Heterogeneous behavior, obesity and storability in soft drink consumption: A dynamic demand model

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Abstract

In this paper we applied a dynamic estimation procedure to investigate the role of obesity on the demand for soda. The dynamic model accounts for storing behaviors, and allowed us to study price sensitivity as well as sale sensitivity of soda consumers. By matching store level data to obesity data, we considered the effect of obesity rates on soda demand. We found that higher obesity rates were associated with a higher attitude to anticipate future needs and respond to sale prices. Conversely, according to our results, a higher rate of obesity was also associated to lower price sensitivity. We also considered how some obesity predictors affected the demand for soda. Our results contribute to the existing literature by raising important elements to help establish correct policies to fight obesity. For instance, our research suggests that a policy intervention restricting the magnitude of sales would be more successful than a tax increase in modifying the behavior of obese consumers.

1 Introduction

Despite the slight decrease in soft drink consumption recently registered among some population groups (Welsh et al., 2011), the average level of soda consumption in the United States is close to 50 gallons per person per year. Scientific evidence links the high volume of soda consumed to the worrisome obesity incidence, which affects 34% of the U.S. population.[1] Soda is nowadays considered the single most important source of calorie intake in the U.S. (Block and Willett, 2011; Wang et al., 2008; Block, 2004).

Fighting obesity has become a priority in the political agenda, primarily because of the high external costs associated with the phenomenon. Higher mortality incidence as a result of food diseases, increasing medical expenses resulting in more expensive health insurance premiums, and productivity losses in the labor market (Fletcher, 2011), are reasons that make public intervention compelling. Most of the political interventions at various levels (state, county, and city) during the last decades have consisted of a set of taxes, in particular small sales taxes as well as some excise taxes.

The argument frequently used to justify soda taxes is the success obtained by cigarette taxes in decreasing cigarette consumption. However, cigarettes and soda are different in a number of ways. First, cigarette taxes are often designed to cause significant price increases (up to 57% in New York State, that is, a $4.34 price increase per pack). High taxation levels might not be possible or justifiable for soft drinks given that, as opposed to cigarettes, moderate soda consumption is considered safe. A second difference with cigarettes is that soda has many substitutes (Block and Willett, 2011). A third difference is that soda consumers can take advantage of sales and discounts and buy large quantities to store, as opposed to cigarette consumers.

On the other hand, soda is similarity to cigarettes is that the most common ingredients in soda manufacturing, caffeine and sugar, are thought to cause addiction according to the medical literature. This aspect may have an impact on frequency and volumes of purchase. Caffeine, for instance, known as a mildly addictive psycho-active chemical, is contained in over 60% of soft-drinks sold in the United States. The psychological and physiological influence of caffeine on consumers may help ensure repeat purchase of the product (Riddell et al., 2012), which suggests that caffeine may be added to modify consumer behavior (Riddell et al., 2012; Yeomans et al., 2005; Keast and Riddell, 2007; Riddell and Keast, 2007; Griffiths and Vernotica, 2000). Furthermore, the high glycemic index characterizing some foods and drinks like soda, is considered to be the key mediator of food addictive potential, and it is thought to be an important factor responsible for the obesity

[1] http://www.cdc.gov/obesity/

epidemic (West, 2001). In the case of soft drinks, which contain high levels of both sugar and caffeine, this addictive potential may be more reinforced than for foods or drinks containing one of the two ingredients alone.

At the core of the social problem is the fact that there are households purchasing extremely large quantities of soda that are therefore more exposed to obesity and to several health problems[2] caused by soft drink ingredients, while other consumers are moderate in their consumption.[3] The reasons for high intensity consumption levels can be various, but brand loyalty and addiction are possible explanations. Thus, simple taxing policies are unlikely to be effective for these heavy consumers. Further, as noted above, soda maybe subject to temporary price reductions, as opposed to other taxed goods (i.e., cigarettes), allowing soda consumers to stockpile this storable good.

In this research we investigate the role of obesity on the demand for soda by considering a dynamic setting; the presence of temporary price reductions and the possibility of storing for future consumption makes the incorporation of this dimension essential. Prior research that accounts for both storability and product differentiation of soft drinks (Hendel and Nevo, 2012; Wang, 2012), has shown that a dynamic model of consumer inventory behavior is necessary to estimate accurate price sensitivity parameters, and that realistic substitution patterns for differentiated products are obtained by including consumer heterogeneity in the model. Following the dynamic model of Hendel and Nevo (2012) we identify the percentage of consumers that are *storers* (consumers that stockpile purchases) versus those that are not and estimate their price elasticity parameters. We then extend the model to study how the fraction of *storers* as well as their price sensitivity in a geographic area varies by the percentage of obese individuals in the area. Specifically, we match store-level soft drinks sales data to county-level obesity rates (and other demographic data), and use these data in estimation of the demand for soda products. Results from this study highlight several effects related to the rate of obesity suggesting that higher-BMI consumers, despite being less price-sensitive for soda, are more inclined to store, and therefore more sale-sensitive. We find that price-sensitivity and sale-sensitivity are

[2]Scientific evidence associates high levels of obesity rate with high levels of soda consumption (Ludwig and Ebbeling, 2001; Apovian, 2004; Malik et al., 2006; Vartanian et al., 2007; Libuda and Kersting, 2009).

[3]A level of consumption considerate moderate because, for example, does not appear to be linked to a higher risk of vascular events, corresponds to less than 6 cans per week (Gardener et al., 2012)

not necessarily equivalent and may need to be treated as separate concepts. This distinction may appear counterintuitive at first. In reality, though, by allowing storing behavior, we have to cope with the possibility that some consumers may buy more at lower prices even if they are less sensitive to the overall price of soda. To better envision this behavior we shall again invoke the parallelism between soda and cigarette consumption: the same way smokers (by and large characterized by low price sensitivity) buy cigarette cartons at airports' duty free shops to benefit of discounted prices, assiduous soda consumers that face strong consumption desire may take advantage of sales and stockpile.

These and other results illustrated below identify important elements that can help establish correct policies to pursue in order to fight the obesity epidemic. The rest of this paper is organized as follows: section 2 reviews the previous literature; section 3 illustrates the theoretical framework, the behavioral model and the methodology applied; section 4 presents the results and the policy implications; and section 5 concludes.

2 Previous Literature

A number of studies have estimated the price elasticity of demand for soda in order to predict the extent of the decrease in consumption that would result from a potential price increase due to taxation. Studies typically report that demand for soft drinks (as a product category) is largely price-inelastic. A few of such studies found that the elasticity of demand for soda is close to -0.78 (Brownell and Frieden, 2009), or lower (Wang, 2012). A recent review on demand estimates for food products reports an own-price elasticity for soda and other beverages that ranges between -0.8 and -1 (Andreyeva et al., 2011). Lin et al. (2010) estimated two beverage demand systems using retail purchase data for high-income and low-income households. The authors found that, among high-income households, the demand for CSD is price elastic (mean of -1.29) while among low-income households demand is price inelastic (mean of -0.95). A large variance of price elasticity estimates is illustrated by the results in 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. Given that, for the most part, low demand elasticity estimates are expected for soda, a price increase due to a tax is in turn expected to yield a comparatively small decrease in quantity demanded. In addition to the relatively small effect on consumption, some authors show that the ultimate impact of a tax on body weight is negligible (Fletcher et al., 2010a,b; Powell and Chaloupka, 2009; Sturm et al., 2010, Finkelstein et al., 2010, Duffey et al., 2010, and Schroeter et al., 2008). This may be due to substitution with other beverages or sugary food of those who reduce soda purchases as a consequence of a tax.

Zhen et al. (2011), using homescan panel data, estimated the demand for sugary nonalcoholic beverages. By applying a dynamic extension of the almost ideal demand system, they found evidence of habit formation and explained that, for this reason, consumers are more likely to respond to taxes in the long run than in the short run. Patel (2012) accounts for body mass index (BMI) and demographics characteristics in the context of a static model of demand and preferences for soda. Patels estimates suggest that consumers with higher body tend to be less price-sensitive and prefer diet sodas. The predicted decrease in BMI due to a soda tax would not be likely to yield meaningful reductions in social and medical costs (Patel, 2012). Patel concludes that, given the static nature of his demand estimations, his estimates of the price sensitivity are likely overstated. While our results confirm Patels findings that high obesity rates are associated to lower own price elasticities, by accounting for dynamics, we add confidence that our demand elasticity estimates are not overstated (Hendel and Nevo, 2006, 2012). In fact, consumption dynamics are important for a storable good as soda as static models are shown to overstate own price elasticity and understate cross price elasticity (Hendel and Nevo, 2006; Patel, 2012; Wang, 2012). In addition, by explicitly considering temporary price reductions in our model, we do not overstate moves to the outside option that would result from failing to consider the stockpiling behavior when soda is on sale (Hendel and Nevo, 2006). Patel concludes, also, that if obese consumers engage in stockpiling more than non-obese consumers, than his obese-specific price-sensitivity estimates will be overstated. In contrast to Patels procedure, we are able to verify that high obesity rates result in more stockpiling than low obesity rates, implying that estimated price sensitivities for obese consumers in a static model will be, to some extent, overstated.

As opposed to previous studies that have conducted welfare analysis and quantified the possible effects of existing or proposed taxes on consumption, we account for the effects of temporary price discounts and the consequent stockpiling behavior that occurs during these periods. To the best of our knowledge, no previous research has studied sale responsiveness for obese consumers.

As in Hendel and Nevo (2013), we first distinguish soda consumers in *storers* and $non - stores$. In their research on intertemporal price discrimination for storable goods, Hendel and Nevo make this distinction to explain why soft drink companies and/or retailers offer temporary price reductions. They find that there are consumers who make most of their soda purchases at a discounted price. These consumers are assumed to be price-sensitive consumers and consumers who anticipate future needs by buying large quantities on sale (*storers*). Other consumers are, instead, less price sensitive consumers who buy about the same amount regardless of the discount ($non - storers$). The existence of these two consumer types in the market justifies why optimal pricing involves discounts. Hendel and Nevo do not distinguish sale-sensitivity from price-sensitivity and assume that more price sensitive consumers are the ones who store. With our extension of Hendel and Nevos model, we find that in areas characterized by higher obesity rates the sale-responsiveness (or storing propensity) is higher, but at the same time a high obesity rate contributes to decrease soda price sensitivity. In other words, even consumers who are less sensitive to soda prices (i.e. low price elasticity of demand), because of either brand loyalty, strong preference or possible addiction, do respond to sales. Inventory behavior for a sizable part of the population may help explain why the impact of soda sales taxes on purchased soda volumes has been found to be null in a comparative statics study that compares the effect of these taxes on soda consumption in jurisdictions where the taxes were enacted to no-soda tax similar areas (Colantuoni and Rojas, 2012).

3 Empirical Model for the demand estimation

In this section we illustrate the behavioral model that describes consumers' decisional process when buying soda. We build on Hendel and Nevo (2012) (H&N, henceforth) given that their model allows to handle the demand dynamics due to product storability in a relatively simple way. We will point out analogies and different specifications we include in the model as they appear in the following description.

Let consumer h utility function at time t be:

$$U_{ht}(\mathbf{q}, m) \equiv U(\mathbf{q}, m) \tag{1}$$

where $\mathbf{q}$ is the vector of consumption of the J varieties of the good (soda), and m is the numeraire good. The consumer's problem is how much soda to buy in every purchase occasion ($\mathbf{x}_t$), and how much to consume ($\mathbf{q}_t$).

$$\text{Obj: Max } U_{ht} \tag{2}$$

Like H&N, we can assume that the inventory lasts only T periods (shelf life of the product) and that consumers know their needs T periods in advance. In our case, given that soda has a long shelf life, we will assume that rational consumers will store just enough soda to last between one sale and another, because they know the price history, they can anticipate soda price up to T ahead, so they can minimize storage costs. This assumption leads to simple dynamics, otherwise stockpiles and periods would overlap.

We consider the possibility of storing behavior by allowing the presence of the following types of consumers:

- $Storers$ and $non - storers$.

H&N make the assumption that consumers would not consider stockpiling during non-sale periods. This is a strong assumption as there may be consumers who prefer to make fewer trips to the grocery store, so they may buy large quantities of their favorite brands, not intended for immediate consumption, despite the price period. But, in this research we are interested in how much consumers are inclined to buy on sale, allowing them to store. In this sense, we explicitly consider the storing behavior pinned down by patterns between purchases and frequency of sale as the measure of sale sensitiveness. Hence, consistently with H&N's exposition, we name "$storers$" the fraction of the population that buys on sale.

For $non - storers$ (NS), the quantity demanded is a static problem (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 demanded is a dynamic problem. Their purchasing patterns are determined by the solution of the following maximization problem:

$$\text{Max} \sum_{t=0}^{R} \mathbb{E}\left[u_t^S(\mathbf{q}_t, m_t)\right] \tag{3}$$

s.t.

$$0 \geq \sum_{t=0}^{R} [(y_t - (\mathbf{p}_t'\mathbf{x}_t + m_t)] \quad \text{(Budget Constraint), and} \tag{4}$$

$$\mathbf{q}_t \leq \mathbf{x}_t + \sum_{\tau=0}^{t-1} (\mathbf{x}_\tau - \mathbf{q}_\tau - \mathbf{e}_\tau) \quad \text{(Inventory Constraint)} \tag{5}$$

when $t = t^s : \mathbf{x}_\tau = \mathbf{q}_\tau$, where t^s is the sale time; τ is the time when the inventory gets empty, and R is the last period considered for the analysis; $\mathbf{e}_\tau$ is the vector of unused units expiring in period τ.

The dynamic problem is nicely solved by H&N by replacing prices with *effective prices*. The definition of effective price is based on the determination of a sale price. In our specification, a sale price is any price equal or less than \$1.05. This definition, though arbitrary, is established based on price distributions across chains, stores and cities. As well as H&N, we noticed two modal values in price distributions. The lowest modal value is consistently equal to \$1.05, therefore we selected this value as the threshold for sale prices. Let's define a sale period (S) as the period when p_{jt} is a sale price, and a non-sale period (N) otherwise. *Storers*' purchases may not be contemporaneous with the period of consumption, because they respond to sale incentives and they can stockpile. By allowing *storers*' purchases to be a function of effective prices, that is, by updating the current price with the price in effect in a relevant sale period (*effective price*), the dynamic optimization problem for *storers* becomes a system of R static optimization problems.

Given that effective prices are used also 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 demand of all other storable goods ($-j$). Thus, optimal consumption for *storers* in period t is:

$$\mathbf{q}_t^S = Q_t^S(\mathbf{p}_t^{ef}) \tag{6}$$

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

$$X_{jt}(\mathbf{p}_{t-T}, ..., \mathbf{p}_{t+T}) = Q_{jt}^{NS}(\mathbf{p}_t) + X_{jt}^S(\mathbf{p}_{t-T}, ..., \mathbf{p}_{t+T}) \tag{7}$$

It follows a brief description of purchasing patterns; more details can be found in Hendel and Nevo (2012). The idea is that *storers*' purchases in period t are the sum over current and future needs up to $t+T$ (recall: consumers know prices up to T periods ahead). They decide when 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 we compare $\mathbf{p}_{jt}$ with $\mathbf{p}_{jt+T}$ prices to see if consumers buy also some units at t for T periods ahead consumption. Effective prices of j and $-j$ need to be used in the demand equation to convert the dynamic problem into a static one. In order to visualize this idea, let's consider the case of $T=1$. With this example we can show how to determine whether current period (t) consumption is purchased in t or in $t-1$, and whether the consumption for period $t+1$ is purchased in t or $t+1$. *Storers*' behavior can be predicted by defining four types of periods: a sale preceded by a non-sale (NS), a non-sale preceded by a sale (SN), two sale periods (SS) and two non-sale periods (NN). Considering each type of period defined above and given perfect foresight, product j aggregate purchases (the sum of $non-storers$ and $storers$ purchases), as defined in equation 7, need to be scaled up and down in the following way:

$$X_j(\mathbf{p}_{t-1},\mathbf{p}_t,\mathbf{p}_{t+1}) = \begin{cases} \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)Q_{jt}(p_{jt},p_{-jt}), & \text{NN} \\ \omega Q_j(p_{jt},p_{-jt}), & \text{SN} \\ \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)(Q_{jt}(p_{jt},p_{-jt}) & \\ \quad +Q_{jt}(p_{jt},p_{-jt+1})), & \text{NS} \\ \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)Q_{jt}(p_{jt},p_{-jt+1}), & \text{SS} \end{cases} \tag{8}$$

Where $Q_j(.)$ is the static demand for $storers$ and $non-storers$, and ω is the fraction of $non-storers$. For $non-storers$ demand and consumption coincide, thus, $\omega Q_j(p_{jt},p_{-jt})$ contributes in all types of period to the aggregate demand. In NN periods $storers$ and $non-storers$ buy for current consumption; clearly the first expression in the system of equation results in $Q_j(p_{jt},p_{-jt})$, but we reported the two components for completeness, and to show how the demand is scaled in the different regimes. In SN periods, $storers$ do not purchase in t for current or future consumption, they must have purchased in $t-1$, when there was a sale. During NS periods, $storers$ purchase for current consumption as well as for future $t+1$ consumption. In SS periods, $storers$ only purchase for future consumption in t, while their current consumption units were purchased in $t-1$. Importantly, apart from scaling the demand for *storers* depending on the type of period, the dynamics is incorporated also by updating p_{-jt+1} with p^{ef}_{-jt+1}. All consumers in all periods will compare p_j and p_{-j}, and it may be the case that, for example, while j is not on sale in t nor was in $t-1$, $-j$ was on sale in $t-1$ and it's not on sale in t. Therefore, *storers*' purchases in NN are $Q^S_{jt}(p_{jt}, p^{ef}_{-jt})$ and not $Q^S_{jt}(p_{jt}, p_{-jt})$, to account for storage of substitute products. This updating procedure is needed in every period, meaning that we have to consider the different regimes also for substitutes products. In fact, using contemporaneous prices for substitutes products would generate a bias in the estimated cross price effect.

3.1 Estimation procedure

For estimation, we defined the regimes as specified in equation 8 and we replaced the price of $-j$ good with its effective price, as defined earlier. We assume that the demand for product j at store s in week t is log-linear:

$$\log q^h_{jst} = \omega^h \alpha_{sj} - \beta^h_j p_{jst} + \gamma^h_{ji} p_{ist} + \epsilon_{jst}, \quad j = 1,2 \quad i = 3-j \quad h = S, NS \tag{9}$$

Where, ω^h is a parameter that allows for different intercept depending on the consumer type, in particular $\omega = \omega^{NS} = 1 - \omega^S$, it represents the fraction of $non-storers$ when prices are zero. As a consequence, in order to account for store and product fixed effects, equation 9 can be rewritten as:

$$Q^{NS}_{jst}(p_{jst}, \mathbf{p}_{-jst}) = \omega e^{\alpha_{sj}} e^{(-\beta^{NS}_j p_{jst} + \gamma^{NS}_{ji} p_{ist})} e^{\epsilon_{jst}} \tag{10}$$

$$Q^S_{jst+\tau}(p_{jst+\tau}, \mathbf{p}^{ef}_{-jst+\tau}) = (1-\omega) e^{\alpha_{sj}} e^{(-\beta^S_j p_{jst} + \gamma^S_{ji} p^{ef}_{ist+\tau})} e^{\epsilon_{jst+\tau}} \tag{11}$$

$$x_{jst} = e^{\alpha_{sj}} (Q^{NS}_{jst} + \sum_{\tau=0}^{T} Q^S_{jst+\tau})$$

$$\log x_{jst} = \alpha_{sj} + \log(Q^{NS}_{jst} + \sum_{\tau=0}^{T} Q^S_{jst+\tau})$$

$$\log x_{jst} - \overline{\log x_{jst}} = \log(Q^{NS}_{jst} + \sum_{\tau=0}^{T} Q^S_{jst+\tau}) - \overline{\log(Q^{NS}_{jst} + \sum_{\tau=0}^{T} Q^S_{jst+\tau})} \tag{12}$$

Fixed effects are considered to account for different stores that operate at a different scale. Estimation is carried out via nonlinear least squares. We considered the effect of the obesity rate and some obesity predictors on the fraction of non-storing population and on the price-sensitivity parameter for *storers*. This was possible by breaking up the parameter ω and the *storers*' price sensitivity parameter into two components, one is fixed and the other is interacted with the variable of interest, in the following way, in order to analyze the contribution of different factors to the demand for soda:

$$\omega = \omega' + \omega'' * \textit{obesity-predictor} \tag{13}$$

$$\beta_j^S = \beta'^S_j + \beta''^S_j * \textit{obesity-predictor} \tag{14}$$

3.2 Data

For this analysis, we use data collected by IRI's sample of supermarkets across the U.S. This data set contains store sales data on carbonated beverage volume sales and prices during the 2001-2006 period. Data consist of weekly observations and include 47 IRI's metropolitan areas.[4] Data are available at the store level for each chain. IRI only includes chains and not independent stores, and the observations are drawn from IRI's national sample of stores. A potential limitation of this data set is the exclusion of convenience stores, bars, restaurants and other retail outlets for soft drinks. For each store in each week, over 250 different Universal Product Codes (UPCs) for carbonated beverage products are observed. Thus, each brand (e.g. Coke) has multiple UPCs associated to it, each representing the particular presentation of the brand (i.e. such as packaging 6-pack vs. single bottles) and presentation (e.g. can vs. bottle; see Bronnenberg et al., 2008).

The year chosen for the analysis is 2006; supermarkets for which there are missing observations for any of the products considered for the analysis are dropped from the data set. Furthermore, we retain only the stores that show a clear break in the price distribution, corresponding to the value considered as threshold for sale prices. We also drop the supermarkets whose prices are smaller than $0.50 for a 2-liter bottle in more than 5% of the instances. In fact, we noticed that a higher frequency of such small (unrealistic) prices

[4] IRI's metropolitan area definitions are similar to those used by the Bureau of Labor Statistics.

was driving the results; 5% or lower frequency of outliers permits the results to be stable. This procedure leaves us with 181 supermarkets located in 33 States. The products we focus on are Coke, Pepsi and private label colas. The size we choose is the 2-liter bottle, which is the most popular size in our data set. Specifically, the market share in the original data set for Coke, Pepsi and private label colas together is 91%, and the market share of 2 liter bottle size for these three brands is 35% with respect to all brands-sizes. We report descriptive statistics of the data used in (Table 1).

Table 1: Descriptive statics IRI dataset

			% of the variance explained by:		
Variable	Mean	Std	Chain	Week	Chain-Week
Price Coke	1.21	0.22	16	4	78
Price Pepsi	1.17	0.21	16	6	83
Units sold Coke	222.37	189.86	30	3	65
Units sold Pepsi	222.41	226.31	46	3	72
Sale Coke	0.33	0.47	13	4	82
Sale Pepsi	0.37	0.48	11	7	82

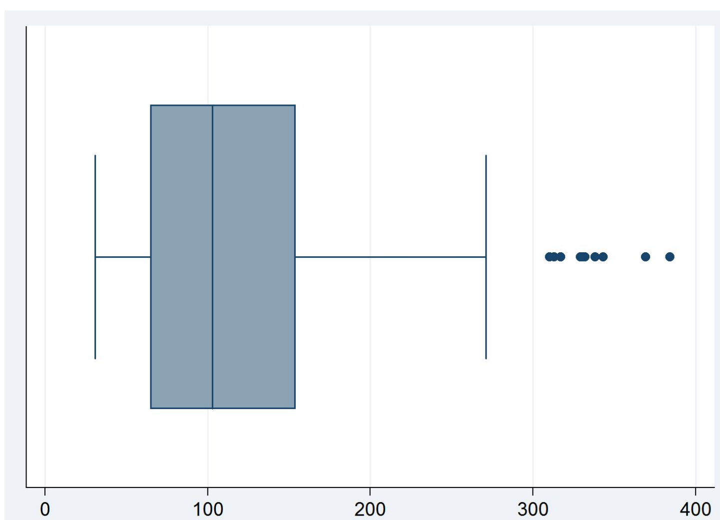
Note: 9231 observations per brand. A sale occurs when the price drops to $1.05 or below.

In order to explore some facts about soda drinkers, we use data on households' purchases collected by Nielsen (Homescan Consumer Panel Data from Chicago Booth and Kilts Center for Marketing) during the same time period (2006), which contains information on households' characteristics (i.e. income, level of education, type of employment, household size, race, type of residence) and information on the characteristics of the good purchased (i.e. regular, caffeine free, diet soda), quantities purchased on a specific day, the price paid and whether the item was purchased at regular or discounted price. This data set contains purchases from all Nielsen-tracked categories including soft drinks and potential substitute beverages. It represents approximately 40,000 - 60,000 US households, covering the period 2004 - 09.

To have a clearer understanding of soda drinkers personal habits and to discern possible confounding factors, we selected only the households composed of one person (single-size households). We observe about 9,000 single-size households that are soda drinkers. Among these, soda consumption has substantial variation: it ranges from one can per year to several hundreds of gallons/year (in 2006). Soda volume purchased per year calculated using the Homescan data set is a conservative measure of actual consumption, given that it relies on the discipline with which panelists scanned their purchases, and it only considers soda purchased from supermarkets (not from bars, restaurants, vending machines, etc.). Assuming the probability of misreporting is the same for all the panelists, we take the values computed from this data set as a conservative indication of soda consumers' actual purchases. We dropped from our sample households that appear to have repeatedly (more than twice) imputed inconsistent values for price, otherwise we dropped only the likely wrong value. Several individuals in our data set purchased a considerable volume of soda in 2006. Panelists whose purchased volume was higher than 21000 oz (164 gallons/year), are considered "binge drinkers"; there are 122 in our data set. We investigate the frequency of purchase for this category of consumers. Specifically, we are interested in knowing whether they frequently purchase small quantities or they purchase large quantities less frequently.

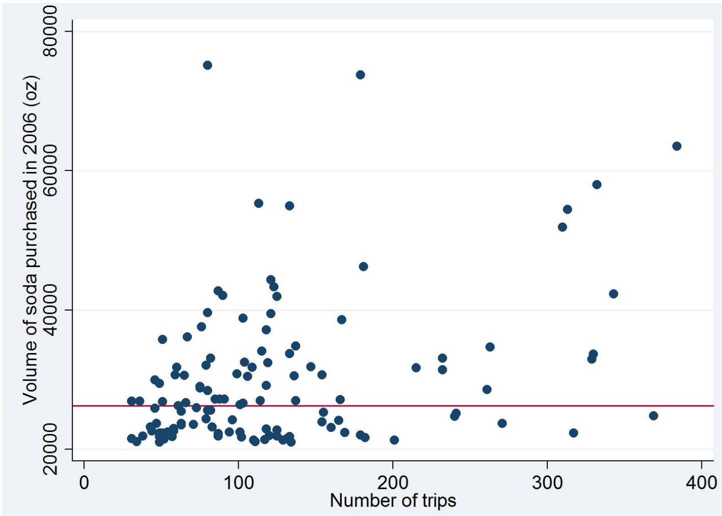
In Figure 1 we report the distribution of number of trips for these consumers. The distribution in Figure 1 shows that most of these consumers

Figure 1: Distribution of number of trips made by binge drinkers in 2006



made fewer trips to the supermarkets to buy soda, presumably buying larger quantities, suggesting a storing behavior. Fewer consumers appear to buy soda more frequently; some even made more than one trip per day to buy soda, but they are considered outliers. Table 2 reports the correlation be-

Figure 2: Total volume purchased in 2006 by single-size households and number of trips



Note: The reference line is at level 26280 oz (six 12 oz cans/day).

tween the two variables. We observe that the correlation is positive but low. In Figure 2 we show a plot of total volume purchased in 2006 by single-size households and number of trips. The reference line is at a level of 26,280

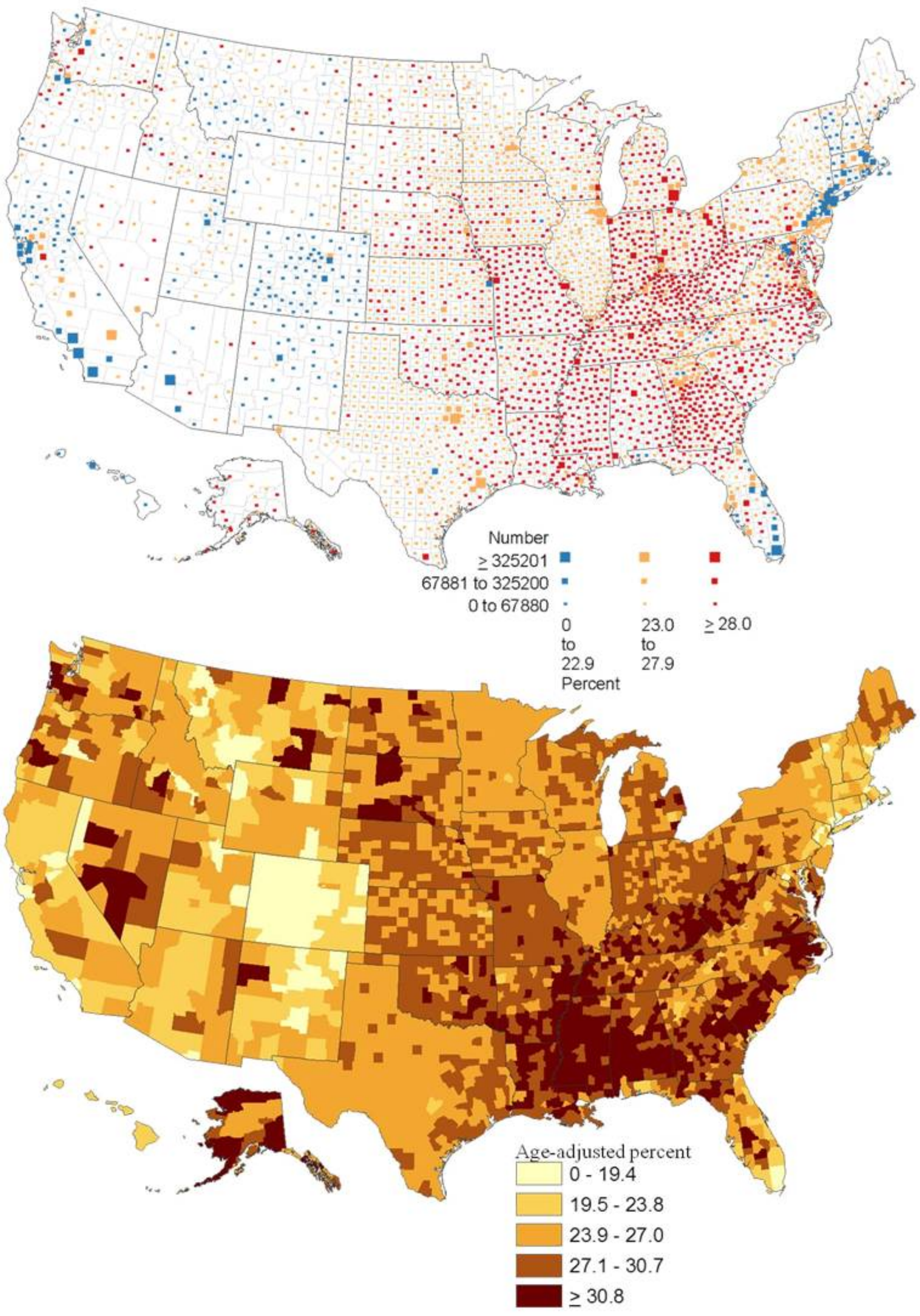
Table 2: Pearson Correlation Coefficient for total yearly volume purchased and number of trips

	Total volume	Number of trips
Total volume	1	
Number of trips	0.35 (0.000)	1

Note: p-value in parentheses

oz, which corresponds to six 12 oz cans per day. We notice that most of the consumers who purchased large quantities made less than two hundred trips to supermarkets, in 2006, to purchase soda.

Figure 3: County-level Estimates of Obesity among Adults aged $\geq$ 20 years: United States 2006



Source: www.cdc.gov/diabetes

We obtain county-level data on the rate of obesity from CDCs Behavioral Risk Factor Surveillance System (BRFSS) in 2006, Figure 3. The BRFSS is an ongoing, monthly, state-based telephone survey of the adult population. Respondents were considered obese if their BMI was 30 or greater.[5] The BRFSS used 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 2005 estimate. Estimates were restricted to adults 20 years of age or older to be consistent with population estimates from the U.S. Census Bureau. The U.S. Census Bureau provides year-specific county population estimates by demographic characteristics (age, sex, race, and Hispanic origin). Obesity rates were age-adjusted by calculating age-specific rates for the following three age groups, 20-44, 45-64, 65+. A weighted sum based on the distribution of these three age groups from the 2000 census was then used to adjust the rates by age.[6]

Data on demographic characteristics of the population[7] in our sample were retrieved from the American Community Survey (ACS).[8] Yearly data on age, gender, race, income, education, disabilities, etc. are provided. This survey is administered by the U.S. Census Bureau, sent to approximately 250,000 addresses monthly (or 3 million per year). It regularly gathers information previously contained only in the long form of the decennial census. It is the largest survey other than the decennial census that the Census Bureau administers. Data are available for local areas and small population subgroups with the release of 3-year and 5-year estimates. From the available data sets, the selection of demographic characteristics is based on socioeconomic factors that, at the aggregate level, are thought to have a strong correlation with obesity (*obesity predictors*) (Sobal and Stunkard, 1989; Rosmond and Bjrntorp, 1999; Patterson et al., 2004; Lutfiyya et al., 2007; Sodjinou et al., 2008). The obesity predictors considered in these analyses were tested for correlation

[5]Body mass index formula: $BMI = weight(kg)/height^2(m)$. It was derived from self-report of height and weight.

[6]Data and description available online at:
http://apps.nccd.cdc.gov/DDTSTRS/default.aspx. Retrieved 5/8/2013.

[7]Data for the percentage of rural population were obtained from Decennial Census Data 2010 (http://factfinder2.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t). Retrieved 6/10/2013.

[8]Data and description available online at:
http://www.census.gov/acs/. Retrieved 29/6/2013

Table 3: Distribution of obesity rate and obesity predictors

Variable	Mean	Std	Min	I Quartile	Median	III Quartile	Max
% Obesity	25.55	3.34	17.10	23.10	25.70	28.00	40.10
% of Households received food stamps	6.65	3.20	1.81	4.09	6.64	8.32	21.02
% African-American Population	12.92	13.42	0.57	2.93	8.64	19.04	64.19
% Attained High School Diploma or less	42.48	9.01	21.60	36.30	42.15	48.80	63.70
% Rural Population†	15.98	16.31	0.00	3.03	9.85	24.90	67.71

Note: The obesity rate refers to the county level age adjusted percentage of obesity (see text for description); descriptive statistics for this variable are computed considering 126 counties across 33 states.
†Percentages obtained from Decennial Census Data 2010.

with the obesity rate in our sample. Specifically, after collecting data on several variables thought to be drivers for obesity (age, gender, race, gender and race interaction, etc.), we regressed the obesity rates in our sample on these variables in order to highlight significant positive relations. Results from these auxiliary regressions are reported in the Appendix (Table 9). Selected obesity predictors using this procedure are: the percentage of households that received food stamps; the percentage of African-American population; the percentage of population that attained high school diploma or less; the percentage of rural population. Selected demographic characteristics are listed in Table 3, where descriptive statistics for these variables in our sample are also reported.

4 Results

The results from demand estimations are reported in Tables 4, 5 and 6. All results, unless otherwise specified, are significant at 5% or better. As specified in equation 9, the dependent variable is the log of units of 2-liter bottles of Coke or Pepsi sold in a week/supermarket. All results are obtained via least squares and all the regressions include store fixed effects and the price of private label colas. Table 4 presents the results from static models. Columns 4 and 5 display estimates of the impact of a sale on the units demanded. We notice that a sale in the current period has a positive effect

Table 4: Static model estimates of the demand function

	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Own Price	-1.90	-2.02	-1.45	-1.12	-1.79	-2.26
	(0.02)	(0.02)	(0.02)	(0.01)	(0.12)	(0.07)
Cross Price	0.32	0.46	0.34	0.42	0.35	0.43
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Sale t			0.25	0.30		
			(0.01)	(0.01)		
Sale t-1			-0.05	-0.05		
			(0.01)	(0.01)		
Sale t-2			0.01	0.006		
			(0.00)	(0.007)		
%obesity*Own Price					0.01	0.03
					(0.00)	(0.00)
%obesity*Sale t					0.01	0.01
					(0.00)	(0.00)

Note: Standard errors in parentheses

on the quantity demanded, as expected, and that sales in preceding periods (weeks) consistently alternate in sign. This result implies that the relevant storage period is one week ($T = 1$). Columns 6 and 7 display the impact of the interaction between the rate of obesity and the own price, and the interaction between the rate of obesity and sale in the current period, on the quantity demanded. We observe, in support to our expectations, that both effects are positive, meaning that as the rate obesity increases, the own price sensitivity for both brands decreases, while the sale sensitivity increases, holding other variables constant.

Table 5 and 6 present the results from dynamic models, where we distinguish fractions of the population as $storers$ and $non-storers$, and consider different specifications. In Table 5, Model I provides estimates obtained by imposing two restrictions following H&N. The first restriction concerns the

Table 5: Dynamic model estimates of the demand function (I)

Specification:	I		II		III		IV		V		VI	
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Own Price non-storers	-1.63	-1.76	-1.64	-1.77	-1.64	-1.77	-1.52	-1.96	-1.66	-1.74	-1.66	-1.74
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.11)	(0.10)	(0.03)	(0.03)	(0.03)	(0.03)
Own Price non-storers"* %obesity							0.00†	0.01				
							(0.00)	(0.00)				
Cross Price non-storers	0.44		0.44		0.44		0.44		0.37	0.50	0.37	0.50
	(0.01)				(0.01)		(0.01)		(0.02)	(0.02)	(0.02)	(0.02)
Own Price storers	-2.22	-2.29	-2.20	-2.27	-3.09	-2.91	-2.23	-2.29	-2.28	-2.26	-2.27	-2.24
	(0.14)	(0.14)	(0.14)	(0.14)	(0.42)	(0.39)	(0.14)	(0.14)	(0.16)	(0.15)	(0.15)	(0.12)
Own Price storers"* %obesity					0.03	0.02						
					(0.01)	(0.01)						
Cross Price storers	-0.62		-0.64		-0.64		-0.62		-0.67	-0.53	-0.68	-0.56
	(0.10)		(0.07)		(0.10)		(0.10)		(0.14)	(0.14)	(0.10)	(0.09)
ω	0.57				0.57		0.57		0.57			
	(0.05)				(0.05)		(0.05)		(0.05)			
ω'			0.75								0.75	
			(0.08)								(0.08)	
ω" * %obesity			-0.007								-0.007	
			(0.002)								(0.002)	

Note: Standard errors in parentheses; †Non statistically significant.

cross price effect between Coke and Pepsi, which is imposed to be symmetric. This restriction is released in Models III VI. The second restriction consists of imposing the same fraction of $non-storers$ (ω) for both brands, but consistent with the idea of one population and two substitute products, we do not release this constraint. Models II and VI show the results of restricted and unrestricted models obtained by considering the potential impact of the rate of obesity on the non-storing population (Equation 13). We observe that, as the rate of obesity increases, the fraction of $non-storers$ decreases, other conditions being equal, and that this effect is statistically significant. The fraction of non-storing population is 57% for both the restricted and the unrestricted models that do not include the interaction with the rate of obesity. The parameter ω represents the relative intercept of the demand for $non-storers$. As we can observe from the results in Table 5, the demand from $non-storers$ accounts for more than half of the quantity sold. By separating the effect on the intercept due to the rate of obesity (Models II and VI), we found that the percentage of non-storing population is effectively decreased as the rate of obesity increases. Specifically, the percentage of $non-storers$ in the areas with the highest rate of obesity in our data set (40.1%), would be as low as just under 47%. In Model III, we report the results of a model obtained by considering the impact of the rate of obesity on the own-price elasticity for $storers$ (Equation 14). In this case, in line with our expectations, the effect was positive and statistically significant, implying that as the rate of obesity increases the price elasticity for $storers$ decreases, keeping the other variables constant. Model IV allows us to evaluate the impact of the rate of obesity on the own-price elasticity for $non-storers$. From the table we observe positive but small effects. The effect for Coke is not statistically significant.

We observe that the results from static and dynamic models are similar, but we can highlight some interesting differences. By comparing columns 2 and 3 in Table 4 with the results in Table 5, we notice that price sensitivities are lower if we consider the demand dynamics. This confirms results in the previous literature that show how not accounting for inter-temporal substitution and storability can lead to an overestimate of the price elasticity and of the effect of taxes on consumption (Wang, 2012; Hendel and Nevo, 2012). We notice that the own price sensitivity for both brands is higher for $storers$ than for $non-storers$. The (restricted and unrestricted) cross price effect for $storers$ is negative and statistically significant; this reflects the fact that, in a dynamic setting, $storers$ may consider the two product as intertemporal complements. They complement each other over the course of one year in the sense that if the price of product goes up, consumption of both goes down. Even when releasing the constraint of the symmetric cross price elasticities, we obtained a negative sign for both coefficients for $storers$, and this result holds for all the sub-samples we used to test the stability of the model. Overall, storing consumers are more price-sensitive than non-storing ones, and the negativity of the cross price elasticity reflects the fact that storing consumers may be more prone to switch to other sugary alternatives as a result of a price increase. This feature can only be captured in a dynamic setting and, to some extent, may help anticipate unintended consequences of soda taxes.[9] Even when releasing the constraint of the symmetric cross price elasticities, we obtained a negative sign for both coefficients for $storers$, and this result holds for all the sub-samples we used to test the stability of the model.

In Table 6, results from the dynamic models that include obesity predictors are displayed. Recall that selected obesity predictors are: the percentage of households that received food stamps; the percentage of African-American population; the percentage of population that attained high school diploma or less; and the percentage of rural population. We replaced the obesity rate with one of these variables to obtain the same specifications as in Table 5 (Models II and III). Results are similar to the ones from models using the percentage of obesity, reflecting the high correlation between the selected demographic variables and obesity rates. In particular, the obesity predictor that yielded the comparatively largest effect on the own price elasticity for $storers$ and on the fraction of $non-storers$ was the percentage of households that received food stamps. Households that received food stamps[10] are generally low income, therefore it is not surprising that higher rates for this variable result in a greater sensitivity to discounted prices and higher inclination to store. According to our results, though, low income households are also comparatively less sensitive to soda prices. The impact of the African-American population rate was found to be small and not statistically significant.

[9]Some of those who reduce soda purchases as a consequence of a tax, may direct their consumption towards other sugary beverages (e.g. juices or sugar-sweetened water) or other high-sugar products such as candies and pastries.

[10]The *SNAP/Food Stamp Program*, administered by the United States Department of Agriculture (USDA), considers soft drinks, candy, cookies, snack crackers, and ice cream food items and are therefore households can use SNAP benefits to buy them (http://www.fns.usda.gov/snap/retailers/eligible.htm)

Table 6: Dynamic models estimates of the demand function (II)

Obesity predictor being considered:	*% of Households received food stamps*				*% African-American Population*				*% Attained High School Diploma or less*				*% Rural Population*‡			
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Own Price	-1.63	-1.76	-1.64	-1.76	-1.64	-1.77	-1.63	-1.76	-1.62	-1.74	-1.63	-1.76	-1.64	-1.76	-1.64	-1.76
non-storers	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Cross Price	0.44		0.44		0.44		0.44		0.43		0.42		0.44		0.43	
non-storers	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
Own Price			-2.22	-2.30			-2.22	-2.28			-2.22	-2.28			-2.21	-2.27
storers			(0.14)	(0.13)			(0.14)	(0.14)			(0.13)	(0.13)			(0.14)	(0.14)
Own Price	-2.45	-2.43			-2.22	-2.20			-3.46	-3.19			-2.29	-2.39		
storers'	(0.17)	(0.17)			(0.15)	(0.15)			(0.30)	(0.27)			(0.15)	(0.14)		
Own Price storers"*	0.03	0.02			0.001†	0.005†			0.03	0.02			0.004	0.007		
obesity predictor	(0.01)	(0.01)			(0.003)	(0.004)			(0.00)	(0.00)			(0.003)	(0.003)		
Cross Price	-0.65		-0.68		-0.64		-0.62		-0.45		-0.46		-0.59		-0.59	
storers	(0.10)		(0.10)		(0.10)		(0.10)		(0.10)		(0.10)		(0.10)		(0.10)	
ω	0.57				0.57				0.58				0.58			
	(0.05)				(0.05)				(0.04)				(0.05)			
ω'			0.63				0.57				0.86				0.60	
			(0.05)				(0.05)				(0.06)				(0.05)	
ω"*			-0.01				-0.00†				-0.005				-0.001	
obesity predictor			(0.00)				(0.00)				(0.00)				(0.000)	

Note: Standard errors in parentheses; †Non statistically significant.

Table 7: Predicted percentages of storing population

Rate and demographic variable considered:	% Storers Mean	Min	I Quartile	Median	III Quartile	Max
% Obesity	43	37	41	43	45	53
% of Households received food stamps	44	39	41	44	45	58
% African-American† Population	43	43	43	43	43	44
% Attained High School Diploma or less	36	26	33	36	39	47
% Rural Population	42	40	40	41	42	47

†Note: Results for this variable were found to be not statistically significant.

In Table 7 we report the estimated distributions of storing population based on the results of the different model specifications and on the distribution of the obesity rate and obesity predictors. Notice that the distribution of the fraction of *storers* is very similar when considering the obesity rate and the percentage of households that received food stamps, despite the fact that the obese population in our sample is, on average, well over the number of household received food stamps (Table 3).

As a side investigation, we examine companies' conduct in terms of temporary price reductions, to verify whether sales and discounts regimes are randomly set or they follow certain patterns. We find that prices of Coke and Pepsi tend to follow opposite trends, and that discount periods appear to alternate weekly (Figure 4, Appendix). The Appendix includes a table comparing mean non-sale prices for Coke and Pepsi, computed when the competitor does not run a sale, with mean non-sale prices computed when the competitor runs a sale. The values for mean non-sale prices are larger if computed when there is a sale for the other brand than if computed when the other brand is not on sale regime. These differences are statistically significant according to a two-sample mean-comparison test (Table 10). Conversely, when the two brands are both on non-sale regime, the mean price is the same. The values of the mean non-sale prices support the conjecture that store prices are established at the company level and that Coke and Pepsi engage in collusive behavior, or sale-coordination. In addition, we investigate the often cited claim that soda companies are to blame for the obesity epidemic since they are more likely to disproportionately target with temporary price reductions areas where the obesity rate is higher. According to our results, areas characterized by a higher rate of obesity are also characterized by a higher sale-sensitivity; therefore, targeting these areas with more discounts would exacerbate obesity rates where BMI is already high. To shed light on this hypothesis, we obtained results from county-level auxiliary regressions of an index of sales intensity on the rate of obesity. They show no statistical evidence of an association (Appendix, Table 11).

4.1 Policy implications

In this section we examine the policy implications of our estimates. We consider two policy scenarios:

1. a 5.2% soda sales tax (current average sales tax for soda in the U.S.);

2. a scenario in which soda promotions are banned.

For this exercise we used the estimated coefficients obtained from the specifications reported in Table 5, Models II, III, and equations 10 and 11. To compute the percent variations in quantity demanded predicted for scenario 1, we increased all prices by 5.2%. For scenario 2, we increased only the sales prices (recall: all prices less or equal to \$1.05), so that the minimum price is equal to \$1.05. These procedures yield a price percent variation of 2% for Coke, and 3% for Pepsi. In all computations we also considered the estimated cross price elasticities for private label colas.

Results from our counterfactual analyses are reported in Table 8. Specification I refers to the results from the Model II (Table 5), where we let the coefficient ω (fraction of non-storing population) be function of the obesity rate; specification II refers to model III (Table 5), where we considered the impact of the rate of obesity on the own price elasticity of $storers$. We report the results computed at mean, minimum, quartile I, median, quartile III and maximum rate of obesity in our sample.

Overall, scenario 2 yields a larger decrease in quantity consumed than scenario 1. In fact, the effect of a price increase due to the tax is mitigated by the presence of discounts. In particular, specification I yields the largest

Table 8: Quantity demanded variations under two policy scenarios

	Obesity Rate (%):	Mean 25.55	Min 17.10	I Quart. 23.10	Median 25.70	III Quart. 28.00	Max 40.10
Policy Scenario:		% Quantity Variation (Corresponding Elasticity in parentheses)					
Sales Tax	Specific. I	-6.96	-6.79	-6.91	-6.97	-7.02	-7.34
		(-1.33)	(-1.30)	(-1.32)	(-1.34)	(-1.35)	(-1.41)
	Specific. II	-6.72	-6.65	-6.70	-6.73	-6.74	-6.83
		(-1.29)	(-1.27)	(-1.28)	(-1.29)	(-1.29)	(-1.31)
TPR[1] Banned	Specific. I	-11.81	-11.41	-11.69	-11.82	-11.94	-12.65
		(-4.72)	(-4.56)	(-4.67)	(-4.72)	(-4.77)	(-5.06)
	Specific. II	-11.11	-11.09	-11.10	-11.11	-11.11	-11.10
		(-4.44)	(-4.43)	(-4.44)	(-4.44)	(-4.44)	(-4.44)

Note: [1]Temporary Price Reduction. The sales tax applied is equal to 5.2%. The ban of TPRs has been obtained by increasing the sale prices only up to the $1.05 threshold. This procedure generates a 2% increase in the price of Coke and 3% increase for Pepsi.

variability in the distribution of the quantity variation for both scenarios, implying that storing behavior and sale responsiveness have a greater impact on quantity demanded variations than price sensitivity. On the other hand, a price increase appears to limit consumers' propensity to store; for this reason, the reduction in consumption would be slightly larger in areas where the obesity rate is higher (recall that the storing fraction of the population is predicted to increase as the obesity rate increases).

Under specification II, we observe that the variability of quantity reduction is considerably lower for both scenarios. Despite the fact that high obesity rates diminish the predicted price sensitivity, this effect is not large enough to generate substantial differences in quantity decrease across areas with high or low obesity rates. Nevertheless, notice that the impact of a 5.2% tax is estimated to be well below the effect of less attractive discounts, for all levels of obesity. Notice that, under scenario 1 (sales tax), when the maximum rate of obesity is considered, quantity demanded is predicted to decrease by 7.34% and by 6.83%, for specification I and II, respectively. Under scenario 2 (TPR banned), the quantity decrease is predicted to be much larger in areas with high obesity rates (12.65% and 11.10%, for specification I and

II, respectively). As a consequence, limiting the magnitude of discounts would have a comparatively higher impact than increasing soda prices via taxes, because fewer consumers would be able to store. These predictions, while confirming the main results from previous studies (i.e. Patel, (2012)), highlight the importance of considering the demand dynamics when studying soda consumers' behavior.

Furthermore, consider that in this study predicted elasticities are brand elasticities, and that a brand level demand is typically elastic for the presence of substitutes. Quantity variations predicted in this exercise refer to only a subgroup of the soda category, but for the whole product category, the demand is expected to be more rigid. Thus, our estimates are to be taken as conservative. In light of these considerations, we suggest that a soda tax would not be able to induce appreciable improvements in the health conditions of those with high BMI, because this type of policy intervention would not successfully change soda consumers' behavior.

5 Discussion and concluding remarks

In this research we investigated the role of obesity on the demand for soda in a dynamic setting. The dynamic model we applied accounts for storing behaviors, and allowed us to identify a heterogeneous price sensitivity and sale sensitivity of soda consumers characterized by high BMI. Our results highlight several effects related to the rate of obesity suggesting that higher-BMI consumers, despite having a less price-sensitive demand for soda, are more inclined to store (and therefore more sale-sensitive). As a consequence, areas characterized by a higher rate of obesity are also characterized by a lower price elasticity of demand and by a larger portion of the population that has a tendency to store. Of these two results, the latter is more quantitatively significant when assessing how price changes affect demand. Results from the dynamic model show that higher rates of obesity are associated with lower own price sensitivities for soda products. In fact, the impact of obesity on own price elasticity is positive and statistically significant, meaning that the elasticity decreases as the obesity rate increases. However, this effect is relatively small and does not appreciably translate in heterogeneity of the variation in quantity demanded to a price increase, across different rates of obesity. We also found that obesity predictors affect the demand for soda in the same direction as the obesity rate, reflecting the positive correlations among some demographic factors and the obesity incidence.

In addition to our central analysis, we investigate the often cited claim that soda companies are to blame for the obesity epidemic since they are more likely to disproportionately target areas where the obesity rate is higher with temporary price reductions. According to our results, if true, this strategy would exacerbate obesity rates where BMI is already high. Results from county-level auxiliary regressions of an index of sales intensity on the rate of obesity show no statistical evidence of an association.

We translate our results in policy implications by computing the potential decrease in quantity demanded after a sales tax. In addition, we consider a counterfactual where price discounts (sales) would be less attractive. Our estimates indicate that a price increase due to a tax would fail to yield large reductions in total quantity demanded. The main explanation is that sales and discounts mitigate the effect of the tax. Conversely, our research suggests that a policy intervention restricting the magnitude of sales would be more successful (than a tax increase) in modifying the behavior of high BMI consumers and thus in reducing soda consumption. The reason is that, according to our estimates, consumers in areas with higher obesity rates are more inclined to store than in other regions. We would like to point out that sales taxes are often silent (i.e., they do not show on the shelf price). This feature may further limit the effectiveness of this type of policy intervention, if the goal of the policy is to reduce soda consumption, rather than to increase the tax revenue of the state (Colantuoni and Rojas, 2012).

Our predictions, while confirming the main results from previous studies (i.e. Patel, (2012)), highlight the importance of considering the demand dynamics when studying soda consumers behavior. Overall, lower price-sensitivity for high BMI consumers does not translate to substantial differences in quantity decreases across different obesity rates as reactions to a pricing policy.

In summary, our work suggests that a policy would be more effective if designed to selectively change the behavior of the consumers that need the public intervention most. To the best of our knowledge, no previous research has studied sale responsiveness for obese consumers.

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A Appendix

$$Sale = \begin{cases} 1 & \text{if sale} \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

$$Index_{ji} = \sum_t \left(Sale_{jit} \frac{Vol_{jit}}{TotVol_{ji}} \right), \quad j = Coke, Pepsi \quad i = County \quad t = Week \tag{16}$$

Table 9: Results from regressions of a sale index for Coke and Pepsi on the rate of obesity

Dep. Variable:	Sale index Coke	Sale index Pepsi
Indep. Variables:		
% Obesity	0.00	-0.01
	(0.00)	(0.01)
Const.	0.38	0.75
	(0.13)	(0.24)

Note: sample size of 126 counties. The R^2 for both models is 0.00. Standard errors in parentheses.

Table 10: Results from regressions of obesity rate over variables considered obesity predictors

Dep. Variable:	% Obesity
Indep. Variables:	
% of Households received food stamps	0.16
	(0.08)
% African-American Population	0.08
	(0.03)
% Attained High School Diploma or less	0.09
	(0.02)
% Rural Population	0.06
	(0.02)
Const.	18.76
	(1.18)

Note: sample size of 126 counties. The R^2 is 0.42. Standard errors in parentheses.

Figure 4: Mean-price weekly trend for Coke and Pepsi

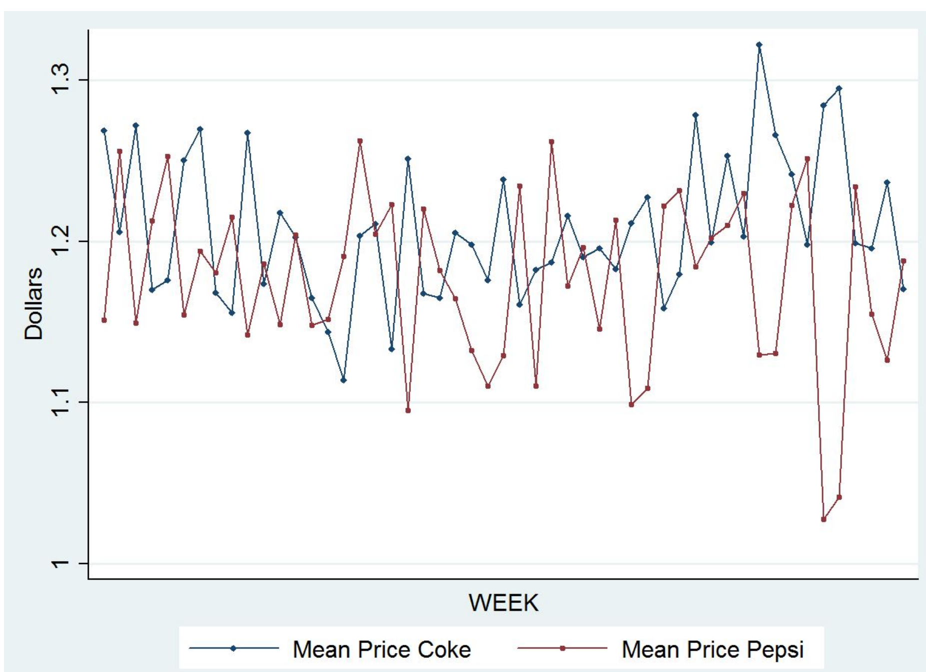

Table 11: Comparison between mean non-sale prices for Coke and Pepsi, computed when the competitor does not run a sale and when the competitor runs a sale

	Mean Price Coke		Mean Price Pepsi
Sale Coke=0 & Sale Pepsi=0	1.30	Sale Pepsi=0 & Sale Coke=0	1.30
Sale Coke=0 & Sale Pepsi=1	1.37	Sale Pepsi=0 & Sale Coke=1	1.32
Two sample T-test†: t-stat (p-value)	-27.32 (0.000)		-6.65 (0.000)

†Two sample mean-comparison test. The null hypothesis that the two mean prices are equal is rejected at the 1% level of confidence or better, for both Coke and Pepsi.