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By Ounce or By Calorie: The Different Effects of Alternative Sugar-Sweetened Beverage Tax Strategies

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June 2013

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC August 4-6, 2013

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Acknowledgement: We thank Tamara Dumanovsky, Ann Lowenfels, and Anne Sperling for helpful discussions. Financial supports are provided by grants from the Robert Wood Johnson Foundation's Healthy Eating Research Program (66971), Centers for Disease Control and Prevention (3U58DP001963-01S4), and National Institute of Health (1R21HL108121). The findings and conclusions in this article are those of the authors and do not represent the views of the New York State Department of Health, New York City Department of Health and Mental Hygiene, or the Centers for Disease Control and Prevention.

ABSTRACT

The obesity epidemic and excessive consumption of sugary beverages has led to proposals of economics-based interventions to promote healthy eating. We quantify the differential effects of taxing sugar-sweetened beverages by calories and by ounce on consumer demand, using a fully modified distance metric model of differentiated product demand that endogenizes the representation of group and rival product prices. The novel demand model outperformed the conventional distance metric model in both goodness-of-fit and economic significance of model predictions. A calorie-based beverage tax was estimated to cost \$0.29 less in consumer's surplus per 1,000 beverage calories reduced than an ounce-based tax.

Keywords: obesity, sugar-sweetened beverage tax, distance metric demand model

JEL codes: D12, D61, H20

With obesity rates remaining at epidemic levels in the United States (Ogden et al., 2012) and obesity-related noncommunicable diseases inflicting large economic burdens on society, public policy makers have given increased consideration to policies with potential to promote healthy eating. To address the fundamental imbalance between energy intake through foods and energy expenditure that underlies excess body weight, policy proposals have targeted calorie-dense foods with minimal nutritional value. Sugar-sweetened beverages (SSBs), which include carbonated soft drinks (CSDs), fruit drinks, and sports and energy drinks, accounted for an estimated 7% of total energy intake for an average American in 2005–2006 (National Cancer Institute 2010) and are a significant risk factor for obesity and obesity-related health complications (e.g., Schulze et al. 2004). Therefore, public health advocates and some policy makers have made SSBs the focus of potential policy interventions.

Policy interventions aimed at reducing SSB intake have focused on two factors affecting demand: accessibility and affordability. Examples of access restrictions include state or local bans on regular or all carbonated soft drinks in schools (Huang and Kiesel 2012) and policies that limit the availability of SSBs at meetings and events (New York City Department of Health, 2013). Targeted taxes on SSBs represent the most common policy aimed at making SSBs less affordable. In 2012, eight states and two cities filed SSB tax legislation (Rudd Center for Food Policy & Obesity, 2013). New York City's proposed policy restricting the sale of SSBs to containers no more than 16 ounces in size in food service establishments was intended to reduce access to SSBs in large portion sizes.

Interventions aimed at restricting access to SSBs have received relatively broad support from public health advocates and the public. Recently, the use of pricing strategies to reduce energy intake for the overall population has been debated. A number of states currently apply a sales tax to soft drinks, including SSBs. However, the existing tax rates on soft drinks are trivial, on average 5% of the retail price (Bridging the Gap 2011), and are not reflected in the posted shelf price. Hence, a small sales tax is not expected to substantively reduce consumption and obesity (Zheng et al. 2013). Notwithstanding numerous state and municipal legislative attempts to enact larger SSB excise taxes in magnitudes up to 1 cent per ounce of SSB, no jurisdiction has enacted such a large SSB tax. Although many leading public health institutions have come out in support of SSB taxes as a health improvement strategy, others have concerns about the economic implications of SSB taxes. Taxing SSBs may have the unintended consequence of causing consumers to substitute other calorie-dense but untaxed beverages and foods (Fletcher et al. 2010). An SSB tax may also reduce consumer surplus in the short run before any potential long-term health benefits are realized. Despite a reduction in short-term consumer surplus, taxing SSBs represents an important policy tool to address obesity because of consumers' responsiveness to price and its potential to have population impacts on health and long-term economic wellbeing, such as reduced medical costs.

If a tax on SSBs were to be implemented, the optimal strategy would achieve a given level of reduction in SSB calories at the lowest cost to consumer surplus. The majority of existing SSB excise tax proposals specify levying a per volume tax (i.e., cent

per ounce). Such a strategy does not consider that a large variety of SSB products on the market are differentiated by brand, flavor and most importantly, caloric content. For example, the 91 top-selling SSB products in New York markets over the 2007–2011 period had an average energy content of 91.6 kcal/8-ounce serving with a standard deviation of 33.7.¹ Assuming similar administrative costs across alternative SSB tax strategies, a tax levied based on the caloric density of an SSB product would presumably be more efficient in reducing SSB calories than an ounce-based SSB tax.

The objective of this study is to quantify the efficiency gain from a calorie-based tax scheme compared with an ounce-based one using parameter estimates from a product-level demand model. Our product-level demand model encompasses 178 beverage products accounting for 95% of all nonalcoholic regular and diet beverages (excluding milk, liquid coffee and tea, and soft drink powder) in volume in four New York markets. We measured SSB tax efficiency by per capita compensating variation (CV) per thousand beverage calories reduced. The extant literature on SSB demand (Zhen et al. 2011, 2013; Dharmasena and Capps 2012; Lin et al. 2011; Finkelstein et al. 2013) simulates the effects of ounce-based SSB taxes using parameters estimated from category-level demand models, where product-level substitutions are not explicitly modeled. Because a calorie-based SSB tax changes the relative prices of SSB products of different energy levels, it is essential that product-level substitutions be estimated. By allowing for product-level substitutions, our study fills an important gap in the SSB tax literature.

We also contribute to the methodology literature on modeling demand for differentiated products. Our demand model is based on the distance metric (DM)

approach originated by Pinkse et al. (2002) to specifying cross-price effects among differentiated products based on their closeness in product attributes. The linear approximate almost ideal demand system (AIDS) of Deaton and Muellbauer (1980) is the most popular functional form in the DM literature. We identified two common practices in previous applications of the DM method to improve. First, in applying the DM method to the AIDS model, previous studies (Rojas and Peterson 2008; Pofahl and Richards 2009; Bonanno 2013) have used the Laspeyres price index, where product prices are weighted by *base* budget shares, as the deflator for total expenditures. Second, in the demand equation for each product, the cross-price variables that are used to measure the cross-price effects were calculated as the *unweighted* means of rival product prices. With both practices, when there are large changes in relative prices, for example, caused by a large targeted food tax, the assumption that budget shares are fixed is not tenable. This makes the Laspeyres index and unweighted mean cross prices less accurate in representing true price variations in a DM AIDS model.

To account for the effects of concurrent changes in product budget shares on deflated total expenditures and the cross-price terms, we modified the conventional DM AIDS by using the Stone price to deflate total expenditures and by using mean rival prices weighted by current-period budget shares to measure the cross-price effects of demand. We derived the correct conditional and unconditional price elasticities for the fully modified DM AIDS.

We applied the conventional and the fully modified DM AIDS to supermarket scanner data on nonalcoholic beverage sales in four New York markets. The fully

modified model was found to outperform the conventional model in goodness-of-fit measures and to generate significantly higher degrees of product substitution than the conventional model. Our simulation based on demand estimates from the fully modified model suggests that a calorie-based SSB tax would cost \$0.29 less in per capita consumer surplus loss per 1,000 kcal of beverage energy reduced than an ounce-based SSB tax. We demonstrate that the conventional DM AIDS underestimates the reduction in consumer surplus loss, attainable by switching from an ounce-based SSB tax to a calorie-based one, by a factor of more than three.

BEVERAGE DEMAND AND THE DM METHOD

Because no state has enacted a large targeted tax on SSBs and existing small sales taxes on soft drinks do not distinguish between full-calorie and diet beverages, studies of targeted SSB taxes have relied on simulation. In this approach, a demand model is estimated at the category level, and the demand parameter estimates are used to predict the effects of tax-induced SSB price changes on beverage and food demand. Zhen et al. (2011) examined household demand for nine nonalcoholic beverages using a dynamic AIDS and found evidence for habit formation in all beverage categories. Dharmasena and Capps (2012) and Lin et al. (2011) estimated beverage demand under static AIDS models and simulated the effects of SSB taxes on beverage consumption and body weight.

Two studies have attempted to predict the effect of a large SSB tax on demand for selected food categories. Finkelstein et al. (2013) estimated a two-part reduced-form model of food and beverage demand and did not find significant substitution between SSBs and the food categories examined in their study. In contrast, Zhen et al. (2013) used

a utility-theoretic incomplete demand system and found that about one-half of the reduction in SSB calories would be compensated by an increase in energy intake from food.

For most food and beverage categories on the U.S. market, there are a large number of products within a category that are differentiated by various attributes. In the most unrestricted product-level demand model, the number of price coefficients is equal to n^2 , where n is the number of products. Although imposing the symmetry, homogeneity, and adding-up restrictions helps reduce the number of parameters, the dimension of the parameter space is still too large to estimate for a model with more than a few dozen products. All five studies of SSB demand above circumvented this dimensionality issue by aggregating purchases to the category level but at the expense of not being able to model product-level demand. To compare the performance of an ounce-based tax with a calorie-based tax, we needed to specify an alternative approach to confronting the constraint imposed by dimensionality.

Three conventional approaches have been used to reduce the dimension of the parameter space. First, assuming the consumer chooses at most one unit of a product in a category at each shopping trip, a family of discrete-choice models is available for modeling product substitutions within a category (e.g., Nevo 2001). However, this approach does not shed light on consumer choices among categories. The second approach uses multistage budgeting to limit the number of products or product categories the consumer has to choose from at each stage of the budget decision (e.g., Ellison et al. 1997). Although this method no longer restricts the consumer to one unit of a product as

a discrete-choice model does, it places restrictions on substitution or complement effects between products classified into different categories. Because products can often be categorized in more than one way, the estimated product-level cross-price effects are dependent on the categorization specified. In addition, if there are a large number of products, more than two budgeting stages may be needed to keep the number of goods (e.g., individual products, categories, or groups of categories) tractable at each stage. The third approach, the DM method proposed by Pinkse et al. (2002), specifies the cross-price effect between two products as a function of the distance between the two in attribute space. When there are fewer product attributes than the number of products, the DM method solves the dimensionality problem by casting the n^2 -dimensional price effects into the lower-dimensional attribute space. In contrast to the discrete-choice models, the DM method assumes that the consumer can purchase any number of products within the budget constraint. Unlike the multistage budgeting approach to dimension reduction, the cross-price effects in the DM method are not solely determined by a categorization scheme but also by other product attributes. A DM-based demand model is linear in parameters. This is an important practical advantage over the highly nonlinear random coefficient discrete-choice model in light of the recent findings about the numerical performance of the latter (Dubé et al. 2012; Knittel and Metaxoglou 2013).

THE FULLY MODIFIED DM AIDS

We used the following linear approximate AIDS to represent preferences for beverage products

$$(1) \quad w_{iht} = \alpha_{iht} + \gamma_{ii} \ln p_{iht} + \sum_{j \in N_{-i,ht}} \gamma_{ij,ht} \ln p_{jht} + \beta_i \ln(x_{ht}/P_{ht})$$

where w_{iht} is the budget share of product i in market h and period t ; p_{jht} is the price of product j normalized to one at product-specific sample mean (Moschini, 1995); x_{ht} is per capita total beverage expenditure; $\ln P_{ht} = \sum_{j \in N_{ht}} w_{jht} \ln p_{jht}$ is the Stone price index for deflating total expenditures; N_{ht} represents the full set of products available in market h and period t ; set $N_{-i,ht}$ excludes product i but otherwise equals N_{ht} ; and α , γ , and β are parameters. The conventional DM AIDS specified P_{ht} as a Laspeyres index, that is, $\ln P_{ht} = \sum_{j \in N_{ht}} w_{j0} \ln p_{jht}$, where w_{j0} is the base share of product j . There are two concerns with using the Laspeyres price as the expenditure deflator. First, because the Laspeyres index does not account for budget share changes, it may be a less accurate index when changes in relative prices are large. Second, one of the main motivations for applying the DM method is its ability to model demand for a large number of products. As the product set N_{ht} gets larger, it becomes more likely that not all products are sold in all markets and time periods. In this case, $\sum_{j \in N_{ht}} w_{j0}$ is not guaranteed to be one for all h and t , which is required for a budget share-weighted price index. In this study, we used the Stone price index to address these concerns. Because budget shares appear on both sides of equation (1), we used instrumental variables to account for this simultaneity (see the “Estimation and Results” section for estimation details).

The DM method reduces the dimension of the parameter space by specifying the cross-price effect between two products to be functions of their closeness in attribute space. Although some studies also restrict the own-price coefficients (γ_{ii}) and

expenditure coefficients (β_i) to be functions of product attributes (Pinkse and Slade 2004; Rojas and Peterson 2008; Bonanno 2013), we do not impose these restrictions to give full flexibility to the estimated own-price and expenditure effects. In our fully modified DM AIDS, the cross-price coefficient $\gamma_{ij,ht}$ ($i \neq j$) is a function of observed discrete product attributes:

$$(2) \quad \gamma_{ij,ht} = \sum_{m=1}^M d_{m,i,ht} w_{m,ij,ht}^*,$$

where $d_{m,i,ht} = d_m + d_{m,w} w_{iht}$, d_m and $d_{m,w}$ are parameters associated with the m th discrete attribute, and M is the total number of discrete attributes. The term $w_{m,ij,ht}^*$ is used to weigh the effect of product j 's price on demand for product i through the m th attribute and is defined as

$$(3) \quad w_{m,ij,ht}^* = \begin{cases} \frac{w_{jht} \kappa_{m,ij}}{\sum_{k \in N_{-i,ht}} w_{kht} \kappa_{m,ik}}, & \text{if } \sum_{k \in N_{-i,ht}} w_{kht} \kappa_{m,ik} \neq 0 \\ 0, & \text{otherwise} \end{cases}$$

where $\kappa_{m,ij}$ is a binary variable equal to 1 if product i and its rival j share the m th attribute (e.g., flavor or product category), and 0 otherwise.

Several considerations led to the specification of equation (2). First, because not all products are available for all markets and time periods, $w_{m,ij,ht}^*$ was constructed such that $\sum_{j \in N_{-i,ht}} w_{m,ij,ht}^* = 1$ for all h and t . It then follows that $\sum_{j \in N_{-i,ht}} w_{m,ij,ht}^* \ln p_{jht}$ is the share-weighted average price of rival products that take the same value in the m th

attribute as product i . The intuition is that demand for a product is more affected by prices of rivals with similar attributes than prices of more dissimilar products. In a conventional DM AIDS, $w_{m,ij,ht}^*$ is reduced to $w_{m,ij,ht}^* = \kappa_{m,ij} / \sum_{k \in N_{-i,ht}} \kappa_{m,ik}$ for $\sum_{k \in N_{-i,ht}} \kappa_{m,ik} \neq 0$, and 0 otherwise; and $\sum_{j \in N_{-i,ht}} w_{m,ij,ht}^* \ln p_{jht}$ becomes the *unweighted* average price of rival products. When there are large variations in product market share, share-weighted rival prices may be more accurate than unweighted rival prices in capturing the degree of price competition.

Second, the magnitude of the effect on demand of a unit change in the share-weighted average price of rival products might not be uniform across products. The coefficient $d_{m,w}$ is interacted with w_{iht} to account for this heterogeneity in cross-price effects. In contrast, $d_{m,w}$ is set to zero in a conventional DM AIDS model or in restricted versions of the fully modified model.

Conditional Price Elasticities

Deriving elasticities for the fully modified DM AIDS is complicated by budget shares appearing on both sides of equation (1). For brevity of notation, we dropped the market and time subscripts h and t from the mathematical expressions for elasticities. The Marshallian price elasticity conditional on total beverage expenditures is

$$(4) \quad \eta_{ij} = \frac{d \ln q_i}{d \ln p_j} = -\delta_{ij} + \frac{d \ln w_i}{d \ln p_j} = -\delta_{ij} + \frac{1}{w_i} \left\{ \gamma_{ij} + \sum_{r \in N_{-i}} \ln p_r \frac{\partial \gamma_{ir}}{\partial \ln p_j} - \beta_i \frac{\partial \ln P}{\partial \ln p_j} \right\},$$

where q_i is the quantity of product i ; $\delta_{ij} = 1$ for $i = j$, and 0 otherwise;

$$\frac{\partial \gamma_{ir}}{\partial \ln p_j} = \sum_{m=1}^M \left\{ d_{m,i} \frac{\partial w_{m,ir}^*}{\partial \ln p_j} + w_{m,ir}^* d_{m,w} \frac{\partial w_i}{\partial \ln p_j} \right\}; \text{ and } \frac{\partial \ln P}{\partial \ln p_j} = w_j + \sum_{r \in N} w_r \ln p_r \frac{\partial \ln w_r}{\partial \ln p_j}$$

(Green and Alston 1990). Differentiating $w_{m,ir}^*$ ($i \neq r$) with respect to $\ln p_j$ yields

$$(5) \quad \begin{aligned} \frac{\partial w_{m,ir}^*}{\partial \ln p_j} &= \frac{w_r \kappa_{m,ir}}{\sum_{k \in N_{-i}} w_k \kappa_{m,ik}} \left\{ \frac{\partial \ln w_r}{\partial \ln p_j} - \frac{1}{\sum_{k \in N_{-i}} w_k \kappa_{m,ik}} \left[\sum_{k \in N_{-i}} w_k \kappa_{m,ik} \frac{\partial \ln w_k}{\partial \ln p_j} \right] \right\} \\ &= w_{m,ir}^* \left[\delta_{rj} + \eta_{rj} - \sum_{k \in N_{-i}} w_{m,ik}^* (\delta_{kj} + \eta_{kj}) \right] \end{aligned}$$

Substituting (5) into (4) gives

$$(6) \quad \eta_{ij} = -\delta_{ij} + \frac{1}{w_i} \left\{ \begin{aligned} &\gamma_{ij} + \sum_{r \in N_{-i}} \sum_{m=1}^M d_{m,i} w_{m,ir}^* \ln p_r \left[\delta_{rj} + \eta_{rj} - \sum_{k \in N_{-i}} w_{m,ik}^* (\delta_{kj} + \eta_{kj}) \right] \\ &+ \sum_{r \in N_{-i}} \sum_{m=1}^M d_{m,w} w_{m,ir}^* w_i \ln p_r [\delta_{ij} + \eta_{ij}] \\ &- \beta_i \left[w_j + \sum_{r \in N} w_r \ln p_r (\delta_{rj} + \eta_{rj}) \right] \end{aligned} \right\}.$$

Equation (6) can be written in matrix form as

$$(7) \quad \begin{aligned} E &= A + B \left[\sum_{m=1}^M D_m \right] (E + I) - B \left[\sum_{m=1}^M H_m F_m \right] (E + I) + \left[\sum_{m=1}^M D_{m,w} \right] (E + I) \\ &\quad - (UV)(E + I) \end{aligned}$$

where the matrix elements are $E_{ij} = \eta_{ij}$ in E ($n \times n$ matrix), $A_{ij} = -1_{ij} + \gamma_{ij}/w_i - \beta_i w_j/w_i$

in A ($n \times n$ matrix), $B_{ii} = 1/w_i$ in B ($n \times n$ diagonal matrix), $D_{m,ij} = d_{m,i} w_{m,ij}^* \ln p_j$ in D_m

($n \times n$ matrix), $D_{m,w,ii} = \sum_{r \in N_{-i}} d_{m,w} w_{m,ir}^* \ln p_r$ ($n \times n$ diagonal matrix), $H_{m,ii} = \sum_{r \in N_{-i}} w_{m,ir}^* \ln p_r$

in H_m ($n \times n$ diagonal matrix), $F_{m,ij} = d_{m,i} w_{m,ij}^*$ in F_m ($n \times n$ matrix), $U_i = \beta_i / w_i$ in U

($n \times 1$ vector), $V_j = w_j \ln p_j$ in V ($1 \times n$ vector), and I is a $n \times n$ identity matrix. Solving equation (7) for E gives the conditional price elasticity matrix:

$$(8) \quad E = \left\{ B \left[\sum_{m=1}^M H_m F_m \right] - B \left[\sum_{m=1}^M D_m \right] - \left[\sum_{m=1}^M D_{m,w} \right] + (UV) + I \right\}^{-1} (A + I) - I.$$

Expenditure Elasticities

The expenditure elasticities for the fully modified DM AIDS model are also more complicated than those for the conventional model because of the presence of current budget shares on the right-hand side of equation (1). The expenditure elasticity is

$$(9) \quad \eta_{ix} = \frac{d \ln q_i}{d \ln x} = 1 + \frac{d \ln w_i}{d \ln x} = 1 + \frac{1}{w_i} \left\{ \sum_{r \in N_{-i}} \ln p_r \frac{\partial \gamma_{ir}}{\partial \ln x} + \beta_i \left[1 - \frac{\partial \ln P}{\partial \ln x} \right] \right\},$$

where $\partial \gamma_{ir} / \partial \ln x = \sum_{m=1}^M (d_{m,i} \partial w_{m,ir}^* / \partial \ln x + w_{m,ir}^* d_{m,w} \partial w_i / \ln x)$ and

$\partial \ln P / \partial \ln x = \sum_{r \in N} \ln p_r (\partial w_r / \partial \ln x)$. Differentiating $w_{m,ir}^*$ ($i \neq r$) with respect to $\ln x$

yields

$$(10) \quad \begin{aligned} \frac{\partial w_{m,ir}^*}{\partial \ln x} &= \frac{w_r \kappa_{m,ir}}{\sum_{k \in N_{-i}} w_k \kappa_{m,ik}} \left\{ \frac{\partial \ln w_r}{\partial \ln x} - \frac{1}{\sum_{k \in N_{-i}} w_k \kappa_{m,ik}} \left[\sum_{k \in N_{-i}} w_k \kappa_{m,ik} \partial \ln w_k / \partial \ln x \right] \right\} \\ &= w_{m,ir}^* \left[\eta_{rx} - 1 - \sum_{k \in N_{-i}} w_{m,ik}^* (\eta_{kx} - 1) \right] \end{aligned}$$

Substituting (10) into (9) gives

$$(11) \quad \eta_{ix} = 1 + \frac{1}{w_i} \left\{ \begin{aligned} & \sum_{r \in N_{-i}} \sum_{m=1}^M d_{m,i} w_{m,ir}^* \ln p_r \left[\eta_{rx} - 1 - \sum_{k \in N_{-i}} w_{m,ik}^* (\eta_{kx} - 1) \right] \\ & + \sum_{r \in N_{-i}} \sum_{m=1}^M d_{m,w} w_{m,ir}^* w_i \ln p_r [\eta_{ix} - 1] \\ & + \beta_i \left[1 - \sum_{r \in N} \ln p_r (\eta_{rx} - 1) \right] \end{aligned} \right\}.$$

Equation (11) can be expressed in matrix form as

$$(12) \quad E_x = A_x + B \left[\sum_{m=1}^M D_m \right] (E_x - \iota) - B \left[\sum_{m=1}^M H_m F_m \right] (E_x - \iota) + \left[\sum_{m=1}^M D_{m,w} \right] (E_x - \iota) - (UV_x)(E_x - \iota)$$

where, in addition to matrices defined in equation (7), the matrix elements are $E_{i,x} = \eta_{ix}$

in E_x ($n \times 1$ vector), $A_{i,x} = 1 + \beta_i / w_i$ in A_x ($n \times 1$ vector), $V_{j,x} = \ln p_j$ in V_x ($1 \times n$

vector), and ι is a $n \times 1$ vector of ones. Solving (12) for the vector of expenditure

elasticities E_x gives

$$(13) \quad E_x = \left\{ B \left[\sum_{m=1}^M H_m F_m \right] - B \left[\sum_{m=1}^M D_m \right] - \left[\sum_{m=1}^M D_{m,w} \right] + (UV_x) + I \right\}^{-1} (A_x - \iota) + \iota.$$

Unconditional Price Elasticities

In predicting the demand effects of SSB taxes, unconditional demand estimates are

required for two reasons. First, previous research has shown that the group expenditure

x_{ht} cannot be assumed to be exogenous in many cases (LaFrance 1991). Second, a

conditional demand model generally yields biased estimates of the impacts of price

changes on consumer surplus (Hanemann and Morey 1992). To derive unconditional demand elasticities and perform welfare analysis, we assumed weak separability of preferences for beverages and all other consumption goods. This allowed us to characterize the consumer's consumption decision as a two-stage budgeting process, where expenditures on beverages as a group and all other goods are allocated at the first stage, and product-level demand decisions are made at the second stage according to equation (1) conditional upon x_{ht} . Following the DM literature, we specified the first-stage demand as

$$(14) \quad q_{ht} = a_{ht} + b \times p_{ht} + c \times y_{ht}$$

where q_{ht} is the per capita volume of nonalcoholic beverages sold in market h and period t ; a_{ht} is the intercept; p_{ht} and y_{ht} are the beverage group price in dollar/ounce and per capita income, respectively, both deflated by the consumer price index; and b and c are parameters. Equation (14) is an incomplete demand equation that can be used to calculate the exact measure of changes in consumer's surplus associated with changes in p_{ht} (Hausman 1981). To derive product-level unconditional price elasticities, it is important to realize that a change in price of product j affects demand for product i in two ways: first through the price effect conditional on total beverage expenditure and second through an expenditure effect.

The unconditional price elasticity of demand for product i with respect to a change in price of product j can be written as

$$(15) \quad \varepsilon_{ij} = \eta_{ij} + \eta_{ix} \left(\partial \ln x / \partial \ln p_j \right)$$

where

$$\begin{aligned}
(16) \quad \frac{\partial \ln x}{\partial \ln p_j} &= \partial \ln(pq) / \partial \ln p_j = (\partial \ln(pq) / \partial \ln p) (\partial \ln p / \partial \ln p_j) \\
&= (1+b(p/q)) \left\{ w_j + \sum_{r \in N} w_r \ln p_r \frac{\partial \ln w_r}{\partial \ln p_j} \right\} \\
&= (1+b(p/q)) \left\{ w_j + \sum_{r \in N} w_r \ln p_r \left[\frac{\partial \ln w_r}{\partial \ln p_j} + \frac{\partial \ln w_r}{\partial \ln x} \frac{\partial \ln x}{\partial \ln p_j} \right] \right\} \\
&= (1+b(p/q)) \left\{ w_j + \sum_{r \in N} w_r \ln p_r \left[\eta_{rj} + \delta_{rj} + (\eta_{rx} - 1) \frac{\partial \ln x}{\partial \ln p_j} \right] \right\}
\end{aligned}$$

is the marginal effect of log price j on log total beverage expenditure, and the market and time subscripts are dropped for notational brevity. The w_j term in the curly brackets in (16) measures the first-order effect of a change in p_j on the beverage group price p , while the remaining terms in the curly brackets sum up the second-order effect of changing p_j on p through changes in budget shares.

In matrix notation, equation (16) can be expressed as

$$(17) \quad E_{xp} = (1+b) [W + V(E+I) + V(E_x - \iota)E_{xp}]$$

where E_{xp} is $1 \times n$ with $E_{j,xp} = \partial \ln x / \partial \ln p_j$ and $W_j = w_j$ ($1 \times n$ vector). Solving (17) for E_{xp} gives

$$(18) \quad E_{xp} = \frac{(1+b)[W + V(E+I)]}{1 - (1+b)V(E_x - \iota)}.$$

Therefore, the unconditional price elasticity (15) in matrix form can be written as

$$(19) \quad \bar{E} = E + E_x E_{xp},$$

where the $n \times n$ matrix \bar{E} has ε_{ij} as its elements.

DATA AND VARIABLES

The nonalcoholic beverage sales data used were Nielsen's ScanTrack market-level scanner data from four Nielsen New York markets: Albany, Buffalo, New York City, and Syracuse. Each market consists of a cluster of counties and is not confined by city or state boundaries. The Albany market includes not only counties in the neighborhood of Albany city but also counties in Massachusetts and Vermont; the Buffalo market incorporates several counties in Pennsylvania; and the New York City market covers parts of Connecticut and New Jersey. The scanner data are collected from a sample of supermarkets with annual sales of at least \$2 million and projected to the market level by Nielsen for this store format. Data on milk, liquid tea and coffee, and soft drink powder and sales at convenience stores, drug stores, club stores, and mass merchandisers were not included. Sales data were recorded at the Universal Product Code (UPC) level and cover 64 four-weekly periods between January 28, 2007, and December 24, 2011. The scanner data included UPC-specific information such as package and container sizes, product module, brand, and others. Information on the caloric content of products was collected from manufacturers' websites and linked with the ScanTrack data. To limit the number of products in the demand model and preserve as much product differentiation as possible, we created unique products in ScanTrack by aggregating similar UPC items

based on brand and product module. For example, Coke, Diet Coke, Caffeine-Free Coke, and Caffeine-Free Diet Coke are four unique products in our demand model, but 2-liter Coke and Coke in 12-ounce cans are considered the same product.

The beverage market is characterized by a large number of products with small market shares. In 2007–2011, 18 products had market shares of 1% or above and collectively represented 43% of the beverage market in dollar sales. Lowering the market share threshold to 0.5% increases the number of products to 45 and combined market share to 61%, which still seems low for our purposes. To capture as much of the market in the demand model as feasible, we included all products whose total dollar sales over the 2007–2011 period represented 0.1% or more of the four Nielsen markets combined. As a result, our analysis sample for demand estimation was an unbalanced panel of 43,087 four-weekly observations for 178 products from four markets accounting for 92% of the total ScanTrack market in dollar sales.

Table 1 presents per capita annual volume, energy, and expenditures for the 178 products by product category. In New York markets, CSDs account for the majority of beverage energy (51.5%) and a smaller share of total beverage expenditures (24.1%). Because ScanTrack does not account for sales at retail outlets other than supermarkets, it is useful to examine supermarket shares of total retail sales from all outlet types. Zhen et al. (2013) report estimates of national average household beverage purchases by category based on the 2006 Nielsen Homescan—household-based scanner data on food purchases from all retail outlets. Assuming comparable consumer demand between 2006 and 2007–2011 and between New York and the rest of the country, a comparison of table 1 with

purchase estimates in Zhen et al. (2013) indicates that ScanTrack supermarket volume sales accounted for about 64% of total regular and diet CSD sales, 46% of total sports and energy drink sales, 73% of total 100% juice sales, 39% of total fruit drink sales, and 76% of total bottled water sales. The lower shares for sports and energy drinks and fruit drinks are partly because our ScanTrack data do not include soft drink powder, while Zhen et al.'s estimates accounted for powdered drinks.

Attribute Variables

We specified eight discrete attributes that could potentially be important in determining the cross-price effects. The variable *BRAND_FAM* takes 92 distinct values associated with 92 brand families. For example, Coke is a brand family that encompasses regular and Diet Coke and Caffeine-Free Coke. It is reasonable to expect products under the same brand family to be closer substitutes than products under different brand families. The *NAME_BRAND* variable identifies all name-brand products, which are defined as any product that is not a private-label product. The *MAJOR_PROD* variable indicates which products had an average market share of 0.5% or more over the 2007–2011 period. Because these products are likely to receive larger shelf space and be available in more stores, they may be closer substitutes to one another than to products having much smaller market shares. The *PROD_CAT* variable classifies the 178 products into six product categories (see table 1 for list of categories) consistent with the categorization scheme used in previous category-level demand analyses of SSB taxes (e.g., Zhen et al. 2011; Dharmasena and Capps 2012). The *ENERGY_CAT* variable distinguishes regular CSDs, full-calorie sports and energy drinks, and full-calorie fruit drinks from low-calorie

(defined as ≤ 10 kcal/8-ounce serving) versions of these beverages and bottled water. The rationale is that consumers might perceive soft drinks with more similar energy contents to be more substitutable. The variable *CAFFEINE* indicates the presence of caffeine, which is found in some CSDs and all energy drinks. The *FLAVOR* variable takes nine distinct values for the following nine flavors: cola, root beer, citrus for CSDs/fruit drinks/sports drinks, citrus for 100% juice, ginger ale, pepper, seltzer, apple, and cranberry.

Although the attribute variable *PROD_CAT_C* equals *PROD_CAT* across all 178 products, *PROD_CAT_C* is used differently in the calculation of the weighted average rival price associated with this attribute. When *PROD_CAT_C* is the attribute of interest, $\kappa_{m,ij}$ in (3) becomes a binary variable equal to 1 if products i and j are *not* from the same product category, and 0 otherwise. We use *PROD_CAT_C* to allow for potential nonzero cross-price effects between two products that are otherwise unrelated in terms of the other seven discrete attributes.

ESTIMATION AND RESULTS

To control for time and market fixed effects, the intercept a_{ht} in the first-stage demand equation (14) was augmented to include 13 dummies for the 13 four-weekly periods in a year; 4-year dummies for 2008 through 2011; and three market dummies for Buffalo, New York City and Syracuse. Albany and year 2007 were set as the reference market and year, respectively. The real group price p_{ht} in equation (14) was calculated as

$p_{ht} = \bar{p} \times P_{ht} / cpi_t$, where \bar{p} is the sample mean nominal beverage price denominated in

dollar/ounce, P_{ht} is the Stone price index from equation (1), and cpi_t is the consumer price index for period t . p_{ht} may be endogenous for two reasons. First, the product prices that form p_{ht} could be jointly determined by supply and demand. Second, the Stone price index P_{ht} weighs product prices by current budget shares, which are also endogenous variables in the second-stage demand.

We performed two Hausman specification tests (Hausman 1978) to determine the significance and source(s) of endogeneity in p_{ht} . First, we replaced the Stone price index in p_{ht} with the Laspeyres price index, which uses base budget shares as weights, and created an instrument for p_{ht} using product prices from neighboring markets. Prices from adjacent markets are valid instruments under the assumption that demand shocks are independent across markets after controlling for time and market fixed effects (Hausman 1997). Because base budget shares are fixed, finding endogeneity in the group price p_{ht} is evidence for endogenous product prices and vice versa. Columns I and II of table 2 present results from ordinary least squares (OLS) and two-stage least squares (2SLS) estimation of equation (14). The Hausman test for endogeneity is 0.06, which is not statistically significant at 21 degrees of freedom. Therefore, there is little evidence that product prices are endogenous once seasonal, year, and market fixed effects are accounted for.

Second, to examine the degree of endogeneity in p_{ht} attributable to endogenous budget shares in the Stone price, we used the Laspeyres price index as an instrument for p_{ht} and received a Hausman test statistic of 5.46. Although this is much higher than the

first Hausman test statistic of 0.06, it is still statistically insignificant with 21 degrees of freedom. Table 2 columns III and IV present the OLS and 2SLS results when equation (14) is estimated using Stone price-based p_{ht} . The (unconditional) mean price elasticity of total beverage demand implied by the 2SLS estimates is -0.90 compared with -0.77 based on the OLS estimates. Although not statistically significant, this difference is consistent with the hypothesis that the endogenous Stone price biases the OLS estimate of price response toward zero. Therefore, our analysis of SSB taxes in the remainder of this section is based on the 2SLS estimates.

DM AIDS Estimates

To evaluate the performance of the fully modified DM AIDS model, we estimated four versions of the DM AIDS model with varying degrees of resemblance to the fully modified model. Model 1 is the conventional model but using the Stone price index as the deflator for total beverage expenditure. Model 2 replaces current budget shares in (3) by base budget shares. This creates weighted mean rival prices and still allows $w_{m,ij,ht}^*$ to be treated as exogenous, which simplifies formulas for price elasticities. Model 3 is a fully modified DM AIDS model but with the restriction $d_{m,w} = 0$ imposed. Finally, Model 4 is the fully modified model without restricting $d_{m,w}$ to 0.

The luxury of a large unbalanced panel allows us to control for a significant portion of the heterogeneity in product-level demand across products, markets, and time through fixed effects. For all four models, we augmented the intercept α_{iht} in equation (1) as follows:

$$(20) \quad \alpha_{iht} = \alpha_{ih} + \alpha_{i,temp} \times temp_{ht} + \alpha_{i,trend} \times trend_t$$

where α_{ih} is a constant specific to product i in market h , $temp_{ht}$ is the temperature for market h and period t , $trend_t$ is a linear time trend, and $\alpha_{i,temp}$ and $\alpha_{i,trend}$ are product-specific parameters.

Depending on how rival prices are weighted by $w_{m,ij,ht}^*$ to create the mean rival price associated with the m th attribute (i.e., the $\sum_{j \in N_{-i,ht}} w_{m,ij,ht}^* \ln p_{jht}$ term), there are different numbers of endogenous covariates in equation (1) across the four models that need to be instrumented. In all four models, total beverage expenditure x_{ht} is instrumented by the mean of total expenditures for market h during the same time in other years; the Stone price index P_{ht} is instrumented by the Laspeyres price index. For Model 1, the unweighted mean rival prices tied to the eight discrete attributes need not be instrumented. Model 2 uses mean rival prices weighted by base budget shares, which are assumed to be exogenous conditional on the fixed effects in equation (20). For Model 3, because current budget shares appear in $w_{m,ij,ht}^*$, we instrumented the weighted mean rival prices using base-share weighted mean rival prices. In addition to all the endogenous variables instrumented in Models 1 through 3, Model 4 has an additional source of endogeneity from the interaction of $w_{m,ij,ht}^*$ with w_{iht} in equation (2), which we instrumented using the base share w_{i0} .

We estimated all four DM AIDS models using fixed-effects (FE) 2SLS. Table 3 reports the estimation results. The generalized R^2 (GR^2) of Pesaran and Smith (1994) is

used to measure goodness-of-fit for Models 1 through 4 because the standard R^2 has been shown to be an invalid model selection criterion for instrumental variables' regressions. The model fit continued to improve as we moved from Model 1, the conventional model, to Model 4, the fully modified model. The difference in GR^2 between Model 2 and Model 1 is 0.002, a nontrivial improvement considering that restricting $d_m \forall m$ in Model 1 reduced GR^2 by only 0.0038. Because base share-weighted mean rival prices from Model 2 are used to instrument current share-weighted mean rival prices in Model 3, the GR^2 , which is based on prediction errors, is identical for Models 2 and 3. Model 4 has the best fit to the data with a GR^2 that is 0.008 higher than Model 3 and 0.01 higher than Model 1.

In Models 1 through 3, d_m estimates for attributes *NAME_BRAND*, *MAJOR_PROD*, *PROD_CAT*, *ENERGY_CAT*, *CAFFEINE*, and *FLAVOR* are positive and statistically significant, consistent with the a priori expectation that the degree of substitution between two products increases with their closeness in the attribute space. The estimated d_m coefficient for *BRAND_FAM* is negative, although statistically insignificant except for Model 1. This less intuitive result may be partly caused by collinear relationships between *BRAND_FAM* and other attributes such as *FLAVOR*. The d_m estimate for *PROD_CAT_C* is negative and statistically significant, suggesting that not being from the same product category tends to reduce the degree of substitution or increase the degree of complementarity between the two.

In Model 4, the net effect of rival prices associated with attribute m on demand varies across observations because of adjustment through the interaction between budget share w_{iht} and coefficient $d_{m,w}$. Estimates of $d_{m,w}$ are positive for *MAJOR_PROD*, *PROD_CAT*, *ENERGY_CAT*, and *FLAVOR*; and negative for *NAME_BRAND*, *CAFFEINE*, and *PROD_CAT_C*. Because d_m is estimated to be positive for *NAME_BRAND* and *CAFFEINE*, the net effects of rival prices associated with the two attributes, $d_{m,i,ht}$, could still be positive for some values of w_{iht} .

Estimated Price Elasticities

Because of differences in how budget shares are used to weigh rival prices, similarity in parameter estimates across models does not necessarily mean comparable demand elasticities across models. For Model 1, where rival prices are not weighted by budget shares, the conditional price and expenditure elasticities are obtained by setting H_m , F_m , D_m , and $D_{m,w}$ to null matrices in equations (8) and (13), respectively. Although rival prices are weighted by base budget shares in Model 2, Model 2's elasticity formulas are identical to those of Model 1 because of the constancy of the base budget shares. Table 4 reports summary statistics for unconditional price elasticities from all four models. The median own-price elasticity is close in value across models at around -2.0 .

The median cross-price elasticity is small in magnitude in all models. Approximately 57% of all cross-price elasticities are negative for Models 1 through 3 in contrast to the 43% for Model 4. Therefore, the fully modified DM AIDS model produces a higher degree of substitution across beverage products than the conventional model

(i.e., Model 1) and restricted versions (i.e., Models 2 and 3) of the fully modified model. Negative cross-price elasticities are not unexpected. For example, Finkelstein et al. (2013) and Zhen et al. (2013) both found that some food and beverage categories are complements. Unlike discrete choice models where products are restricted to be substitutes, the DM method does not restrict the sign of coefficients on rival prices and, therefore, does not a priori force any two products to be substitutes through functional form restriction.

As the DM AIDS model is incrementally modified toward the fully modified model, we observe monotonic declines in the proportions of own-price and cross-price elasticities that are positive and negative, respectively. Although the decrease is small in magnitude in some cases, this is evidence in support of the fully modified DM AIDS model. The distributions of unconditional own-price and cross-price elasticities from Model 4 are illustrated in figures 1 and 2, respectively.

Simulation of Ounce- and Calorie-Based SSB Taxes

To evaluate the efficiency of ounce-based and calorie-based SSB taxes, we simulated two excise tax scenarios: in the first, a half-cent per-ounce tax is levied on all SSBs with more than 10 kcal/8-ounce serving; in the second, a 0.04-cent per kcal tax (equivalent to a half-cent per ounce of regular Coke²) is imposed on the same SSB products. In both scenarios, we assumed the excise tax is passed one-for-one to retail prices. Using the estimated unconditional elasticities, we simulated both scenarios for all markets and time periods. The standard error for each point estimate of the simulated tax effect was generated by taking 100 random draws from a multivariate normal distribution with the mean vector

and variance-covariance matrix set to the estimated values of the first- and second-stage demand models. The mean point estimates and t-values for the two simulated scenarios are reported in table 5.

In the first and second panels of table 5, the first-order effect measures the direct effect of tax-induced price changes on the group price index P_{ht} holding budget shares constant at the pretax levels. However, the second-order effect reflects the indirect effect of changing budget shares on P_{ht} (see equation [16] for discussion). The second-order effect gauges the importance of using the Stone price rather than the Laspeyres price index, which ignores the second-order effect, in deflating total expenditure x_{ht} and predicting unconditional demand. On average, the first-order effect of a half-cent per ounce SSB tax is to raise P_{ht} by 7.56% compared with 7.25% from a 0.04-cent per kcal SSB tax. The second-order effect is statistically significant but much smaller in magnitude (between 0.11% and 0.22% depending on the model and tax strategy) than the first-order effect.

The third panel of table 5 presents simulated reductions in beverage calories caused by SSB taxes. Two noteworthy patterns emerge from these results. First, within each model, the ounce-based tax always produces less reduction in beverage calories than the calorie-based tax despite the fact that the calorie-based tax is less expensive in terms of its impact on group price. Second, the total amount of beverage energy reduced continues to get smaller as the DM AIDS model is increasingly modified. This is consistent with our finding that the fully modified model and its restricted versions produce stronger product substitution than the conventional model. Based on the fully

modified DM AIDS model, a half-cent per-ounce and a 0.04-cent per kcal SSB taxes are predicted to reduce per capita beverage energy from the 178 products in ScanTrack supermarkets by 1,916 and 2,001 kcal per year, respectively.

We calculated the CV associated with each SSB tax strategy using the first-stage demand estimates, the combined effect of the SSB tax on P_{ht} , and the CV formula in Hausman (1981, equation [19]). The mean CV estimates (in absolute values) and predicted tax burdens are reported in the fourth and fifth panels of table 5, respectively. Consistent with the above discussion of predicted group price increases and calorie reduction, the tax burden is higher in the modified models than in the conventional model, and a calorie-based tax implies a lower CV (in absolute value) and tax burden than an ounce-based tax within each DM AIDS model.

Finally, the last panel of table 5 presents the difference in CV per 1,000 kcal reduced between a calorie-based tax and an ounce-based tax. A positive difference indicates that a calorie-based SSB tax is less costly to consumers than an ounce-based tax for the same level of energy reduction. On average, the fully modified model predicts that a calorie-based SSB tax would result in \$0.29 less in consumer surplus loss than an ounce-based tax per 1,000 kcal reduced; in contrast, the savings predicted by the conventional DM AIDS model is \$0.09 per 1,000 kcal reduced. This difference is too large to be ignored considering that annual U.S. per capita energy intake from SSBs at home and away from home is about 50,000 kcal.³ Therefore, in addition to better goodness-of-fit, modifying the DM AIDS is also justified by the economic significance of its predictions.

CONCLUSION

Policy makers across the country continue to propose SSB tax legislation as a means to curb obesity and raise government revenue. When the main objective of a SSB tax is to improve public health, we show that a calorie-based SSB tax is more efficient than an ounce-based SSB tax in the sense that the former is able to achieve a given SSB energy reduction target with smaller loss in consumer surplus. This result is intuitive. A food or beverage product is composed of a number of nutrients and characteristics, the levels of which may vary widely from one product to another. An optimal obesity-aimed food or beverage tax policy should directly target the ingredient(s) or nutrient(s) of concern. Because almost all calories in a SSB product come from added sugars, a calorie-based SSB tax is equivalent to a tax on sugars.

We proposed a fully modified DM AIDS to quantify the efficiency gain in switching from an ounce-based tax to a calorie-based one. Like the conventional DM AIDS, the fully modified model is able to handle hundreds of differentiated products. In addition, the new model is shown to outperform the conventional DM AIDS in terms of goodness-of-fit and economic significance of predicted demand and consumer surplus changes caused by SSB taxes.

In the empirical analysis of New York supermarket beverage sales, the fully modified DM AIDS estimated product-level demand for 178 beverage products covering well over 90% of total beverage sales in Nielsen ScanTrack scanner data. For every 1,000 beverage calories reduced, the estimated consumer surplus loss due to a calorie-based tax is \$0.29 lower than the loss caused by an ounce-based tax. A 0.04-cent per kcal SSB tax

is predicted to reduce beverage energy from ScanTrack supermarkets by 9.4%, compared to 9.0% from a half-cent per ounce tax. Applying this percentage change to beverages obtained from all sources and assuming comparable demand elasticities between beverages from supermarkets and other sources, we calculated that a 0.04-cent per kcal tax on SSBs will reduce total beverage energy by about 5,900 kcal per capita per year.⁴ Relative to an ounce-based SSB tax that also achieves a 5,900 kcal reduction in beverage energy, the 0.04-cent per kcal SSB tax is estimated to save \$1.71/year per capita in CV measure of consumer surplus.

It is unlikely that there is a one-for-one relationship between reductions in beverage energy and in total dietary energy because of compensation. Zhen et al. (2013) found that about one-half of the reduction in SSB energy is compensated by increases in purchases of other untaxed foods. Because the energy contents of foods other than the six categories of beverage products (see table 1 for list) were not explicitly modeled by our demand model, we could not quantify the net effect of an SSB tax on overall energy intake. Nevertheless, at 50% compensation, an energy reduction of 2,950 kcal per capita per year would still substantially contribute to weight gain prevention at the population level.

A rationale for ounce-based SSB taxes is their ease of implementation compared to the more sophisticated calorie-based tax. However, a calorie-based tax may incentivize beverage manufacturers to reformulate SSBs to contain less sugar, while an ounce-based tax is much less likely to have such an effect on product formulation. Modeling these

aspects of the beverage market is beyond the scope of this study but should be pursued in future research.

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Table 1. Average Annual per Capita Purchases, 2007–2011

	Per capita		
	Volume	Energy	Expenditure
	(oz/year)	(kcal/year)	(\$/year)
Regular CSD	870	10,969	20.08
Diet CSD	653	0	15.43
Sports/energy drinks	106	654	4.44
100% juice	435	6,142	21.17
Fruit drinks	339	3,538	12.16
Bottled water	840	0	10.04
Total	3,243	21,303	83.31

Notes: These data represent sales of the 178 brands that are included in the DM AIDS model, which account for 95%, 92%, and 94% of ScanTrack total nonalcoholic beverage sales in volume, dollars, and energy, respectively. The ScanTrack data we have exclude milk, bottled tea and coffee, and soft drink powder. Expenditures were deflated by the consumer price index using the 2007–2011 average as the base.

Table 2. First-Stage Demand Estimates

	I	II	III	IV
Regressor	OLS	2SLS	OLS	2SLS
y_{ht}	0.090*** (0.020)	0.089*** (0.020)	0.085*** (0.020)	0.090*** (0.021)
p_{ht}	-6,050.1*** (1,098.4)	-5,601.6*** (2,125.4)	-5,281.8*** (1,020.1)	-6,150.3*** (1,085.7)
Mean income elasticity	0.71	0.70	0.67	0.71
Mean price elasticity	-0.88	-0.82	-0.77	-0.90

Notes: Asterisks (***) indicate statistical significance at the 1% level. Standard errors are in parentheses. All regressions include seasonal, year, and market fixed effects. p_{ht} in columns I and II (III and IV) is based on the Laspeyres (Stone) index. The instrument for p_{ht} in column II is the Laspeyres index with product prices from neighbor markets. In column IV, the Stone price-based p_{ht} is instrumented by the Laspeyres price index.

Table 3. Estimated Parameters for the Cross-Price Effects from the Second-Stage Demand

Attributes	Model 1	Model 2	Model 3	Model 4	
	d_m	d_m	d_m	d_m	$d_{m,w}$
<i>BRAND_FAM</i>	-0.048*** (0.014)	-0.016 (0.016)	-0.020 (0.017)	-0.013 (0.019)	0.591 (2.441)
<i>NAME_BRAND</i>	0.657*** (0.197)	0.348** (0.172)	0.272* (0.150)	0.876*** (0.200)	-82.901*** (16.443)
<i>MAJOR_PROD</i>	0.717*** (0.114)	0.867*** (0.118)	0.927*** (0.128)	-0.198 (0.179)	136.230*** (21.836)
<i>PROD_CAT</i>	0.150*** (0.046)	0.185*** (0.045)	0.208*** (0.045)	0.039 (0.056)	7.502 (6.205)
<i>ENERGY_CAT</i>	0.432*** (0.080)	0.464*** (0.071)	0.567*** (0.086)	-0.142 (0.101)	119.942*** (8.816)
<i>CAFFEINE</i>	0.798*** (0.166)	0.908*** (0.124)	0.911*** (0.133)	0.085 (0.177)	-31.330*** (10.383)
<i>FLAVOR</i>	0.222*** (0.033)	0.283*** (0.033)	0.281*** (0.033)	0.007 (0.039)	48.277*** (4.715)
<i>PROD_CAT_C</i>	-0.922*** (0.171)	-0.819*** (0.156)	-0.840*** (0.149)	-0.437** (0.197)	-131.825*** (23.742)
Total number of parameters	720	720	720	728	

adj GR^2	0.4740	0.4760	0.4760	0.4840
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Notes: Asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses. All estimates and standard errors are multiplied by 100 for readability. The adj GR^2 is the Pesaran and Smith (1994) generalized R^2 for instrumental variables regressions and is adjusted for the number of explanatory variables.

Table 4. Summary Statistics for Estimated Unconditional Price Elasticities

	Model 1	Model 2	Model 3	Model 4
Median own-price elasticity	−1.954	−2.035	−2.041	−1.987
Median cross-price elasticity	−0.003	−0.001	−0.001	0.001
% positive own-price elasticities	3.9%	3.5%	3.3%	3.0%
% negative cross-price elasticities	57.7%	57.5%	57.4%	43.4%

Table 5. Simulated per Capita Effects of Ounce-Based and Calorie-Based SSB**Taxes on Demand and Consumer Surplus**

	Model 1	Model 2	Model 3	Model 4
<hr/> % change in beverage group price, ounce-based tax				
First-order effect ^a	7.56%	7.56%	7.56%	7.56%
Second-order effect	0.10%	0.11%	0.19%	0.16%
	(1.8)	(2.0)	(2.9)	(2.1)
<hr/> % change in beverage group price, calorie-based tax				
First-order effect ^a	7.25%	7.25%	7.25%	7.25%
Second-order effect	0.13%	0.13%	0.22%	0.18%
	(2.3)	(2.4)	(3.4)	(2.5)
<hr/> Reduction in energy intake from beverages (kcal/year)				
Ounce based	2,798	2,686	2,305	1,916
	(57.6)	(58.8)	(55.4)	(62.3)
Calorie based	2,811	2,794	2,396	2,001
	(57.4)	(59.7)	(56.2)	(62.9)
<hr/> Compensating variation (\$/year, absolute value)				
Ounce based	6.20	6.21	6.27	6.25
	(68.4)	(68.2)	(66.6)	(67.0)
Calorie based	5.98	5.98	6.05	6.02
	(68.3)	(68.5)	(66.9)	(67.0)
<hr/> Tax burden (\$/year)				

Ounce based	5.03	5.10	5.21	5.40
	(39.2)	(39.9)	(42.8)	(47.6)
Calorie based	4.85	4.88	5.01	5.17
	(37.3)	(38.8)	(41.4)	(45.5)
<hr/>				
Difference in CV per 1,000 kcal reduced (\$)				
	0.0886	0.1727	0.1953	0.2923
	(4.1)	(3.9)	(3.1)	(2.8)

Notes: Results are for the 178 products in ScanTrack accounted for by the DM AIDS model. The reported simulated effects and the associated t statistics (in parentheses) are averages over all markets and time periods.

^a The first-order effect is deterministic and based on baseline budget shares and after-tax retail prices.

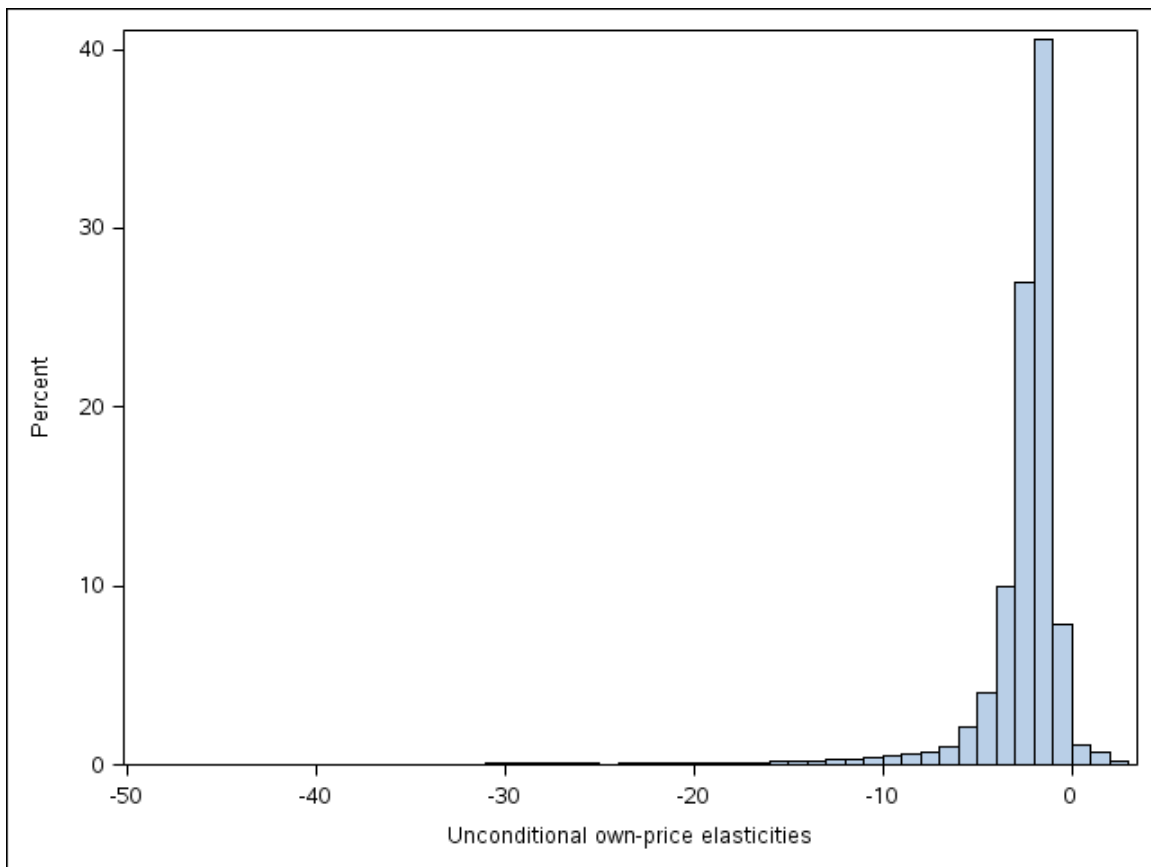


Figure 1. Distribution of estimated unconditional own-price elasticities for the fully modified DM AIDS model

Notes: The distribution is based on Model 4 elasticity estimates with the top and bottom 1% of the estimates trimmed.

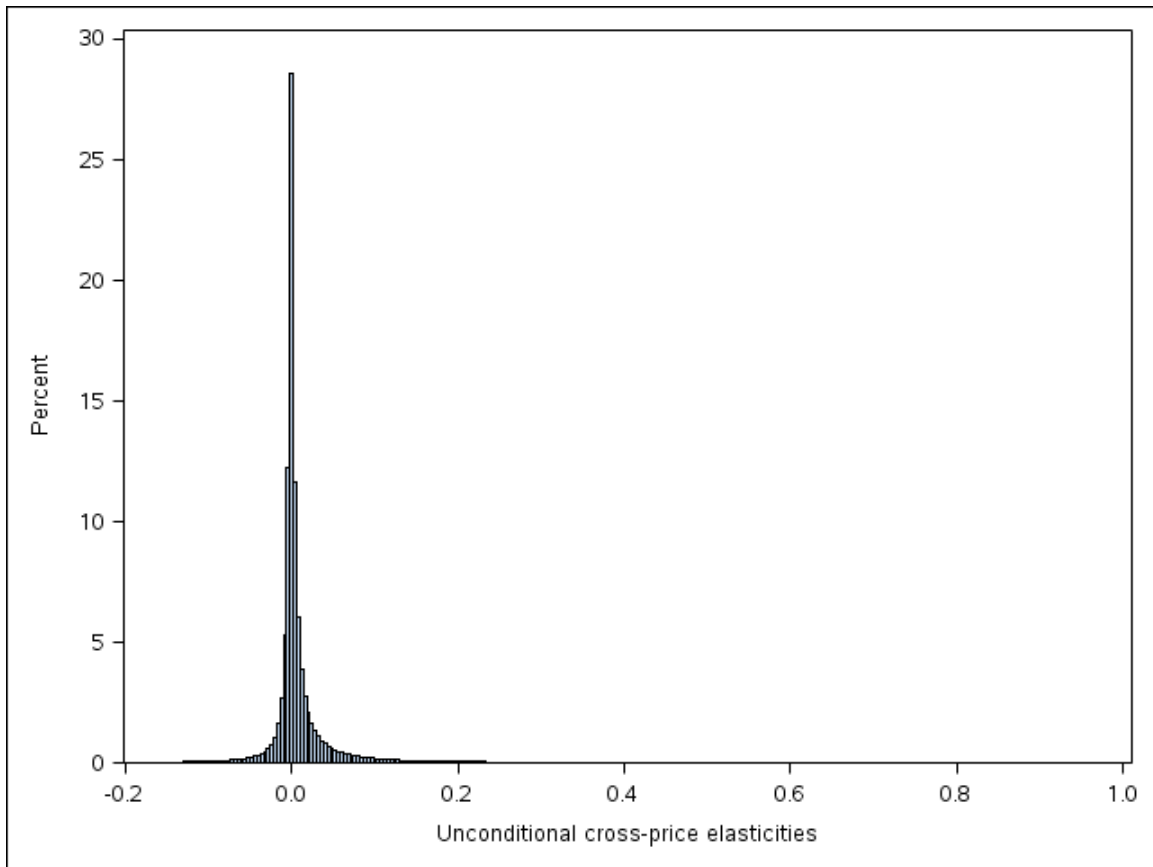


Figure 2. Distribution of estimated unconditional cross-price elasticities for the fully modified DM AIDS model

Notes: The distribution is based on Model 4 elasticity estimates with the top and bottom 1% of the estimates trimmed.

¹ Authors' calculation based on Nielsen ScanTrack data on supermarket beverage sales and calorie information collected from manufacturers' websites.

² There are 100 kcal in 8 ounces of regular Coke.

³ Authors' calculation based on dietary intake data from respondents ages 5 and above in the 2007–2008 National Health and Nutrition Examination Survey (NHANES).

⁴ Total energy intake from regular CSD, sports and energy drinks, fruit drinks, and 100% juice is about 63,000 kcal per capita per year for people ages 5 and above based on the 2007–2008 NHANES.