Journal of Agricultural and Resource Economics 46(1):37–55 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.303601

Revisiting Sugar Taxes and Sugary Drink Consumption: Evidence from the Random-Coefficient Demand Model

Yinjunjie Zhang and Marco A. Palma

Berkeley's sugar tax policy is currently under intense scrutiny and debate, while similar tax policies are rapidly expanding to other U.S. states. Contrary to theoretical predictions and policy expectations, previous literature documents short-term evidence of increased consumption of sugary drinks in response to a sugar tax policy. We investigate the underlying mechanism behind this behavioral anomaly using the Berry, Levinsohn, and Pakes (BLP) random coefficient (RC) logit demand model in characteristic space. We find that the consumption increase is mainly driven by a change in the average valuation of the sugar content going from negative to positive following enactment of the sugar tax policy.

Key words: demand in characteristic space, food policy, sugar tax

Introduction

As a pressing health issue, obesity has received widespread attention from researchers and policy makers. According to a report from the World Health Organization, obesity is strongly associated with chronic illnesses such as diabetes, heart conditions, and other life-threatening diseases (World Health Organization, 2014). In the United States, about 70% of adults older than 20 are overweight or obese (National Center for Health Statistics, 2017).[1] Sugar-sweetened beverages (SSB) are typically seen as products with "empty calories," devoid of nutritional value (e.g., Malik, Schulze, and Hu, 2006; Jacobson and Brownell, 2000; Fletcher, Frisvold, and Tefft, 2015). A significant body of literature argues that, among other genetic factors, obesity is directly related to SSB consumption. Imposing a tax on SSB is expected to alleviate this health issue by reducing calorie intake (e.g., Malik, Schulze, and Hu, 2006; Pereira, 2006; Vartanian, Schwartz, and Brownell, 2007; Malik et al., 2010; Lin et al., 2011; Dharmasena and Capps Jr, 2012; Zhen, Brissette, and Ruff, 2014; Luger et al., 2017).

To overcome the obesity epidemic and other chronic diseases caused by SSB consumption, many countries have taken measures—such as levying taxes—to discourage the consumption of sugary drinks. Denmark was one of the early adopters of "soda tax" policies starting in the 1930s. More recently, Finland, France, and Hungary introduced taxation policies for sugary drinks around 2011–

Yinjunjie Zhang is a research fellow in the Tax and Transfer Policy Institute at the Crawford School of Public Policy at Australian National University. Marco A. Palma (corresponding author) is a professor in the Department of Agricultural Economics at Texas A&M University.
Researchers own analyses are calculated (or derived) based in part on data from The Nielsen Company (US), LLC, and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Review coordinated by Darren Hudson.

[1] https://www.cdc.gov/nchs/fastats/obesity-overweight.htm

2012. Mexico launched a national soda tax policy in 2014. Unlike these national soda tax policies, the United States has implemented SSB tax policies for smaller geographical areas. In March 2015, Berkeley, California, became the first city in the United States to impose an excise tax on sugary drinks, known as *Measure D*. Following Berkeley, other cities in California, Pennsylvania, Colorado, Illinois, Oregon, and Washington have either passed or proposed legislation to adopt sugary drink taxation policies.

Evaluating the effect of Berkeley's initiative on beverage consumption is of importance before extending similar soda tax policies to other states. However, current evidence opens a debate as to whether imposing a sugar tax on beverages leads to the intended results (Fletcher, Frisvold, and Tefft, 2010a,b; Bonnet and Requillart, 2011; Dharmasena and Capps Jr, 2012; Dharmasena, Davis, and Capps Jr, 2014; Cawley and Frisvold, 2015).

In particular, Debnam (2017) documents an increase in the consumption of soda drinks in Alameda County following the Berkeley's tax on sugary drinks. The main objective of this paper is to study the underlying mechanism behind this behavior, which appears to contradict neoclassical economic theory. We first investigate the potential concerns raised in the literature about the effects of sugar tax policies and then use Nielsen data to conduct a demand analysis in product characteristic space. The main topics of discussion in the literature related to sugar tax policies are (i) the extent to which a tax imposed on distributors will be passed on to consumers, (ii) the extent to which the increase in price will discourage consumers' sugary drink consumption and drive them to substitute their consumption toward untaxed diet beverages, and (iii) whether the induced response comes primarily from the population at high health risk.

Previous research about the pass-through rate of sugar tax polices is inconclusive. In early 2014, Mexico implemented a national tax on sugary beverages. Grogger (2017) finds that the policy caused the price of SSB to increase by more than the amount of the levied tax, suggesting an over-shifting of the tax to the retail price of soda products. Primary data collected by Cawley and Frisvold (2015) indicates that Berkeley's Measure D has had only modest effects on prices, with the pass-through tax rate ranging from 13.7% to 40.0%, depending on the brand and size of the product. Falbe et al. (2015) document that the pass-through rate for Berkeley's soda tax is about 47% for all SSBs.

Using Nielsen's Retail Scanner data, we estimate the pass-through rate for nondiet soda products (defined as beverages in regular formula in the data source, e.g., regular Coca Cola, regular Pepsi) in our sample. Using a difference-in-difference (DiD) framework, Appendix Table A1 suggests that following the soda tax policy, the average price of SSB increased by \$0.10–\$0.16 per 12-pack of 12-ounce beverages across several identification specifications using different geographical areas as the comparison group.[2] Since Measure D levies \$0.01/oz of the SSB, the pass-through rate can be calculated by dividing the DiD coefficients by the collected tax after deflation.[3] Across all the model specifications, the pass-through rate is statistically significant, ranging from 9% to 12%.

Basic economic theory predicts a decrease in the quantity demanded of SSBs in response to a price increase. However, Debnam (2017) provides empirical evidence that this is not necessarily the case for Berkeley's soda consumption. In fact, the author documents a 8.89-ounces increase in SSB consumption among Alameda County households following the passage of Measure D. The underlying mechanism behind this behavior is contrary to neoclassic economic theory and requires further analysis under a structural demand model. We contribute to the literature by presenting the first structural demand analysis to explain this behavioral anomaly. We show that this seemingly inconsistent behavior can be explained under a utility theory framework. Using the Berry, Levinsohn, and Pakes (BLP) random coefficient (RC) logit demand model in characteristic space, we fill the gap in the literature by quantitatively examining the mechanism through which consumers increase SSB

[2] The outcome prices are deflated and standardized to the size of 12-packs of 12-ounce beverages, which is the unit equivalent to 144 ounces of soda.

[3] In particular, the pass-through rate is obtained by dividing the DiD coefficients by 131.51 (deflating 144 cents in 2010 dollar yields $(144/109.5) \times 100 = 131.51$ cents).

consumption in response to a price increase. More specifically, we examine variation in consumers' valuation of product characteristics (i.e., sugar content) following the policy change.

Berkeley's Measure D passed on November 2014 and was adopted in March 2015. There were heated discussions and campaign activities supporting and countering this policy before it made it onto the voting ballot. These social events might potentially affect the preference for sugar content in beverages. Using data from this period may contaminate the results for the policy evaluation on preference changes. To solve this issue, we define the pre-policy period from 2006 to 4 months before the ballot and the post-policy period as 4 months after the passage which includes the time this policy became effective. By excluding from the analysis the 8-month period between July 2014 and March 2015, we isolate from our estimates the effect that could be produced by the intense campaign activities rather than the policy change.

Identifying potential heterogeneous responses of households is another dimension of interest of this article. Since households with high SSB consumption patterns constitute a vulnerable population with high health risks, a substantial amount of research provides empirical evidence regarding their consumption responses. For example, using a standard almost ideal demand system (AIDS), Debnam (2017) identifies heterogeneous elasticities of demand for households with different SSB consumption patterns. Etilé and Sharma (2015) employ a finite mixture instrumental variables (IV)-Tobit approach to compare the impact of SSB taxes on the price elasticity of demand between moderate and high SSB consumers using data from Australian households. Income is another important driver of SSB demand. Colchero et al. (2016) find a sizable reduction in the sales of taxed beverages among lower-income households. Lal et al. (2017) provide an analysis on the potential health and financial impacts on different income groups of a hypothetical SSB tax in Australia.

To model potential heterogeneous effects of sugar tax policies on consumers' sensitivity to product characteristics, we expand the BLP RC logit demand to control for demographic factors. Under this framework, we identify the extent to which the marginal valuation of product characteristics (i.e., sugar content) varies by household demographics, including income and SSB consumption levels.

One of the goals of Measure D is to induce consumers to switch their consumption of sugary drinks in favor of healthier beverages. We evaluate this effect by checking whether sugar taxes affect substitution patterns toward healthier drinks (i.e., diet drinks). In previous studies, the substitution patterns of sugary drinks have been examined using the price (Grogger, 2017) and consumption levels of food or beverage substitutes (Finkelstein et al., 2013; Zhen et al., 2013). Alternatively, we measure the sugar tax effect on the substitution patterns by examining the cross-price elasticities of beverages with different caloric content during the pre- and post-policy periods. By making this comparison, we are able to obtain a direct answer to the question of whether consumers substitute SSB for diet beverages after the policy change.

Our results indicate that the adoption of the sugar tax policy temporarily shifts consumers' average sugar content valuation from negative to positive. This finding provides a behavioral explanation on the mechanism behind the "reactance" response suggested in Debnam (2017). To adequately model the variation of household SSB consumption, we construct it as the proportion of time within a year-month market that a household median weekly consumption of sugary drinks is higher than the weekly median consumption of households across the sample. In this heterogeneous analysis, we do not find that the increase in soda consumption comes primarily from households with high SSB consumption. The elasticity matrix indicates that consumers become far more responsive to price changes after the policy intervention in Berkeley, but they do not necessarily substitute toward untaxed diet drinks.

Sugar tax in Berkeley, California

The Measure D sugar tax was passed on November 4, 2014, in the city of Berkeley in Alameda County, California. On March 2015, Berkeley became the first city in the United States to levy an excise tax on sugary drinks. In particular, it "imposes a general tax of one cent ($0.01) per ounce on the distribution of sugar-sweetened beverages and added-calorie sweeteners ('sweetener')" (City of Berkeley, 2014). Beverages subject to Measure D include sodas, sports drinks, energy drinks, and sweetened ice teas; diet drinks are excluded from the tax.

Berkeley's Measure D was originally proposed by the Berkeley Healthy Child Coalition, a group composed primarily of community members. Before the soda tax was on the ballot, a promotional campaign to say "Yes on D" was launched in Berkeley. Meanwhile, advertising campaigns managed by the American Beverage Association countered the passage of the sugar tax policy (Reich, 2014). For some time, Berkeley residents had extremely polarized opinions regarding the sugar tax policy.[4] It is possible that the highly contentious environment in Berkeley preceding the vote may to some extent have driven the post-policy temporary increase in sugary drink consumption.

Analytical Framework

Demand models for studying consumer behavior can be modeled in product space or in characteristics space. To solve the dimensionality problem in demand systems, product-based models assume *separability* of utility, and the products are normally grouped into categories. Examples of these demand models include the well-known Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), the translog model (Christensen, Jorgenson, and Lau, 1975), and the Rotterdam model (Theil, 1965). On the other hand, the characteristics-space demand system deals with the dimensionality issue by projecting the products onto a characteristics space. This type of demand model treats the product as a bundle of attributes rather than as a single product. The most popular model in this class is the BLP RC logit demand model, which was first introduced by Berry, Levinsohn, and Pakes (1995). The BLP RC logit demand model solves the dimensionality issue while allowing individual substitution patterns across products to be associated with characteristics of differentiated products.

BLP RC Logit Demand Model Setup

Following the standard framework of the BLP RC logit model (Berry, Levinsohn, and Pakes, 1995; Nevo, 2001), the utility function is written as

$$U_{ijt} = \alpha_i(y_i - p_{jt}) + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt}, \tag{1}$$

with household i's indirect utility from purchasing product j at market t represented by U_{ijt}. We define a market as a location–year–month combination. Location is the city (in our case Berkeley, California) adopting the soda tax; years are 2006–2016, with the pre-policy period ranging from January 2006 to June 2014 and the post-policy period ranging from March 2015 to December 2016, giving us $t = \{1,2,\ldots,102\}$ for the pre-policy period and $t = \{1,2,\ldots,22\}$ for the post-policy period. The period from July 2014 to February 2015 is excluded to rule out potential preference changes driven by campaign activity.

In each market, purchase quantities and prices are aggregated at the market level. y_i represents the income of consumer i;[5] x_{jt} refers to the K-dimensional product characteristics, including a constant, sugar content, and sodium level obtained from the beverage's nutrition facts; j indexes the attribute bundles of products; and ξ_{jt} captures unobserved product-specific shocks in each market. Each household is assumed to purchase one of j products or make no purchases at all. ε_{ijt} is the logit error term, which is assumed to follow a Type I extreme value distribution.

[4] A short documentary entitled "Berkeley vs. Big Soda" showcases the environment preceding the actual vote: https://ecologycenter.org/blog/one-year-after-soda-tax-watch-new-short-film-berkeley-vs-big-soda/

[5] Note that in some utility representations of the BLP model, the term y is omitted as it will be eventually canceled out when constructing the logit estimation model.

The household taste heterogeneity parameter is modeled as

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \Pi D_i + \Sigma v_i, v_i \sim P_v(v), D_i \sim P_D(D), \tag{2}$$

where D_i and v_i refer to the $d \times 1$ observed and $(K+1) \times 1$ unobserved household characteristics. Π with dimension $(K+1) \times d$ represents the interaction parameter matrix, which measures how demographic variables affect the taste parameters. The $(K+1)$ dimensional scaling matrix Σ captures the effect of unobserved household characteristics. Since v_i is unobserved, in practice $P_v(v)$ is assumed to be a standard multivariate normal distribution. $P_D(D)$ is the empirical distribution of real households in the data.

By combining equations (1) and (2), the indirect utility is specified as

$$\begin{aligned} U_{ijt} &= \alpha_i y_i + \delta(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) + \varepsilon_{ijt} \\ &\text{where } \delta(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} \\ &\text{and } \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) = [-p_{jt}, x_{jt}](\Pi D_i + \Sigma v_i), \end{aligned} \tag{3}$$

where $[-p_{jt}, x_{jt}]$ represent the $K+1$ dimensional vector of product characteristics—such as price, sugar content, and sodium level—in the beverage's nutritional facts; δ_{jt} is the mean utility associated with the consumption of good j and is common across all consumers in market t; $\mu_{ijt} + \varepsilon_{ijt}$ represent the mean-zero heteroskedastic deviation from the mean utility δ_{jt}; $\boldsymbol{\theta}_1$ is a vector of parameters (α, β) that enters linearly into the utility function; and θ_2 refers to the nonlinear parameters (Π, Σ).

Assuming that households' observed and unobserved characteristics are independent and their purchasing decisions have ties with 0 probability, then the analytical form of the market share is given by

$$s_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP(\varepsilon) dP(v) dP(D), \tag{4}$$

where $A_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \{(D_i, v_i, \varepsilon_{ijt}) | u_{ijt} \geq u_{ilt} \ \forall \ l = 0, 1, \ldots, J\}$. As mentioned previously, the error term ε is assumed to follow a Type I extreme value distribution; integrating it out yields the logit formula of individual household's probability of purchase. With the assumed distributions of v and D and simulated draws, the integral in equation (4) can be solved numerically by

$$s_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \frac{1}{ns} \sum_{i=1}^{ns} s_{ijt} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{exp(\delta_{jt} + \mu_{ijt})}{\sum_{j=0}^{J} exp(\delta_{jt} + \mu_{ijt})}. \tag{5}$$

Finally, the own- and cross-price elasticities of the market share with respect to product j are obtained by

$$\eta_{jjt} = \frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt}(1 - s_{ijt}) dP_D(D) dP_v(v); \tag{6}$$

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \frac{p_{kt}}{s_{jt}} \int \alpha_i s_{ijt} s_{ikt} dP_D(D) dP_v(v). \tag{7}$$

The associated integral is also evaluated using Monte Carlo integration, assuming *ns* individuals.

Identification and Estimation

A key research question in this article is whether household with higher SSB consumption would be more (or less) sensitive to prices and the sugar content of beverages after the implementation of

Berkeley's tax. A second question is whether substitution patterns across beverages with differing sugar content were affected by the policy change. We address the first question by estimating the parameters α, β. and the interaction matrix $\mathbf{\Pi}$. The second question is tested by comparing the elasticity matrix for SSB products before and after the policy change.

In the BLP model, the presence of unobserved product attributes, ξ, what Berry, Levinsohn, and Pakes (1995) term structural error, might introduce a potential source of endogeneity, since ξ could be correlated with other observed product characteristics, such as price. Typical examples of ξ are local advertising and promotions, which can affect the price and they are observed by consumers; however, this information is not available in the data.[6] Thus, proper identification requires us to instrument for the relationship between price and ξ. A standard solution to this issue is to use an exogenous cost-shifter as an instrumental variable (IV), which could determine the price but is uncorrelated with unobserved product attributes. Unfortunately, since cost-related information is not available in the data, this IV is not feasible in our case. We take a different approach.

As suggested in Hausman (1996) and Nevo (2001), we assume that after controlling for brand fixed effects and demographic characteristics, location-specific product valuations are independent across locations. Given that assumption, product prices in other locations qualify as valid instruments, since prices of one product in different locations are only correlated through common marginal costs and not through product-specific shocks in each market (e.g., local advertising and promotions). We follow this procedure to estimate the demand model for beverage consumption. Specifically, we control for SSB brand categorical variables and use as instruments the monthly average prices for each of the same products in 20 other locations outside of California.

We estimate the demand using the standard procedure for the BLP-type model. The estimation algorithm is a nested fixed point (NFP) algorithm (Berry, Levinsohn, and Pakes, 1995), which roughly includes two loops—an inner, contract-mapping loop to infer mean utility, δ, and an outer loop for nonlinear GMM estimation (Hansen, 1982)—to obtain the parameter matrix $\boldsymbol{\theta}_2$. (See Berry, Levinsohn, and Pakes, 1995; Nevo, 2001, for a detailed description.) Since we specify brand dummy variables, the taste parameters for product characteristics (except for price) are retrieved using the minimum-distance method suggested in Chamberlain (1982) and Nevo (2001).

Data Source

To evaluate the impact of the sugar tax policy, we use Nielsen Homescan Consumer Panel and Retail Scanner datasets, which can be accessed through Kilts Center for Marketing at the University of Chicago Booth School of Business. The latest year of data available to us is 2016; we concentrate on evaluating the impact of Berkeley's Measure D, implemented in 2014. The Retail Scanner Data include weekly prices and unit sales by UPC code from participating stores in all U.S. markets. We restrict the estimation to 20 geographical areas indexed by the first three digits in the store's ZIP code, along with Berkeley, California. As pointed out earlier, the price data outside of Berkeley serve as an instrument for the endogenous price in Berkeley.

Beverages are sold in different package sizes and in formulas with or without sugar (i.e., regular or diet). Following the general practice in empirical estimation of the BLP model, we refer to brand–formula–size combinations as products. The predominant package sizes include 1-, 6-, 12- and 24-packs. The volume of drinks in a single package also varies, ranging from 12 to 128 ounces. We measure sales of each product by standardizing to a 144-ounce equivalent unit, which is the size of a 12-pack of 12-ounce beverages. Price is equivalised to reflect revenue per equivalent unit.[7]

[6] As noted in the Retail Scanner manual, Nielsen only observes promotions and advertisement activities and records them in a feature and display variable for a subset of stores (called "audited stores"); those stores change on a weekly basis, which implies that we do not have constant reliable observations for advertising information.

[7] For example, a sale of a 24-pack of 16.9-oz beverages will be counted as 2.8; price is recalculated by dividing it by the sales number of the equivalent unit.

Table 1. Product List

Brand/Size Combination	Description
Product 1	A&W, Diet, 12-pack, 12 oz
Product 2	A&W, regular, 1-pack, 67.6 oz
Product 3	A&W, regular, 12-pack, 12 oz
Product 4	Arizona, regular tea, 1-pack, 128 oz
Product 5	Arizona, regular tea,1-pack 23.5 oz
Product 6	Arizona, diet, 1-pack, 128 oz
Product 7	Canada Dry, regular, 1-pack, 67.6 oz
Product 8	Canada Dry, regular, 12-pack, 12 oz
Product 9	Coca-Cola, diet caffeine-free, 12-pack, 12 oz
Product 10	Coca-Cola, diet cherry, 12-pack, 12 oz
Product 11	Coca-Cola, diet, 1-pack, 20 oz
Product 12	Coca-Cola, diet, 1-pack, 67.6 oz
Product 13	Coca-Cola, diet, 12-pack, 12 oz
Product 14	Coca-Cola Zero, diet, 1-pack, 67.6 oz
Product 15	Coca-Cola Zero, diet, 12-pack, 12 oz
Product 16	Fresca, diet, 12-pack, 12 oz
Product 17	Pepsi, regular, 1-pack, 67.6 oz
Product 18	7 Up, diet, 12-pack, 12 oz
Product 19	7 Up, regular, 1-pack, 67.6 oz
Product 20	Seven Up, regular, 12-pack, 12 oz
Product 21	Sprite, regular, 1-pack, 67.6 oz
Product 22	Sprite, regular, 12-pack, 12 oz

Based on the adjusted sales, we select 22 products (see Table 1) with the highest market shares in Berkeley from 2006 to 2016. These 22 brand–formula–size combinations are built by aggregating 72 UPC-level goods. Accordingly, eight flagship brands of carbonated/noncarbonated soft drinks and iced tea are left in the sample.[8] The brands included in the sample are A&W, Arizona Iced Tea, Canada Dry, Coca-Cola, Fresca, Pepsi, 7 Up, and Sprite.

Sales data are averaged to year–month–product level. In total, there are 2,244 observations from January 2006 to June 2014 before "Measure D" was passed and 484 observations from March 2015 to December 2016 in the post-policy period. The only treated location in our case is Berkeley, California. We use the first three digits of the ZIP code to identify stores located in Berkeley, CA (947). Berkeley has a relatively unique leading 3-digit ZIP code. Albany is the only area of California with which Berkeley shares part of its ZIP code. Considering that Albany has only about one-tenth of Berkeley's population (and, as of 2016, had not implemented a sugar tax), using the same ZIP code will, at worst, underestimate the policy effect. Our estimates provide a lower bound for the preference change driven by the policy intervention.

To implement the numerical integration in equation (5), we randomly select household-level draws and use Nielsen's Homescan data to simulate the household demographics. Households in Alameda County are the potential source of consumers in Berkeley stores.[9] The BLP literature suggests procedures for simulating demographic information and discusses whether the same random draws should be taken across markets. For example, Miller and Weinberg (2017) take different simulation draws for each market. Here, we follow Berry, Levinsohn, and Pakes (1995) and use the same draws for all markets. Furthermore, Nevo (2001) suggests that without any prior

[8] Powdered drinks, instant tea bags, tea mixes, and cocktail mixes are excluded. Branded water is also excluded.

[9] This is done because we found a nontrivial amount (about 15%) of purchases in stores in the Berkeley area (stores with ZIP codes starting with "947") that were made by residents living in other places within the Alameda County. While Nielsen Homescan data have households' full ZIP codes, only a portion of the stores in which they shop report the ZIP code information in the Homescan data. To precisely model the consumer behavior, it is plausible to also simulate people living outside of Berkeley but within Alameda County as the potential population affected by the sugar tax policy.

information about the parametric distribution of demographics, it is better to sample real individuals to avoid making arbitrary distributional assumptions. Reynaert and Verboven (2014) suggest that estimates based on Monte Carlo integration are less biased when the number of draws exceeds 200. Following these guidelines, we sample 500 households over the whole sample based on the empirical distribution of demographics and use the same draw for each market.

Homescan's annual household income is reported as a categorical variable of income ranges.[10] We construct the log income variable by taking the median value of the income range of each category and dividing it by household size before taking the logarithm transformation. The constructed income and price variables are deflated and reported in 2010 dollars. To address the first research question, one key demographic information is each household's SSB consumption. We construct this variable as the proportion of time within a year-month market that a household median weekly consumption of sugary drinks is higher than the weekly median consumption of households across the entire sample. Compared to using binary indicator variables of whether a household belongs to a high- or low-SSB-consuming type, our definition of SSB consumption naturally has more variation and hence provides a better fit for our identification strategy.

Results

Measure D came into effect in March 2015, 4 months appearing on the ballot in November 2014. Accordingly, we divide our sample into three periods: (i) January 2006–June 2014, (ii) July 2014–February 2015, and (iii) March 2015–December 2016. These three periods correspond to the time before the policy change; the policy discussion, voting, and adoption stage; and the time after the policy went into effect. We define the first, pre-policy period from 2006 to 4 months before the sugar tax appeared on the ballot. During this period, we assume that potential consumers of stores located in Berkeley did not anticipate a policy shock. The third period is considered the post-policy period, in which consumer preferences were potentially affected by Measure D. The second period is from 4 months preceding the vote to four months after the vote, when the sugar tax was ultimately adopted. This is the stage when both pro- and anti-tax campaigns were evident in Berkeley, creating heated debates about Measure D.[11] Adding this sample period to the estimation could arguably contaminate the results of the policy impact on preference changes. Potential changes in consumer demand may have occurred in anticipation to the policy implementation due to the announcement of Measure D voting by the general population. However, it is not possible to isolate this possible anticipation effect on preference changes from the impact of the actual policy change. In order to obtain a clean identification, we exclude the second period from our analysis.

Estimating the BLP RC Logit Demand

Table 2 presents the results of the full demand model illustrated in the modeling section. Columns 1 and 2 report estimates for the pre-policy period. The corresponding results for the post-policy period are given in columns 3 and 4. As described in the identification section, we employ the minimum-distance procedure to retrieve the taste parameters of product characteristics, including sugar and sodium content. The parameter for price is estimated using the GMM process.

Due to sample size limitations, we consider only two demographic factors of interest: SSB consumption patterns and income. SSB consumption is constructed as the proportion of times within a year-month-defined market in which a household has weekly median consumption of SSBs higher than the median consumption of all households in the sample. Overall, we present different specifications, allowing for heterogeneity in the valuation of product characteristics to vary by SSB

[10] Notice that the household income is reported in 20 levels, ranging from <$5,000 to >$200,000. For different years of data, the income variable is top-coded at $100,000 or $200,000. We take the common range from <$5,000 to >$100,000, which is separated into 15 categories.

[11] The "Berkeley vs. Big Soda" documentary summarizes the situation at the time; see footnote 4.

Table 2. Parameter Estimates of the Random Coefficient Demand Model

	Pre-Policy		Post-Policy	
	1	**2**	**3**	**4**
Constant	1.647	1.237	−2.939	−4.915
	(0.303)	(0.409)	(0.227)	(1.096)
Price	−0.112	−0.112	−0.307	−0.304
	(0.049)	(0.093)	(0.135)	(0.233)
Sugar	−4.650	−12.364	2.298	31.236
	(0.235)	(1.463)	(1.106)	(2.805)
Sodium	−10.350	−7.277	−0.399	−1.630
	(0.486)	(0.594)	(0.197)	(1.835)
Demographic interactions				
SSB-consumption × constant	−3.772	−3.713	5.220	−3.585
	(20.691)	(22.809)	(10.290)	(9.947)
SSB-consumption × price	0.046	0.044	−0.731	0.101
	(0.831)	(1.551)	(0.446)	(0.792)
SSB-consumption × sugar	0.988	0.785	−25.415	−22.389
	(31.660)	(52.284)	(18.040)	(26.291)
SSB-consumption × sodium	6.361	6.333	9.676	11.096
	(47.454)	(59.319)	(18.929)	(15.784)
Income × constant		−0.083		−7.414
		(43.665)		(7.467)
Income × price		0.008		−0.054
		(3.222)		(0.442)
Income × sugar		0.690		4.295
		(58.211)		(8.806)
Income × sodium		−0.144		13.177
		(96.665)		(7.620)

Notes: Brand dummies are included in all specifications. Except for price, average taste parameters are all retrieved using a minimum-distance procedure (Nevo, 2001). Asymptotically robust standard errors are given in parentheses.

consumption or by both SSB consumption and income. All specifications control for brand dummies and use monthly prices in 20 other locations as instrumental variables.

The first four rows of Table 2 display the means of the distribution of marginal utilities with respect to each product characteristic. The following eight rows present the effect of demographics on the slope coefficients. As seen in columns 1–4, the point estimates for the average marginal utility with respect to sugar content are all statistically significant.

In particular, the estimates in columns 1 and 2 of Table 2 show that the valuation of sugar content was negative for the average consumer before Berkeley's "Measure D," indicating a decrease in utility as the sugar content of the beverage increases. The magnitude of the slope coefficient is even larger when allowing for heterogeneous effects from both income and SSB consumption patterns in column 2. The interaction of sugar content with demographics suggests that households a larger volume of SSB consumption tend to be less sensitive to the amount of sugar in SSBs. This result is the same for higher income households. However, the effects of demographics on the slope coefficients are not statistically significant. After the adoption of the sugar tax policy, consumer valuation of sugar content in beverage drinks significantly changed. Columns 3 and 4

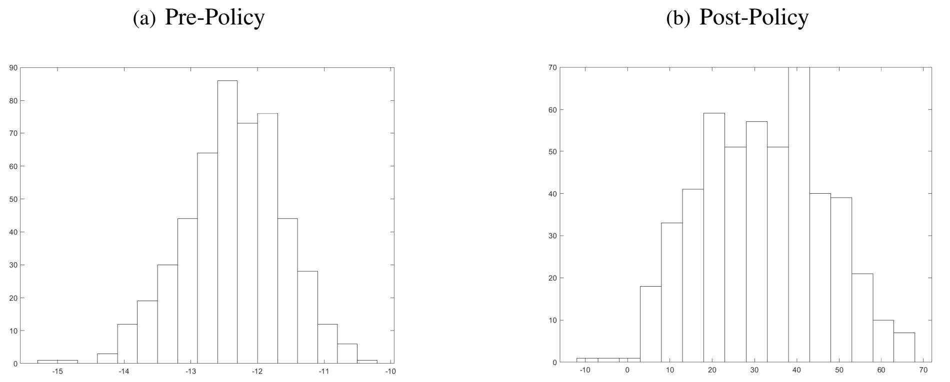

Figure 1. Frequency Distribution of the Taste Parameter for Sugar Content

present the results of estimations analogous to those presented in columns 1 and 2, except that the sample is restricted to the post-policy period. As the table shows, sugar increases the mean utility of the average consumer; this relationship is sustained across all model specifications controlling for demographic variables.

Within a structural modeling framework, this result provides insights on the behavioral mechanism through which a price increase may result in a temporary increase in soda consumption following the policy implementation. Notably, sugar content is the only characteristic of the product that changes sign from the pre- to the post-policy period. This result provides suggestive evidence that the consumer demand response is mainly driven by changes in the mean utility of sugar content. Although sugar content increases the mean utility for the average consumer, households with high SSB consumption do not show the same utility preference. Similar to the pre-policy period, they are less sensitive to sugar content. The marginal valuation of sugar decreases with household SSB consumption in the post-policy period. We present the full range of the taste parameter distribution for sugar content before and after the policy change in the two panels of Figure 1. Clearly, before the policy change, consumers valued the amount of sugar in beverages in a negative way. After the sugar tax policy, however, consumer preferences for sugar content temporarily shifted to the right.

While the mean utilities for price are all negative during the two examined periods, the magnitude of the price coefficient slightly increases in absolute value following the policy change. This increase indicates that price has a slightly higher penalty term in the utility function post-policy. The average consumer became more sensitive to the price of sugary drinks due to the intervention. However, this result does not seem to offset the policy-induced increase in sugar valuation. Figure 2 presents the overall change in the distribution of the price coefficient over the sugar tax policy and confirms the results of the changes in the estimates of the mean utility. While the distribution of the taste parameter for sugar moves its entire range almost completely from negative to positive, the price parameter remains negative, with a slight shift to the left after the sugar tax is implemented. An examination of heterogeneity effects shows that households with high income or high SSB consumption patterns tend to be less sensitive to price.

Overall, sodium content is a less attractive characteristic for beverage products. Higher sodium content in a beverage reduces consumer utility. Based on market shares, we choose eight brands of beverages and standardize package size to 12-pack (see Table 1). Since energy and sports drinks are not included in the sample, the interpretation of this result on preferences for sodium content should be limited to the specific products analyzed in this article. These results do not necessarily apply to energy and sports drinks, for which sodium may be more relevant.

The results presented above show that in order to effectively discourage sugary drink consumption, it is necessary to drive consumers to derive enough disutility from consuming sugary drinks in order to offset the increase in sugar content valuation. Recall that as presented in Table A1,

(a) Pre-Policy (b) Post-Policy

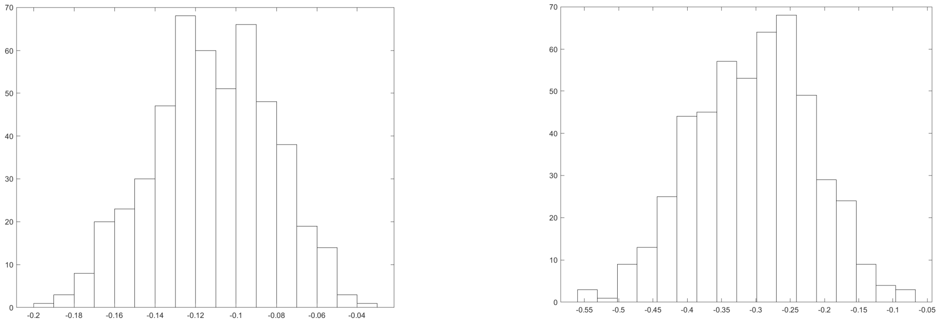

Figure 2. Frequency Distribution of the Price Coefficient

the tax pass-through rate is only around 9%–12% for the products in our sample. Hence, it seems that Measure D's temporary inefficiency in discouraging soda consumption could be attributed to the low tax pass-through rate in the short term.

Estimating Substitution Patterns

By nature, consumers do not have the same taste preferences for diet drinks as for nondiet drinks. Some people might inherently have stronger preferences for the taste of nondiet soda over diet soda or vice versa. There is an implied assumption that people with a "sweet tooth" tend to consume more sweet foods or drinks. Frank-White and Frank (2010) find that people with the strongest taste preference for SSBs have the highest SSB consumption. Block et al. (2013) document that young adults choose SSB for flavor reasons, given similar prices for water and SSB. However, unless this difference in taste preference is absolutely inelastic, people would still substitute between drinks of different flavors. Admittedly, there are extreme cases in which people consume only nondiet drinks and would not substitute with diet drinks regardless of the sugar tax. Individuals who only consume diet soda or always consume regular soda are considered as never-takers and always-takers in our identification of the policy intervention. These preferences are not likely to be shifted by the sugar tax policy. Our results identify the local average change on the mean utility of sugar content and substitution patterns for consumers whose preferences were moved by the sugar tax policy.

Tables A2 and A3 show the full elasticity matrix for the pre- and post-policy periods, respectively. Each cell represents the elasticity of product j with respect to a change in the price of product k. The flexible substitution patterns in the BLP type of demand allows the cross-price elasticity to change over differentiated products. We present the median of each cell over the 102 year-month defined markets in the pre-policy period and 22 year-month defined markets in the post-policy period. We label the formula of a product with (D) or (R) to indicate whether it is a diet or nondiet (regular) formula. The median own-price elasticities across the 22 products changed from inelastic to temporarily elastic as a result of the policy, with the variation changing as much as 200%. In other words, the estimates indicate that Berkeley's Measure D drove consumers to become much more sensitive to price changes of sugary drinks in the short term.

This result should be interpreted with caution. As suggested by Cawley and Frisvold (2015), consumers may avoid higher prices by making soda purchases outside of the city of Berkeley. If this is the case, our model might overestimate the changes in own-price elasticities. Colchero et al. (2015) examined the own-price elasticity of general soft drinks and SSBs in Mexico and found the range of price elasticities from -0.9 to -1.5 across demographic groups. In our case, except for one product, the own-price elasticity of demand is roughly within this range in the post-policy period.

Andreyeva, Long, and Brownell (2010) document a price-elasticity range for soft drinks of 0.13–3.18 in absolute value in the United States; the estimates we obtained before and after the tax policy implementation are also within this range.

Our second research question is whether consumers substitute beverages with high sugar content with diet beverages. We address this question by comparing the cross-price elasticity of regular-formula products with diet-formula products for the pre- and post-policy period. The elasticity is allowed to vary by product in the BLP RC logit demand model and the substitution patterns are driven by consumers' variation in price sensitivity or the marginal utility of income (Nevo, 2000). Since Berkeley's Measure D tax policy does not apply to diet drinks, we examine whether the change in the price of regular-formula products produces an increase in the consumption of diet products. Of the 22 products of interest, half of them are regular formula, with an average sugar content of 13g–45g per serving, and half of them are diet formula, with 0g of sugar oer serving.[12]

Tables 3 randomly selects six products to present the changes in the substitution patterns due to the policy change (see Appendix Tables A2 and A3 for the full elasticity matrices). Prior to the implementation of Measure D, the potential substitutes for regular drinks can be diet beverages or other nondiet drinks, with similar percentage changes in quantity. This is reflected in the off-diagonal elements of the substitution matrix in Panel A of Table 3. The magnitudes of the cross-price elasticities are similar. However, after the policy was adopted, the substitutes became more concentrated toward nondiet drinks and the quantity changes significantly increased, as shown in Panel B. In the pre-policy period, a given price change in product 19, for instance, would lead consumers to substitute almost evenly toward the other 21 products in our sample, which include both diet and nondiet drinks. Following the policy change, an equal change in the price of product 19 results in a stronger substitution toward nondiet (regular) beverages (e.g., products 7, 17, and 20).

Similar substitution patterns are found for other products. Given a price increase in product 5, consumers would substitute more toward products 4 and 6 before the policy change, while in the post-policy period, consumers would heavily substitute toward product 4 (i.e., the nondiet, regular formula). Since this change is not specific to any particular regular-formula product but common to almost every product in our sample, we argue that this finding is not likely driven by product-level special offers. The variations in general substitution patterns are also consistent with the results shown in Table 2, which suggests an increase in consumers' valuation for sugar after the policy implementation.

Conclusions and Discussion

While the main purpose of a sugar tax is to reduce consumption of sugary drinks in an attempt to mitigate obesity, recent short-term evidence indicates that this might not necessarily be the case. Previous research documents an unintended increase in SSB consumption as the price of sugary drinks rises. This empirical finding is contrary to the predictions of neoclassical economic theory. Further investigation about the underlying mechanism within a structural demand model framework is required to shed light on this apparently inconsistent behavioral response.

Using Nielsen data from 2006 to 2016, this article provides insights on these research questions using a BLP RC logit model. A sample of the top 22 consumed products (brand-size combinations) suggests that the adoption of Berkeley's sugar tax policy significantly changed consumers' valuation of sugar content in the short term. Prior to the policy intervention, the valuation of sugar content was on average negative, but the adoption of the sugar tax policy drove consumers' average valuation to increase with sugar content. This finding provides suggestive evidence about the potential mechanism that explains the previously documented soda consumption increase in response to a price increase following the sugar tax policy in Berkeley.

[12] In particular, products 2–5, 7, 8, 17, and 19–22 are regular (i.e., not diet) formula.

Table 3. Median Own- and Cross-Price Elasticities for Selected Products: Pre- versus Post-Policy Period

	Product5 (R)	**Product6 (D)**	**Product7 (R)**	**Product17 (R)**	**Product18 (D)**	**Product19 (R)**
Panel A: Pre-policy						
Product5(R):	−0.661	0.008	0.003	0.007	0.005	0.004
Product6(D):	0.011	−0.414	0.003	0.007	0.005	0.004
Product7(R):	0.005	0.003	−0.342	0.005	0.004	0.004
Product17(R):	0.009	0.006	0.004	−0.379	0.004	0.004
Product18(D):	0.007	0.005	0.004	0.005	−0.482	0.004
Product19(R):	0.006	0.004	0.004	0.005	0.004	−0.351
Panel B: Post-policy						
Product5(R):	−1.193	0.080	0.017	0.038	0.001	0.017
Product6(D):	0.049	−0.450	0.001	0.001	0.002	0.001
Product7(R):	0.011	0.001	−1.037	0.059	0.001	0.083
Product17(R):	0.052	0.003	0.122	−1.056	0.000	0.098
Product18(D):	0.001	0.004	0.002	0.000	−1.061	0.001
Product19(R):	0.022	0.001	0.163	0.098	0.001	−1.086

Notes: This table provides the median elasticities of demand for 12-packs of 12-ounce equivalent product based on the specifications of columns 2 and 4 in Table 2. The cell in row j and column k represents the percentage change in the quantity of product j with respect to the price change in product k. Median level is calculated over year–month–brand–size combinations. (D) and (R) represent whether the product's formula is sugar-free (i.e., diet) or regular (i.e., not diet).

Contrary to previous literature, results on the interaction of product characteristics with household income and SSB consumption patterns suggest that such a "reactance" response does not necessarily come from households with high SSB consumption but may be driven by households with higher-than-average income. However, due to sample size limitations, the analysis of heterogeneous effects is not statistically significant.

Our result on substitution patterns confirms the parameter estimation of product characteristics. Due to an increase in the valuation of sugar content after the sugar tax policy, the substitution patterns shifted significantly toward nondiet (regular) drinks. In other words, for a given increase in the price of soft drinks with sugar content, we do not find evidence that consumers are more likely to substitute toward untaxed diet soft drinks in the short term after the policy intervention.

These findings have significant policy implications for expanding sugar tax policies to other U.S. states and other countries. As the unintended short-term increase in sugary drinks consumption appears to be driven by increases in the valuation of sugar content, altering product characteristics that could generate disutility would potentially contribute to offset this response. One candidate for such product characteristics is price. As the tax level increases, the saliency of price will rise accordingly. Once the negative utility generated from the price increase becomes dominant, the sugar tax would eventually discourage consumption. In this sense, the inefficiency of the current sugar tax policy may be attributed to the low tax pass-through rate of Berkeley's Measure D (see Appendix Table A1).

Another nonpecuniary approach to generating sugar disutility and discouraging sugary drink consumption could be using label warnings showcasing the potential negative health effects of chronic diseases such as diabetes. This approach is likely to create friction; based on experience from other products (e.g., cigarettes), it might not be well received by beverage manufacturers.

Before expanding sugar taxes to other states, additional focus on increasing the pass-through rate or directly increasing the consumer tax level might also be reasonable solutions to the unintended impacts on consumption found in this article and previously documented by Debnam (2017). Due to data availability, the results obtained in this paper represent only short-term consumption patterns. Long-term evaluation of the consumer response to the sugar tax policy merits further investigation.

[First submitted January 2020; accepted for publication April 2020.]

References

Andreyeva, T., M. W. Long, and K. D. Brownell. "The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food." *American Journal of Public Health* 100(2010):216–222. doi: 10.2105/AJPH.2008.151415.

Berry, S., J. Levinsohn, and A. Pakes. "Automobile Prices in Market Equilibrium." *Econometrica* (1995):841–890. doi: 10.2307/2171802.

Block, J. P., M. W. Gillman, S. K. Linakis, and R. E. Goldman. "'If It Tastes Good, I'm Drinking It': Qualitative Study of Beverage Consumption among College Students." *Journal of Adolescent Health* 52(2013):702–706. doi: 10.1016/j.jadohealth.2012.11.017.

Bonnet, C., and V. Requillart. "Does the EU Sugar Policy Reform Increase Added Sugar Consumption? An Empirical Evidence on the Soft Drink Market." *Health Economics* 20(2011):1012–1024. doi: 10.1002/hec.1721.

Cawley, J., and D. Frisvold. "The Incidence of Taxes on Sugar-Sweetened Beverages: The Case of Berkeley, California." Working paper w21465, National Bureau of Economic Research, 2015. doi: 10.3386/w21465.

Chamberlain, G. "Multivariate Regression Models for Panel Data." *Journal of Econometrics* 18(1982):5–46. doi: 10.1016/0304-4076(82)90094-X.

Christensen, L. R., D. W. Jorgenson, and L. J. Lau. "Transcendental Logarithmic Utility Functions." *American Economic Review* 65(1975):367–383.

City of Berkeley. "City of Berkeley Sugary Beverages and Soda Tax Question, Measure D (November 2014)." 2014. Available online at https://ballotpedia.org/City_of_Berkeley_Sugary_Beverages_and_Soda_Tax_Question,_Measure_D_%28November_2014%29.

Colchero, M., J. Salgado, M. Unar-Munguia, M. Hernandez-Avila, and J. Rivera-Dommarco. "Price Elasticity of the Demand for Sugar Sweetened Beverages and Soft Drinks in Mexico." *Economics & Human Biology* 19(2015):129–137. doi: 10.1016/j.ehb.2015.08.007.

Colchero, M. A., B. M. Popkin, J. A. Rivera, and S. W. Ng. "Beverage Purchases from Stores in Mexico under the Excise Tax on Sugar Sweetened Beverages: Observational Study." *BMJ* 352(2016):h6704. doi: 10.1136/bmj.h6704.

Deaton, A., and J. Muellbauer. "An Almost Ideal Demand System." *American Economic Review* 70(1980):312–326.

Debnam, J. "Selection Effects and Heterogeneous Demand Responses to the Berkeley Soda Tax Vote." *American Journal of Agricultural Economics* 99(2017):1172–1187. doi: 10.1093/ajae/aax056.

Dharmasena, S., and O. Capps Jr. "Intended and Unintended Consequences of a Proposed National Tax on Sugar-Sweetened Beverages to Combat the U.S. Obesity Problem." *Health Economics* 21(2012):669–694. doi: 10.1002/hec.1738.

Dharmasena, S., G. C. Davis, and O. Capps Jr. "Partial versus General Equilibrium Calorie and Revenue Effects Associated with a Sugar-Sweetened Beverage Tax." *Journal of Agricultural and Resource Economics* 39(2014):157–173. doi: 10.22004/ag.econ.186559.

Etilé, F., and A. Sharma. "Do High Consumers of Sugar-Sweetened Beverages Respond Differently to Price Changes? A Finite Mixture IV-Tobit Approach." *Health Economics* 24(2015):1147–1163. doi: 10.1002/hec.3157.

Falbe, J., N. Rojas, A. H. Grummon, and K. A. Madsen. "Higher Retail Prices of Sugar-Sweetened Beverages 3 Months after Implementation of an Excise Tax in Berkeley, California." *American Journal of Public Health* 105(2015):2194–2201. doi: 10.2105/AJPH.2015.302881.

Finkelstein, E. A., C. Zhen, M. Bilger, J. Nonnemaker, A. M. Farooqui, and J. E. Todd. "Implications of a Sugar-Sweetened Beverage (SSB) Tax When Substitutions to Non-Beverage Items Are Considered." *Journal of Health Economics* 32(2013):219–239. doi: 10.1016/j.jhealeco.2012.10.005.

Fletcher, J. M., D. Frisvold, and N. Tefft. "Can Soft Drink Taxes Reduce Population Weight?" *Contemporary Economic Policy* 28(2010a):23–35. doi: 10.1111/j.1465-7287.2009.00182.x.

Fletcher, J. M., D. E. Frisvold, and N. Tefft. "The Effects of Soft Drink Taxes on Child and Adolescent Consumption and Weight Outcomes." *Journal of Public Economics* 94(2010b):967–974. doi: 10.1016/j.jpubeco.2010.09.005.

———. "Non-Linear Effects of Soda Taxes on Consumption and Weight Outcomes." *Health Economics* 24(2015):566–582. doi: 10.1002/hec.3045.

Frank-White, N. E., and E. Frank. "Diet vs. Sugar-Sweetened Soda Preferences and Attitudes in a Sample of Adolescents." *The Open Pediatric Medicine Journal* 4(2010). doi: 10.2174/1874309901004010023.

Grogger, J. "Soda Taxes and the Prices of Sodas and Other Drinks: Evidence from Mexico." *American Journal of Agricultural Economics* 99(2017):481–498. doi: 10.1093/ajae/aax024.

Hansen, L. P. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* (1982):1029–1054. doi: 10.2307/1912775.

Hausman, J. A. "Valuation of New Goods under Perfect and Imperfect Competition." In T. F. Bresnahan and R. J. Gordon, eds., *The Economics of New Goods,* Chicago, IL: University of Chicago Press, 1996, 207–248.

Jacobson, M. F., and K. D. Brownell. "Small Taxes on Soft Drinks and Snack Foods to Promote Health." *American Journal of Public Health* 90(2000):854. doi: 10.2105/ajph.90.6.854.

Lal, A., A. M. Mantilla-Herrera, L. Veerman, K. Backholer, G. Sacks, M. Moodie, M. Siahpush, R. Carter, and A. Peeters. "Modelled Health Benefits of a Sugar-Sweetened Beverage Tax across Different Socioeconomic Groups in Australia: A Cost-Effectiveness and Equity Analysis." *PLoS Medicine* 14(2017):e1002,326. doi: 10.1371/journal.pmed.1002326.

Lin, B.-H., T. A. Smith, J.-Y. Lee, and K. D. Hall. "Measuring Weight Outcomes for Obesity Intervention Strategies: The Case of a Sugar-Sweetened Beverage Tax." *Economics & Human Biology* 9(2011):329–341. doi: 10.1016/j.ehb.2011.08.007.

Luger, M., M. Lafontan, M. Bes-Rastrollo, E. Winzer, V. Yumuk, and N. Farpour-Lambert. "Sugar-Sweetened Beverages and Weight Gain in Children and Adults: A Systematic Review from 2013 to 2015 and a Comparison with Previous Studies." *Obesity Facts* 10(2017):674–693. doi: 10.1159/000484566.

Malik, V. S., B. M. Popkin, G. A. Bray, J.-P. Després, W. C. Willett, and F. B. Hu. "Sugar-Sweetened Beverages and Risk of Metabolic Syndrome and Type 2 Diabetes: A Meta-Analysis." *Diabetes Care* 33(2010):2477–2483. doi: 10.2337/dc10-1079.

Malik, V. S., M. B. Schulze, and F. B. Hu. "Intake of Sugar-Sweetened Beverages and Weight Gain: A Systematic Review." *American Journal of Clinical Nutrition* 84(2006):274–288. doi: 10.1093/ajcn/84.1.274.

Miller, N. H., and M. C. Weinberg. "Understanding the Price Effects of the MillerCoors Joint Venture." *Econometrica* 85(2017):1763–1791. doi: 10.3982/ECTA13333.

National Center for Health Statistics. *Health, United States, 2016: With Chartbook on Long-Term Trends in Health*. Washington, DC: U.S. Government Printing Office, 2017.

Nevo, A. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." *Journal of Economics & Management Strategy* 9(2000):513–548. doi: 10.1111/j.1430-9134.2000.00513.x.

———. “Measuring Market Power in the Ready-to-Eat Cereal Industry.” *Econometrica* 69(2001):307–342. doi: 10.1111/1468-0262.00194.

Pereira, M. “The Possible Role of Sugar-Sweetened Beverages in Obesity Etiology: A Review of the Evidence.” *International Journal of Obesity* 30(2006):S28–S36. doi: 10.1038/sj.ijo.0803489.

Reich, R. “Berkeley vs. Big Soda.” *Huffington Post* (2014). Available online at https://www.huffingtonpost.com/robert-reich/berkeley-vs-big-soda_b_5786028.html.

Reynaert, M., and F. Verboven. “Improving the Performance of Random Coefficients Demand Models: The Role of Optimal Instruments.” *Journal of Econometrics* 179(2014):83–98. doi: 10.1016/j.jeconom.2013.12.001.

Theil, H. “The Information Approach to Demand Analysis.” *Econometrica* (1965):67–87. doi: 10.2307/1911889.

Vartanian, L. R., M. B. Schwartz, and K. D. Brownell. “Effects of Soft Drink Consumption on Nutrition and Health: A Systematic Review and Meta-Analysis.” *American Journal of Public Health* 97(2007):667–675. doi: 10.2105/AJPH.2005.083782.

World Health Organization. “The Top 10 Causes of Death.” 2014. Available online at https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death.

Zhen, C., I. F. Brissette, and R. R. Ruff. “By Ounce or by Calorie: The Differential Effects of Alternative Sugar-Sweetened Beverage Tax Strategies.” *American Journal of Agricultural Economics* 96(2014):1070–1083. doi: 10.1093/ajae/aau052.

Zhen, C., E. A. Finkelstein, J. M. Nonnemaker, S. A. Karns, and J. E. Todd. “Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System.” *American Journal of Agricultural Economics* 96(2013):1–25. doi: 10.1093/ajae/aat049.

Appendix A

Table A1. Effect of Sugar Tax on Price over Different Comparison Areas: Difference-in-Difference Estimates (N= 2,904)

	Price 1	Price 2	Price 3
Post(=1) × Berkeley(=1)	0.133***	0.119***	0.156***
	(0.029)	(0.030)	(0.029)
Berkeley(=1)	0.292***	0.206***	0.176***
	(0.012)	(0.012)	(0.012)
A&W, regular, 12-pack, 12 oz	1.101***	0.948***	1.065***
	(0.025)	(0.026)	(0.026)
Arizona, regular tea, 1-pack, 128 oz	0.286***	0.107***	0.245***
	(0.025)	(0.026)	(0.026)
Arizona, regular tea, 1-pack, 23.5 oz	2.442***	2.330***	2.284***
	(0.025)	(0.026)	(0.026)
Canada Dry, regular, 1-pack, 67.6 oz	0.068***	0.027	0.090***
	(0.025)	(0.026)	(0.026)
Canada Dry, regular, 12-pack, 12 oz	1.346***	1.099***	1.309***
	(0.025)	(0.026)	(0.026)
Pepsi, regular, 1-pack, 67.6 oz	0.201***	0.155***	0.167***
	(0.025)	(0.026)	(0.026)
7 Up, regular, 1-pack, 67.6 oz	0.073***	0.039	0.050*
	(0.025)	(0.026)	(0.026)
7 Up, regular, 12-pack, 12 oz	1.152***	0.999***	1.122***
	(0.025)	(0.026)	(0.026)
Sprite, regular, 1-pack, 67.6 oz	0.376***	0.223***	0.279***
	(0.025)	(0.026)	(0.026)
Sprite, regular, 12-pack, 12 oz	1.171***	1.029***	1.229***
	(0.025)	(0.026)	(0.026)
Constant	2.817***	3.020***	2.964***
	(0.019)	(0.019)	(0.019)
Comparison area	Arizona	North Dakota	Nevada
(three leading digits of zipcode)	(852)	(581)	(895)
Adj. R^2	0.875	0.849	0.859

Notes: Single, double, and triple asterisks ($*, **, ***$) indicate significance at the 10%, 5%, and 1% level, respectively. All prices are deflated and standardized to the price for a size of 12-packs of 12-ounce equivalent beverage. Estimation is performed with sample restricted to products in regular formula, product fixed effect is estimated relative to the reference product A&W, diet, 12-pack, 12 oz. All specifications control for year-month fixed effect. The first row refers to the difference-in-difference estimates of the sugar tax policy on the price of sugary drinks in Berkeley, California.

Table A2. Median Own- and Cross-Price Elasticities: Pre-Policy Period, January 2006–June 2014

	Prod1 (D)	Prod2 (R)	Prod3 (R)	Prod4 (R)	Prod5 (R)	Prod6 (D)	Prod7 (R)	Prod8 (R)	Prod9 (D)	Prod10 (D)	Prod11 (D)	Prod12 (D)	Prod13 (D)	Prod14 (D)	Prod15 (D)	Prod16 (D)	Prod17 (R)	Prod18 (D)	Prod19 (R)	Prod20 (R)	Prod21 (R)	(R) (R)
Prod1(D):	-0.384	0.003	0.004	0.003	0.002	0.001	0.004	0.005	0.006	0.003	0.012	0.006	0.025	0.002	0.007	0.003	0.003	0.004	0.003	0.004	0.006	0.010
Prod2(R):	0.005	-0.306	0.004	0.004	0.002	0.002	0.004	0.006	0.006	0.003	0.012	0.006	0.026	0.002	0.007	0.003	0.003	0.004	0.004	0.005	0.006	0.009
Prod3(R):	0.005	0.003	-0.397	0.004	0.002	0.002	0.004	0.006	0.006	0.003	0.012	0.006	0.026	0.002	0.007	0.003	0.003	0.004	0.004	0.005	0.006	0.009
Prod4(R):	0.001	0.001	0.001	-0.400	0.012	0.008	0.003	0.006	0.011	0.005	0.016	0.008	0.043	0.004	0.012	0.007	0.007	0.005	0.004	0.005	0.002	0.004
Prod5(R):	0.001	0.001	0.001	0.021	-0.661	0.008	0.003	0.006	0.011	0.005	0.016	0.008	0.043	0.004	0.012	0.007	0.007	0.005	0.004	0.005	0.002	0.004
Prod6(D):	0.001	0.001	0.001	0.020	0.011	-0.414	0.003	0.006	0.012	0.005	0.016	0.008	0.044	0.004	0.012	0.007	0.007	0.005	0.004	0.004	0.002	0.004
Prod7(R):	0.003	0.002	0.003	0.009	0.005	0.003	-0.342	0.006	0.008	0.004	0.013	0.007	0.031	0.003	0.008	0.004	0.005	0.004	0.004	0.005	0.005	0.008
Prod8(R):	0.003	0.002	0.003	0.011	0.006	0.004	0.004	-0.487	0.009	0.004	0.014	0.007	0.033	0.003	0.009	0.004	0.005	0.004	0.004	0.004	0.004	0.007
Prod9(D):	0.002	0.002	0.002	0.014	0.008	0.005	0.004	0.006	-0.485	0.005	0.015	0.008	0.038	0.003	0.010	0.005	0.005	0.004	0.004	0.004	0.003	0.006
Prod10(D):	0.002	0.002	0.002	0.014	0.008	0.005	0.004	0.006	0.010	-0.489	0.015	0.008	0.038	0.003	0.010	0.005	0.005	0.004	0.004	0.004	0.003	0.006
Prod11(D):	0.003	0.002	0.003	0.011	0.007	0.005	0.004	0.006	0.009	0.004	-1.204	0.007	0.035	0.003	0.009	0.005	0.005	0.004	0.004	0.004	0.004	0.006
Prod12(D):	0.003	0.002	0.003	0.012	0.007	0.005	0.004	0.006	0.009	0.004	0.015	-0.382	0.036	0.003	0.010	0.005	0.005	0.004	0.004	0.004	0.004	0.006
Prod13(D):	0.002	0.002	0.002	0.013	0.008	0.005	0.004	0.006	0.010	0.005	0.015	0.008	-0.460	0.003	0.010	0.005	0.005	0.004	0.004	0.004	0.003	0.006
Prod14(D):	0.002	0.002	0.002	0.014	0.008	0.006	0.004	0.006	0.010	0.005	0.015	0.008	0.038	-0.401	0.010	0.005	0.005	0.004	0.004	0.004	0.003	0.006
Prod15(D):	0.002	0.002	0.002	0.014	0.008	0.005	0.004	0.006	0.010	0.005	0.015	0.008	0.038	0.003	-0.498	0.005	0.005	0.004	0.004	0.004	0.003	0.006
Prod16(D):	0.002	0.001	0.002	0.015	0.009	0.006	0.004	0.006	0.010	0.005	0.015	0.008	0.039	0.004	0.011	-0.492	0.006	0.005	0.004	0.004	0.003	0.005
Prod17(R):	0.002	0.002	0.002	0.016	0.009	0.006	0.004	0.006	0.010	0.005	0.015	0.007	0.037	0.003	0.010	0.005	-0.379	0.004	0.004	0.005	0.003	0.006
Prod18(D):	0.003	0.002	0.003	0.012	0.007	0.005	0.004	0.006	0.009	0.004	0.014	0.007	0.036	0.003	0.010	0.005	0.005	-0.482	0.004	0.004	0.004	0.006
Prod19(R):	0.003	0.002	0.003	0.011	0.006	0.004	0.004	0.006	0.009	0.004	0.014	0.007	0.033	0.003	0.009	0.004	0.005	0.004	-0.351	0.005	0.004	0.007
Prod20(R):	0.003	0.002	0.003	0.011	0.006	0.004	0.004	0.006	0.008	0.004	0.014	0.007	0.033	0.003	0.009	0.004	0.005	0.004	0.004	-0.458	0.004	0.007
Prod21(R):	0.004	0.003	0.004	0.005	0.003	0.002	0.004	0.006	0.007	0.003	0.013	0.006	0.028	0.002	0.007	0.003	0.004	0.004	0.004	0.005	-0.337	0.009
Prod22(R):	0.004	0.003	0.004	0.006	0.003	0.002	0.004	0.006	0.007	0.003	0.013	0.006	0.028	0.002	0.007	0.003	0.004	0.004	0.004	0.005	0.005	-0.419

Notes: This table provides the median elasticities of demand for 12-packs of 12-ounce equivalent product based on the specification of column (2) in Table 2. The cell in row j and column k represents the percentage change in the quantity of product j with respect to the price change in product k. Median level is calculated over year–month–brand–size combinations. (D) and (R) represent whether the product's formula is sugar-free (i.e., diet) or regular.

Table A3. Median Own- and Cross-Price Elasticities: Post-Policy Period, March 2015–December 2016

	Prod1 (D)	Prod2 (R)	Prod3 (R)	Prod4 (R)	Prod5 (R)	Prod6 (D)	Prod7 (R)	Prod8 (R)	Prod9 (D)	Prod10 (D)	Prod11 (D)	Prod12 (D)	Prod13 (D)	Prod14 (D)	Prod15 (D)	Prod16 (D)	Prod17 (R)	Prod18 (D)	Prod19 (R)	Prod20 (R)	Prod21 (R)	Prod22 (R)
Prod1(D):	-0.562	0.003	0.004	0.000	0.000	0.000	0.001	0.004	0.004	0.002	0.010	0.011	0.019	0.003	0.006	0.000	0.000	0.005	0.000	0.000	0.006	0.010
Prod2(R):	0.004	-1.097	0.235	0.002	0.000	0.000	0.117	0.049	0.001	0.000	0.002	0.001	0.004	0.001	0.001	0.000	0.013	0.001	0.042	0.036	0.226	0.312
Prod3(R):	0.004	0.191	-1.427	0.002	0.000	0.000	0.115	0.049	0.001	0.000	0.002	0.002	0.004	0.001	0.001	0.000	0.013	0.001	0.042	0.036	0.223	0.309
Prod4(R):	0.000	0.001	0.001	-0.609	0.144	0.041	0.030	0.036	0.002	0.001	0.003	0.001	0.009	0.002	0.004	0.002	0.071	0.000	0.032	0.033	0.004	0.005
Prod5(R):	0.000	0.000	0.000	0.299	-1.193	0.080	0.017	0.025	0.003	0.001	0.004	0.001	0.011	0.002	0.005	0.003	0.038	0.001	0.017	0.017	0.002	0.003
Prod6(D):	0.000	0.000	0.000	0.053	0.049	-0.450	0.001	0.003	0.012	0.005	0.023	0.004	0.045	0.008	0.021	0.015	0.001	0.002	0.001	0.001	0.000	0.000
Prod7(R):	0.000	0.045	0.062	0.041	0.011	0.001	-1.037	0.103	0.002	0.001	0.003	0.002	0.008	0.001	0.003	0.001	0.059	0.001	0.083	0.079	0.113	0.158
Prod8(R):	0.002	0.015	0.022	0.038	0.014	0.003	0.082	-1.397	0.006	0.003	0.012	0.007	0.028	0.004	0.011	0.002	0.030	0.003	0.040	0.040	0.049	0.074
Prod9(D):	0.002	0.000	0.000	0.003	0.002	0.011	0.002	0.007	-1.009	0.011	0.065	0.024	0.112	0.016	0.043	0.012	0.001	0.011	0.001	0.001	0.001	0.002
Prod10(D):	0.002	0.000	0.000	0.003	0.002	0.011	0.002	0.007	0.025	-0.991	0.065	0.024	0.112	0.016	0.043	0.011	0.001	0.011	0.001	0.001	0.001	0.002
Prod11(D):	0.002	0.000	0.000	0.001	0.001	0.008	0.001	0.005	0.025	0.011	-2.366	0.024	0.110	0.015	0.044	0.011	0.000	0.011	0.000	0.000	0.001	0.001
Prod12(D):	0.007	0.001	0.001	0.001	0.001	0.003	0.002	0.008	0.024	0.011	0.062	-0.899	0.108	0.015	0.041	0.008	0.000	0.013	0.001	0.001	0.002	0.003
Prod13(D):	0.003	0.000	0.000	0.002	0.002	0.009	0.002	0.007	0.025	0.011	0.065	0.025	-0.934	0.016	0.043	0.011	0.001	0.011	0.001	0.001	0.001	0.002
Prod14(D):	0.002	0.000	0.000	0.003	0.002	0.011	0.002	0.007	0.025	0.011	0.064	0.025	0.112	-0.876	0.043	0.011	0.001	0.011	0.001	0.001	0.001	0.002
Prod15(D):	0.002	0.000	0.000	0.003	0.002	0.011	0.002	0.007	0.025	0.011	0.066	0.024	0.112	0.016	-1.028	0.012	0.001	0.011	0.001	0.001	0.001	0.002
Prod16(D):	0.001	0.000	0.000	0.006	0.005	0.031	0.001	0.006	0.026	0.012	0.066	0.019	0.110	0.016	0.045	-0.964	0.001	0.009	0.001	0.001	0.001	0.001
Prod17(R):	0.000	0.011	0.013	0.191	0.052	0.003	0.122	0.083	0.001	0.001	0.001	0.001	0.005	0.001	0.002	0.001	-1.056	0.000	0.098	0.098	0.033	0.048
Prod18(D):	0.007	0.001	0.001	0.001	0.001	0.004	0.002	0.008	0.024	0.011	0.063	0.029	0.108	0.015	0.041	0.008	0.000	-1.061	0.001	0.001	0.002	0.003
Prod19(R):	0.000	0.033	0.040	0.085	0.022	0.001	0.163	0.099	0.001	0.001	0.002	0.001	0.006	0.001	0.002	0.001	0.098	0.001	-1.086	0.097	0.082	0.115
Prod20(R):	0.000	0.031	0.039	0.085	0.022	0.001	0.160	0.099	0.001	0.001	0.002	0.001	0.006	0.001	0.003	0.001	0.098	0.001	0.100	-1.385	0.079	0.112
Prod21(R):	0.004	0.115	0.146	0.006	0.001	0.000	0.132	0.078	0.001	0.001	0.003	0.003	0.008	0.001	0.003	0.000	0.020	0.001	0.049	0.049	-1.204	0.255
Prod22(R):	0.004	0.107	0.135	0.006	0.002	0.000	0.132	0.082	0.002	0.001	0.003	0.003	0.008	0.001	0.003	0.000	0.021	0.001	0.050	0.049	0.176	-1.318

Notes: This table provides the median elasticities of demand for 12-packs of 12-ounce equivalent product based on the specification of column 4 in Table 2.
The cell in row j and column k represents the percentage change in the quantity of product j with respect to the price change in product k. Median level is calculated over year–month–brand–size combinations. (D) and (R) represent whether the product's formula is sugar-free (i.e., diet) or regular.