HETEROGENEOUS BEHAVIOR, OBESITY, AND STORABILITY IN THE DEMAND FOR SOFT DRINKS

EMILY WANG, CHRISTIAN ROJAS, AND FRANCESCA COLANTUONI

We apply a dynamic estimation procedure to investigate the effect of obesity on the demand for soda. The dynamic model accounts for consumers' storing behavior, and allows us to study soda consumers' price sensitivity (how responsive consumers are to the overall price) and sale sensitivity (the fraction of consumers that store soda during temporary price reductions). By matching store-level purchase data to county-level data on obesity incidence, we find higher sale sensitivity in populations with higher obesity rates. Conversely, we find that *storers* are less price sensitive than *non-storers*, and that their price sensitivity decreases with the obesity rate. Our results suggest that policies aimed at increasing soda prices might be less effective than previously thought, especially in areas where consumers can counteract that price increase by stockpiling during sale periods; according to our results, this dampening effect would be more pronounced precisely in those areas with higher obesity rates.

Key words: Storability, soda, obesity, demand, sales.

JEL codes: D12, L66, I18.

Despite the slight decrease in soft drink consumption among some population groups (Welsh et al. 2011), soda consumption in the United States is still close to 50 gallons per person per year (Lustig, Schmidt, and Brindis 2012).[1] Scientific evidence links the high volume of soda consumed to obesity incidence (Ludwig and Ebbeling 2001; Apovian 2004; Malik, Schulze, and Hu 2006; Vartanian, Schwartz, and Brownell 2007; Libuda and Kersting 2009), which affects 34% of the adult population in the United States (Centers for Disease Control and Prevention 2015). This link is not surprising, as soda is considered the single most important source of calorie intake in the United States (Block and Willett 2011; Wang, Bleich, and Gortmaker 2008; Block 2004). Fighting obesity has become a priority in the political agenda, primarily because of its high

associated costs. Higher mortality incidence, increased medical expenses, and the increased health insurance premiums that result, as well as productivity losses in the labor market (Fletcher 2011), are some of the main justifications for public intervention. The estimated figure of annual U.S. health care cost for obesity-related illnesses is $190.2 billion, which is approximately 21% of annual U.S. medical expenditures (Cawley and Meyerhoefer 2012).

Policy interventions at the state, county, or city level attempting to reduce soda consumption have largely been sales and excise taxes (Jacobson and Brownell 2000). Proponents of soda taxes often reference the success of cigarette taxes in decreasing cigarette use (Block and Willett 2011). However, cigarettes and soda differ in a number of ways. First, cigarette taxes increase prices significantly (e.g., in New York State, taxes represent more than 50% of the retail price; New York State, 2016), a tactic that may be unjustifiable for soft drinks given that, unlike cigarette use, moderate soda consumption is considered safe. Second, the many available soda substitutes may render soda taxes

Emily Wang is an Assistant Professor, Christian Rojas is an Associate Professor, and Francesca Colantuoni is a former Ph.D. student, all in the Department of Resource Economics, University of Massachusetts Amherst. The authors thank Aviv Nevo and Igal Hendel for kindly sharing their code. Correspondence may be sent to: rojas@umass.edu.
[1] We use the terms "soda" and "soft drinks" interchangeably.

ineffective, in that consumers will replace the highly taxed beverages with low-tax alternatives with the same health consequences (Block and Willett 2011). Lastly, the ubiquitous presence of temporary price reductions (sales) on virtually all soda products allows consumers to bypass the high-price barriers created by taxes by buying (and storing) large quantities of soda for future consumption, a dampening effect that we do not see in the cigarette market.[2]

On the other hand, soda is similar to cigarettes in that the most common ingredients used to manufacture soft drinks, caffeine and sugar, are, according to the medical literature, known to cause addiction. Caffeine, a mildly addictive psycho-active chemical, is contained in over 60% of soft-drinks sold in the United States, and the psychological and physiological influence of caffeine on consumers may drive repeat purchases of a product (Riddell et al. 2012), meaning that caffeine may be intentionally added to a product to modify consumer behavior (Riddell et al. 2012; Yeomans, Durlach, and Tinley 2005; Keast and Riddell 2007; Griffiths and Vernotica 2000). As for sugar, a high glycemic index is considered the key variable determining a food's addictive potential, and an important contributing factor to the obesity epidemic (West 2001). Because soft drinks contain high levels of both sugar and caffeine, their addictive potential may be compounded, and both purchase frequency and volume bought (and consumed) may be especially inflated compared to those of more nutritious food products.[3]

One difficulty in regulating soda consumption is that some households purchase extremely large quantities of soda (unsafe from a health perspective), while others consume the product in moderate quantities (considered safe).[4] While several reasons may account for unsafe high consumption—brand

loyalty and addiction are possible explanations—the high-volume consumers display a relative unwillingness to abandon consumption, even when prices increase, which makes a tax less effective for the group of greatest concern. Further, as noted above, soda, as opposed to other specially taxed goods like cigarettes, is frequently subject to temporary price reductions allowing the high-volume consumers in particular—especially those who stock and store soda—to bypass the tax-imposed barriers to consumption, meaning the regulation falls most heavily on the segment of the population it does not need to regulate.

In this article we estimate a model of soft drink demand that takes into account the unique characteristics of this dichotomous market. The model specifies that some consumers, termed *storers*, buy larger quantities of soda during sale periods in order to store the product for future consumption. Specifically, we identify the fraction of consumers that exhibit this type of behavior. We use the term "sale sensitivity" to describe the extent to which a given population contains *storers* (i.e., a population with a large fraction of *storers* is more sale sensitive than a population with few *storers*).[5] Further, our model considers product differentiation (i.e., we model demand at the brand level), which allows us to calculate and account for substitution patterns across brands. One of the main features of our model is that we are able to estimate consumer heterogeneity, that is, whether and how price sensitivity and sale sensitivity vary across populations with differing degrees of obesity incidence.[6]

Prior research that accounts for both storability and product differentiation of soft drinks (Hendel and Nevo 2013; Wang 2015) has shown that a dynamic model of consumer inventory behavior is necessary to estimate more accurate price sensitivity parameters, and that more realistic substitution patterns for differentiated products are

---

[2] 25 states have minimum price laws for cigarettes, which significantly limit, and in some cases (eight states) prohibit, temporary price reductions in cigarettes (CDC 2010).

[3] We point out the possibility of addiction only to illustrate the importance of this factor on the degree to which consumers in this market (in comparison to other food markets) may exhibit a larger propensity to store. We note at the outset that our econometric approach does not consider nor model either habit persistence or addiction.

[4] A level of consumption considered to be moderate is less than six cans per week; consumption of soda beyond this threshold appears to be linked to a higher risk of vascular complications (Gardener et al. 2012).

[5] Since in our model a greater sale sensitivity is directly related to a greater propensity to stockpile product, we can also refer to this feature as "storability sensitivity"; we therefore use these two terms interchangeably.

[6] We study other possible sources of consumer heterogeneity, for example, whether sensitivity parameters (storability and price) depend on the level of other demographic characteristics such as low income, race, rural areas, and low education.

obtained by including consumer heterogeneity in the model. Following the dynamic model of Hendel and Nevo (2013), we identify the percentage of consumers who are *storers* and the percentage who are not, and estimate their respective price elasticity parameters. Our main contribution is to use a variant of this model to study whether and how a population's sale sensitivity and price sensitivity varies with the percentage of obese individuals in that location. To fulfill this objective, we match store-level soft drinks sales data to county-level obesity rates (and other demographic data), and use these data in the estimation of our dynamic demand model. Our results suggest that populations characterized by higher rates of obesity are more sale sensitive—that is, more likely to contain households that stockpile soda. Further, we find that *storers* are less price sensitive than *non-storers*, and that their price sensitivity decreases with the obesity rate.

Our demand estimates imply that sale sensitivity is important in this market, which suggests that soda taxes might be less effective than otherwise believed as consumers will partially dampen the effect of price increases by taking advantage of temporary low price periods to stockpile products. Further, our estimates suggest that taxes will have the weakest behavioral effects precisely in those areas where the policy concern is greatest because: a) there is a larger fraction of *storers* in areas where obesity is more prevalent; b) *storers* are less price sensitive than *non-storers*; and c) *storers* in areas with higher obesity rates are less price sensitive than *storers* elsewhere. The main takeaway from our work is that a more realistic model is crucial to the design of more effective policy interventions.

Previous Literature

Andreyeva, Chaloupka, and Brownell's (2011) review of prior work shows that own-price elasticity estimates for soda and other beverages range between -0.8 and -1. A more recent review of empirical studies suggests that soft drink consumption is more price sensitive than previously reported (Powell

et al. 2013).[7] A large variance in price elasticity estimates is illustrated by Zheng and Kaiser (2008) and Dharmasena and Capps (2012), who place the price elasticity estimate for soft drinks at -0.15 and -1.90, respectively. Some studies use demand response to examine how soda taxes may affect body weight. Several authors suggest that studies that find soda taxes unlikely to decrease body mass index (BMI) significantly (e.g., Fletcher, Frisvold, and Tefft 2010a, b; Powell and Chaloupka 2009; Sturm et al. 2010, Finkelstein et al. 2010, Duffey et al. 2010, and Schroeter, Lusk, and Tyner 2008), might be due to the small nature of taxes, and that larger taxes might have a measurable effect on weight (Powell and Chaloupka 2009; Powell et al. 2014). Nevertheless, Fletcher, Frisvold, and Tefft (2013) caution that for hefty taxes to be effective, they would need to shift consumption toward healthier drinks, something that currently small taxes appear not to do. These considerations imply that a decrease in the obesity rate is more likely if the tax applied to several food and beverage groups (see Miao, Beghin, and Jensen [2013] for a quantification of this possible effect).

Using Homescan panel data, Zhen et al. (2011) estimated the demand for sugary non-alcoholic beverages. By applying a dynamic extension of the almost ideal demand system, they found evidence of habit formation and argue that, because of this behavioral feature, any positive effects of increased taxes are likely to be delayed. Similar to what we do in this paper, Patel (2012) accounted for obesity rates and demographic characteristics in the context of a static model of demand for soda. Patel's estimates suggest that consumers with higher body weight tend to be less price-sensitive and prefer diet sodas. In Patel's work, however, the predicted decrease in BMI due to a soda tax would be unlikely to yield meaningful reductions in social and medical costs. Patel concluded that, given the static nature of his demand estimation, the resulting estimates of price sensitivity are likely overstated.

While our results confirm Patel's (2012) findings that high obesity rates are associated with lower (in absolute value) own price elasticities, our model does account for dynamics (i.e., a consumer's forward-looking decision to stockpile product during temporary price reductions), and thus provides more reliable demand elasticity estimates (Hendel and Nevo 2006; 2013). Indeed, as conjectured by

---

[7] Sharma et al. (2014) and Zhen et al. (2014) report that corrections for price endogeneity might result in a smaller (in absolute value) own-price elasticity for soda.

Patel, consumption dynamics are important for a storable good such as soda since static models are shown to overstate own-price elasticity and understate cross-price elasticity (Hendel and Nevo 2006; Patel 2012; Wang 2015). In addition, by explicitly considering both temporary price reductions and the resulting stockpiling behavior, our model does not overstate substitution towards goods other than the ones included in the estimation (or to the no-purchase option) when soda is not on sale (Hendel and Nevo 2006). Patel also noted that if obese consumers engage in stockpiling more than non-obese consumers, this would lead to an overstatement of his price-sensitivity estimates for the obese population. Our work confirms this conjecture: we find that high obesity rates are associated with a greater degree of stockpiling behavior and that the estimated price sensitivities for obese consumers in a static model would be overstated.

Hendel and Nevo (2013) developed a dynamic demand model that allows the researcher to determine the proportion of soda consumers who are *storers* and *non-storers*. Hendel and Nevo used their model to study intertemporal price discrimination of storable goods. These authors also used estimates from the model to explain why soft drink companies and/or retailers offer temporary price reductions in the first place. Hendel and Nevo divided customers into two categories: *storers*, who stockpile soda during sale periods and thereby significantly reduce their purchase needs during non-sale periods, and *non-storers*, who buy more or less the same quantity of soda during sale and non-sale periods. The existence of these two consumer types, according to Hendel and Nevo, explains why optimal pricing involves discounts. We utilize a variant of Hendel and Nevo's model to explore the question of whether sale sensitivity and/or price sensitivity exhibit heterogeneity across populations with different obesity rates. As stated earlier, our results suggest that our variant of Hendel and Nevo's model can play a crucial role in policy interventions.

Empirical Model

We build on Hendel and Nevo's (2013) model which handles demand dynamics

generated by product storability in a relatively simple way.

Let **q** be the vector of consumption of the J varieties of soda and m be the numeraire good. Consumer utility function at time t is written as $U_t(\mathbf{q}, m)$. The consumer's problem is how much soda to buy in every purchase occasion ($\mathbf{x}_t$), and how much to consume ($\mathbf{q}_t$).

As in Hendel and Nevo (2013), we assume that inventory lasts only T periods, and that consumers know their needs T periods in advance. In our case, we assume that rational consumers store just enough to last between sales because they know the price history and can anticipate soda price up to T ahead (perfect foresight) in order to minimize storage costs. This assumption leads to simple dynamics in which stockpiling occurs exactly at and only when inventory from the prior stockpile runs out. The model allows us to incorporate stockpiling behavior by assuming that the population is made up of two types of consumers: *storers* (S) and *non-storers* (NS).

Non-storers buy during sale and non-sale periods to satisfy current consumption needs; they do not stockpile during a sale period. Conversely, *storers*' purchase decisions are dynamic because their purchase behavior is determined by: a) their own current inventory; b) the product's current price (sale or non-sale); c) anticipated future prices (that is, when the next sale will occur); and d) future consumption needs. Because Hendel and Nevo's model accommodates aggregate data (i.e., for each product, data are aggregated across purchases made by all consumers), we can estimate the fraction of consumers in the population that are *non-storers* ω, and, reciprocally the fraction of *storers* $(1 - \omega)$, as a measure of the population's sale sensitivity. Identification between *storers* and *non-storers* is straightforward: if the data reveal that purchases dramatically increase during sale periods, then the fraction of *storers* that would rationalize this data pattern ought to be higher.

We enrich HN's model by allowing price coefficients to vary by the population's obesity incidence, defined as the percentage of population with a BMI > 30, and other demographic variables recognized by the literature as predictors of obesity.

Formally, for *non-storers* (NS) the quantity purchased is a static problem (i.e., the quantity purchased in t is equal to the quantity

consumed in t): $\mathbf{x}_t^{NS} \equiv \mathbf{q}_t^{NS}$. For storers (S), the quantity purchased is determined by solving the following expected flow of future utility:

$$(1) \quad \text{Max} \sum_{t=0}^{R} E\big[u_t^S(\mathbf{q}_t, m_t)\big]$$

s. t.

$$(2) \quad 0 \leq \sum_{t=0}^{R} \big[(y_t - (\mathbf{p}_t'\mathbf{x}_t + m_t))\big]$$

(Budget Constraint), and

$$(3) \quad \mathbf{q}_t \leq \mathbf{x}_t + \sum_{\tau=0}^{t-1} (\boldsymbol{x}_\tau - \mathbf{q}_\tau - \mathbf{e}_\tau)$$

(Inventory Constraint)

where $\mathbf{x}_t$ is the vector of purchases in period t, and $\mathbf{e}_\tau$ is the vector of unused units that expire in period τ. Equation (3) allows current consumption ($\mathbf{q}_t$) to be satisfied by either current purchases ($\mathbf{x}_t$) or past purchases ($\mathbf{x}_\tau$ where $\tau < t$), or both. A direct implication is that the price paid for the units consumed in period t is not necessarily the current price (p_t). Thus, consumers' current consumption is a function of effective price; that is, the price of the currently consumed product when it was purchased. Intuitively, if there had been a sale in any of the preceding T periods, then the effective price of current consumption is that sale price, not the current market price, since the storer is consuming product purchased during a sale; otherwise, the effective price is the current market price. Formally, the effective price is defined as the minimum price (from those that are below or equal to the sale price threshold) registered in the relevant $T + 1$ periods. By replacing current prices with effective prices, the dynamic problem collapses to a static problem, thereby making estimation straightforward.

Define a sale period (s) as the period when p_{jt} is a sale price (defined later), and a non-sale period (n) otherwise.[8] In a given period,

a *storer*'s purchases may not equal current consumption, as the *storer* may be stockpiling for future consumption or consuming from its own stockpiled inventory. Consequently, the dynamic optimization problem for *storers* becomes one of static optimization, since *storers* solve their optimization problem T periods in advance by buying what they need when the price is a sale price. In our estimation procedure, current prices are replaced with effective prices ($\mathbf{p}_t^{ef}$). For instance, if the current period is a non-sale period, but the previous period was a sale, then storers are assumed to have purchased soda in the previous period for current consumption. Hence, the current price is replaced with the sale price in effect in the previous period. If none of the $T + 1$ preceding periods was a sale period, there is no price replacement.

Given that effective prices are also used for substitute goods, they are equivalent to opportunity costs of period t consumption, and they fully capture the impact of stored units of j on the purchase of all other storable goods ($-j$). Thus, optimal consumption for *storers* in period t is:

$$(4) \quad \mathbf{q}_t^S = q_t^S\big(\mathbf{p}_t^{ef}\big).$$

The sum of the purchases of the two types of consumers is given by

$$(5) \quad x_{jt}\big(\mathbf{p}_{t-T}, \ldots, \mathbf{p}_{t+T}\big) = x_{jt}^{NS}(\mathbf{p}_t) \\ + x_{jt}^S\big(\mathbf{p}_{t-T}, \ldots, \mathbf{p}_{t+T}\big).$$

In what follows we provide a brief description of purchasing patterns (more details can be found in Hendel and Nevo 2013). Essentially, *storers*' purchases in period t are the sum over current and future needs up to $t + T$ (recall the assumption that consumers know with perfect foresight the prices up to T periods ahead); they decide when it is best to purchase by comparing the price in t to the T preceding prices. If p_{jt} is a sale price, then *storers*' are predicted to purchase in t for their current consumption and/or next periods' consumption. Then, by comparing p_{jt} with prices up to p_{jt+T}, we determine if consumers also buy some units at t for consumption T periods ahead.

To illustrate how total quantity purchased in the market (by both *storers* and *non-storers*) is defined, we consider $T = 1$. In this case, *storers*' behavior can be predicted by

---

[8] To avoid confusion with the notation between the type of period (n and s) and the type of consumer (S and NS), we use lower case letters for the former and upper case letters for the latter.

defining four types of periods: (1) the current period is a sale period but was preceded by a non-sale period (*ns*); (2) the current period is a non-sale period but was preceded by a sale period (*sn*); (3) the present period is a sale period and was also preceded by a sale period (*ss*); and (4) the current period is a non-sale period and was also preceded by a non-sale period (*nn*). Considering each type of period defined above and assuming perfect foresight, product purchases $(x_j(\mathbf{p}_{t-1}, \mathbf{p}_t, \mathbf{p}_{t+1}))$, as defined in equation (5), need to be scaled up and down accordingly (see the supplemental appendix online for details).

Estimation Procedure

Let x_{jst} denote the purchases of product j in supermarket s during week t. Purchases predicted by the model are given by:

$$(6) \quad x_{jst} = q_{jst}^{NS}\left(p_{jst}, \mathbf{p}_{-jst}\right)$$
$$+ \sum_{\tau=0}^{T} q_{jst+\tau}^{S}\left(p_{jst}, \mathbf{p}_{-js,t+\tau}\right) 1\left[p_{jst} = \mathbf{p}_{js,t+\tau}^{ef}\right].$$

In the case of $T = 1$, the predicted purchases consist of three components: purchases by *non-storers* and purchases by *storers* for consumption at t and $t+1$. As implied by equation (6), one or both of the components of the demand for *storers* can be zero, depending on the sale/non-sale term. The regime is determined by the argument of the indicator function $1[\cdot]$. Recall that for product j, current market prices are always used to determine consumption (i.e., j's prices are used to dictate the regime, but these are never changed). We assume that the demand for product j at store s in week t is (natural) log-linear:

$$(7) \quad \log q_{jst}^{h} = \omega^{h}\alpha_{js} - \beta_{j}^{h}p_{jst} + \sum_{j\neq i}\gamma_{ji}^{h}p_{ist} + \epsilon_{jst}$$
$$j,i = 1,\ldots,n \qquad h = S, NS$$

where ω^{h} is a parameter that allows for different intercepts depending on consumer type (i.e., overall demand for *non-storers* would be scaled up/down by ω^{h}) and may vary by demographics or obesity incidence. Fixed effects, represented by the term α_{js}, are included to account for brand-store-specific effects.

We augment the model by interacting the obesity rate with the fraction of *non-storers* in the population as well as with the own-price coefficient:

$$(8) \quad \omega = \omega_1 + \omega_2 * obesity\_rate$$

$$(9) \quad \beta_j^h = \beta_{1j}^h + \beta_{2j}^h * obesity\_rate.$$

To operationalize the inclusion of store-brand fixed effects, we re-write equation (7) for each type of consumer as:

$$(10) \quad q_{jst}^{NS}\left(p_{jst}, \mathbf{p}_{-jst}\right) = \omega e^{\alpha_{sj}} e^{\left(-\beta_j^{NS}p_{jst} + \sum_{j\neq i}\gamma_{ji}^{NS}p_{ist}\right)} + e^{\epsilon_{jst}}$$

$$(11) \quad q_{jst+\tau}^{S}\left(p_{jst}, \mathbf{p}_{-js,t+\tau}^{ef}\right)$$
$$= (1-\omega)e^{\alpha_{sj}} e^{\left(-\beta_j^S p_{jst} + \sum_{j\neq i}\gamma_{ji}^S p_{is,t+\tau}^{ef}\right)} + e^{\epsilon_{js,t+\tau}}$$
$$x_{jst} = e^{\alpha_{sj}}\left(q_{jst}^{NS*} + \sum_{\tau=0}^{T} q_{jst+\tau}^{S*}\right)$$

where

$$q_{jst}^{NS*} = \omega e^{\left(-\beta_j^{NS}p_{jst} + \sum_{j\neq i}\gamma_{ji}^{NS}p_{ist}\right)} + e^{\epsilon_{jst}}$$

and

$$q_{jst+\tau}^{S*} = (1-\omega)e^{\left(-\beta_j^S p_{jst} + \sum_{j\neq i}\gamma_{ji}^S p_{-is,t+\tau}^{ef}\right)} + e^{\epsilon_{js,t+\tau}}$$

thus

$$\log x_{jst} = \alpha_{sj} + \log\left(q_{jst}^{NS*} + \sum_{\tau=0}^{T} q_{jst+\tau}^{S*}\right)$$

$$(12) \quad \log x_{jst} - \overline{\log x_{jst}} = \log\left(q_{jst}^{NS*} + \sum_{\tau=0}^{T} q_{jst+\tau}^{S*}\right)$$
$$- \log\left(\overline{q_{jst}^{NS*} + \sum_{\tau=0}^{T} q_{jst+\tau}^{S*}}\right).$$

Finally, we assume that the error term, μ, enters equation (12) in an additively separable fashion (not displayed), and that $E(\mu - T, \ldots, \mathbf{p}_{t+T}) = 0$. These assumptions allow us to carry out estimation of equation (12) via nonlinear least squares.

Data

We use data collected by IRI's Infoscan in a sample of supermarkets across the United States. This data set contains store-level data on carbonated beverage sales by price and volume during 2006. Data consist of weekly observations and include 47 of the metropolitan areas from IRI's sample.[9] Data are available at the individual store level for each supermarket chain, but not for independent stores. A potential limitation is the exclusion of convenience stores, bars, restaurants, and other retail outlets for soft drinks. Importantly, IRI does not include every-day-low-price (EDLP) stores such as Walmart and Target, which may introduce sample bias. Specifically, supermarkets' price promotion strategies (upon which our estimation strategy is based) might differ in frequency, magnitude, and effect on a consumer's willingness to store where competition from EDLP stores is strongest. We perform several robustness exercises that address this and other potential concerns (see the supplemental appendix online).

For each store in each week, over 250 different Universal Product Codes (UPCs) for carbonated beverage products are observed. A given brand (e.g., Coke) likely comprises multiple UPCs, each representing a particular presentation of the brand (i.e., a 6-pack vs. a 2-liter bottle) and the type of container itself (e.g., can vs. bottle; see Bronnenberg, B.J., M.W. Kruger, and C.F. Mela 2008).[10] We choose data from 2006 for our analysis since this was the most recent year available when this research was initiated.

Our baseline regressions focus the analysis on the two most popular presentations, 2-liter bottles and 12-packs of 12-ounce cans, and the two most popular brands, regular Coke and regular Pepsi. While we focus on these in particular, we *do* include all brands in our estimation by aggregating all other observations into a composite brand named "Other."[11] To be precise, our analysis captures the dynamics (as discussed earlier) of the presentation-brand combinations that are the focus of our analysis (2-liter and 12-pack Pepsi and Coke), while treating all other brands in a static and aggregated way. Finally, in our robustness exercises we confirm our main results when we consider expanding the dynamic analysis to include the next two most popular brands.[12] The combined market share of Coke and Pepsi (in the two noted presentations) with respect to all soft drink sales in the IRI database is 20.65% by volume (11.53% for Coke and 9.12% for Pepsi), whereas the combined market share by volume of all observations used in the analysis (Coke, Pepsi, and the composite brand) amounts to 72.02%.[13]

We retain stores that show a clear split in price distribution, revealing an easily determined threshold between sale and non-sale periods. For 2-liter bottles, that threshold is $1.05, while for 12-packs it is $3.35.[14] Clearly, not all supermarkets in the IRI database show such clear modal values in the distribution of prices. Thus, we first use an iterative graphical process to identify the most common modal price across all supermarkets to identify essentially a sample-wide threshold. In a second stage, we select only those supermarkets whose individual data reasonably conforms to that sample-wide threshold. This procedure leaves us with 181 stores distributed over 33 states, and representing 12.25% of stores in the IRI database. We present examples of these reasonably conforming price distributions with descriptive statistics for the four featured brands in the supplemental appendix online.

---

[9] The IRI's metropolitan area definitions are similar to, but larger than, those used by the U.S. Bureau of Labor Statistics.

[10] Different variants of the same brand (e.g., Coke and Diet Coke) have different UPC codes.

[11] We compute the volume sold of the composite brand by summing the volume over all the 2-liter and 12-pack units sold (in each week-supermarket pair) across all brands (except those for which we model dynamics) that registered sales in either presentation. The average weekly unit price (in a supermarket-week pair) of the composite brand is given by the total dollar sales across all these observations divided by the total units sold in that category. The diet versions of Coke and Pepsi are included in the composite diet brand.

[12] The dynamic nature of our analysis requires us to search for and define sale and non-sale periods for each brand and presentation. This requires searching through weekly prices in all store-week combinations to establish those stores in which a consistent threshold price can objectively distinguish sale from non-sale periods. Determining the subset of stores with a clear price threshold for multiple brands significantly reduces the number of stores we can use in our analysis. We conjecture, however, that our qualitative conclusions are robust to the incorporation of dynamic effects for more (or all) brands. Specifically, we suspect that we are only partially registering stockpiling effects, as consumers may also store other brands during sales that we were unable to register as sales.

[13] The combined share of Coke, Pepsi, Sprite, and 7 UP (in the two presentations) that we consider in robustness checks is 25.96%.

[14] Our conclusions remained unchanged as we experimented with different possible threshold definitions.

We augment the IRI store-level data with both obesity incidence data (percentage of people with $BMI \geq 30$) and demographic indicators, both at the county level. Obesity rates are used in our baseline specification to investigate our hypothesis of whether price and sale sensitivity in a given population vary according to obesity rates. Demographic information is used in robustness tests where the obesity rate is replaced by demographic variables (detailed later) known to be strong "obesity predictors" (according to the medical and health literature). These alternative specifications are designed to (indirectly) address the possible endogeneity of our obesity variable.

Obesity rates estimates for 2006 are obtained from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (CDC; BRFSS), which is an ongoing, monthly, state-based telephone survey of the adult population. A respondent was considered obese if his BMI was $30 \, \text{kg/m}^2$ or greater.[15] The BRFSS uses three years of data to improve the precision of the year-specific, county-level estimates of obesity (selected risk factor for diabetes). For example, 2005, 2006, and 2007 were used for the 2006 estimate and 2006, 2007, and 2008 were used for the 2007 estimate (and so on). Estimates are restricted to adults 20 years or older to be consistent with population estimates from the U.S. Census Bureau, which provides year-specific county population estimates by demographic characteristics (age, sex, race, and Hispanic origin). Obesity rates are age-adjusted by calculating age group-specific rates for the following three age groups: 20–44 years, 45–64 years, and 65+ years. A weighted sum based on the distribution of these three age groups from the 2000 census is then used to adjust the rates by age (CDC 2014).

County-level demographic characteristics data were retrieved from the American Community Survey (ACS; U.S. Census Bureau 2006) and the U.S. Census Bureau (2010). In selecting particular demographic characteristics, we looked for factors that, at the aggregate level, are thought to predict obesity (Sobal and Stunkard 1989; Rosmond and Bjrntorp 1999; Patterson et al. 2004; Lutfiyya et al. 2007; Sodjinou et al. 2008).

These obesity predictors were tested for correlation with the obesity rates in our sample. Specifically, we regressed age, gender, race, and key interactions on obesity rates to highlight significant positive relationships (see the supplemental appendix online). Selected obesity predictors using this procedure are as follows: the percentage of households that receive food stamps; the percentage of the population that is African American; the percentage of population with a highest completed education level of high school or less; and the percentage of population that lives in rural areas. Selected demographic characteristics and their distribution characteristics for counties studied in this research appear in table 1. Finally, we match IRI data to both obesity rates and demographic characteristics data based on the location of each store in our data set.

Results

Demand estimation results are reported in tables 2 and 3. All results, unless otherwise specified, are significant at 5%. The dependent variable is the natural log of quantity of Coke or Pepsi (or a modified version of that log quantity, as in equation [12]) sold in a given week-store pairing. The right-hand side variables include own-price and cross-price of the chosen brand-presentation pairs for which we perform the dynamic analysis, as well as the composite brand's price (coefficients withheld for brevity). All results in tables 2 and 3 are obtained via least squares regressions including store-week fixed effects.[16]

Static Estimates

Table 2 presents the estimated coefficients from static models.[17] We keep these static models parsimonious, restricting the cross-price coefficient to that of the other brand in the same presentation (e.g., the cross-price coefficient for a 2-liter Coke is the price coefficient of a 2-liter Pepsi). The second column within each of the four sets of brand-

---

[15] $BMI = weight(kg)/height^2(m^2)$. Computation is performed using self-reported height and weight.

[16] Regressions for the static model (table 2) are estimated separately (via linear least squares). Estimates for the dynamic model are obtained via estimation of a simultaneous equations system where a non-linear least squares procedure is used.
[17] Other specifications that include all rivals' cross-price terms (individually or via a composite good) yield similar results.

Table 1. Distribution of Obesity Rates and Obesity Predictors

Variable	Mean	St. Dev.	Min.	I Quartile	Median	III Quartile	Max.
Percentage obesity	25.08	3.22	17.10	22.70	25.10	27.50	40.10
Percentage of households receiving food stamps	6.54	3.18	1.81	4.21	6.36	8.10	21.02
Percentage African American	12.96	13.19	0.57	2.93	8.58	20.41	64.19
Percentage Highest Education High School or Less	41.56	8.67	21.60	35.10	41.30	48.00	63.70
Percentage Rural Population[a]	12.94	14.93	0.00	2.17	6.45	21.19	67.71

Note: The obesity rate refers to the county-level, age-adjusted percentage of the population that is obese (see text for description); descriptive statistics for this variable were computed considering 126 counties across 33 states; (a) percentages obtained from Decennial Census Data 2010.

Table 2. Static Model Estimates

Variable	Coke 2-Liter			Pepsi 2-Liter			Coke 12-pack			Pepsi 12-pack		
	I	II	III	I	II	III	I	II	III	I	II	III
Own-Price	−1.94	−1.52	−1.90	−2.11	−1.60	−2.30	−2.16	−1.97	−0.92	−2.30	−2.30	−1.68
	(0.02)	(0.03)	(0.13)	(0.03)	(0.04)	(0. 13)	(0.02)	(0.03)	(0.11)	(0.03)	(0.03)	(0.12)
Cross-Price[b]	0.43	0.44	0.46	0.53	0.49	0. 51	0.09	0.04 [a]	0.09	0.30	0.29	0.26
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0. 02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
$Sale_t$	0.21		0.25		0.15		0.01[a]					
	(0.01)		(0.01)		(0.02)		(0.01)					
$Sale_{t-1}$	−0.06		−0.05		−0.10		−0.02					
	(0.02)		(0.01)		(0.01)		(0.01)					
$Sale_{t-2}$	0.02		0.006		−0.03		−0.019[a]					
	(0.01)		(0.01)[a]		(0.01)		(0.01)					
% obesity* $Sale_t$		0.01		0.01			0.01			0.01		
		(0.001)		(0.001)			(0.001)			(0.001)		

Note: Standard error appears in parentheses; (a) not statistically significant at the 95% level; (b) cross-price included corresponds to that of the rival in the same presentation.

presentation regressions displays estimates of whether a current and/or past sale is impacting current purchases, whereas the third column displays the coefficient on the interaction of the current-period sale dummy with the obesity rate.[18] Own- and cross-price coefficients in the static model have the expected signs and all but one are statistically significant.

Of importance to our dynamic analysis is the choice of the length of storage period. The sign of the current and past sale indicator variables in the static regressions guide this choice. Specifically, the static regressions

indicate that a sale in the current period has a positive effect on the quantity demanded (i.e., consumers, on average, purchase more than they would if the current period is not a sale period); as expected, this sign is consistent with some consumers' decision to purchase beyond their consumption during sale periods. The sign on the $Sale_{t-1}$ indicator variable is negative in all specifications, which indicates that a sale period during the previous week followed by a non-sale period in the current week (i.e., $Sale_{t-1} = 1$ and $Sale_t = 0$) reduces purchases in the current week. This evidence is consistent with the fact that some consumers store product at least one week ahead (i.e., the relevant storage period is $T \geq 1$).

Now, if consumers took advantage of a sale period to store for at least *two* weeks in advance (i.e., $T \geq 2$), the coefficient on $Sale_{t-2} = 1$ would also be negative and

---

[18] We also interacted the rate of obesity with the own-price coefficient (not displayed), but results vary across specifications—the interaction is in some cases positive and in some cases negative. This variability in coefficient sign also appears in the same interactions in our dynamic estimates displayed ahead.

Table 3. Dynamic Estimates

	Variable	I	II	III	IV
Whole population	ω	0.2984 (0.0386)	0.6044 (0.0708)	0.3474 (0.0414)	0.3486 (0.0418)
	$\omega \times$ % Obesity		−0.0109 (0.0014)		
Non-storer					
Own-Price Coefficients	2-Liter Coke	−1.5084 (0.0302)	−1.5213 (0.0298)	−1.5076 (0.0303)	−1.6100 (0.1231)
	2 Liter Coke x %Obesity				0.0044[a] (0.0049)
	2-Liter Pepsi	−1.5717 (0.0333)	−1.5905 (0.0329)	−1.5626 (0.0335)	−2.0421 (0.1230)
	2 Liter Pepsi x %Obesity				0.0196 (0.0049)
	12-Pack Coke	−1.8830 (0.0226)	−1.8807 (0.0223)	−1.8880 (0.0226)	−1.1199 (0.0766)
	12 Pack Coke x %Obesity				−0.0309 (0.0031)
	12-Pack Pepsi	−2.0828 (0.0224)	−2.0783 (0.0221)	−2.0864 (0.0224)	−1.5829 (0.0784)
	12 Pack Pepsi x %Obesity				−0.0198 (0.0031)
	Cross Price	0.4958 (0.0278)	0.4873 (0.0277)	0.4727 (0.0277)	0.7285 (0.1184)
	Cross Price x %Obesity				−0.0102 (0.0046)
Storer					
Own-Price Coefficients	2-Liter Coke	−3.1065 (0.0952)	−3.1255 (0.0956)	−2.5444 (0.5368)	−3.1133 (0.0948)
	2 Liter Coke x %Obesity			−0.0228[a] (0.0204)	
	2-Liter Pepsi	−2.9196 (0.0812)	−2.9528 (0.0816)	−1.5720 (0.4959)	−2.9098 (0.0805)
	2 Liter Pepsi x %Obesity			−0.0531 (0.0191)	
	12-Pack Coke	−3.2462 (0.0912)	−3.1994 (0.0876)	−4.4121 (0.3809)	−3.2986 (0.0938)
	12 Pack Coke x %Obesity			0.0450 (0.0133)	
	12-Pack Pepsi	−3.4216 (0.0860)	−3.3663 (0.0827)	−4.6899 (0.3966)	−3.4178 (0.0852)
	12 Pack Pepsi x % Obesity			0.0492 (0.0141)	
	Cross Price	0.0872 (0.0123)	0.0800 (0.0121)	0.1569 (0.0326)	0.0728 (0.0121)
	Cross Price x % Obesity			0.0338 (0.0115)	
R^2		0.984815	0.994825	0.994835	0.994841

Note: Number of observations: 36,912; standard errors in parentheses; (a) not statistically significant at the 95% level.

statistically significant across all specifications (i.e., conditional on $Sale_{t-1} = 0$ and $Sale_t = 0$, a sale two weeks ago would reduce purchases today); however, we find that in two of the four specifications (Coke 2-liter and Pepsi 2-liter), this coefficient is positive and statistically significant, and that in one (Pepsi 12-pack) it is statistically insignificant. One of the four specifications (Coke 12-pack) shows a negative and statistically significant coefficient on $Sale_{t-2} = 1$, although it is only about 30% the size of the coefficient on $Sale_t = 1$. Taken together, we consider this evidence to

support a choice of $T = 1$ for the relevant storage period for our dynamic model.

Regarding the obesity interaction with the indicator of a current sale, we observe that, consistent with our dynamic model findings (presented later), it is positive and highly statistically significant. Further, the magnitude of this interaction is economically important: a county with the largest percentage of obese population (40.10%; see table 1) would, all else being equal, exhibit sale period volume purchases about 23% larger than that of a county with the smallest percentage of obese population (BMI index of 17.10).[19] This result suggests that, *ceteris paribus*, areas where the population has a higher rate of obesity are more sensitive to sales.

Dynamic Estimates

Specification I in table 3 provides the baseline estimates of the dynamic model, whereas specifications II, III, and IV add a series of interactions of the obesity rate with different sets of coefficients. In all specifications we report three sets of coefficients: (1) the whole population (ω); (2) *non-storers* only (own-price and cross-price); and (3) *storers* (own-price and cross-price). In specification II we consider the interaction of the obesity rate with ω, whereas in specifications III and IV we report interactions of the obesity rate with own- and cross-price coefficients of *storers* and *non-storers* (respectively).

To preserve parsimony, we restrict the cross-price coefficient within each group of consumers (*non-storers* and *storers*) to be the same for all possible brand-presentation pairs.[20] We also estimate (for all consumers) the cross-price elasticity with respect to the composite good and also restrict it to be equal across all possible combinations between the composite good and each of the brand-presentation pairs considered.[21] Finally, we estimate a single ω for the whole population, which picks up the average *non-storers* population across the brand-presentation pairs considered. Attempting to estimate separate ω for each brand-presentation considered makes the model computationally intractable.

As in Hendel and Nevo (2013), we find that *storers* are much more price sensitive than *non-storers* across all specifications. Specification II shows that as the rate of obesity of a population increases, the fraction of *non-storers* (ω) decreases, and that this effect is statistically significant. The fraction of *non-storers* lies between 29.84% and 34.67% for the specifications that do not include the interaction with the rate of obesity (I, III, and IV). Specifically, the percentage of *non-storers* in a population with the highest rate of obesity in our data set (Dallas County, AL; 40.1%) is estimated to be as low as 16.73% (percentage of *storers*=83.27%), whereas ω is estimated as high as 41.80% (percentage of *storers* = 58.20%) in the area with the lowest rate of obesity (Fairfield County, CT; 17.1%). Across all the specifications we experiment with (including those reported in the supplemental appendix online), the coefficient on this interaction is the most robust.

In specification III, we report the results of a regression that considers the impact of the rate of obesity on the own-price and the cross-price elasticities for *storers*. Three out of the five interactions we consider (12-pack Coke, 12-pack Pepsi, and cross price) are statistically significant and positive. This finding suggests that consumers who like to stockpile 12-packs are less price sensitive in populations where the obesity rate is larger. In specification IV we explore whether this finding is also present for *non-storers*. The results of these interactions, however, are mixed: of the five, three are negative, one is positive, and one is statistically insignificant. These divergent results bar any definitive conclusion regarding the role of obesity on the brand-level own-price sensitivity of *non-storers*. A definitive answer to this question is more adequately addressed by studying aggregate elasticities (presented in the next section).

Robustness Checks

Our main result (the association of larger obesity rates with greater sale sensitivity) is robust to a number of alternative specifications (reported in the supplemental appendix online). We first check that our conclusions remain valid if we extend our dynamic

---

[19] $(40.10 - 17.10) \times 0.01 = 0.23$.

[20] For instance, for *non-storers* the cross-price coefficient between 2-liter Pepsi and 12-pack Coke is restricted to be the same as the cross-price coefficient between 2-liter Pepsi and 2-liter Coke (0.4958); this same restriction applies to *storers* (i.e., the cross-price coefficient is 0.0872). Relaxing this assumption was computationally untenable.

[21] The cross-price elasticity with respect to the composite good is consistently estimated at -0.18 across all specifications.

modeling to four (instead of two) brands. We then turn to tests that estimate the model using stores that are close to the center of the county; since we match county-level obesity data with store-level data, one possible concern is that some stores (those located in the periphery of the county) may attract consumers with a different obesity profile than that of the county where the store is located. Thirdly, we restrict the sample of stores to those that do not face competition from EDLP stores such as Walmart or Target, which are not included in the IRI database. These specifications address the possible concern that the dynamic effects we measure might differ in importance between stores that face significant EDLP competition (where *storers* are arguably likely to make their purchases) and those that are fairly isolated from this type of competition (surprisingly, we find evidence that runs contrary to this possibility). Finally, we look at whether replacing the obesity rate with one of several demographic predictors of obesity alters our result; these regressions are designed to provide evidence that the *possible* endogeneity of the obesity rate is unlikely to change our main conclusions.[22]

Aggregate Elasticities and Policy Considerations

The policy impact of our work relies on its ability to predict overall consumption responses to price changes. While results in table 3 (and in robustness checks) are quite conclusive about the positive role of obesity on stockpiling behavior (as measured by the percentage of *storers*), these figures cannot be used to directly infer the overall degree of consumers' price responsiveness. This is because price affects consumption through different channels (brand-level, own-price, and cross-price coefficients, as well as through the amount of stockpiling carried out). Aggregate elasticities capture the effects of all components.

Table 4 reports aggregate elasticities. The table uses specification II (table 3), but conclusions remain unchanged if specifications III or IV are used instead (see the

supplemental appendix online). We compute elasticities for the whole population, as well as for *storers* and *non-storers* separately. Further, to assess the role of obesity on overall price responsiveness, we report elasticities for counties located in different ranges of obesity rate: below the 25th percentile, between the 25th and 75th percentile, and above the 75th percentile. Two results emerge from table 4. First, *storers* are consistently less price sensitive than *non-storers*. Second, price sensitivity decreases with the obesity rate. From a policy perspective, these findings suggest that policies that rely on price increases (i.e., taxes) to reduce soda purchases may be less effective where the problem is more acute (i.e., in areas with higher obesity incidence and where stockpiling occurs more regularly).

Another valuable feature of our dynamic model is that we can contrast the effect of a temporary price change (e.g., a more heavily discounted sale price) to a permanent one (e.g., a price increase/decrease in both sale and non-sale periods, much like a soda tax would affect this market). To do this, we simulate consumption changes under two scenarios: a 5% price increase across the board (sale and non-sale periods) and a 5% increase in sale periods only. To appropriately contrast the short-run versus long-run effect of these two scenarios, we calculate the elasticities that result from only analyzing how consumption changes during sale periods; this allows us to isolate the effect of dynamic behavior.[23] The resulting short-run elasticity is -2.403, while the long-run elasticity is -1.445.[24] Earlier work has found a large range of price elasticity for soda (between -0.15 and -1.90; see Dharmasena and Capps 2012); our long-run elasticity lies in the upper (in absolute value) portion of this range and is in line with those estimated using dynamic demand frameworks (Wang 2015). Our short- and long-run elasticity estimates confirm the key role that dynamics play in this market: when faced with a temporary price reduction, consumers react much more (i.e., stockpile) than when faced with a permanent price reduction. In terms of policy implications, a

---

[22] In the supplemental appendix online we also provide a discussion on the role that price endogeneity may play in our setting.

[23] If dynamics played no role in the model, then we would expect these two elasticities to be the same as the only element consumers would consider in their decisions is current prices.

[24] We use specification II to compute these elasticities. See the supplemental appendix online for elasticities computed using specifications III and IV.

Table 4. Aggregate Price Elasticities

Type of Consumer	Counties with Obesity Rate **< 25th** Percentile	Counties with Obesity Rate **between 25th and 75th** Percentile	Counties with Obesity Rate **> 75th** Percentile
Storer	−1.911	−1.549	−1.182
Non-storer	−2.425	−2.324	−2.019
All	−2.234	−1.898	−1.821

Note: Calculated using specification II from table 3.

more pronounced short-run elasticity (as defined here) suggests that a policy aimed at combating temporary price promotions would be more effective than an across-the-board price increase.

Conclusions

In this paper we estimate a demand model that is able to capture, in a simple manner, the essence of complex purchase dynamics in the market for soft drinks. In particular, the model is able to: a) identify the fraction of consumers in a given region that stockpile soda when a price promotion is offered (*storers*), and b) estimate price sensitivities for both types of consumers (*storers* and *non-storers*).

Using data from stores located in over 100 counties in the United States, we find strong evidence that counties with higher obesity rates also contain a higher fraction of *storers*, as well as evidence that *storers*' price sensitivity decreases as obesity incidence grows. To the best of our knowledge, this research is the first to study these two questions in a dynamic demand setting.

Our results suggest a positive association between BMI and forward-looking behavior: stockpiling (as measured by the percentage of *storers*) is greater in areas with larger obesity incidence. This finding seems to be at odds with recent literature documenting a positive association between obesity and time discount rates (i.e., those with greater BMI appear to discount the future more heavily; see, e.g., Ikeda, Kang, and Ohtake 2010, and references therein). However, we conjecture that this discrepancy might be due to the fact that the "future" in our model is different from the one usually conceived elsewhere in the literature: we consider a very short horizon (1 week ahead) and a very specific domain (trading current versus future soda consumption). Conversely, studies that elicit time preferences typically rely on much longer horizons and define time preferences as a tradeoff between current and future financial rewards.

We find that a substantial fraction of the population (approximately 65%) stockpiles during temporary price reductions, a strategy that allows consumers to avoid paying higher prices when a sale expires. These estimates, together with our finding of a larger percentage of *storers* and a lower price sensitivity in areas characterized by high obesity rates, can have important policy implications.

Specifically, our results suggest that policies designed to increase the price of soda via taxes might be less effective than otherwise believed: consumers can, and some will, at least partially shield themselves from price increases by taking advantage of temporary sales. Further, the weakened effect of a price increase on purchases will be larger precisely in those areas where the policy concern is greatest; the reason for this is that: a) there is a larger fraction of *storers* in areas where obesity is more prevalent; b) *storers* are less price sensitive than *non*-storers; and c) *storers* in areas with higher obesity rates are less price sensitive than *storers* elsewhere.

We use the results of our model to study the role that dynamics play in this market. Specifically, we contrast consumers' reaction to a temporary price change (i.e., a more heavily discounted sale price) versus a permanent one (a price reduction in all periods) and find that consumers' tendency to stockpile is more pronounced (and therefore their price sensitivity is greater) when faced with a temporary price change. This finding further confirms the relatively limited impact that tax policies (which affect prices permanently) can have on overall soda consumption. Policy interventions aimed at preventing stockpiling (e.g., banning sales) would, according to our results, produce more effective results.

Taken together, our findings may explain why the impact of soda sales taxes on purchased soda volumes has been found to be null in a recent retrospective study that compares the effect of these taxes on soda consumption in jurisdictions where the taxes were enacted versus nearby locations where they were not (Colantuoni and Rojas 2015).

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/.

References

Andreyeva, T., F.J. Chaloupka, and K.D. Brownell. 2011. Estimating the Potential of Taxes on Sugar-sweetened Beverages to Reduce Consumption and Generate Revenue. *Preventive Medicine* 52 (6): 413–6.

Angrist, J., and J-S Pischke. 2009. *Mostly Harmless Econometrics* 1st ed. New Jersey: Princeton University Press.

Apovian, C.M. 2004. Sugar-sweetened Soft Drinks, Obesity, and Type 2 Diabetes. *JAMA: The Journal of the American Medical Association* 292 (8): 978–9.

Berry, S. 1994. Estimating Discrete-choice Models of Product Differentiation. *RAND Journal of Economics* 25 (2): 242–62.

Block, G. 2004. Foods Contributing to Energy Intake in the U.S.: Data from NHANES iii and NHANES 1999–2000. *Journal of Food Composition and Analysis* 3 (17).

Block, J.P., and W.C. Willett. 2011. Can Taxing Sugary Soda Influence Consumption and Avoid Unanticipated Consequences? *Choices* 3 (26).

Bronnenberg, B.J., M.W. Kruger, and C.F. Mela. 2008. The IRI Marketing Data Set. *Marketing Science* 27 (4): 745–8.

Cawley, J., and C. Meyerhoefer. 2012. The Medical Care Costs of Obesity: An Instrumental Variables Approach. *Journal of Health Economics* 31 (1): 219–30.

Centers for Disease Control and Prevention. 2010. State Cigarette Minimum Price Laws. *Morbidity and Mortality Weekly Report* 59 (13): 389–92.

———. 2014. Behavioral Risk Factor Surveillance System. Overview. Available at: http://www.cdc.gov/brfss/annual_data/2014/pdf/overview_2014.pdf.

———. 2015. Adult Obesity Facts. Available at: http://www.cdc.gov/obesity/data/adult.html.

Colantuoni, F., and C. Rojas. 2015. The Impact of Soda Sales Taxes on Consumption: Evidence from Scanner Data. *Contemporary Economic Policy* 33 (4): 714–30.

Dharmasena, S., and O. Capps. 2012. Intended and Unintended Consequences of a Proposed National Tax on Sugar-sweetened Beverages to Combat the U.S. Obesity Problem. *Health Economics* 21 (6): 669–94.

Duffey, K.J., P. Gordon-Larsen, J.M. Shikany, D. Guilkey, D.R. Jacobs, and B.M. Popkin. 2010. Food Price and Diet and Health Outcomes: 20 Years of the CARDIA Study. *Archives of Internal Medicine* 170 (5): 420–6.

Finkelstein, E.A., C. Zhen, J. Nonnemaker, and J.E. Todd. 2010. Impact of Targeted Beverage Taxes on Higher-and Lower-income Households. *Archives of Internal Medicine* 170 (22): 2028–34.

Fletcher, J. 2011. Soda Taxes and Substitution Effects: Will Obesity be Affected? *Choices* 26 (3).

Fletcher, J., D. Frisvold, and N. Tefft. 2013. Substitution Patterns Can Limit the Effects of Sugar-Sweetened Beverage Taxes on Obesity. *Preventing Chronic Disease* 10.

Fletcher, J.M., D. Frisvold, and N. Tefft. 2010a. Can Soft Drink Taxes Reduce Population Weight? *Contemporary Economic Policy* 28 (1): 23–35.

———. 2010b. The Effects of Soft Drink Taxes on Child and Adolescent Consumption and Weight Outcomes. *Journal of Public Economics* 94 (1112): 967–74.

Gardener, H., T. Rundek, M. Markert, C.B. Wright, M.S.V. Elkind, and R.L. Sacco. 2012. Diet Soft Drink Consumption is Associated with an Increased Risk of Vascular Events in the Northern Manhattan Study. *Journal of General Internal Medicine* 27 (9): 1120–6.

Griffiths, R.R., and E.M. Vernotica. 2000. Is Caffeine a Flavoring Agent in Cola Soft Drinks? *Archives of Family Medicine* 9 (8): 727–34.

Hendel, I., and A. Nevo. 2013. Intertemporal Price Discrimination in Storable Goods

Markets. *American Economic Review* 103 (7): 2722–51.

———. 2006. Measuring the Implications of Sales and Consumer Inventory Behavior. *Econometrica* 74 (6): 1637–73.

Ikeda, S., M. Kang, and F. Ohtake. 2010. Hyperbolic Discounting, the Sign Effect, and the Body Mass Index. *Journal of Health Economics* 29 (2): 268–84.

Jacobson, M.F., and K.D. Brownell. 2000. Small Taxes on Soft Drinks and Snack Foods to Promote Health. *American Journal of Public Health* 90 (6): 854–7.

Keast, R.S., and L.J. Riddell. 2007. Caffeine as a Flavor Additive in Soft-drinks. *Appetite* 49 (1): 255–9.

Libuda, L., and M. Kersting. 2009. Soft Drinks and Body Weight Development in Childhood: Is There a Relationship? *Current Opinion in Clinical Nutrition & Metabolic Care* 12 (6).

Ludwig, D.S., and C.B. Ebbeling. 2001. Type 2 Diabetes Mellitus in Children. *JAMA: The Journal of the American Medical Association* 286 (12): 1427–30.

Lustig, R.H., L.A. Schmidt, and C.D. Brindis. 2012. Public Health: The Toxic Truth About Sugar. *Nature* 482 (7383): 27–9.

Lutfiyya, M.N., M.S. Lipsky, J. Wisdom-Behounek, and M. Inpanbutr- Martinkus. 2007. Is Rural Residency a Risk Factor for Overweight and Obesity for U.S. Children? *Obesity* 15 (9): 2348–56.

Malik, V.S., M.B. Schulze, and F.B. Hu. 2006. Intake of Sugar-sweetened Beverages and Weight Gain: A Systematic Review. *The American Journal of Clinical Nutrition* 84 (2): 274–88.

Miao, Z., J.C. Beghin, and H.H. Jensen. 2013. Accounting for Product Substitution in the Analysis of Food Taxes Targeting Obesity. *Health Economics* 22 (11): 1318–43.

Patel, K.R. 2012. Essays in Industrial Organization. PhD dissertation, Northwestern University.

Patterson, P.D., C.G. Moore, J.C. Probst, and J.A. Shinogle. 2004. Obesity and Physical Inactivity in Rural America. *The Journal of Rural Health* 20 (2): 151–9.

Powell, L.M., and F.J. Chaloupka. 2009. Food Prices and Obesity: Evidence and Policy Implications for Taxes and Subsidies. *Milbank Quarterly* 87 (1): 229–57.

Powell, L.M., J.F. Chriqui, T. Khan, R. Wada, and F.J. Chaloupka. 2013. Assessing the Potential Effectiveness of Food and Beverage Taxes and Subsidies for Improving Public Health: A Systematic Review of Prices, Demand, and Body Weight Outcomes. *Obesity Reviews* 14 (2): 110–28.

Powell, L.M., R. Wada, J.J. Persky, and F.J. Chaloupka. 2014. Employment Impact of Sugar-sweetened Beverage Taxes. *American Journal of Public Health* 104 (4): 672–7.

Riddell, L.J., D. Sayompark, P. Oliver, and R.S. Keast. 2012. Caffeine as an Ingredient in Sugar-sweetened Beverages. In *Caffeine: Chemistry, Analysis, Function and Effects*, ed. V.R. Preedy, 22–38. Cambridge, England: Royal Society of Chemistry.

Rosmond, R., and P. Bjrntorp. 1999. Psychosocial and Socio-economic Factors in Women and their Relationship to Obesity and Regional Body Fat Distribution. *International Journal of Obesity and Related Metabolic Disorders: Journal of the International Association for the Study of Obesity* 23 (2): 1–38.

Schroeter, C., J. Lusk, and W. Tyner. 2008. Determining the Impact of Food Price and Income Changes on Body Weight. *Journal of Health Economics* 27 (1): 45–68.

Sharma, A., K. Hauck, B. Hollingsworth, and L. Siciliani. 2014. The Effects of Taxing Sugar-sweetened Beverages across Different Income Groups. *Health Economics* 23 (9): 1159–84.

Sobal, J., and A.J. Stunkard. 1989. Socioeconomic Status and Obesity: A Review of the Literature. *Psychological Bulletin* 105 (2): 260–75.

Sodjinou, R., V. Agueh, B. Fayomi, and H. Delisle. 2008. Obesity and Cardio-metabolic Risk Factors in Urban Adults of Benin: Relationship with Socio-economic Status, Urbanisation, and Lifestyle Patterns. *BMC Public Health* 8 (1): 84.

Sturm, R., L.M. Powell, J.F. Chriqui, and F.J. Chaloupka. 2010. Soda Taxes, Soft Drink Consumption, and Children's Body Mass Index. *Health Affairs* 29 (5): 1052–8.

U.S. Census Bureau. American Community Survey. 2006. Available at: http://www.census.gov/acs/.

———. Decennial Census Data. 2010. Available at: http://www.census.gov/2010census/data/.

Vartanian, L.R., M.B. Schwartz, and K.D. Brownell. 2007. Effects of Soft Drink Consumption on Nutrition and Health: A Systematic Review and Meta-analysis. *American Journal of Public Health* 97 (4): 667–75.

Wang, E.Y. 2015. The Impact of Soda Taxes on Consumer Welfare: Implications of Storability and Taste Heterogeneity. *RAND Journal of Economics* 46 (2): 409–41.

Wang, Y.C., S.N. Bleich, and S.L. Gortmaker. 2008. Increasing Caloric Contribution from Sugar-sweetened Beverages and 100% Fruit Juices Among U.S. Children and Adolescents, 1988–2004. *Pediatrics* 121 (6): e1604–e1614.

Welsh, J.A., A.J. Sharma, L. Grellinger, and M.B. Vos. 2011. Consumption of Added Sugars is Decreasing in the United States. *The American Journal of Clinical Nutrition* 94 (3): 726–34.

West, R. 2001. Glucose for Smoking Cessation. *CNS Drugs* 15 (4): 261–5.

Yeomans, M.R., P.J. Durlach, and E.M. Tinley. 2005. Flavour Liking and Preference Conditioned by Caffeine in Humans. *The Quarterly Journal of Experimental Psychology Section B* 58 (1): 47–58.

Zhen, C., M.K. Wohlgenant, S. Karns, and P. Kaufman. 2011. Habit Formation and Demand for Sugar-sweetened Beverages. *American Journal of Agricultural Economics* 93 (1): 175–93.

Zhen, C., E. Finkelstein, J. Nonnemaker, S. Karns, and J. Todd. 2014. Predicting the Effects of Sugar-sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System. *American Journal of Agricultural Economics* 96 (1): 1–25.

Zheng, Y., and H.M. Kaiser. 2008. Advertising and U.S. Nonalcoholic Beverage Demand. *Agricultural and Resource Economics Review* 37 (2): 147–59.