities in the –2.0 to –3.5 range for specific sizes and brands of CSDs. Andreyeba, Long, and Brownell (2010) reported elasticities for fourteen soft drink products that had 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) reported –2.7 to –4.4. On the high side, Chan (2006) reported own-price elasticities for CSDs at a household level of –5 to –11.

Given the robustness of the results and the plausibility of the estimated price elasticities relative to previously published studies, we determined that the empirical demand results were reasonable for use in our simulations of the four policy scenarios.

Policy Simulations

The estimated parameters in the demand equation allowed us to capture how price, advertising, package size, and calorie content affect consumers' demand for and choices of CSDs. We next consider the effects of alternative policies on CSD consumption by simulating market outcomes over the sample period for the following four policy scenarios,[12] which change the characteristics of CSD products in consumers' utility functions:

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[12] The only out-of-sample simulation of pertinent product characteristics is the complete ban on advertising of all brands and sizes included (regular Sunkist is rarely advertised on television). In fact, there was no television advertising in many city/time periods for the brands in the study. We assume that the tax on CSDs would exceed any existing taxes in the locations included in the study.

Table 4. Own-Price Elasticities

Company	Brand	Container Size in Ounces	Price Elasticity
Coca-Cola	Coke regular	12	–1.023
		20	–4.183
		67	–1.178
Coca-Cola	Coke diet	12	–1.046
		20	–3.867
		67	–1.069
Coca-Cola	Coke Zero diet	12	–1.093
		20	–4.673
		67	–1.161
Coca-Cola	Sprite regular	12	–1.186
		20	–4.341
		67	–1.342
PepsiCo	Pepsi regular	12	–1.044
		20	–4.042
		67	–1.050
PepsiCo	Pepsi diet	12	–1.076
		20	–4.215
		67	–1.022
PepsiCo	Mountain Dew regular	12	–1.125
		20	–4.404
		67	–1.128
PepsiCo	Mountain Dew diet	12	–1.139
		20	–4.505
		67	–1.178
Dr. Pepper	Dr. Pepper regular	12	–1.141
		20	–4.620
		67	–1.146
Dr. Pepper	Dr. Pepper diet	12	–1.134
		20	–4.578
		67	–1.140
Dr. Pepper	Sunkist regular	12	–1.204
		20	–4.724
		67	–1.370
Dr. Pepper	7·Up regular	12	–1.187
		20	–4.247
		67	–1.291

1. *Television advertising ban:* We impose the equivalent of an absolute voluntary industry ban on advertising or a government-imposed ban by setting television advertising goodwill for all CSD products to zero while assuming other forms of advertising at constant levels.
2. *A soda tax at the point of consumption:* We impose a tax of one cent per ounce on soft drinks, and the net price the consumer pays for CSD product *j* is increased by one cent per ounce. This represents a 100 percent price transmission.

3. *Product reformulation (reducing sugar content):* We limit the calories in a 12-ounce container of a sugar-sweetened CSD to 100. The calorie restriction can be obtained by either reducing the amount of sugar in the drink or by increasing the amount of low- or no-calorie sweetener.
4. *Downsizing of packages:* We ban 2-liter bottles, leaving consumers to choose between 12-ounce cans and 20-ounce bottles.

Using our estimates of demand, we first solve for new equilibrium prices using equation 7 and then calculate new beverage market shares using the product characteristics from each scenario to determine how consumption of CSDs is likely to be affected by the policy alternatives. We report the results of the simulations in Table 5. The changes in beverage market share translate directly into changes in consumption since the size of the market for all beverages (the denominator of market share) remains fixed by design.

S0 represents the benchmark scenario—the status quo with no new policy imposed.

Imposition of a television advertising ban (S1) results in a dramatic 15.4 percent decline in market share for CSDs, which are replaced by outside goods (milk, juices, and water). The decline in consumption of regular CSDs (–16.57 percent) in response to an advertising ban is significant and similar in magnitude to banning 2-liter bottles (S4). The effect that these reductions in CSD consumption would have on calorie intake would depend on the outside choices made, which cannot be determined from our model.

Imposition of a one cent per ounce tax on CSDs at the retail level (S2) translates to a 12-cent tax on 12-ounce cans and a 67-cent tax on 2-liter bottles. Thus, this scenario represents a significant tax that is consistent with proposals put forth in many states in recent years. As shown in Table 5, however, this level of tax induces only a 6.32 percent decline in total consumption of CSDs, and its effect on consumption of regular sodas is the smallest of the four policy options (–7 percent). In fact, such a tax is shown to have the smallest impact on overall CSD consumption. A larger tax, such as three or four cents per ounce, might have a greater impact on consumption, but even taxes of one cent per ounce have been defeated at the polls (Fernandez 2013). Arguments against a tax policy are that it not only interferes with free choice (Lusk 2013) but also is regressive since low-income consumers are the most frequent drinkers of CSDs (Chen, Liu, and Binkley 2012) with smaller price elasticities of demand (Zhen et al. 2011).

The policy scenario of restricting calories in sugar-sweetened CSDs (S3) to 100 per 12 ounces is consistent with the number of calories in many food and beverage products that are advertised as healthy or low in calories. The results of our simulation indicate that this policy would generate a substantial 15.52 percent decline in total consumption of CSDs, making it slightly more effective than a ban on advertising. This policy, which is designed, in principle, to make sugar-sweetened drinks *more* attractive to people who are relatively calorie-conscious, would instead result in an overall increase in consumption of diet CSDs and other types of beverages to the detriment of the reformulated sugar-sweetened drinks, as shown by the increase in the market share of diet drinks. This policy option produces the greatest decline in consumption of regular CSDs (–28.89 percent) and thus would have the greatest impact on reducing calories from CSDs.

The ban on 2-liter bottles, which would force consumers to purchase smaller containers of soda (S4), would, while increasing consumption of 12-ounce

Table 5. Estimated Percent Market Shares under Alternative Policy Scenarios

Company and Brand		Bottle Size in Ounces	S0: Benchmark	S1: All Gross Ratings = 0	S2: Sales Tax of One Cent per Ounce	S3: Restricted Calorie Content	S4: No 2-Liter-Size Bottles
Coca-Cola	Coke regular	12	1.650	1.382	1.573	1.321	1.827
		20	0.054	0.042	0.050	0.041	0.058
		67	0.404	0.324	0.378	0.325	0
Coca-Cola	Coke diet	12	1.535	1.257	1.437	1.594	1.689
		20	0.055	0.040	0.050	0.056	0.060
		67	0.380	0.293	0.349	0.403	0
Coca-Cola	Coke Zero diet	12	0.220	0.179	0.198	0.228	0.252
		20	0.011	0.009	0.010	0.011	0.012
		67	0.075	0.065	0.067	0.082	0
Coca-Cola	Sprite regular	12	0.333	0.310	0.310	0.264	0.381
		20	0.014	0.013	0.013	0.009	0.015
		67	0.134	0.127	0.124	0.104	0
PepsiCo	Pepsi regular	12	1.324	1.033	1.250	0.919	1.456
		20	0.036	0.024	0.034	0.023	0.037
		67	0.547	0.450	0.517	0.397	0
PepsiCo	Pepsi diet	12	0.970	0.871	0.907	1.002	1.067
		20	0.025	0.021	0.023	0.026	0.027
		67	0.353	0.324	0.328	0.365	0
PepsiCo	Mtn Dew regular	12	0.428	0.384	0.400	0.247	0.497
		20	0.017	0.015	0.016	0.009	0.018
		67	0.124	0.114	0.114	0.077	0
PepsiCo	Mtn Dew diet	12	0.143	0.124	0.133	0.147	0.161
		20	0.006	0.005	0.006	0.007	0.007
		67	0.058	0.049	0.053	0.058	0
Dr. Pepper	Dr. Pepper regular	12	0.536	0.396	0.508	0.360	0.603
		20	0.017	0.011	0.015	0.011	0.018
		67	0.177	0.133	0.168	0.110	0
Dr. Pepper	Dr. Pepper diet	12	0.335	0.342	0.313	0.360	0.373
		20	0.009	0.008	0.008	0.009	0.009
		67	0.127	0.128	0.118	0.142	0
Dr. Pepper	Sunkist regular	12	0.175	0.208	0.161	0.066	0.212
		20	0.006	0.007	0.006	0.003	0.007
		67	0.104	0.119	0.095	0.051	0
Dr. Pepper	7·Up regular	12	0.192	0.143	0.175	0.126	0.214
		20	0.005	0.004	0.005	0.003	0.006
		67	0.109	0.088	0.099	0.075	0
All regular CSDs			6.386	5.328	6.011	4.541	5.350
All diet CSDs			4.304	3.716	4.003	4.489	3.656
All CSDs			10.690	9.044	10.014	9.030	9.006
Percent change of regular CSDs			—	−16.57	−5.87	−28.89	−16.22
Percent change of diet CSDs			—	−13.67	−7.00	4.30	−15.05
Percent change of total CSDs			—	−15.40	−6.32	−15.52	−15.75
Percent outside goods			89.31	90.95	89.98	90.97	90.99

Note: In this analysis, all regular CSDs, all diet CSDs, and all CSDs refer to all relevant CSD products in our sample.

and 20-ounce CSDs, result in an overall 15.75 percent decline in total CSD consumption. Although this policy provides the greatest decline in overall CSD consumption, it is third in terms of decreasing consumption of *regular* CSDs (–16.22 percent), closely following the decline in regular CSD consumption from the tax policy (S1). This result is consistent with previous findings on the effects of sizes of containers and servings on calorie and volume consumption (e.g., Flood, Roe, and Rolls 2006). Despite defeat recently of a similar policy in New York City that was supported by Mayor Bloomberg, this policy appears to have promise when the objective is reduction of consumption of sweetened CSDs.

Table 6 reports estimated impacts of the four policy alternatives on reducing calories consumed from regular CSDs. Restricting calorie content (S3) turns out to be the most effective in terms of reducing the caloric intake of an average consumer. As shown in Table 5, this policy results in the largest volume decline in consumption of regular CSDs; it amounts to an almost 20 percent reduction in regular CSD calories every year. The next most effective policies are downsizing packages and banning television advertising. The least effective policy is the one cent soda tax per ounce (a reduction in CSD calories of around 6 percent per

Table 6. Simulated Percentage Change per Capita Annually in CSD Calories Consumed under Alternative Policy Scenarios

Company and Brand		**Bottle Size in Ounces**	**S0: Benchmark**	**S1: All Gross Ratings = 0**	**S2: Sales Tax of One Cent per Ounce**	**S3: Restricted Calorie Content**	**S4: No 2-Liter-Size Bottles**
			Calories Consumed	Percent Change in Calories Consumed			
Coca-Cola	Coke regular	12	1,798	–16.24	–4.63	–14.24	10.77
		20	59	–21.08	–6.40	–17.32	8.74
		67	440	–19.74	–6.29	–13.88	–100
Coca-Cola	Sprite regular	12	373	–6.87	–6.82	–14.49	14.27
		20	15	–4.43	–6.21	–21.72	10.05
		67	150	–4.79	–7.09	–15.26	–100
PepsiCo	Pepsi regular	12	1,547	–22.00	–5.63	–20.42	9.97
		20	42	–31.49	–4.83	–23.96	5.39
		67	639	–17.68	–5.47	–18.32	–100
PepsiCo	Mtn Dew regular	12	567	–10.44	–6.63	–24.95	16.01
		20	22	–11.38	–5.74	–26.53	7.50
		67	164	–7.96	–8.12	–22.15	–100
Dr. Pepper	Dr. Pepper regular	12	626	–26.17	–5.19	–21.89	12.40
		20	19	–34.07	–8.09	–21.44	6.89
		67	206	–24.51	–5.19	–25.07	–100
Dr. Pepper	Sunkist regular	12	259	18.63	–8.11	–32.84	20.92
		20	10	4.60	–7.29	–29.98	9.71
		67	154	14.27	–9.00	–26.94	–100
Dr. Pepper	7·Up regular	12	209	–25.32	–9.01	–24.43	11.56
		20	6	–29.22	–8.34	–29.15	5.43
		67	119	–19.80	–9.70	–22.45	–100
All regular CSDs in sample			7,426	–16.09	–5.92	–19.34	–16.31

year). Since a reduction of approximately 3,500 calories is required to reduce a person's weight by one pound (Lopez and Fantuzzi 2012), the tax would lead to a 0.125-pound decrease in weight and a 0.02 point decrease in a person's body mass index when we translate calorie reductions into weight changes. This result is consistent with previous studies that have demonstrated the failure of taxes on sugar-sweetened beverages in combating obesity (e.g., Fletcher, Frisvold, and Tefft 2010) and the difficulty of reducing people's consumption of unhealthy foods and beverages (Ha et al. 2009, Block et al. 2010, Centers for Disease Control and Prevention 2010).

Conclusion

We examine the potential impact of four policies aimed at curbing consumption of CSDs: (i) a ban on television advertising, (ii) a specific tax at the point of sale (one cent per ounce), (iii) limiting the calories in sweetened CSDs to 100 per 12 ounces, and (iv) banning large containers (proxied by 2-liter bottles in this analysis). We apply Berry, Levinsohn, and Pakes' (1995) demand model to data for twelve CSD brands supplied in three sizes of container in seven cities over 36 months to estimate consumers' preferences for CSD characteristics, including price, calories, and size of the container and the effect of advertising on consumption.

The empirical results indicate that all four policies have the potential to reduce consumption of CSDs overall and those containing calories in particular since calories are the main concern associated with obesity. Three of the four policies produced similar reductions in total consumption of CSDs. Limiting the size of containers was most effective in decreasing total consumption of all CSDs (regular and diet); it resulted in a nearly 16 percent decline, followed closely by banning television advertising and limiting caloric content. The one cent per ounce tax on calorie-containing CSDs was the weakest option, generating only a 6.3 percent reduction in overall consumption despite the significant tax imposed. When the objective is to reduce consumption of caloric CSDs, the most effective policy is limiting the number of calories in a 12-ounce serving; taxation is once again the least effective policy alternative.

Our results provide first-order approximations of the impact of the policies considered. Further research is needed to assess the full extent of their impacts, including fully accounting for substitution of other caloric beverage options and forms of advertising. The results outlined here also can provide a segue to more focused and in-depth analyses of the impacts of various policies on CSD consumption and associated health effects. Choice experiments and natural experiments show promise as a way to better assess policy-driven changes in consumer behavior with respect to beverages.

Per capita soda consumption has trended downward over the last decade and consumption of bottled water has been rising. Nevertheless, CSDs are still the king of beverages in American diets. Shifts in consumer preferences and/or imposition of government policies may further reduce CSD consumption. At the same time, since total per capita beverage consumption remains essentially fixed, there is room for private strategies to increase company profits while still reducing calories associated with beverages—products can be reformulated, new products can be developed, and companies can emphasize the growing market for bottled waters. In terms of bottled water, CSD companies immediately began to invest in that market when CSD consumption first began to decline in the late 1990s and successfully captured some of the top leading brands, including Dasani (Coca-Cola) and Aquafina (PepsiCo). In spite of the ability of public policy to potentially curb consumption of sugary CSDs, our results suggest that no single CSD policy would be effective in curbing obesity. Thus, a more comprehensive approach involving policies to promote education, exercise, private industry initiatives, and a wider choice of foods and beverages are likely necessary to effectively address the obesity epidemic.

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