Revisiting the Effects of Sugar Taxes on Sugary Drink Consumption: Evidence from the Random-Coefficient Demand Model

Yinjunjie Zhang[a] and Marco A. Palma[b]

[a] Research Assistant, Department of Agricultural Economics. Texas A&M University. 2124 TAMU, College Station, Texas, 77843. (979) 571-5230. E-mail: zyjj1982@tamu.edu

[c] Associate Professor and Extension Economist, Department of Agricultural Economics. Texas A&M University. 2124 TAMU, College Station, Texas, 77843. E-mail: mapalma@tamu.edu

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Yinjunjie Zhang*and Marco A. Palma†

Abstract

Berkeley's initiative on sugar tax policy is currently debated and it is quickly expanding to other states in the United States. Previous literature highlights the importance of consumer heterogeneity in evaluating the effect of sugar taxes. In this study, we use a demand model in characteristic space —BLP RC Logit demand— to identify the policy effect on preferences for sugary drinks and potential substitution patterns over 22 sugary drink products. Our results suggest that sugar taxes cause average valuation of sugar content to change from negative to positive. This type of "reactance" response is not driven by consumers with higher than average SSB consumption patterns. An examination on demand elasticities suggests Berkeley consumers become more responsive to prices of sugary drinks due to the policy implementation; however, it does not drive consumers to shift to diet drinks.

Introduction

As a pressing health issue, obesity has received widespread attention from both researchers and policymakers. According to a report from the World Health Organization, obesity is strongly associated with chronic illness such as diabetes, heart conditions, and other life-threatening diseases [World Health Organization et al.,

*Department of Agricultural Economics, Texas A&M University, 2124 TAMU, College Station, TX 77843-2124, USA. Email: zyjj1982@tamu.edu

†Department of Agricultural Economics, Texas A&M University, 2124 TAMU, College Station, TX 77843-2124. Email: mapalma@tamu.edu

2014]. In the United States, about 69% of the adult population are overweight, while 35% are obese [Ogden et al., 2014]. Sugar-sweetened beverages (SSB) are typically seen as product with "empty calories", devoid of nutritional content [e.g., Malik et al., 2006, Jacobson and Brownell, 2000, Fletcher et al., 2015]. A significant body of literature has argued that obesity is directly linked to the consumption of SSB, in addition to other generic factors [e.g., Malik et al., 2006, Pereira, 2006, Vartanian et al., 2007, Malik et al., 2010].

To overcome the obesity epidemic and other chronic diseases due to SSB consumption, many countries have taken measures such as imposing taxes to discourage the consumption of sugary drinks. Denmark is one of the early adopters of 'soda tax' policies starting in the 1990s. France introduced a similar tax in January 2012. With a comparable proportion of the population being overweight and obese, Mexico launched a nationwide soda tax policy in January 2014. Unlike other countries passing federal soda tax regulations, the United States adopted the SSB tax more gradually and on a city by city basis. 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 either passed or proposed to have a sugary drink tax over the next several years.

Evaluating the effect of Berkeley's initiative on beverage consumption is of critical importance before expanding the soda tax to other states. However, the question of whether imposing a sugar tax will lead to the intended results is subject to debate among researchers [Fletcher et al., 2010b,a, Cawley and Frisvold, 2015]. The potential concerns are raised by 1) the extent to which a tax imposed on distributors will be passed on to the consumers; 2) the extent to which the induced response to the price change will come primarily from the population at risk; 3) the extent to which the affected consumers will shift their consumption towards untaxed diet beverages. The sugar tax policy is effective only when the tax induces higher prices and consumers respond by shifting consumption to other low-calorie beverages.

Past research on pass-through taxes are inconclusive. Grogger [2017] finds an over-shift of a nationwide soda tax to retail prices in Mexico. Specifically, a 9% tax

increased the price of high-calorie soda by about 12%. A similar finding is reported in Berardi et al. [2016], while examining the effect of a soda tax in France enacted in 2012. While evidence from Cawley and Frisvold [2015] implies that Berkeley's soda tax might only have modest effects on prices, Falbe et al. [2015] suggest that the pass-through rate for this type of tax is about 47% for SSB overall, and 69% for soda only.

Even when the the tax fully translates to higher prices, it is still uncertain whether it will be effective within the population at risk, i.e., overweight and obese individuals or people with health issues. At risk people can be roughly measured by their sugary drink consumption habits. As a result when evaluating sugar tax policies, it is important to identify the effect for consumers with different SSB consuming patterns, while accounting for consumer heterogeneity.

A substantial amount of research provide empirical evidence regarding consumption responses for different household consuming types. Using a standard AIDS demand, Debnam [2017] identifies heterogeneous elasticities of demand over households of different SSB consumption types. Debnam [2017] argues for a "reactance" response among high-consuming households to the adoption of a sugar tax.

By employing a finite mixture IV-Tobit approach, Etilé and Sharma [2015] compare the impact of SSB taxes on the price elasticity of demand between moderate and high consumers using data from Australian households. Lal et al. [2017] provide an analysis on the health and financial impacts for different demographic groups based on a hypothetical 20% SSB tax in Australia. Evaluations using observational data show consistent findings. Colchero et al. [2016] find a larger than average reduction in purchasing taxed beverages among lower-income households.

To fully model heterogeneous effects on household's sensitivity to price and sugar content in beverage consumption, we expand the BLP RC-Logit demand to control for household factors such as income and SSB consumption. Under the framework of BLP RC-Logit demand, we can identify to what extent the marginal valuation of product characteristics, i.e. sugar content, vary by household demographics such as household level SSB consumption. Using the BLP RC-Logit model, we answer the question of whether households with high SSB consumption patterns will be more

or less sensitive to product characteristics after the policy change.

The amount of sugar ingredient in different sodas and other sugary drinks is also an important perspective to analyze potential substitution patterns and to further evaluate the policy effects. Grogger [2017] investigates consumers' substitution patterns by examining whether the price of substitutes (e.g., diet sodas) change along with the taxed drinks. We measure substitution patterns by directly examining own- and cross- elasticities over beverages of different caloric content. Due to the curse of dimensionality, the class of product space demand models, such as AIDS, aggregate products into high level groups. Hence substitution can not be evaluated on a product basis. (i.e. product characteristics basis). Characteristics based demand models allow us to identify the substitution of products which are simply defined as bundles of attributes. By testing changes in substitution patterns over soft drinks with different sugar content, we obtain a direct answer of whether people substitute towards diet beverages after the policy change.

We use Nielsen consumer panel and retail data from 2006 to 2016, to address these questions under a BLP RC-Logit demand framework. The adoption of a sugar tax policy actually drives consumer's average valuation with respect to sugar content in beverage changes from negative to positive. Our results are in line with what has been found in Debnam [2017], in which similar "reactance" response for Berkeley's sugar tax has been found. However, contrary to their conclusions, our findings do not suggest this response comes from households with high-SSB consumption patterns. Examination on the elasticity matrix indicates that consumers become far more responsive to price changes after the policy change in Berkeley, but they do not necessarily change their substitution patterns to diet drinks.

Sugar tax in Berkeley, California

The "Measure D" soda tax was passed on November 4, 2014 in the city of Berkeley in Alameda County, California. On March 2015, Berkeley, California became the first city in the United States to start levying an excise tax on sugary drinks, but not on diet 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") used to make them."[1]. Beverages subject to Measure D include sodas, sports drinks, energy drinks, and sweetened ice teas.

Analytical Framework

The most commonly used demand model for studying consumer behavior consists of two categories: demand model in product-space and in characteristics-space. In order to solve the dimensionality problem in demand systems, the product based model assumes separability of utility and the products are grouped into categories. Examples of these demand models include the well-known Almost Ideal Demand Systems [Deaton and Muellbauer, 1980] the translog model [Christensen et al., 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 attributes bundles, rather than a single product. The most popular model in this class is the BLP Random Coefficient Logit demand, which was first introduced by Berry, Levinsohn, and Pakes (BLP) [Berry et al., 1995].

Not only the BLP RC-Logit demand solves the dimensionality issue, but it also allows for individual substitution patterns across products to be associated with characteristics of differentiated products.

BLP RC-Logit Demand Setup

Following the standard framework of BLP RC- Logit [Berry et al., 1995, Nevo, 2001], the utility function is written as:

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

[1] https://ballotpedia.org/City_of_Berkeley_Sugary_Beverages_and_Soda_Tax_Question,_Measure_D_%28November_2014%29

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 adopting a soda tax: Berkeley, California; years are from 2006 through 2016, with the pre-period ranging from January 2006 to June 2014 and the post-period from March 2015 to December 2016. Thus, we have $t = \{1, 2, ..., 102\}$ for the pre-period and $t = \{1, 2, ..., 22\}$ for the post-period.

In each market, purchased quantities and paid prices are aggregated at the market level. x_{jt} refers to the K-dimensional product characteristics, including a constant, sugar content and sodium level in the beverage's nutrition facts; j indexes the product (attributes bundle) of a product. ξ_{jt} captures the unobserved product-specific shock in each market. Each household is assumed to purchase one of the j products or not to purchase at all. ε_{ijt} is the Logit error term which follows a Type I extreme value distribution.

The household taste heterogeneity parameter is modeled as:

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

with D_i and v_i referred 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 to the researcher, 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 equation 1 and 2, the indirect utility is specified as:

$$U_{ijt} = \alpha_i y_i + \delta(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) + \varepsilon_{ijt} \tag{3}$$

$$\text{where} \quad \delta(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}, \tag{4}$$

$$\text{and} \quad \mu_{ijt}(x_{jt}, p_{jt}, v_i, D_i; \theta_2) = [-p_{jt}, x_{jt}](\Pi D_i + \Sigma v_i) \tag{5}$$

where $[-p_{jt}, x_{jt}]$ represent the $K+1$-dimensional vector of product characteristics with price; δ_{jt} is the mean utility associated with the consumption of good j, and it is common across all consumers in market t; $\mu_{ijt} + \varepsilon_{ijt}$ represent the mean-zero heteroscedastic deviation from the mean utility δ_{jt}. θ_1 is a vector of parameters (α,β) which enters linearly into the utility function, while θ_2 refers to the nonlinear parameters (Π, Σ).

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

$$s_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP(\varepsilon) dP(v) dP(D) \tag{6}$$

where $A_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \{(D_i, v_i, \varepsilon_{ijt}) | u_{ijt} \geq u_{ilt} \forall l = 0, 1, ..., J\}$. As mentioned previously, the error term ε was assumed to follow a Type I extreme value distribution, integrating it out yields the Logit format of individual household's probability of purchase. With the assumed distribution of v and D, and simulated draws, the integration in equation 6 can be evaluated numerically by

$$s_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \frac{1}{ns} \sum_{i=1}^{ns} s_{ijt} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{exp(\delta_{jt} + \mu_{ijt})}{\sum_{j=0}^{J} exp(\delta_{jt} + \mu_{ijt})} \tag{7}$$

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

$$\eta_{jjt} = \frac{\partial s_{jt} p_{jt}}{\partial p_{jt} s_{jt}} = -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt} (1 - s_{ijt}) dP_D(D) dP_v(v) \tag{8}$$

$$\eta_{jkt} = \frac{\partial s_{jt} p_{kt}}{\partial p_{kt} s_{jt}} = \frac{p_{kt}}{s_{jt}} \int \alpha_i s_{ijt} s_{ikt} dP_D(D) dP_v(v) \tag{9}$$

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

Identification and Estimation

One research question in this article is to investigate, after the Berkeley's Measure D, whether household with higher volume of SSB consumption would be more or less sensitive to prices and the sugar content of beverages. The second question is to ask whether household's substitution patterns across beverages with different amounts of sugar content were affected by the policy change. We address the first question by estimating the parameters α, β and the interaction matrix Π. The second question is tested by comparing the elasticity matrix for the 22 products *before* and *after* the policy change.

In the BLP model, the presence of unobserved product attributes ξ, termed as structural error in Berry et al. [1995], 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 or promotions, which can affect the price and they are observed by consumers, but this information is not available in the survey data. [2] Thus, the identification requires to instrument for the relation between price and ξ. A standard solution to this issue is to find an exogenous cost shifter which determines the price but uncorrelated with unobserved product attributes. Unfortunately, since cost related information is not available in the data, this IV is not feasible in this study. We take a different approach outlined below.

As suggested in Hausman [1996] andNevo [2001], we assume that after controling 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. We follow this procedure to estimate the demand model for beverage consumption. In particular, we control for 22 brand dummy variables and we use as instruments the monthly average prices for each of

[2] As noted in RMS' manual, Nielsen only observed promotions and advertisement activities and recorded them in feature and display variable for a subset of stores (called "audited store"), and those stores changed on weekly basis, which implies that we do not have constant reliable observations for those information.

the same products in 20 other locations outside of California.

We estimate the demand using the standard procedure for the BLP-type of model. The estimation algorithm is a nested fixed point (NFP) algorithm [Berry et al., 1995], which roughly includes two loops. An inner contract-mapping loop to infer the mean utility δ and an outer loop for nonlinear GMM estimation [Hansen, 1982] to obtain parameter matrix of θ_2. (see Berry et al. [1995] and 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 a sugar tax, we use Nielsen Homescan Consumer Panel (HMS) and Retail Scanner (RMS) datasets which can be accessed through Kilts Center for Marketing at the University of Chicago Booth School of Business. The most recently available data is 2016. Due to this limitation, in this article we concentrate on evaluating the impact from Berkeley's Measure D, implemented in 2014. The Retail Scanner Data includes weekly pricing and unit sales by UPC code from participating stores in all U.S. markets. We restrict the estimation to 20 geographic 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 serves as instruments for the endogenous price in Berkeley.

Beverages are sold in different size packages, with or without sugar (formula). Following the general practice in empirical estimation studies of the BLP model, we refer to brand×formula×size combinations as products. The predominant package sizes include 1-pack, 6-pack, 12-pack and 24-pack. The numeric quantity of beverages in individual packaging also differs, ranging from 12 ounces to 128 ounces. We measure the sales of each product by standardizing it to a 144-ounce equivalent unit, which is the size of a 12-pack of 12 ounces. Price is adjusted to reflect the revenue per equivalent unit. [3]

[3]For example, one sale of a 24-pack of beverages with the numeric quantity in individual pack-

Based on the adjusted sales, we select 22 products (see Table 1 for the product list) which have the highest market shares from 2006 to 2016 in Berkeley. These 22 brand×formula×size combinations are built by aggregating 72 upc level goods. Accordingly, 8 flagship brands of carbonated/non-carbonated soft drinks and tea measured in ounces [4] are left in the sample. The brands included are A&W, Arizona Iced Tea, Canada Dry, Coco-Cola, Fresca, Pepsi, Seven Up, and Sprite.

Sales data are aggregated to year-month-product level. In total, there are 2,244 observations spanning from January 2006 to June 2014 before the California "Measure D" passed, and 484 observations ranging from March 2015 to December 2016 for the post policy period. The only treated location in this study is Berkeley, California. We use the first three digits of zip code (947) to identify stores located in Berkeley, CA. Berkeley has a relatively unique leading three digit zip code. Albany is the only area of California in which Berkeley shares part of its zip code. Considering that Albany has only about one tenth the population of Berkeley, and as of 2016 Albany did not implement a sugar tax, using the same zip code will, at most, underestimate the policy effect.

In order to implement the numerical integration in equation 7, we select draws at the household level. We use Nielsen's HMS data to simulate the household demographics. Households identified as residing in Alameda County are the potential source for consumers of Berkeley's stores. [5] The BLP literature suggests ways of simulating demographic information and discusses whether the same draws should be taken across markets. For example, in Miller and Weinberg [2017], different simulation draws were taken for each market. Here, we follow Berry et al. [1995] and use

aging as 16.9 ounce will be counted as 2.8 sales; price will be re-calculated by dividing it by the sales number in the equivalent unit.

[4]Powered drink, instant tea bags, tea mixes and cocktail mixes are excluded. Branded water is also excluded.

[5]This is done for the reason that we found a nontrivial amount (about 15%) of purchases at stores in the Berkeley area (stores with zip code started as "947") were made from residents living in other places within the Alameda County. While Nielsen Homescan data has the full zip code for the residence of consumers, only part of the stores in which they shopped has the zip code information in HMS data. To precisely model the consumer behavior, it is plausible to also simulate people living outside of Berkeley but within the Alameda County as the potential population being affected by this policy.

the same draws for all the markets. Furthermore, Nevo [2001] suggests that without any prior information on the parametric forms for the distribution of demographics, it is better to sample real individuals to avoid making arbitrary distributional assumptions. Following this guideline, we sample 500 households over the whole sample based on the empirical distribution of demographics and keep it fixed across markets.

HMS's household income is reported as a categorical variable. We construct the log of income variable by taking the medium of the range within each category and dividing it by the household size. The constructed income and price variables are deflated and reported in 2010 dollars. One key demographic information to address the first research question is the measurement of SSB consumption for each household. Based on Debnam [2017], we define household consumption type to fit the identification strategy in this article. In particular, we construct household level SSB consumption as the percentage 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. Instead of using a binary variable, our definition of SSB consumption will naturally have more variation.

Results

We begin by breaking our sample into three time periods: 1) January 2006 through June 2014;2) July 2014 through February 2015; and 3) March 2015 through December 2016. The three periods correspond to the period before the policy change, during the discussion, voting and passing the Measure D, and after the policy became effective. We call the first period, the pre-policy period, in which we assume potential consumers of stores located in Berkeley do not anticipate the policy change. The third period is the post-policy period, in which consumer preferences were affected by the policy. Since the second period is when the policy was heatedly debated, it is likely that potential changes in people's demand were already taking place in anticipation of the policy. Hence, we exclude this period from our analysis in order to have a clean identification.

Logit Results

We first take a look at the relation derived from a simple Logit demand model (Table 2). For the Logit demand model, since individual heterogeneity over valuation in product characteristics is suppressed, the mean utility can be expressed in $ln(S_{jt}) - ln(S_{0t})$. Regressing it on product characteristics yields consumer's average valuation on product features. We estimate Logit demand with both OLS and 2SLS for data in the pre- and post- policy period. Columns (1) and (2) correspond to the sample in the pre policy period, while columns (3) and (4) correspond to the sample in the post policy period.

The sign of the price coefficient is as expected and the magnitude of the parameter estimate is constant over the two policy periods. As shown, consumer's average taste for sugar content in SSB are all negative and statistically significant across specifications. This result suggests that for an average consumer more sugar will decrease the utility of consuming the soda or iced tea drink. Along with sugar content, sodium also decreases the average valuation of the product. Since the substitution demand patterns implied from the simple Logit model are restrictive and unrealistic [Nevo, 2001], we are cautious on the interpretation of these estimates and simply use them as benchmark.

Results from the BLP RC-Logit demand

Table 3 presents the results from the full demand model illustrated in the modeling section. The estimates for the subsample of data before the policy change are shown in columns (1) and (2). The corresponding results for the post-period sample are given in columns (3) and (4). The taste parameter for product characteristics, including sugar and sodium, are retrieved ex-post with a minimum-distance procedure. The parameter for price is estimated in the GMM process.

Due to sample size limitations, we consider two key demographic factors of interest: SSB consumption patterns and income. SSB consumption is constructed as the percentage of time within a year-month defined market in which each household has weekly median consumption of SSBs higher than the median consumption of all

households in the sample. For both pre- and post- policy periods, we present different specifications, allowing for individual heterogeneity in the valuation of sugar content to vary by SSB consumption or both SSB consumption and income. All specifications employ monthly prices in 20 other locations as instruments and control for brand dummy variables.

The first four rows of Table 3 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 shown in columns (1) and (2), the point estimates for the average marginal utility with respect to sugar content are all statistically significant. In particular, before Berkeley's "Measure D" was enacted, the valuation of sugar content is negative for an average consumer. However, households with higher consumption volume of SSB might be less sensitive to the amount of sugar in beverage drinks. A similar case can be made for wealthier people.

However, after the adoption of the sugar tax policy, consumer's valuation of sugar content in beverage drinks significantly changed. Columns (3) and (4) present the results from analogous estimations as in columns (1) and (2), except that the sample restricted to the post period. The results show that sugar content increases the mean utility of an average consumer, and this relation is sustained across specifications controlling demographic characteristics. This type of "reactance" response is also documented in Debnam [2017], in which they find higher consumption of soda among high-consumption households right after the Berkeley' sugar tax using a reduced form framework estimation. Our results, on the other hand, using the structural modeling provides evidence of the mechanism, through which the soda consumption is surprisingly increased. The difference in our case is that we find consumer responses to the policy actually came from the mean utility. In other words, the reactance response is not limited to the high-consumption-type of households. In fact, although sugar content increases the mean utility of an average consumer, households with high volume of SSB consumption do not show the same preference as overall consumers. The marginal valuation of sugar decreases with household SSB consumption in the post policy period.

We present the overall distribution of taste for sugar content before (column (2))

and after (column (4)) the policy change in Figures 1 and 2, respectively. Clearly, before the policy change, consumers actually valued the amount of sugar in beverages in a negative way. After the sugar tax policy, consumer preferences for sugar content shifted to the right.

While the mean price coefficients are all negative, households with high income or high-consumption patterns tend to be less price sensitive. Overall, sodium content is a less attractive characteristic among average consumers for beverage products (brand-size combinations). [6] Figures 3 and 4 present the distributions of the price coefficients.

Tables 4 and 5 provide 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 k. The feature of flexible substitution patterns of a BLP type of demand allows the cross price elasticity to change over differentiated products. We present the median of each cell over the 102 markets in the pre policy period sample and 22 markets in the post policy period sample. We label the formula of the product with (D) or (R) to indicate whether it is a diet or a regular formula. We find that the median own-price elasticities across the 22 products changed from inelastic to elastic as a result of the policy, with the variation changing as much as 200 percent. In other words, the estimates indicate that Berkeley's Measure D policy drives consumers to be much more sensitive to price changes of sugary drink than before.

This result should be interpreted with caution. As suggested by Cawley and Frisvold [2015], consumers might just avoid the higher prices by making soda purchases outside of the city of Berkeley. If this is the case, our model might overestimate the changes in the own-price elasticity. 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 over different demographic groups. Here in our case, except for product 11th, the post-period own-price elasticity of demand is roughly within

[6] Based on market share, we choose 8 flagship brands of beverage and standardize package size to 12-pack, which mainly include soda and iced tea (See Table 1). Since energy and sport drinks are not included in the sample, the interpretation on consumer preference for sodium content should be limited to the products mentioned in this article and it does not necessarily apply to energy and sport drinks.

this range. Andreyeva et al. [2010] document a price elasticity range for soft drinks from 0.13 to 3.18 in absolute value in the United States, which is within the obtained in our results.

As pointed out, our second research question is whether consumers substitute away from beverages with higher sugar content towards diet beverages. We address this question by comparing the pre and post policy period of the cross-price elasticity of products in regular formula with respect to products in diet formula. BLP RC-Logit demand is known for its flexible and realistic substitution patterns. The cross-price elasticity is allowed to vary by different products and the substitution patterns are driven by consumers' variation in price sensitivity or the marginal utility from income [Nevo, 2000].

As Berkeley' Measure D tax policy does not apply to diet drinks, we examine whether the change in the price of products with regular formula will drive an increase in consumption of diet products. Of the 22 products of interest (brand-size combinations) in our sample, half of them are in regular formula with their average sugar content ranging from 13g to 45g per serving, and half of them are in diet formula with zero sugar content as per the nutrition fact labels. [7]

As shown in Tables 4 and 5, there are sizable changes in the substitution patterns due to the policy change. Before the policy was enacted, the potential substitution of regular drinks can be for either regular or diet drinks, with relatively similar percentage change in quantity. After the policy was launched, the substitutes are more concentrated towards drinks with regular formula and the quantity increased significantly. In the pre policy period, a given price change in product 19th, for instance, leads consumers to substitute evenly towards the rest of the 21 products in our sample, which include regular and diet drinks. However, after the policy change, there are larger substitution patterns towards products 17th and 20th, both of which are drinks in regular formula. This is consistent with the results shown in Table 3, in which we see an increase in consumer's valuation for sugar after the policy change.

[7] In particular, products with regular formula are product 2, product 3, product 4, product 5, product 7, product 8, product 17, product 19, product 20, product 21, product 22.

Conclusion

While the original purpose of a sugar tax is to incentivize people to reduce the consumption of sugary drinks in an attempt to mitigate obesity, recent short-term evidence indicates that this is not necessarily the case. By separating households by SSB consumption volume, previous studies document increased consumption after sugar tax policy among high-consuming type population. This finding highlights the need for taking into consideration individual heterogeneity when conducting sugar tax policy evaluations. Besides heterogeneity, the realization of potential health benefits is also determined by the possibility of soda taxes changing people's substitution patterns towards diet or sugar free beverages. Without carefully modeling potential heterogeneity and allowing for more flexible substitution patterns in consumer's demand, we can not observe a complete picture of the impact of sugar tax policies on consumption of sugary drinks.

In order to incorporate heterogeneous responses and substitution patterns into a structural model, we estimate the demand for beverages using a BLP random-coefficient (RC) Logit framework. In particular, we built a demand model which could effectively model household's SSB consumption patterns, identifying whether the average sensitivity to price and sugar content is affected by consumer heterogeneity, such as SSB consumption patterns and income.

With the sample of 22 products, our results suggest the adoption of Berkeley's sugar tax policy significantly changed consumer's valuation of product characteristics. Before the policy change, the valuation of sugar content is negative for an average consumer. However, the adoption of the sugar tax policy drives consumer's average valuation of soft drink to increase with sugar content. This finding echoes largely what has been found in previous studies, in which consumer increase soda consumption in response to a sugar tax. The results of the interaction of product characteristics with household income and SSB consumption patterns suggest that such "reactance" response does not necessarily come from households with high-consumption patterns. Instead, the effects may come from consumers with higher than average household income and less from households with high SSB consump-

tion patterns. Our results on the substitution patterns support the point estimates obtained from the BLP demand. In particular, for a given increase in the price of soft drinks with sugar content, we do not find consumer substituting towards diet soft drinks.

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.

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Figures and Tables

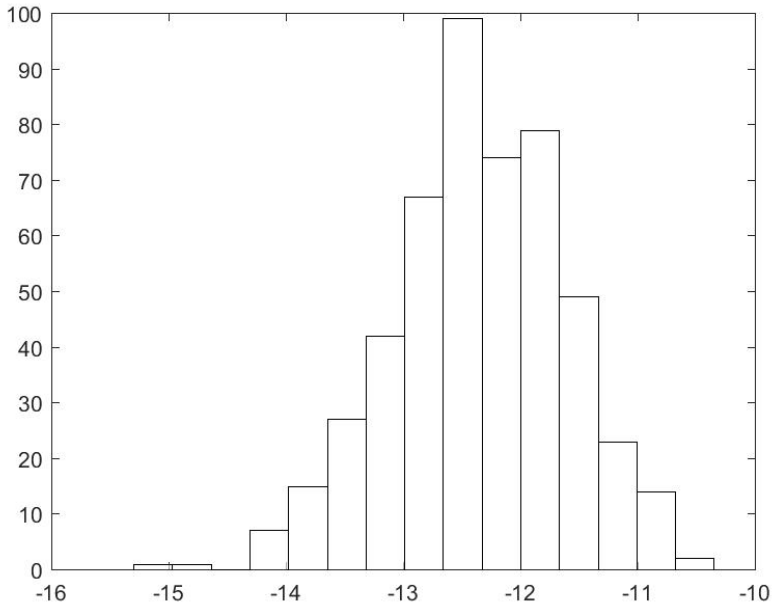

Figure 1: Frequency Distribution of Taste for Sugar: pre-period

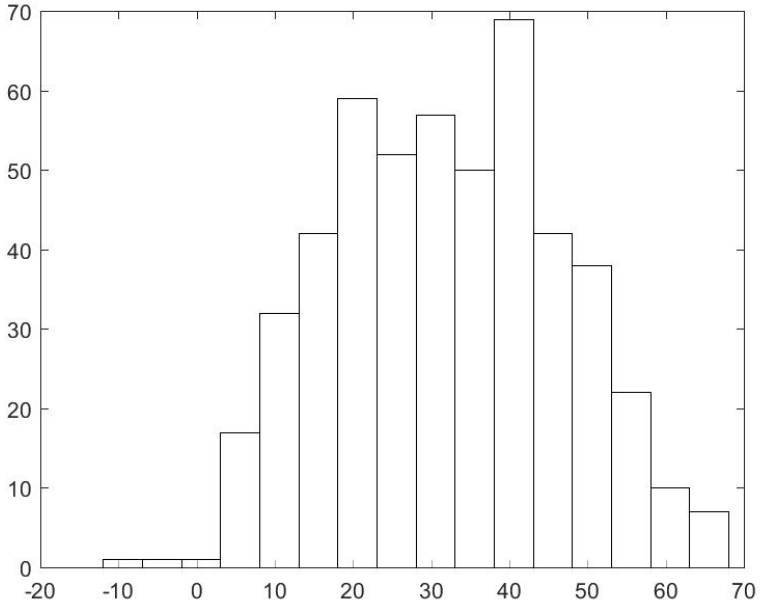

Figure 2: Frequency Distribution of Taste for Sugar: post-period

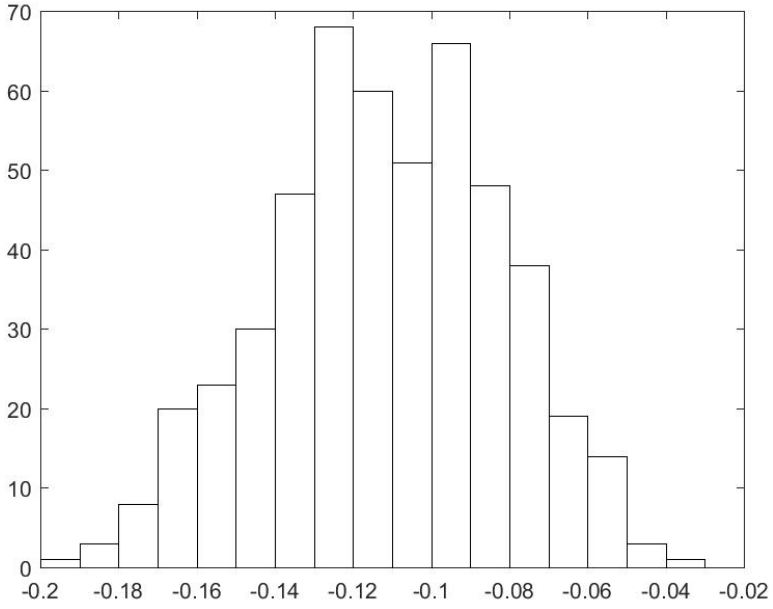

Figure 3: Frequency Distribution of Price Coefficient: pre-period

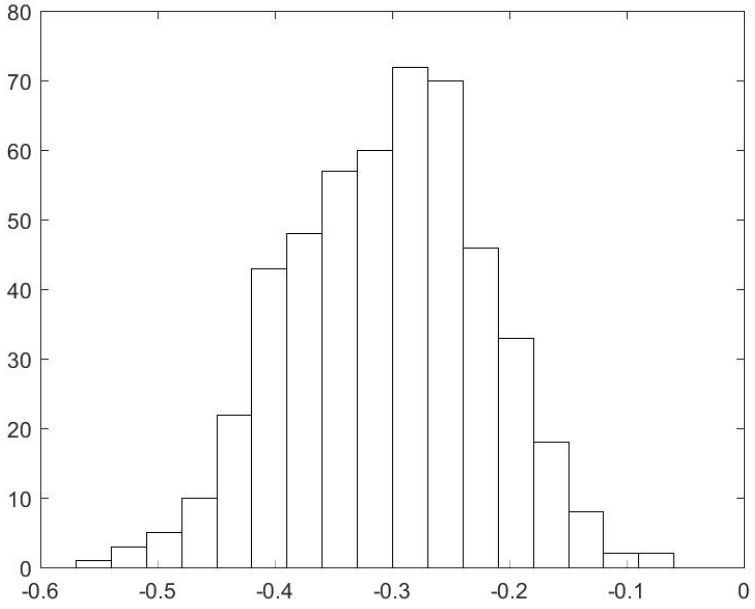

Figure 4: Frequency Distribution of Price Coefficient: post-period

Table 1: Product List

Brand-Size Combinations	Descriptions
Product 1	*A & W*, Diet, 12-pack 12oz
Product 2	*A & W*, Regular, 1-pack 67.6oz
Product 3	*A & W*, Regular, 12-pack 12oz
Product 4	*Arizona*, Regular Tea, 1-pack 128oz
Product 5	*Arizona*, Regular Tea,1-pack 23.5oz
Product 6	*Arizona*, Diet, 1-pack 128oz
Product 7	*Canada Dry*, Regular, 1-pack 67.6oz
Product 8	*Canada Dry*, Regular, 12-pack 12oz
Product 9	*Coca-Cola*, Caffeine Free and Diet,12-pack 12oz
Product 10	*Coca-Cola*, Cherry and Diet,12-pack 12oz
Product 11	*Coca-Cola*, Diet, 1-pack 20oz
Product 12	*Coca-Cola*, Diet, 1-pack 67.6oz
Product 13	*Coca-Cola*, Diet, 12-pack 12oz
Product 14	*Coca-Cola Zero*, Diet, 1-pack 67.6oz
Product 15	*Coca-Cola Zero*, Diet, 12-pack 12oz
Product 16	*Fresca*, Diet, 12-pack 12oz
Product 17	*Pepsi*, Regular, 1-pack 67.6oz
Product 18	*Seven Up*, Diet, 12-pack 12oz
Product 19	*Seven Up*, Regular, 1-pack 67.6oz
Product 20	*Seven Up*, Regular, 12-pack 12oz
Product 21	*Sprite*, Regular, 1-pack 67.6oz
Product 22	*Sprite*, Regular, 12-pack 12oz

Table 2: Parameter Estimates from Logit Demand

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Constant	-3.351	-3.361	-4.021	-4.027
	(0.049)	(0.049)	(0.097)	(0.098)
Price	-0.026	-0.023	-0.022	-0.020
	(0.008)	(0.008)	(0.016)	(0.016)
Sugar	-0.371	-0.367	-0.645	-0.642
	(0.058)	(0.058)	(0.120)	(0.120)
Sodium	-0.800	-0.799	-0.450	-0.450
	(0.051)	(0.051)	(0.106)	(0.106)

Note: Data is in year-month-product(brand-size) level. Column (1) and (2) are for markets from January 2006 to June 2014; (3) to (4) are for markets from March 2015 to December 2016. Column (2) and (4) use average monthly prices in twenty locations, excluding Berkeley, as instrumental variables. Dependent variable is given by $ln(S_{jt}) - ln(S_{0t})$, where S_{0t} is the market share of the outside good. Asymptotically robust standard errors are given in parentheses.

Table 3: Parameter Estimates from Random Coefficient Demand

	pre-period		post-period	
	(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)

Note: Brand dummies are included in the specification. Except for price, average taste parameters are all retrieved using a minimum-distance procedure[Nevo, 2001]. Asymptotically robust standard errors are given in parentheses.

Table 4: Median Own and Cross-Price Elasticities: pre-period from January 2006 to June 2014

	Product1 (D)	Product2 (R)	Product3 (R)	Product4 (R)	Product5 (R)	Product6 (D)	Product7 (R)	Product8 (R)	Product9 (D)	Product10 (D)	Product11 (D)	Product12 (D)	Product13 (D)	Product14 (D)	Product15 (D)	Product16 (D)	Product17 (R)	Product18 (D)	Product19 (R)	Product20 (R)	Product21 (R)	Product22 (R)
Product1(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
Product2(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
Product3(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
Product4(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
Product5(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
Product6(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
Product7(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
Product8(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
Product9(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
Product10(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
Product11(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
Product12(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
Product13(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
Product14(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
Product15(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
Product16(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
Product17(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
Product18(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
Product19(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
Product20(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
Product21(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
Product22(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

Note: This table provides the median elasticities of demand for the 12-packs equivalent product based on the specification of column (2) in Table 3.
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 or regular.

Table 5: Median Own and Cross-Price Elasticities: post-period from March 2015 to December 2016

	Product1 (D)	Product2 (R)	Product3 (R)	Product4 (R)	Product5 (R)	Product6 (D)	Product7 (R)	Product8 (R)	Product9 (D)	Product10 (D)	Product11 (D)	Product12 (D)	Product13 (D)	Product14 (D)	Product15 (D)	Product16 (D)	Product17 (R)	Product18 (D)	Product19 (R)	Product20 (R)	Product21 (R)	Product22 (R)
Product1(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
Product2(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
Product3(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
Product4(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
Product5(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
Product6(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
Product7(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
Product8(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
Product9(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
Product 10(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
Product11(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
Product12(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
Product13(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
Product14(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
Product15(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
Product16(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
Product17(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
Product18(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
Product19(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
Product20(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
Product21(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
Product22(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

Note: This table provides the median elasticities of demand for the 12-packs equivalent product based on the specification of column (4) in Table 3.
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 or regular.