Soda Wars

PRELIMINARY DRAFT

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Abstract: This paper examines how consumers alter their behavior due to a local tax policy change aimed at dealing with the potential health hazards of sugar consumption in soda beverages. Using panel data of product purchases from university residence halls, restaurants, and retailers, we measure the consumption effects of a soda tax campaign and election in Berkeley, California. Our approach has two parts: First we use a difference-in-difference model estimating the change in soda consumed relative to the change in consumption in control product categories. Our results show that the campaign, and in particular the election, causes soda consumption to significantly drop. Second, we estimate a structural model for beverage demand as a function of attributes. We find that soda is an inelastic good, which would imply that a price increase due to a tax would not lead to a significant drop in demand. Our findings have interesting policy implications, suggesting the effects of media coverage and election outcomes on attitudes and behaviors may be larger than the effects of the soda tax itself.

Keywords: taxes, soda, media effects, structural demand, difference-in-differences.
JEL Codes: C23, C25, D12, H20.

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1. Introduction

With the current trend of sugar consumption, exercise, and dietary habits, it is estimated that forty percent of Americans born from 2000 to 2011 will get diabetes in their lifetimes, with the percentages for black women and Hispanics placed even higher at fifty percent (Gregg et al. 2014). While researchers and industry participants agree on the health dangers of sugar, and in particular sugar-sweetened beverages (SSB), there is disagreement on how to design laws and policies to change behavior—with proposals spanning soda bans (Huang and Kiesel 2012); school nutrition education programs (James et al. 2004; Fernandes 2008), warning labels on sugary drinks advising the dangers of obesity and diabetes, and direct soda taxes. This begs the empirical questions: how do consumers react to such policies and how do consumers value information provided by the media and by advisory campaigns highlighting the dangers of sugar consumption? This paper examines how consumers alter their consumption behavior due to changes in news coverage and to changes in policy aimed at curbing consumption of SSBs.

We take advantage of a tax policy change—referred to as Measure D—in the city of Berkeley, California. Measure D imposes a penny-per-fluid-ounce tax to be paid by distributors of sugar-sweetened beverages (SSB), such as soda and energy drinks. The aim of the policy is to lower the consumption of SSBs, or if demand is deemed to be unresponsive,[1] to raise tax revenues which could fund nutritional programs and education. On November 4, 2014, Measure D was put to a vote and passed with a strong percentage of 75% in favor. An aggressive campaign war preceded this vote, dubbed Berkeley vs. Big Soda. This campaign cost $3.4 million, with roughly $1 million spent in favor of Measure D and $2.4 million spent against it.[2]

The specific objective of this paper is to examine how consumers reacted to the pre-soda tax media campaign and election, and then also to the actual soda tax implementation. There is evidence that highlighted news coverage can lead to sharp information updates (Huberman and Regev 2001) and investigating whether that also leads to behavioral changes has important policy implications, especially if behavioral changes happen before the policy change. Our study uses a detailed dataset from university residence halls and campus retailers in Berkeley,

[1] There is suggestive evidence that in the first month tax revenues increased by $116,000, which is consistent with demand having not responded in an elastic fashion to the one cent per ounce price of soda increase (*"1st month of Berkeley 'soda tax' sees $116,000 in revenue."* The Daily Californian. *May 19, 2015*. Online. [*accessed May 21, 2016*]).

[2] *"Around $3.4M spent on Berkeley soda tax campaign."* Berkeleyside. *February 5, 2015*. Online. [*accessed May 21, 2016*].

consisting of monthly store-level purchases by Universal Product Code (UPC). Our approach has two parts. In the first, we use a difference-in-differences strategy to measure the change in SSB consumption against untreated products (in comparable control product categories), and untreated months (the pre-campaign period). Using monthly panel data allows us further to control for seasonality in sales. In a second approach, we estimate a structural multinomial discrete choice model of demand for beverage products (as in Berry, Levinsohn and Pakes 1995; McFadden 1974; McFadden and Train 2000; Nevo 2000; Nevo 2003), and estimate the implied price elasticity to predict the effects of the tax change on soda quantity purchased.[3]

In the reduced form approach, we find a large and significant drop in soda sales following the campaign event. The media campaign surrounding the election, before SSB tax implementation, induced a discontinuous drop in soda quantity sold by approximately 42% relative to other beverages and candy products sold at the same outlets. Importantly, the control categories exhibits very similar pre-campaign trends to the treated soda category. From the structural model we estimate that soda is an inelastic product and therefore, given the tax increase, demand will not drop in an elastic fashion. This implies that a soda tax will not result in elastic behavioral changes in terms of soda quantity reduction, but rather can serve as a category suitable for increasing tax revenues.

Our paper is the first to investigate the effects of a sugar tax campaign on SSB consumption, extending past research that focused on whether soda bans and education programs induce behavioral changes for children at school. While evidence suggests that banning soft drinks decreases calorie consumption at schools (e.g. James et al. 2004; Fernandes 2008), a recent study by Huang and Kiesel (2012) finds that banning soft drinks at schools results in compensation effects at home. New medical evidence about food-related health problems can sometimes permanently alter preferences (Yen et al. 1996; Brown and Schrader 1990; Van Ravenswaay and Hoehn 1991; Chavas 1983) and a number of previous studies examine the impact of food safety-related information on consumer demand. For example, Smith et al. (1988) analyze the impact of an incident involving contamination of milk with heptachlor in Hawaii during 1982 and find that negative media coverage has a larger impact than positive coverage.

[3] Currently, the sample period of our data ends before the soda tax was implemented on campus. In future work, when we have the post-tax data, we will compare the estimated elasticity from our structural model to the elasticity we find from the price change of the tax.

Our approach is close to Schlenker and Villas-Boas (2009) who compare an actual food scare in the beef market with a media-discussed related event and find that the media covered event had almost 50% of the effect of the actual food scare event. While this paper will also rely on a reduced form model to assess responses to the media covered campaign, and later to the actual tax policy change, we extend the methodology of Schlenker and Villas-Boas (2009) by (1) performing a difference-in-differences strategy to net out the media and tax policy effects on soda consumption from other events that could have been occurring at the same time, and by (2) estimating structural demand elasticities to make inferences on the revenue effects resulting from the tax law. Furthermore, identifying the effects of soda tax media coverage on economic outcomes adds to the existing research in this area that has focused on the impact of media expansion and media bias on political attitudes and outcomes (Stroemberg 2004; Gentzkow and Shapiro 2010; DellaVigna and Kaplan 2007).

Finally, this study relates to a growing literature that empirically shows that consumers have an attenuated response to non-salient costs; in other words, they are less sensitive to non-salient costs than to increases in the displayed price. With a labeling experiment, Chetty et al. (2009) find that the sales of taxable products at a grocery store are reduced when their tax-inclusive price is displayed in addition to the tax-exclusive price. In the case of the SSB tax in this study, there was an extensive campaign to inform voters about the tax, however, the tax itself was implemented with little fanfare. Thus, while this tax was much more salient than most tax changes, the campaign itself may have affected soda sales directly even before the tax was implemented.

The rest of the paper proceeds as follows. Section 2 describes the empirical setting and summarizes the data, while Section 3 outlines the research design (i.e., the reduced form and structural empirical strategies). Section 4 presents the results and Section 5 concludes.

2. Empirical Setting and Data

Since 2009, the soda industry has spent more than 117 million dollars nationally to stop soda tax initiatives, such as those considered in by the U.S. Congress and in states such as Maine, Texas and New York.[4] For Measure D in particular, the American Beverage Association

[4] *"Berkeley Officials Outspent but Optimistic in Battle Over Soda Tax."* The New York Times. *October 7, 2014*. Online. [*accessed May 21, 2016*].

of California contributed almost 2.5 million dollars to defeat the tax, while supporters of Measure D spent just under 1 million dollars.[5] One of the strongest supporters of Measure D—"Berkeley vs Big Soda"—gathered industry, individual and lawmakers support and funded an aggressive advertising campaign promoting "yes on D", emphasizing the need to fight "Big Soda." While, as previously mentioned, the sugar tax in Measure D affects all beverages containing sugar, at a rate of one cent per ounce, our research of the media and advertising campaign concluded that the media paid particular attention to soda, rather to the Sugar Sweetened Beverage (SSB) products in general (see figure A.1 in the Appendix for one such example). Thus we will look at the effects of the campaign war and tax change on soda separately from other SSB beverages.

We use a unique data source to estimate the effect of media coverage and campaigning on consumer purchasing decisions: a scanner data set from dinning locations at a large university in the U. S., which includes purchase data from restaurants on the campus as well as from residence halls. The university retailers where we perform the empirical analysis may not be representative of average U.S. purchase outlets, but there are advantages of using this empirical setting for our experimental design. First, the layout and products offered are very uniform across retailers. Second, the promotional effort and posted prices are common across campus. Third, we know when and by how much the soda tax is passed onto consumer.

This dataset includes data on monthly quantities sold, prices, and revenue sales at the product level (i.e., campus retail sold *x* units of product *i* in month *m*, where a product is represented by a unique bar-code (UPC)). The dataset includes all beverages (soda, juice, water, energy drinks, coffee, tea, and milk) as well as chocolate and candy products for the period November 2013 through May 2015.[6]

For the campaign effect analysis, we define regular soda as our treated product category, which we will compare to eight other beverage and snack categories: 1) water, 2) juice, 3) energy drink, 4) milk, 5) coffee, 6) tea, 7) diet soda, and 8) candy. However, it is important to note that regular soda is not the only product that falls under regulation. Given the wording of Measure D— "The City hereby levies a tax of one cent ($0.01) per fluid ounce on the privilege of

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[5] *"Around $3.4M spent on Berkeley soda tax campaign."* Berkeleyside. *February 5, 2015*. Online. [*accessed May 21, 2016*].

[6] While we have data from January 2013 to October 2013, this data is at a more aggregate product level and does not match the product level data we use in our sample.

distributing sugar-sweetened beverage products in the city"—any drinks with added sweeteners are taxed. So for example, 100% juices are not taxed, but juices with sugar (or corn syrup) added are taxed. The following beverage products are taxed: regular soda (i.e. Pepsi), energy drinks (i.e. Gatorade), presweetened tea, and lemonade. Exempted are the following: water, diet soda, beverages containing only natural fruit and vegetable juice, beverages in which milk is the primary ingredient, beverages or liquids sold for use for weight reduction as a meal replacement, medical beverages (beverages used as oral nutritional therapy or oral rehydration electrolyte solutions for infants and children), and alcoholic beverages, although the last two categories are not sold in the campus restaurants.

First we use the pre-campaign period data to investigate whether the pre-period is balanced in terms of pre-existing trends in demand for the treated (soda) and control (other beverages and candy) product categories. Figure 1 presents the quantities sold of each product group per month in the pre-campaign period. The largest category in terms of quantity sold in the pre-campaign period is juice, followed by tea and water. Soda, coffee, milk and energy drinks all see similar levels of sales.[7] While the various products differ in levels, their trends are quite similar, with sales peaking in April (around final exams) and plummeting in June.[8] Thus while soda has different quantities sold than the other products, to the extent that these differences are constant over time, product group fixed effects will control for all possible time invariant determinants of drink and candy demand.

In evaluating the effects of the soda tax campaign, we will compare the pre-campaign period to three separate post-campaign periods: (1) the pre-election campaign period—July 2014-October 2014, (2) the post-election and pre-implementation period—November 2014-February 2015, and (3) the post-implementation period—March 2015-May 2015. Given that time series data on campaign expenditures are not available, we investigate the intensity of the campaign over time by collecting media article count data for the term "soda tax". Figure 2 depicts Google trends data for news coverage of the term "soda tax" in the San Francisco-Oakland-San Jose area from 2008 until present. This figure indicates that news coverage spiked

[7] Diet soda is dropped from the graph as it was indistinguishable from zero.

[8] As a more rigorous test of parallel trends, we regress quantity on a time trend for the treatment and control products separately. We find that the point estimates of the trend in treatment and control products are not statistically different from each other. Furthermore, the time series correlation of the sample averages of soda and the control is high, suggesting that the treatment and control products share broadly similar time varying patterns in the pre-period.

in July 2014, when Measure D was announced, and spiked again to a much greater extent in November 2014, when Measure D was voted on and passed.

3. Empirical Strategy

Our approach has two parts. In the first, we use a difference-in-difference strategy to measure the change in soda consumption against untreated products (in a comparable control product categories), and untreated months (the pre-period). Chocolate and candy snacks exhibit seasonal and trending patterns comparable to soda in the pre period and this category provides a good control for the soda treated category, while using monthly time series data allows us further to control for seasonality in sales. In a second approach, we estimate a structural multinomial discrete choice model of demand for beverage products (among which is soda) and the implied price elasticity.

3.1. Reduced Form Difference-in-Difference

Our empirical strategy to estimate the average effect of the tax campaign on quantity sold is estimate a difference-in-difference (DID) model comparing purchase behavior for soda (i.e., the treated category) with purchase behaviors for other beverages and for candy[9] (i.e., the control categories). In total, products are categorized into nine group: 1) soda, 2) water, 3) juice, 4) energy drink, 5) milk, 6) coffee, 7) tea, 8) diet soda, and 9) candy. Using data from November 2013 through May 2015, we compare the pre-campaign period (Nov 2013-Jun 2014) to three separate post-campaign periods: 1) Pre-Election (Jul 2014-Oct 2014), 2) Post-Election/Pre-Implementation (Nov 2014-Feb 2015), and 3) Post-Implementation (Mar 2015-May 2015). It is important to note here that while the City of Berkeley implemented the soda tax in March 2015, campus retail did not change their prices until June, which is after our sample period.[10] By comparing the soda purchase behavior in the pre-period to each of these post-campaign periods, we attempt to distinguish the effects of the campaign from the effects of the election and the effects of soda prices increasing off-campus.

In the DID regressions, the products are distinguished by a bar code (UPC) and the outcome of interest is the product's quantity sold. The data are collected by month for each

[9] Candy is a related but not completely substitute category, typically stocked by the campus restaurants in the data.
[10] This was reported to us by campus retail staff and confirmed in the data. The Berkeley Sugar Sweetened Beverage Tax is paid by the distributor, who may or may not pass the cost onto the consumers. Campus dining signs long-term contracts with its distributors, making prices sticky in the short-run.

product. So Q_{igm} is the quantity of product i in product group g and month m. The dummy variable $Soda_{ig}$ is equal to one for products in the treated product category (soda) and is equal to zero for the untreated products (other beverages and candy). Three time dummy variables—$Campaign_m$, $PostElection_m$ and $PostPolicy_m$—define four time periods. The pre-campaign period is when all three are zero, the pre-election campaign period is when $Campaign_m = 1$ and the others equal 0, the post-election, pre-policy period is when $PostElection_m = 1$ and the others equal 0, and the pre-policy period is when $PostPolicy_m = 1$ and the others equal zero. We call these periods "pre," "campaign," "post-election," and "post-policy" periods.

There are three DID specifications, with increasing levels of controls. We start by running the following regression:

$$(1)\quad Q_{igm} = \beta_0 + \beta_1 Price_{igm} + \beta_2 Soda_{ig} + \beta_3 Campaign_m + \beta_4 PostElection_m + \beta_5 PostPolicy_m + \beta_6 Soda{*}Campaign_{gm} + \beta_7 Soda{*}PostElection_{gm} + \beta_8 Soda{*}PostPolicy_{gm} + \varepsilon_{igm}.$$

The coefficient on $Soda_{ig}$ is the treatment group specific effect, and the coefficients on $Campaign_m$, $PostElection_m$, and $PostPolicy_m$ are time period effects, common to the control and treatment categories. The coefficient for $Soda{*}Campaign_{igm}$ is the effect of the campaign on soda sales relative to the control product categories, the coefficient on $Soda{*}PostElection_{igm}$ is the effect of the election, and the coefficient on $Soda{*}PostPolicy_{igm}$ is the effect of the policy change. Although useful for examining the average treatment effect of the tax change on the treated soda categories, specification (1) does not control for potentially important covariates that, if omitted, could lead to a biased estimate of the treatment effect. For example, consumer demand may differ by product group, as well as over time and seasons. To reduce the likelihood that the estimated treatment effects are biased, we next include fixed effects for the nine product groups (α_g) and for the month-of-sample (θ_m):

$$(2)\quad Q_{igm} = \beta_1 Price_{igm} + \beta_2 Soda{*}Campaign_{gm} + \beta_3 Soda{*}PostElection_{gm} + \beta_4 Soda{*}PostPolicy_{gm} \alpha_g + \theta_m + \varepsilon_{igm}.$$

In order to directly estimate price elasticities, we also estimate the model in logs:

$$(3)\quad lnQ_{igm} = \beta_1 lnPrice_{igm} + \beta_2 Soda{*}Campaign_{gm} + \beta_3 Soda{*}PostElection_{gm} + \beta_4 Soda{*}PostPolicy_{gm} + \alpha_g + \theta_m + \varepsilon_{igm}.$$

The identifying assumption of the DID model is that of parallel trends, where soda sales would have continued on the same trend as the other products had it not have been for the campaign. To directly test this assumption, we complement the DID model with the following event study model:

$$(4) \quad Q_{igm} = \beta_1 Price_{igm} + \sum_{m=1}^{17} \beta_l \, (Soda * D_l)_{gm} + \alpha_g + \theta_m + \delta_i + \varepsilon_{igm}.$$

where $(Soda * D_l)_{gm}$ is a set of dummies equaling one for soda products in month-of-sample m. The first month-of-sample (*m=1*) will be the omitted dummy. Thus, equation (4) is the same as equation (3), expect for instead of splitting the sample periods into four periods, we compare soda sales to the untreated products in every month of the sample. The β_l vector is the parameter of interest. We will plot the β_l coefficients over time to trace out the adjustment path from before the campaign to the election and policy implementation. Importantly, if the soda campaign is unassociated with underlying trends, there should be no trend in the β_l in the pre-campaign period.[11]

3.2. Structural Demand and Estimation of Price Elasticity of Soda

We model consumer choice with a random utility model framework, where parameters are estimated with random coefficients to allow for consumer heterogeneity (e.g. Berry, Levinsohn and Pakes, 1995; McFadden and Train, 2000; Nevo, 2000; Nevo, 2003). In our random utility framework both the product attributes as well as a random term are assumed to enter linearly, so that the utility from consuming a certain beverage product *j* at time *t* can be described as

$$(5) \quad U_{jt} = X_{jt}\,\beta + T_{jt}\,\gamma + \xi_j + \varepsilon_{jt}$$

where the matrix X_{jt} contains the attributes of the beverage product, T_{jt} is a vector that has elements equal to one after the campaign and equal to zero otherwise. The vector β represents the marginal utility placed on each of the *X* attributes, γ is the marginal utility with respect to the campaign period. ξ_j are unobserved (to the researcher) determinants of utility but observed by consumers, and ε_{jt} denotes remaining unobserved determinants of utility. Distributional assumptions about the unobserved utility (ε_{jt}, the error term) drive the econometric model choice. The logit demand model assumes that ε_{jit} is iid type I extreme value distributed. Assuming that consumers purchase one unit of product *j* among all the possible products available at a certain time *t* that maximizes their indirect utility, then the market share of product *j* during month *t* is given by the probability that good *j* is chosen.

[11] In future work, we will use the Google trend data (shown in figure 2) to interact the treatment effect with the media coverage variable in order to measure the effect of media intensity on soda consumption.

The logit model is estimated using Berry's (1994) approach to linearize the choice model equation. Given the predicted market shares or probabilities equal to:

$$(6) \qquad Prob_j = s_j = \frac{e^{Xjt\,\beta + Tjt\,\gamma + \xi j}}{\sum_{k=0}^{N} e^{Xkt\,\beta + Tkt\,\gamma + \xi k}}$$

and given that the mean utility of not buying any alternative, that we define as the outside option good j=0, is normalized to 0, then:

$$(7)\ Prob_0 = s_0 = \frac{e^0}{e^0 + \sum_{k=1}^{N} e^{Xkt\,\beta + Tkt\,\gamma + \xi k}} = \frac{1}{1 + \sum_{k=1}^{N} e^{Xkt\,\beta + Tkt\,\gamma + \xi k}}.$$

Taking the natural logarithm of the probability in (6) and subtracting the log of the probability of not buying yields (7):

$$(8)\ ln(Prob_j) - ln(Prob_0) = ln\left(\frac{e^{Xjt\,\beta + Tjt\,\gamma + \xi j}}{1 + \sum_{k=1}^{N} e^{Xkt\,\beta + Tkt\,\gamma + \xi k}}\right) - ln\left(\frac{1}{1 + \sum_{k=1}^{N} e^{Xkt\,\beta + Tkt\,\gamma + \xi k}}\right) \Leftrightarrow$$

$$(9) \qquad ln(Prob_j) - ln(Prob_0) = X_{jt}\beta + Tjt\,\gamma + \xi_{jt}\ .$$

It follows that the estimation of the logit model is obtained by regressing the dependent variable in (9), which is the log of each product's observed market share minus the log of the market share of not purchasing, on the variables entering the mean utility, such as price, product type, tax campaign changes, and product attributes.

To sum up, using the panel dataset of beverage product purchases, we estimate a random utility choice model (RUM) of consumer demand for beverage products, including soda. Each beverage product is defined as a bundle of attributes, including price, manufacturer brand, size, product type. Model identification of the price sensitivity parameter, which is central in estimating price elasticities, comes from the fact that prices of products are set at the central level and do not get set depending on demand factors in each campus retailer. Secondary to the primary analysis, we conduct a posterior analysis on the estimated product fixed effects from the primary logit analysis. Using generalized least squares (GLS), we regress the product fixed effects on several time invariant product characteristics.

4. Results

4.1. Average Treatment Effect of the Sugar Tax Campaign on Soda Consumption

We present the results from the reduced form specification of equations (1) to (3) in table 1, where the dependent variable in all columns is the average quantity sold of a product in a certain month, except for column (4) which is in logs. The columns in table 1 are organized as follows: column (1) reports the results from the specification of equation (1); column (2) adds product group fixed effects; column (3) adds month-of-sample fixed effects; and column (4) replicates column (3) in logs. The parameters of interest are the three interactions of the soda indicator and the campaign indicators.

The price coefficient is statistically different from zero and negative in almost all specifications. Thus as one would expect, as price goes up demand goes down. Given the log-log specification in column (4), we can interpret the coefficient on Price per Item (log) in column (4) as a price elasticity. This elasticity estimate equals -0.438, which means we have estimated demand for beverage and the control categories to be inelastic.

From table 1 column (3), we see that consumer purchases of soda relative to the other products is not significantly different in the campaign period. However, on average 113 fewer soda products (or 42 percent fewer) were sold during the post-election period, and 176 fewer soda products (or 65 percent fewer) were sold during the post-policy period, relative to products other than soda in the pre-campaign period. Performing an F-test on the difference between the estimates "Soda*Post-Election" and "Soda*Post-Policy" indicates that these estimates are statistically different from one another at a p-value of 0.091, indicating that that the decline in soda is larger in the post-policy period than in the post-election period. However, the results we find in levels, do not hold in logs, as shown by comparing column (3) and (4). In column (4), the estimates on the soda indicator and campaign indicators are positive instead of negative.

4.2. Average Treatment Effect of the Sugar Tax Campaign on Soda Consumption, by Product Group

To further understand whether and how consumers switch away from soda, we estimate equations (2) and (3) comparing soda to each of the other product groups individually. Table 2 presents the results using equation (2) and table 3 present the results using equation (3). Each column includes the products in the soda category and the products in one other category. In table 2, when using levels, we find that the soda tax campaign leads to fewer purchases of soda compared to all other categories, except for milk (column 4). For the campaign period, only relative to coffee (column 5) and diet soda (column 7) do soda sales decrease significantly compared to the pre-campaign period. For the post-election and post-policy period, the quantity of soda sold declines compared to the majority of other products (i.e., the coefficients in the rows "Soda*Post-Election" and "Soda*Post-Policy" are negative and statistically different from zero in almost every column), with the magnitude of the declines larger in the post-policy period than in the post-election period.

In table 3, when using logs, the results again look different than using levels. Only in column (7), when comparing soda to diet soda, do we find significant decreases in soda sales due to the campaign. This result suggests that consumers switch away from regular soda towards diet soda. In future work we will continue to explore the robustness and sensitivity of our results.

4.3. Event Study

Given the interesting patterns we find in the DID results, with the treatment effects being largest in the post-policy period, we next explore the parallel trends assumption and the dynamics the treatment effects over time using our event study model. Figure 3 plots the estimates we obtain from equation (4), with the β_l plotted in black and the 10 percent confidence intervals plotted in gray. The vertical red lines separate the sample into the four treatment periods. The omitted dummy is D_1, which corresponds to January 2014.

In the periods before the election, we find roughly parallel trends, with none of the β_l statistically different from zero. However, after the election in November 2014, the β_l estimates begin to decline, indicating that soda sales dropped relative to the other category groups. By the time the city implements the policy in March 2015 (in the city of Berkeley but not on campus yet), the β_l are no longer declining, but are at a constant level significantly lower than the pre-campaign period. These event study results are suggestive that the election and campaign drove much of the decline in soda sales. In future work, we will use subsequent data from when the tax was implemented on campus to compare the effects of the campaign versus the effects of the tax itself.

4.5. Structural Demand and Beverage Price Elasticity

Table 4 reports the marginal utility estimates for the discrete choice demand model of the probability of purchasing a particular beverage product in a month as a function of beverage products attributes, as given by equation (9). Product attributes consist of (i) time invariant product determinants of demand captured by product fixed effects, and (ii) time changing attributes such as price. In all columns in table 4, the dependent variable is the log of a product market share minus the log of the market share of the outside option of not buying a beverage. Water is the base category or reference group, and it is not listed in the rows of table 4.

In column (1) we present the OLS model results without fixed effects, in column (2) we add month-of-sample fixed effects, and in column (3) we additionally include product fixed effects. Because product group attributes are time invariant, in column (3) they are multicollinear with product fixed effects. Therefore, to recover those coefficients, we perform a generalized least squares (GLS) regression projecting the estimated product group fixed effects from the specification in column (3) of table 4 on the time invariant product characteristics, labeled by (^): soda, juice, coffee, diet, energy drink, tea, milk, and size.

Starting with column (1), we see that with omitted fixed effects the price coefficient is biased towards zero. Once we control for both month-of-sample and product fixed effects (column 3), the price point estimate becomes negative, and significantly different from zero (-0.740). Looking at the product group attributes in column (3), the empirical results suggest that consumers perceive beverages as differentiated products. Consumers place a significant negative marginal utility on coffee, juice, and energy drink categories relative to buying water, whereas the marginal utility estimates for soda and milk are not statistically different from water.

Willingness to pay (WTP) estimates are calculated by dividing each marginal utility estimate in column (3) by the absolute value of the estimated price coefficient in column (3). For example, the WTP for soda is computed by dividing the marginal utility of soda by the absolute value of the marginal utility of price (i.e., 0.077/0.740 = 0.104), implying consumers are WTP 10.4 cents less for soda than for water. On the other hand, consumers are willing to pay 1.46 and 1.53 dollars less for juice and coffee than for water.

Finally, we use the structural demand model to estimate the implied own price elasticities for soda and for other beverage categories. Given the logit demand specification, the own price elasticities are recovered by taking a derivative of the probability of buying each product with respect to the own product's price, multiplying by average price and dividing by average quantity, which gives the following expression:

$$\epsilon_{jj} = \alpha_{price} s_j \left(1 - s_j\right),$$

where α_{price} is the marginal utility with respect to price. The average own price elasticities' estimates for each of the beverage categories and their standard errors are reported in table 5.

We estimate that bottled water is an elastic good, with an own price elasticity of -1.6, while all the other beverages are estimated to be inelastic, given that their own price elasticity is less than one in absolute value. In particular, soda has an own price elasticity of -0.72. Given the product size of soda, we can compute the average price per ounce of a soda product, which is 9.7 cents. A 1 cent soda tax per ounce of soda corresponds to a 10.3 percent soda price increase when the tax is added. Given the soda elasticity estimate, we predict that soda quantity sold will drop by 7.4 percent when price increases by 10.3 percent, implying that total revenue of soda sold will increase due to the soda tax.

5. Conclusions

This paper uses a detailed, product-level dataset of quantities sold over time to measure the quantity response to a soda tax campaign. We estimate a 42 percent drop in soda consumption in response to the campaign relative to other beverage and candy products. These finding have implications for measuring the actual policy effect, given the campaign itself altered consumption behavior even before a price change due to the tax.

We develop and estimate a structural model of beverage demand, providing an analysis of actual consumer responses that will estimate directly revealed preferences and willingness to pay for beverage product characteristics captured by price and product type. In so doing, we provide policymakers with important information on the efficacy of tax induced price changes as well as a barometer reading on consumer preferences for soda and substitute beverages, subject to negative advertising campaigns for soda.

The structural demand estimates further reinforce the reduced form findings that soda is an inelastic good. Therefore significant revenue can be raised from taxing soda without causing large deadweight losses. However, the low price elasticity means that a very high levy would be necessary to significantly change the behavior of buying soda in order to reduce sugar consumption and impact health. In future work, using post-tax implementation data we can confront the quantity changes predicted by the structural model with the actual quantity changes from the post-tax prices.

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Appendix

Figure A.1. Source: http://www.berkeleyvsbigsoda.com/

Measure D Ballot question - November 2014 Election

Shall an ordinance imposing a 1¢ per ounce general tax on the distribution of sugar-sweetened beverages (e.g., sodas, energy drinks, presweetened teas) and sweeteners used to sweeten such drinks, but exempting: (1) sweeteners (e.g., sugar, honey, syrups) typically used by consumers and distributed to grocery stores; (2) drinks and sweeteners distributed to very small retailers; (3) diet drinks, milk products, 100% juice, baby formula, alcohol, or drinks taken for medical reasons, be adopted? YES ____ NO _____

Source: Ballot Question. City of Berkeley website. Online. [*accessed May 23, 2016*]. Full text of ordinance. City of Berkeley website. Online. [*accessed May 23, 2016*].

Table 1: Difference-in-Difference: Effect of Soda Tax on Campus Retail Soda Sales

	(1) Quantity Sold	(2) Quantity Sold	(3) Quantity Sold	(4) Log Qty Sold
Price per Item	-8.017***	-4.016***	-3.577***	
	(1.568)	(0.926)	(0.964)	
Soda=1	62.705			
	(74.405)			
Campaign=1	-133.201***	-129.729***		
	(42.287)	(32.574)		
Post-Election=1	-148.936***	-140.264***		
	(39.775)	(30.970)		
Post-Policy=1	-54.571	-36.675		
	(54.906)	(43.906)		
Soda=1 × Campaign=1	12.885	8.962	3.205	0.262***
	(93.381)	(89.510)	(32.569)	(0.092)
Soda=1 × Post-Election=1	-99.727	-109.035	-112.875***	0.340***
	(81.445)	(77.649)	(38.012)	(0.102)
Soda=1 × Post-Policy=1	-184.971*	-203.582**	-175.823***	0.031
	(102.735)	(97.481)	(37.148)	(0.139)
Price per Item (log)				-0.438***
				(0.070)
Mean of Dep. Variable	268.910	268.910	268.910	4.050
Num of Obs.	4178	4178	4178	4178
R squared	0.009	0.050	0.072	0.199
Product Group FE	No	Yes	Yes	Yes
Month-of-Sample FE	No	No	Yes	Yes

Clustered errors in parentheses. Clusters are at the product group by month-of-sample level. The outcome variable is the quantity of products sold per month. Products are categorized into eight groups: 1) Soda, 2) Water, 3) Juice, 4) Energy drink, 5) Milk, 6) Coffee, 7) Tea, 8) Diet soda, and 9) Candy.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 2: Difference-in-Difference: Effect of Soda Tax on Campus Retail Soda Sales
(*Product Group Comparisons—levels*)

	(1) Soda|Water	(2) Soda|Juice	(3) Soda|Energy	(4) Soda|Milk	(5) Soda|Coffee	(6) Soda|Tea	(7) Soda|Diet	(8) Soda|Candy
Price per Item	361.226***	25.233***	-4.304***	-176.697***	165.988***	336.263***	215.467***	-70.707***
	(85.834)	(6.867)	(0.700)	(50.573)	(29.978)	(62.831)	(62.469)	(19.566)
Soda=1 × Campaign=1	108.451	29.044	-8.273	384.681***	-108.751***	-60.662	-179.898***	-12.536
	(94.840)	(25.283)	(32.860)	(78.824)	(30.369)	(45.722)	(47.410)	(51.054)
Soda=1 × Post-Election=1	-345.181	-73.711***	-103.038***	373.525***	-218.972***	-195.210***	-401.923***	-123.396***
	(264.899)	(26.179)	(25.925)	(89.275)	(32.863)	(39.962)	(45.324)	(37.523)
Soda=1 × Post-Policy=1	-1231.852**	-120.983***	-126.866***	308.221***	-264.729***	-233.048***	-487.559***	-159.786***
	(605.064)	(20.182)	(29.600)	(86.714)	(27.653)	(39.064)	(41.094)	(49.281)
Mean of Dep. Variable	547.863	286.298	208.683	314.460	262.349	271.907	260.892	185.337
Num of Obs.	483	1595	1389	450	564	558	361	808
R squared	0.114	0.039	0.052	0.088	0.052	0.066	0.055	0.043
Product Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered errors in parentheses. Clusters are at the product group by month-of-sample level. The outcome variable is the quantity of products sold per month (logged). Products are categorized into nine groups: 1) Soda, 2) Water, 3) Juice, 4) Energy drink, 5) Milk, 6) Coffee, 7) Tea, 8) Diet soda, and 9) Candy. Each columns includes the products in Soda and the products from one of the other eight product groups.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 3: Difference-in-Difference: Effect of Soda Tax on Campus Retail Soda Sales
(*Product Group Comparisons—logs*)

	(1) Soda|Water	(2) Soda|Juice	(3) Soda|Energy	(4) Soda|Milk	(5) Soda|Coffee	(6) Soda|Tea	(7) Soda|Diet	(8) Soda|Candy
Price per Item (log)	0.333	-0.353***	-0.517***	-1.308***	-0.105	0.204	-0.551**	-0.545**
	(0.338)	(0.097)	(0.096)	(0.147)	(0.255)	(0.339)	(0.270)	(0.201)
Soda=1 × Campaign=1	0.491**	0.113	0.257*	1.696***	0.064	0.258*	-0.629***	0.450***
	(0.188)	(0.077)	(0.136)	(0.214)	(0.136)	(0.139)	(0.190)	(0.116)
Soda=1 × Post-Election=1	0.733**	0.134	0.489***	1.928***	0.021	0.259**	-0.973***	0.464***
	(0.361)	(0.089)	(0.111)	(0.219)	(0.088)	(0.123)	(0.144)	(0.092)
Soda=1 × Post-Policy=1	-0.367	-0.109	0.188	1.730***	-0.201	0.070	-1.278***	0.146
	(0.334)	(0.106)	(0.159)	(0.198)	(0.137)	(0.101)	(0.182)	(0.210)
Mean of Dep. Variable	4.336	4.125	3.914	4.264	4.284	4.186	4.118	3.710
Num of Obs.	483	1595	1389	450	564	558	361	808
R squared	0.161	0.210	0.186	0.276	0.259	0.215	0.307	0.234
Product Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-Sample FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Clustered errors in parentheses. Clusters are at the product group by month-of-sample level. The outcome variable is the quantity of products sold per month (logged). Products are categorized into nine groups: 1) Soda, 2) Water, 3) Juice, 4) Energy drink, 5) Milk, 6) Coffee, 7) Tea, 8) Diet soda, and 9) Candy. Each columns includes the products in Soda and the products from one of the other eight product groups.

$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

Table 4: Logit Beverage Demand Estimates

	(1) $ln(s_j) - ln(s_0)$	(2) $ln(s_j) - ln(s_0)$	(3) $ln(s_j) - ln(s_0)$
Price per Item	0.001	0.152***	-0.740***
	(0.041)	(0.039)	(0.178)
Soda		-0.826***	-0.077
		(0.182)	(0.121)^
Juice		-0.816***	-1.083***
		(0.169)	(0.150)^
Coffee		-0.920***	-1.131***
		(0.182)	(0.131)^
Diet Soda		-0.792***	-0.218**
		(0.210)	(0.093)^
Energy Drink		-1.048***	-0.848***
		(0.165)	(0.115)^
Tea		-0.861***	-0.449***
		(0.179)	(0.106)^
Milk		-0.524***	0.200
		(0.202)	(0.243)^
Size (fl oz)		0.011**	-0.001
		(0.005)	(0.007)^
Constant	-1.367***	-1.138***	-1.235***
	(0.120)	(0.207)	(0.170)
Num of Obs.	1333	1333	1333
R squared	0.000	0.551	0.928
Month-of-Sample FE	No	Yes	Yes
Product FE	No	No	Yes

Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. Column (3) reports (^) GLS estimates from regressing product fixed effects on product attributes.

Table 5: Logit Own Demand Price Elasticities Estimates

	Elasticity	Std
Soda	-0.72	(0.17)
Juice	-0.54	(0.13)
Coffee	-0.41	(0.10)
Diet	-0.19	(0.05)
Energy Drink	-0.44	(0.10)
Tea	-0.60	(0.14)
Milk	-0.23	(0.05)
Water	-1.58	(0.74)

Robust standard errors in parentheses.

Figure 1: Pre-Soda Tax Campaign: Monthly Quantities Sold by Product Group

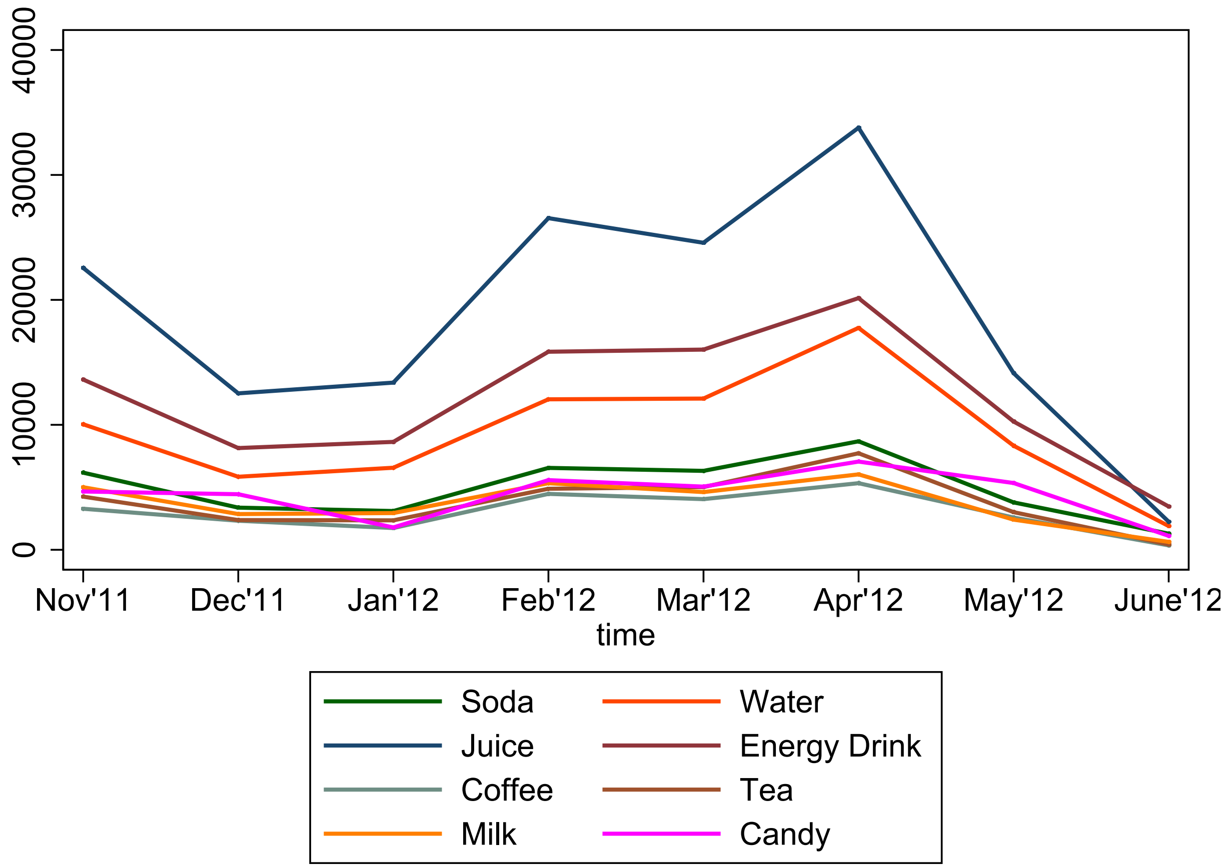
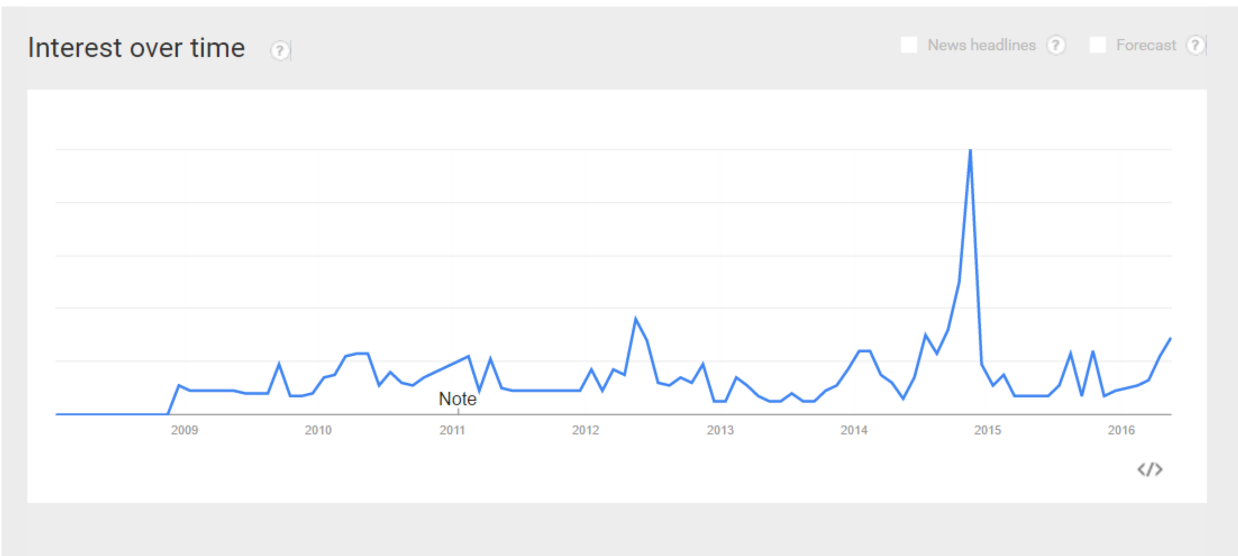


Figure 2: News Coverage of "Soda Tax" in the San Francisco Bay Area



Source: Google Trends. Online. [*accessed May 22, 2016*].

Figure 3: Event Study: Effect Soda Tax on Campus Retail Soda Sales