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Empirical Studies On The Effectiveness Of Soda Taxes To Curb Obesity

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EMPIRICAL STUDIES ON THE EFFECTIVENESS OF SODA TAXES TO CURB OBESITY

A Dissertation Presented

by

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ABSTRACT

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MAY 2014

FRANCESCA COLANTUONI

Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Christian Rojas

This dissertation presents a series of empirical studies to evaluate the effectiveness of soda taxes to curb the obesity epidemic. Chapter 1 describes the extent and severity of the obesity problem in the U.S., and discusses the policy interventions that have been proposed or enacted with the intent to fight obesity (e.g., sales taxes). Chapter 2 contains a study on the effect of two tax events on soda consumption: a 5.5% sales tax on soft drinks imposed by the state of Maine in 1991, and a 5% sales tax on soft drinks levied in Ohio in 2003. We investigate this question by using sales data collected by scanner devices in Maine, Massachusetts, New York and Connecticut, as well as Ohio, Illinois, Michigan and Pennsylvania. Results suggest that these sales taxes had a statistically insignificant impact on the overall consumption of soft drinks. Chapter 3 describes an empirical study that looks at whether the 5% sales tax on soft drinks in Ohio in 2003 had a differential impact on different socio-economic segments of the population. In line with the results described in Chapter 2, this study suggests that the impact of a tax had a homogeneous effect

(and statistically insignificant) across different demographic groups. In Chapter 4 we investigate whether the demand for soda varies with the obesity rate. To this end we develop a demand model that is able to incorporate dynamic properties of this market as well as the resulting possibility that the obesity rate might alter the parameters of the model. Specifically, the model incorporates the dynamics of the market as they relate to the presence of temporary price reductions and the possibility that consumers may use them to stockpile purchases for future consumption (when prices return to higher levels). As opposed to the previous two chapters, which look at the effect of soda taxes retrospectively, recovering the primitives of consumers' behavior directly allows us to provide estimates of how soda consumption will react to different policies. Our results suggest that higher-Body Mass Index (BMI) consumers, despite being less price-sensitive for soda, are more inclined to store (i.e. are more sensitive to "sales"). We use our results to derive policy implications by computing the potential decrease in quantity demanded after a hypothetical sales tax is imposed. In addition, we consider a counterfactual mandate by which price discounts (sales) would be significantly restricted. Our estimates, consistent with our findings in Chapters 2 and 3, indicate that a price increase due to a tax would fail to yield large reductions in total quantity demanded. The main explanation is that the existence of sales and discounts, which persist after the tax increase, mitigate the effect of the tax as storing behavior. Importantly, the reduction in consumption resulting from the imposition of the tax would be lower for those consumers this type of policy is intended (i.e. high BMI consumers). Conversely, results from this investigation suggest that a policy intervention restricting the magnitude and frequency of sales, despite the fact that the average price increase implied by this policy is milder than that of a sales tax, would be more successful than a tax increase in reducing overall soda consumption. Further, we find that this second policy would have a greater impact in reducing the consumption, including that of high BMI consumers. Intuitively, since our estimates indicate that consumers in areas with higher obesity rates are more sale sensitive than in other regions, a policy that would significantly limit temporary price reductions by firms would be effective as it is tailored to those that need be to impacted the most. In summary, our work suggests that capturing and modeling critical characteristics of a market (in this case dynamic behavior) can aid policy makers in designing more effective interventions. Chapter 5 contains additional investigations that have been conducted to answer questions concerning the strategic marketing behavior of soda companies.

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CHAPTER 1

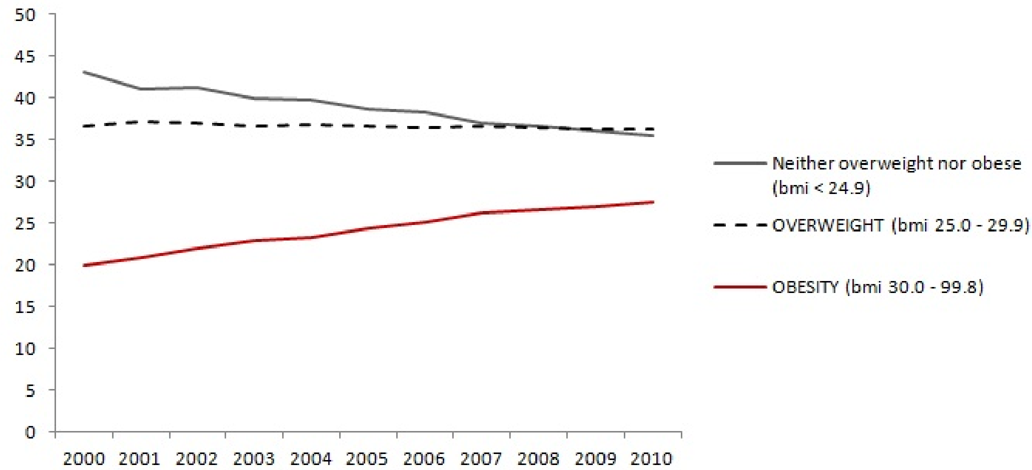
INTRODUCTION

The rate of obesity in the U.S. is increasing dramatically. According to data from the Centers for Disease Control and Prevention (CDC), the percentage of obese (Body Mass Index –BMI$\geq$30) adults in the U.S. has increased from 20% in 2000 to 27.5% in 2010 (Figure 1.1). Americans consume about 25% to 30% more daily calories today than they did 30 years ago.[1] The severity of the rate at which the obesity epidemic is pervading is illustrated by Figure 1.2, which reports two maps of United States that show the incidence of obesity in 1990 and 2010, respectively. In 1990, the obesity rate was lower than 15% in all states. By contrast, in 2010 the obesity incidence was no lower than 20% in all states, and in 13 states more than 3 out of 10 people were obese.

It is interesting to notice the regional distribution of the phenomenon: following the official geographical classification of the states, the highest percentage of obese people in 2010 was located in the South, with an average of 30.7% (max: Mississippi 34.5% - min: Virginia 26.4%); the Midwest had an average incidence of 28.9% (max: Michigan, 31.7% - min: Minnesota, 25.4%); the West had an average of 24.7% (max: Oregon, 27.6% - min: Colorado, 21.4%); Alaska registered 25.2%; and Northeast 25% (max: Pennsylvania, 29.2% - min: District of Columbia, 22.4%). Clearly, the distribution of different obesity rates in different parts of the country raises questions about the possible socioeconomic causes.

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

Figure 1.1. Prevalence and trends: Weight classification by Body Mass Index (BMI)

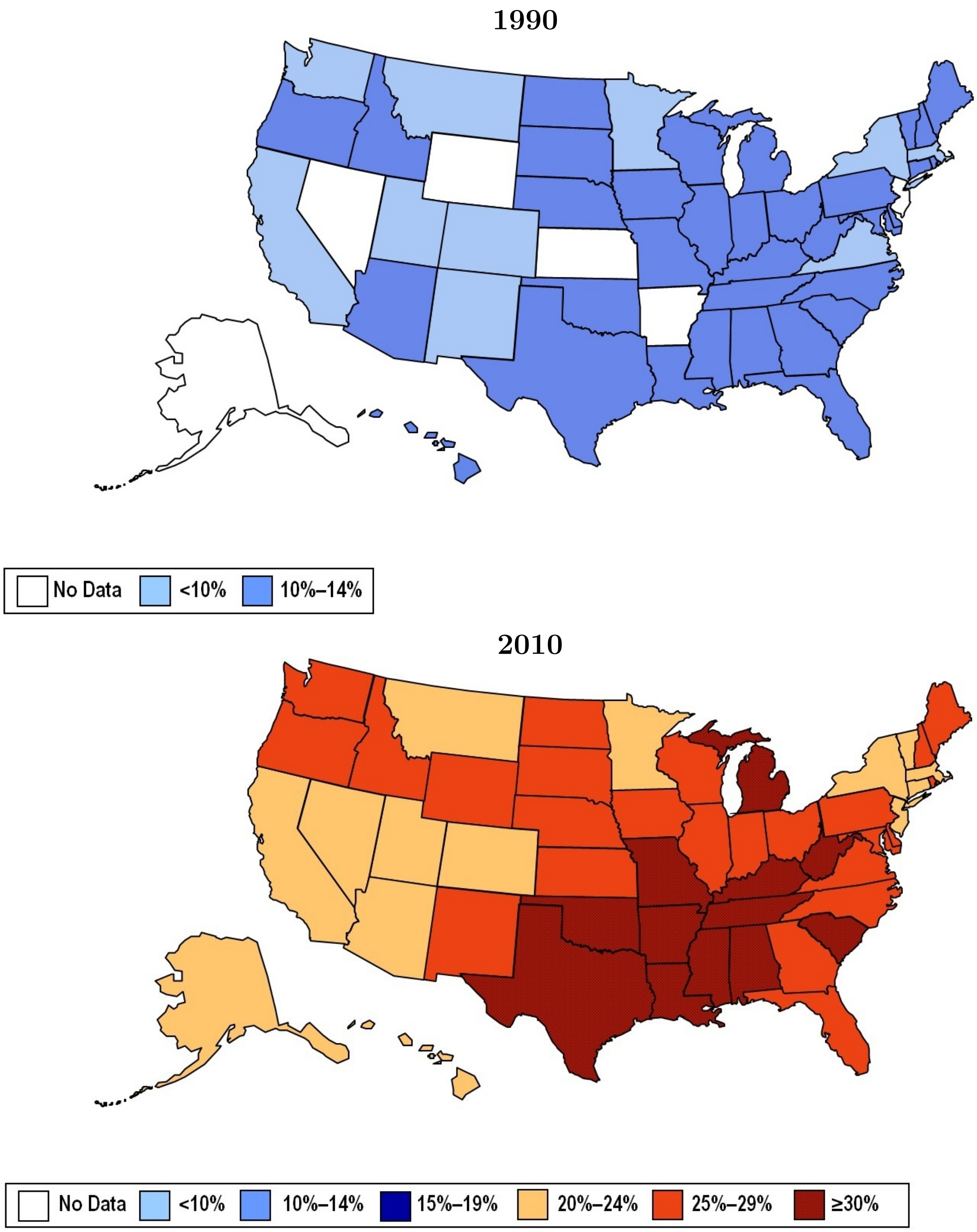


Our elaboration on data from cdc.gov

In view of these trends, it is important to understand the factors that may contribute to this epidemic. According to CDC there is a variety of factors that play a role in obesity. Overweight and obesity conditions result from an energy imbalance that may derive from high calorie intakes and not enough physical activity. However, body weight is the result of genes, metabolism, behavior, environment, culture, and socioeconomic status. To remain in balance and maintain a stable body weight, calories consumed (from foods and beverages) must be approximately the same as calories used (employed in normal body functions, daily activities, and exercise). A sedentary lifestyle accompanied by the consumption of ready-to-eat food and sugary beverages is a key mix that increases the risk of becoming overweight or obese.

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. The estimated figure of annual U.S. health care cost for obesity-related illness is $190.2 billion, about 21% of

Figure 1.2. Obesity Trends* Among U.S. (*BMI ≥30)



Source: Behavioral Risk Factors Surveillance System, CDC.

annual U.S. medical expenditure (Cawley and Meyerhoefer, 2012).

The large increase in calorie intake appears to have been significantly fueled by soda consumption. In 2009, a statement by the American Heart Association indicated that soft drinks and sugar-sweetened beverages were the number one contributor of added sugars in Americans' diets.[2] Consistent with this observation, several studies have shown how the consumption of soft drinks has significantly contributed to the increase in obesity, leading to a higher incidence of obesity-related diseases such as diabetes, heart diseases, stroke, hypertension and cancer (Ludwig and Ebbeling, 2001; Apovian, 2004; Malik et al., 2006; Vartanian et al., 2007).

For instance, Libuda and Kersting (2009) in a review article find that prior research has consistently reported evidence in support of a causal relationship between soft drink consumption and excess weight gain. Similarly, the meta-analysis conducted by Vartanian et al. (2007) shows a clear association of soft drink intake with both increased energy intake and body weight. Hence, even if the cause of overweight and obesity conditions is multifaceted, the limitation of soft drink consumption needs to be incorporated in the strategy mix for obesity prevention.

In addition to the scientific evidence on the effect of sugar consumption on obesity, it is important to note that soft drinks have a very limited nutritional value. These two facts have propelled policy makers in several states across the U.S. to propose the imposition of a tax on soft drink consumption. Excise taxes and special sales taxes on soda are already in place in 33 states. The Carbonated Soft Drinks (CSD) industry has succeeded in avoiding a soda tax to be included in the recent national health reform. While research has investigated the potential consumption reaction to a tax increase, our assessment is that there is still uncertainty as to what the ultimate impact on consumption will be. The main purpose of this dissertation is to

[2] http://www.heart.org, last access 1/27/2014.

analyze the impact of specific soda pricing policies on prices and volume sales of this product. We also study some dynamic aspects of soda consumers' behavior (such as storability and discount responsiveness), in order to contribute to the understanding of the phenomenon and suggest how to improve policies aimed at fighting obesity.

Literature Review

Policy interventions that modify the price of a good are supported by economic motivations based on market failures (Marshall, 2000; Cawley, 2004; Finkelstein et al., 2005; Kim and Kawachi, 2006; Powell and Chaloupka, 2009). In the case of soft drinks, there are several negative externalities associated with their consumption; these externalities manifest themselves most evidently through the increased health care costs of treating diseases caused by obesity. These costs can take several forms, including higher health insurance premiums for all individuals as well as higher health expenditures by the government. Additional social costs may include productivity losses (Cawley, 2004). Further, some people may have time-inconsistent preferences that would require public interventions (Powell and Chaloupka, 2009). For instance, it has been shown that children often do not take into account the future consequences of their actions, and that people, in general, may not appropriately discount the future costs of their behaviors (Komlos et al., 2004; Smith et al., 2005).

Research has investigated the potential consumption reaction to a soda tax. Estimates by Yale University's Rudd Center for Food Policy and Obesity suggest that for every 10% increase in price, consumption decreases by 7.8% (Brownell and Frieden, 2009); this estimate implies an own-price elasticity of demand of -0.78. The authors consider a 100% pass-through rate and compute their estimate based on two specific tax proposals: a 10% sales tax, and a penny-per-ounce tax. Conversely, there is evidence from other studies suggesting that the imposition of a tax would have much milder effects on consumption reduction. For instance, some cross-sectional studies have found minimal to no association among state-level soda taxes and body weight (Fletcher et al., 2010a,b; Powell and Chaloupka, 2009; Sturm et al., 2010). Fletcher et al. (2010a) provide the first empirical examination of the effectiveness of soft drinks taxation in reducing adult obesity. The authors analyze the ultimate impact of changes in state taxation rates in the period from 1990 to 2006 on changes in body mass index (BMI) and obesity, by exploiting the fact that approximately half of all states changed their soft drink tax rate in this period. Using an analysis that employed individual-level survey data, the authors find that soft drink taxes do influence behavior but not enough to lead to significant changes in population weight.

Results in Wang (2012) greatly scale down the ones by Brownell and Frieden (2009). As in Brownell and Frieden (2009), Wang analyzes the impact of a 10% sales tax and a penny-per-ounce tax (assuming a 100% pass-through rate). The methodology consists in specifying a structural dynamic demand model that accounts for storability and heterogeneous tastes for soft drinks; storability turns out to be a crucial element for obtaining accurate predictions for the two possible tax policies. The author argues that this model provides more accurate estimates of consumers' price sensitivity and thus allows for a more reliable prediction of the policy impact. Wang's estimate of the overall price elasticity for soft drinks (-0.33) is less than half of that obtained by Brownell and Frieden. Wang argues that not accounting for inter-temporal substitution and storability can lead to an overestimate of the effect of the tax on consumption.

Studies exclusively looking at the effect of an excise tax approach (a fixed fee per ounce) find that such a tax would reduce consumption of sugar sweetened beverages by a range that spans from 10% to 25% (Andreyeva et al., 2011; Hahn, 2009; Smith et al., 2010). Regardless of the type of tax being analyzed (excise or ad valorem), inference in this empirical work has consisted of a counterfactual approach that relies on an estimate of the own-price elasticity for soft drinks. These estimates differ in the literature since they depend on the methodology used, the type of data available, and whether substitutes (e.g. other beverages) are considered.

The counterfactual nature of earlier studies implies that an assumption on the pass-through rate needed to be made; the common practice has been to assume that the tax would be fully passed through to the final price (i.e. that the tax-exclusive price after the imposition of the tax will remain unchanged). If firms react to the tax change, for example by reducing their prices to dampen the decrease in consumption, then this assumption would not be appropriate.

The structure of the Carbonated Soft Drink Industry and "Soda Taxes"

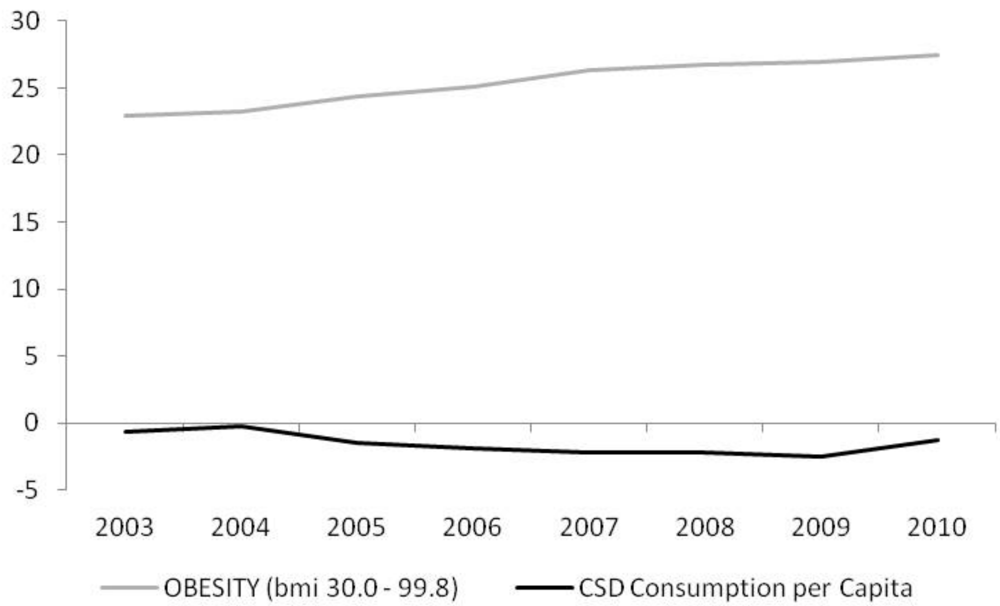
According to ibisworld[3], the Carbonated Soft Drink (CSD) Industry sector is economically important, with over 45,000 employees, about $17 billion in revenue, and $2 billion in wages (as of 2011). The volume market share within the non-alcoholic drink industry, which includes tea and coffee, bottled water, sport drinks and energy drinks, is 46.8%. This sector depends heavily on large economies of scale, high potential for new product development and high brand loyalty. Since 2010, the industry has consolidated on the vertical dimension; that is, the main CSD companies have acquired bottling and distribution companies that used to be independently owned. These factors make the CSD sector more powerful in terms of its ability to set pricing policies and marketing strategies.

On the other hand, this industry's value added is declining at a rate of 3% (on average) per year since 2002. The revenue has decreased at an average rate of 3.6%, while wage payments have declined by 6.7% per year, as of December 2011(ibisworld.com).

[3]ibisworld.com

The reasons for the decline of the sector are partly attributed to the consumption

Figure 1.3. Series of obesity and CSD consumption per Capita (%)



Our elaboration on data from cdc.gov and ibisworld.com

crisis fueled by the high unemployment rate that initiated in 2009, which also dampened the demand for outside dining (when consumers are also likely to drink soda). Also, the augmented popularity of a healthier life style has increased consumers orientation towards other options. The consumption of carbonated soft drinks has dropped from 52.8 gallons per capita per year in the 2002 to 46.9 in the 2011. The industry has reacted by substantially resizing their scale of operation and containing the losses by reducing the number of employees. This number has decreased at an average rate of 6.8% per year in from 2002 to 2011. But the industry also reacted by developing new product lines for consumers that are willing to pay a premium for low-calories, multi functional drinks, such as energy drinks or holistic thirst-quenching drinks.

It is interesting to point out that the trend of CSD consumption per capita and the trend of percentage of obese people in the US population, in the period between 2003 and 2010, go in opposite directions (Figure 1.3). In other words, the overall natural decrease in soft drink consumption noted above, has not translated into an overall decline in percentage of obese population. Thus, it is conceivable that in the absence of a decrease in soda intake, the obesity rate would have grown even larger. The CSD industry has succeeded in avoiding the inclusion of a soda tax in the recent national health care reform, but soda taxes have been proposed in many states, and in some soda taxes are already enforced. The most effective way in which this tax should be imposed is not clear. Different proposals have been discussed, and they differ substantially across states (Table 1.1). For example, Mississippi is considering

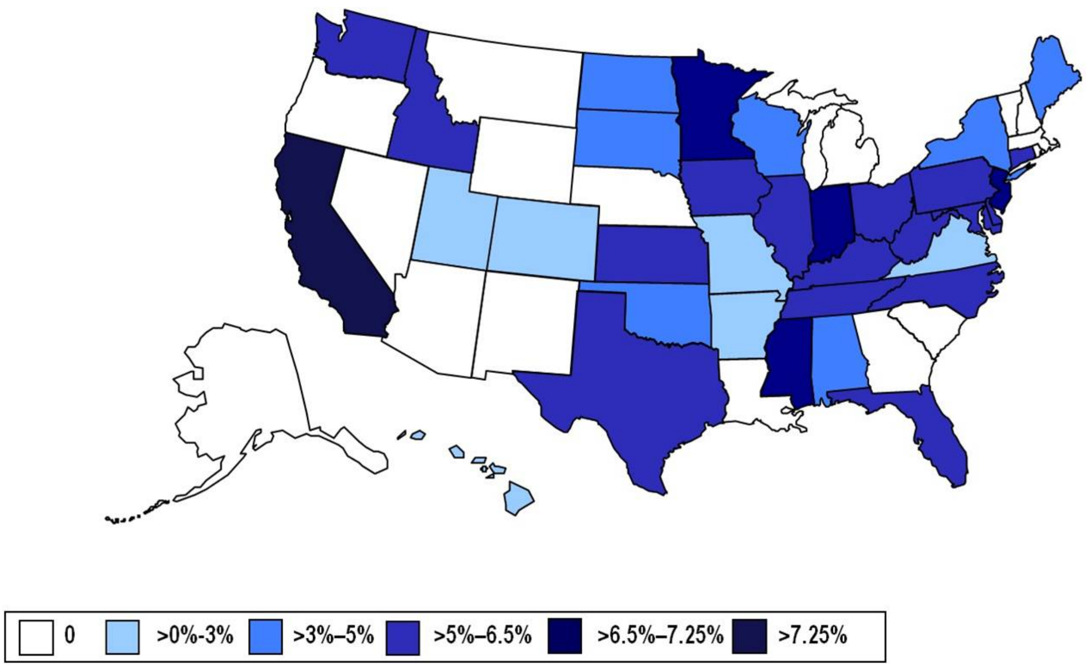
Table 1.1. Current Soft Drink and Snack Food Taxes

State or Locality	Year Enacted or Effective	Tax Specifically Applied	Use of Revenues
Arkansas	1992	\$0.21 per gal of liquid soft drink; \$2 per gal of soft drink syrups	Funds Medicaid
Chicago	1993	Distributors pay 3% on sales of containers, 9% on syrups	General funds
Illinois	Mid-1980s	Sales tax (6.25%) on soft drinks	General funds
Maine	1991	Sales tax (5.5%) on snack foods, soft drinks	General funds
New York	1965	Sales tax (7.5%) on soft drinks, candy, confectionary	General funds
Ohio	2003	Sales tax (5%) on carbonated soft drinks	General funds
Rhode Island	1984	\$0.04 per case (24 12-oz cans) of soft drinks	General funds
Tennessee	1981	1.9% of gross receipts from soda and soda ingredients paid by manufacturers	General funds
Washington	1989	\$1 per gal of syrup	Violence prevention and drug enforcement

Note: Data derived from state and local tax departments and from the State Tax Handbook (Chicago, Ill: Commerce Clearing House), modified from Jacobson and Brownell (2000).

legislation that would tax the syrup used to sweeten soda while the state of New York, in its proposed state budget, recommended a penny-per-ounce tax on sugary beverages. In Washington state, legislators approved a two-cent tax on every 12 ounces of soft drinks sold. The map in Figure 1.4 shows the current level of soda sales taxes per state. We notice that, to this day, 16 states still do not impose sales taxes on soda. Figure 1.4 together with Figure 1.2 suggest that there is no clear association

Figure 1.4. State Soda Sales Tax Rate (as of January 1, 2011)



Source: Bridging the Gap Program, University of Illinois Chicago, 2011.

between the level of the tax and the obesity prevalence in a state; specifically, lower obesity rates do not necessarily appear to be associated with higher levels of taxation or, vice-versa, states characterized by higher obesity incidence not always present low levels of soda sales taxes. The overarching political argument is based on the economic rationale that price increases caused by higher taxes will dampen consumption. In practice, however, the tax effectiveness is an empirical matter.

The following chapters are organized as follows:

- Chapter 2 contains a study on the effect of soda consumption of two tax events: a 5.5% sales tax on soft drinks imposed by the state of Maine in 1991, and a 5% sales tax on soft drinks levied in Ohio in 2003. We investigate this question by using sales data collected by scanner devices in Maine, Massachusetts, New York and Connecticut, as well as Ohio, Illinois, Michigan and Pennsylvania.

Results suggest that these sales taxes had a statistically insignificant impact on the overall consumption of soft drinks.

- Chapter 3 describes an empirical study that looks at whether the 5% sales tax on soft drinks in Ohio in 2003 had a differential impact on different socio-economic segments of the population. In this chapter we present the method applied, and the methods considered for further analyses. Results from this study are also described.

- Chapter 4 illustrates a dynamic estimation procedure to investigate the role of obesity on the demand for soda. The dynamic model accounts for consumers' storing behavior, and allows us to study both price sensitivity as well as sensitivity to temporary price reductions (sale sensitivity) of soda consumers. By matching store-level purchase data to county-level data on obesity incidence, we find a higher propensity to store and higher responsiveness to temporary price reductions in populations characterized by larger obesity rates. Conversely, higher rates of obesity appear to be also associated to lower price sensitivity. We use the results of our demand model to carry out and contrast two possible policy interventions that could curb obesity: a) a sales tax on soda consumption, and b) a ban on temporary price reductions (i.e. sales). Results indicate that the former intervention (not considered before by policy makers) would be more successful in reducing the consumption of more obese populations than the commonly proposed (and implemented) soda taxes.

- Chapter 5 presents the results of analyses aimed at investigating strategic behaviors of soda companies, in particular, whether soda manufacturers run sales more frequently in areas characterized by a higher obesity rate. We did not find statistical evidence of this behavior.

CHAPTER 2

THE IMPACT OF SODA SALES TAXES ON CONSUMPTION: EVIDENCE FROM SCANNER DATA

2.1 Introduction

In this chapter we look at the effect of two tax events on soda consumption and prices:

1. A 5.5% sales tax imposed by the state of Maine in July 1991;

2. A 5% sales tax imposed in Ohio in January 2003.

The first tax, a "snack tax", was enforced in Maine from 1991 to 2001 (when it was reduced by 0.5%). This tax was applied to snack foods, soft drinks, carbonated water, ice cream and pastries. The sales tax levied in Ohio in 2003, was applied exclusively to soft drinks; however, the definition of soft drinks in Ohio is broad as it includes not only "traditional soda pop beverages" but also "any sweetened nonalcoholic beverage, whether sweetened naturally or artificially, (unless it either contains milk products or a milk substitute or it contains greater than fifty percent (50%) fruit or vegetable juice by volume); many fruit drinks or fruit punches that contain fifty percent (50%) or less juice by volume; bottled tea and coffee drinks".[1]

The primary focus of this chapter is to examine the effect of both taxes on brand-level soda volume sales. As an additional exercise we also investigate whether tax-exclusive prices experienced a significant change; this analysis is important as theory

[1] Ohio Department of Taxation, http://tax.ohio.gov/

does not provide unambiguous predictions as to how taxes are passed through to consumers. We investigate these questions using sales data collected by supermarket scanner devices. For the first event, we use 1988-1992 data from Maine (the treatment state) as well as from the neighboring states of Massachusetts, New York and Connecticut (the control states). For the second event, we utilize 2001-2006 data from Ohio (the treatment state), as well as from Michigan, Illinois and Pennsylvania (the control states). Studying two similar events separated by a 12-year period allows us to investigate whether consumers' response toward soda taxes has changed over time; this is an important question to analyze as it is commonly believed that consumers' perception of the negative effects of obesity has heightened in more recent years.

The use of a brand-level data has two main advantages. First, we are able to apply a difference-in-difference matching estimator (DIDM) that provides a more powerful identification strategy than a difference-in-difference estimator (Todd, 2007). In a nutshell, this advantage comes from the fact that we can use a transparent matching procedure that relies on brand identity; we explain this in more detail in section 1.2. A second advantage of a brand-level analysis is that it allows us to study whether the tax imposition causes consumption (and/or pricing behavior) to vary across brands. This is important since a tax increases the final price of different brands by different dollar amounts. In sum, by accounting for differences in time-invariant unobservable factors between treated and control cities, we are able to isolate the sole impact of the tax policy on the volume and prices of soft drinks, at the brand level.

Prior studies have assumed that the soda market would experience a 100% tax pass-through rate; that is, that the price observed by consumers would exactly shift by the same magnitude as the tax increase. If firms react to the tax change, for example by reducing their prices to counter the decrease in consumption, then this assumption would not be appropriate. In imperfectly competitive markets, it can also be the case that the tax is passed through to consumers by more than one hundred percent (Anderson et al., 2001). Second, even in the case that the 100% pass-through rate assumption is accurate, it is not clear that consumers will perceive a tax increase the same way they would perceive a price increase imposed by the manufacturer. Since a price increase caused by a tax is only reflected at the cash register, and to the extent that consumers are primarily guided by the shelf price when making a purchase decision, a price increase through a sales tax is likely (as we find below) to dampen the reaction in consumption. Finally, elasticity-based studies can be sensitive to demand functional form and rely on the accuracy and appropriateness with which price endogeneity is dealt with.

Our study, while limited in its own right, does not suffer from the drawbacks of the earlier literature just mentioned. To the best of our knowledge, this is the first ex-post study that evaluates the impact on prices as a consequence of soda taxes. Further, we directly test whether the tax is fully passed onto the consumer, and we can highlight other likely pricing strategies that ensue from the tax.

Our main finding is that the tax increase did not alter consumption in either state. Conversely, by and large, we find that brand-level tax-exclusive prices did not react to the tax increases, suggesting that the pass-through rate was 100%. While our results are specific to a 5.5% tax increase in Maine, and 5% in Ohio, we believe they are informative since the current mean sales tax rate (across all states) on soft drinks is 5.2%. Despite the fact that consumers' awareness of the negative effects caused by soft drink consumption might have increased over the 12 years that separate the two tax events (and to the extent that consumer behavior in Maine and Ohio is comparable to that of consumers in other states), our results suggest that the current level of soda sales taxes in the US appears to be too small to actually affect consumption in a sizeable way.

This chapter is organized as follows. Section 2.2 contains a description of the methodology applied while section 2.3 describes the data. Section 2.4 contains the main results and section 1.5 concludes.

2.2 Method

In this chapter, we first investigate the consumption effect of a 5.5% sales tax on soft drinks imposed by the state of Maine on July 16, 1991. We employ sales data collected by scanner devices in Portland (Maine-our treatment city) as well as in (the control cities of) Boston (Massachusetts), Albany (New York) and Hartford (Connecticut). Subsequently, we consider a more recent similar tax event, a 5% sales tax on soft drinks levied in Ohio on January 1, 2003. For this latter experiment we employ scanner data collected in Cleveland (Ohio-our treatment city), and (the control cities of) Detroit (Michigan), Chicago (Illinois) and Philadelphia (Pennsylvania). The available data therefore limit our comparison to consumption across cities (rather than across entire states). The data, provided by Information Resources Inc. (IRI), come from a sample of supermarkets in the largest metropolitan areas in the U.S. We use two data sets that include brand-level sales information for the periods 1988-1992 and 2001-2006, respectively. More details on characteristics and differences of the two sets of data are provided in the next session.

To the extent that neighboring states serve as a reasonable control for both Maine and Ohio (respectively), data in such states allow us to isolate the effect of the tax from all other possible factors (e.g., trends, seasonality, nationwide changes in companies' policies, etc.). In addition, the brand-level analysis allows us to study whether the tax imposition causes consumption (or pricing behavior) to vary across brands. To measure the desired effect, we employ a difference-in-difference matching estimator (DIDM). The difference-in-difference matching (DIDM) estimator is superior to a simple DID estimator because comparison of treated and untreated units is based on their similarity. Conversely, a DIDM estimator is superior to a cross-sectional matching estimator since it accounts for differences in time-invariant unobservables between treated and untreated units (Heckman et al., 1997, 1998). In our setting, the DIDM estimator permits the comparison among treatment and control groups based on brand identity; this means that the matching mechanism is simpler, more transparent, and more reliable as it does not rely on propensity scores.

The DIDM estimator tailored for our panel data is given by:

$$\hat{\alpha}_{DIDM} = \frac{1}{N}\sum_{i=1}^{N}\left\{(logV_{t'i} - logV_{ti}) - \frac{1}{\#I_i}\sum_{j\epsilon I_i}(logV_{t'j} - logV_{tj})\right\} \tag{2.1}$$

where i and j denote observations in the treatment and control groups, respectively, while t and t' denote pre- and post-treatment time periods. I_i is the set of units in the control group that are matched to treatment unit i and $\#I_i$ is the number of elements in that set. The variable V denotes the outcome being measured (in our case volume sales or price) and the scalar N is the number of treated units (i.e. brands).

We tailor this estimator to the structure of our data. First, unlike usual matching estimators, we employ all treated units in the analysis rather than only those that would fall into a "common support" set. Second, instead of relying on propensity scores to match treated and untreated units, we define control units to be those brands in the control cities that match the identity of brand i in the treatment city (i.e. we manually choose the unit j that is matched to unit i). Finally, we study the outcome variable in logarithmic form (i.e. V corresponds to the logarithm of the variable of interest: volume sales or price); we adopt this transformation because the variance of volume sales (across brands) in our data set is large (see Table 2.4).

We report results of the estimator both for several control cities (i.e. $\#I_i > 1$) as well as for each control city separately (i.e. $\#I_i = 1$). In the case of $\#Ii > 1$, we consider two control cities (i.e. $\#I_i = 2$) as well as all control cities (i.e. $\#I_i = 3$) and weight all matches equally. Standard errors are calculated using the formula provided by Abadie and Imbens (2008) for nearest neighbor matching estimators.

As a robustness test, we also report results using the standard DID estimator:

$$logV_{bmt} = \theta + \beta D_{treatment} + \gamma D_{post} + \alpha_{DID} \left(D_{treatment} * D_{post} \right) + \varepsilon_{bmt} \tag{2.2}$$

where b, m and t denote brand, city and time (quarter), respectively; V denotes the outcome variable (volume sales or price); $D_{treatment}$ is a dummy variable equal to 1 if the observation is in the treatment city and 0 otherwise, and D_{post} is a dummy variable equal to 1 in the post-tax period. Note that the logarithm of the outcome variable allows interpreting α_{DID} as the percentage change in the outcome variable due to the tax.

2.3 Description of the data

2.3.1 Tax Events

In July of 1991, a sales tax of 5.5% on snacks and soda was instituted by the state of Maine. This information was initially obtained from Jacobson and Brownell (2000) and later confirmed (by phone) with staff in the Law and Legislative Reference Library, an office of the Maine Legislature. In our data set, this date corresponds to the beginning of the third quarter in 1991. For the second exercise, we selected a 5% sales tax on soft drinks sold in grocery stores and through vending machines, levied in Ohio effective January 1, 2003. In our data set, this date corresponds to the beginning of the first quarter in 2003.[2] We selected this event over the others (in the 2001-2006 IRI data set) because the availability of data for at least one city in the state where the tax was applied as well as availability of data for cities that may represent appropriate controls.

[2]http://www.bridgingthegapresearch.org

2.3.2 Data

We employ two sets of scanner data from IRI Infoscan, each for one of the two events we consider. Characteristics of the two databases are different, thus we will label the data sets as A and B, respectively. We next proceed with a brief description of the two.

Data set A was collected from IRI sample of supermarkets across the U.S. in the period 1988-1992. This sample comes from a universe of stores that account for 82% of all the grocery sales in the U.S.; from this universe, IRI samples supermarkets with annual sales of more than 2 million dollars. The data set includes dozens of brands for up to 65 metropolitan areas spanning 20 quarters. The number of metropolitan areas is not the same over the sample period, but it grows over time. The database also contains information on the demographics for each metropolitan area, which is identified with the name of the main city in the area. A potential limitation of data set A is the exclusion of convenience stores, bars, restaurants and other retail outlets for soft drinks. This lack of information may be of secondary concern as there is evidence suggesting that approximately 70% of soft drinks was sold through supermarkets around the time of our study (Higgins et al., 1995).

Data set B contains store sales data on carbonated beverage volume sales and prices during the 2001-2006 period. Data consists of weekly observations and includes 47 IRI metropolitan areas (for both data sets, we refer to a metropolitan area as a "city" henceforth).[3] 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 national sample of stores. For each store in each week, over 250 different Universal Product Codes (UPC) for carbonated beverage products are observed. Thus, each brand (e.g. Coke) has multiple UPCs associated to it, each representing the particular

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

Table 2.1. Brands, Parent Companies and Presence in City-Quarter pairs – Data set A

Brand	Company	# of City-Quarter pairs where present
Canada Dry	Cadbury/Schweppes	24
Canada Dry Light	Cadbury/Schweppes	24
Crush	Cadbury/Schweppes	24
Schweppes	Cadbury/Schweppes	24
Schweppes Light	Cadbury/Schweppes	24
Coke	Coca-Cola	24
Coke Classic	Coca-Cola	24
Diet Coke	Coca-Cola	24
Diet Sprite	Coca-Cola	24
Sprite	Coca-Cola	24
7 Up	Hicks & Haas	24
A & W	Hicks & Haas	24
A & W Light	Hicks & Haas	24
Diet 7 Up	Hicks & Haas	24
Diet Dr Pepper	Hicks & Haas	24
Dr Pepper	Hicks & Haas	24
Diet Pepsi	Pepsi Co	24
Diet Pepsi Free	Pepsi Co	24
Diet Slice	Pepsi Co	24
Mountain Dew	Pepsi Co	24
Pepsi	Pepsi Co	24
Pepsi Free	Pepsi Co	24
Slice	Pepsi Co	24
Diet Rite	Royal Crown	24
Total #obs		**576**

Table 2.2. Brands, Parent Companies and Presence in City-Quarter pairs – Data set B

Brand	Company	# of City-Quarter pairs where present
7 Up	Cadbury/Schweppes	24
A & W	Cadbury/Schweppes	24
Canada Dry	Cadbury/Schweppes	24
Diet 7 Up	Cadbury/Schweppes	24
Diet Dr Pepper	Cadbury/Schweppes	24
Dr Pepper	Cadbury/Schweppes	24
Diet Rite	Cadbury/Schweppes	24
RC	Cadbury/Schweppes	24
Schweppes	Cadbury/Schweppes	24
Squirt	Cadbury/Schweppes	24
Sunkist	Cadbury/Schweppes	24
Caffeine Free Coke Classic	Coca-Cola	24
Caffeine Free Diet Coke	Coca-Cola	24
Cherry Coke	Coca-Cola	24
Coke Classic	Coca-Cola	24
Diet Coke	Coca-Cola	24
Diet Sprite	Coca-Cola	24
Sprite	Coca-Cola	24
Vanilla Coke	Coca-Cola	24
Caffeine Free Diet Pepsi	Pepsi Co	24
Caffeine Free Pepsi	Pepsi Co	24
Diet Montain Dew	Pepsi Co	24
Diet Pepsi	Pepsi Co	24
Mountain Dew	Pepsi Co	24
Mountain Dew Code Red	Pepsi Co	24
Mug	Pepsi Co	24
Pepsi	Pepsi Co	24
Pepsi One	Pepsi Co	24
Sierra Mist	Pepsi Co	24
Wild Cherry Pepsi	Pepsi Co	24
Total #obs		**720**

Table 2.3. Summary statistics of demographic and temperature, data set A

	Portland ME	Albany NY	Boston MA	Hartford CT
Population*	95,883	101,082	574,283	250,304
Median income ($)*	29,615	31,813	37,624	37,308
Annual Mean Min Temp**	39	40	45	42
Annual Mean Max Temp**	56	60	60	61
Mean Price per brand†	4.4	4.1	3.8	3.9
Mean Volume sold‡	95,883	71,346	408,081	250,304
Obesity prevalence††(%)	12	12	10	12

*As of the 1990 Census; **1990-1992 (°F), (http://www.nesdis.noaa.gov/); †volume unit=$/288 oz; ‡288 oz; ††1991 (http://www.cdc.gov/obesity/data/)

presentation of the brand (e.g. packaging –6 pack vs. single bottles) and presentation (e.g. can vs. bottle; see Bronnenberg et al., 2008).

As stated earlier, for each event we included 4 cities in the analyses. In both cases, the three control cities were chosen on the basis of geographical proximity to the city where the tax increase was observed. Also, the chosen cities showed no other event concerning sales taxes during the period of study. We focus our analyses on 6 quarters: 3 quarters immediately before the tax increase and the three quarters following the quarter when the tax increase became effective.[4]

We excluded earlier and later quarters as the common trend assumption needed for the validity of a DID approach is less likely to hold. We excluded the third quarter of 1991 and the first quarter of 2003 (the quarters in which each of the two taxes took place), respectively, for reasons that will be explained later. We selected brands that are present in all quarters and in all cities in our study; this procedure allowed us to have a balanced panel (necessary for our matching procedure). In Table 2.1 and 2.2 we report the selected brands with the corresponding parent companies, as well

[4]Specifically, fourth quarter of 1990, the first, second and fourth quarters of 1991, and first and second quarters of 1992. For the event in Ohio, we employ: the second through fourth quarters of 2002, second through fourth quarters of 2003.

Table 2.4. Summary statistics of demographic and temperature, data set B

	Cleveland OH	Detroit MI	Chicago IL	Philadelphia PA
Population*	478,403	951,270	2,893,666	1,517,550
Median income ($)*	25,928	25,787	38,625	36,669
Annual Mean Min Temp**	42	41	44	47
Annual Mean Max Temp**	57	57	59	62
Mean Price per brand†	3.1	3.4	2.8	3.1
Mean Volume sold‡	104,420	232,984	328,919	106,466
Obesity prevalence††(%)	22	23	21	22

*As of the 2000 Census; **2002-2004 (°F), (http://www.nesdis.noaa.gov/); †$/192 oz; ‡192 oz.; ††2003 (http://www.cdc.gov/obesity/data/)

Figure 2.1. Income distribution for Cleveland as treatment city; Chicago, Detroit and Philadelphia as control cities - As of 1990 U.S. Census -

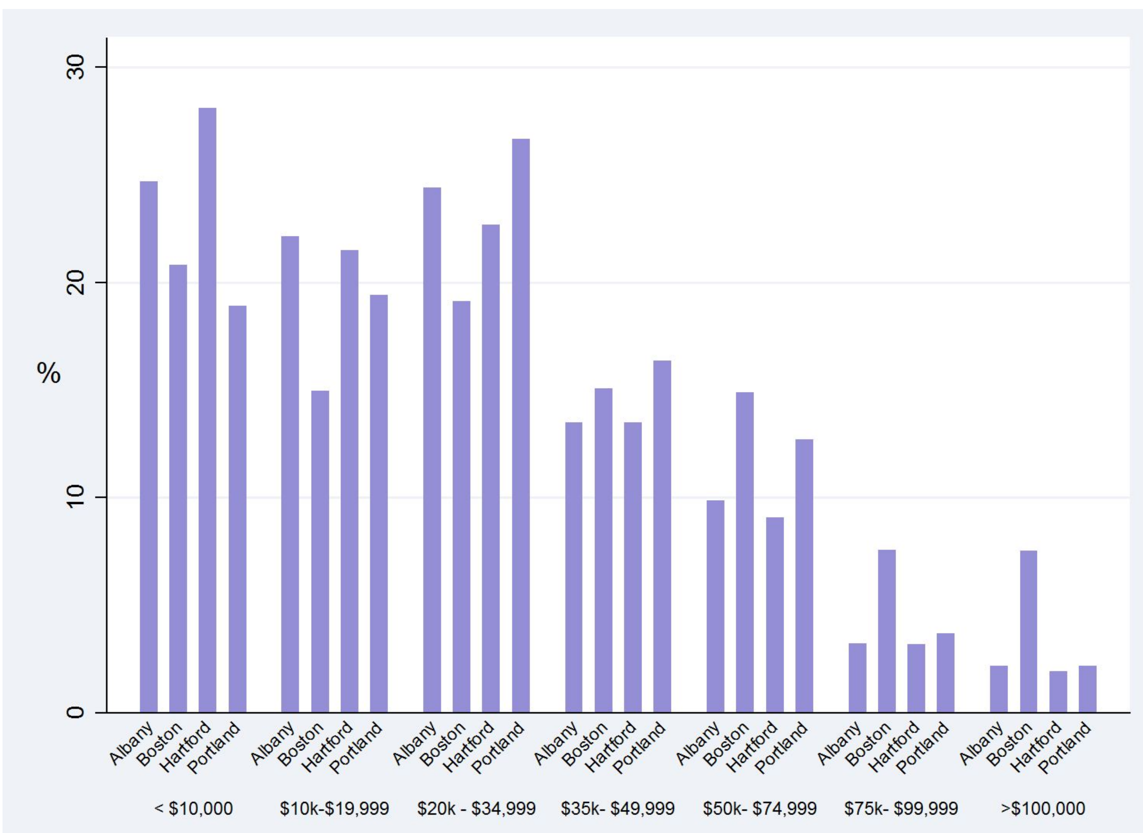
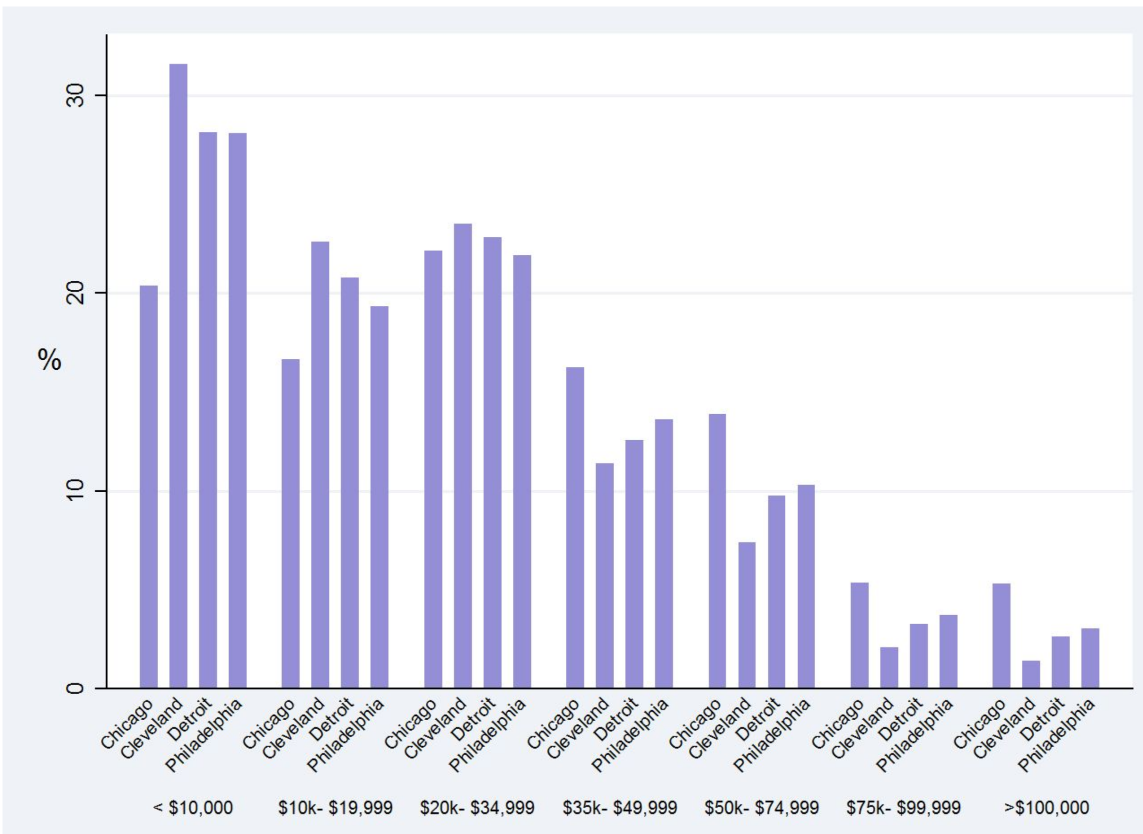


Figure 2.2. Income distribution for Portland as treatment city; Albany, Hartford and Boston as control cities As of 2000 U.S. Census -



as the number of observations. The 24 brands in Table 1.1 account for the 80% of the total volume sales in the selected city-quarter pairs. The 30 brands in Table 1.2 account for the 83% of the respective total volume sales in the selected city-quarter pairs.

A comparison between Table 2.1 and Table 2.2 reveals that some brands have changed company ownership over time. For instance, 7 UP which was initially acquired by Philip Morris in 1978, was sold to Hicks & Haas in 1986; it was then merged with Dr Pepper in 1988, and bought by Cadbury Schweppes in 1995.[5]

Database A contains the total volume and the mean price (before taxes) per unit of volume (288 oz) for every brand, in each city-quarter pair. In data set A, IRI aggregates information by adding the volume sold across all package sizes of a brand into one observation. To generate data set B in a similar format as a data set A (and thus make our analysis comparable across time), we aggregated IRI weekly UPC-level data following the same procedure IRI used to generate the aggregate data set A. Specifically, the average price per unit of volume was obtained by aggregating all revenue generated by a brand (regardless of its UPC) and dividing the resulting aggregate revenue by the aggregate volume sold for that brand.[6] Descriptive statistics for the brands and cities chosen for our study are provided in Table 2.3 and 2.4. These data include information contained in the IRI data set, as well as data collected from specialized sources (i.e. demographics, temperatures). Based on the similarity of demographics, these data suggest that Albany appears to be the most reliable control in the first data set as it is the most similar to Portland in terms of size (population), income and temperature. For the same reasons, Detroit is considered to be the most reliable control in the second data set. Figures 2.1 and 2.2 display a comparison of

[5]Cadbury Schweppes Americas Beverages became Dr Pepper Snapple Group Inc. on May 5, 2008. http://www.sec.gov/

[6]This procedure effectively yields a weighted average price across package sizes.

the income distribution among treatment cities and the control cities. These figures confirm that Albany and Detroit are, respectively, the most ideal control cities.

2.4 Results

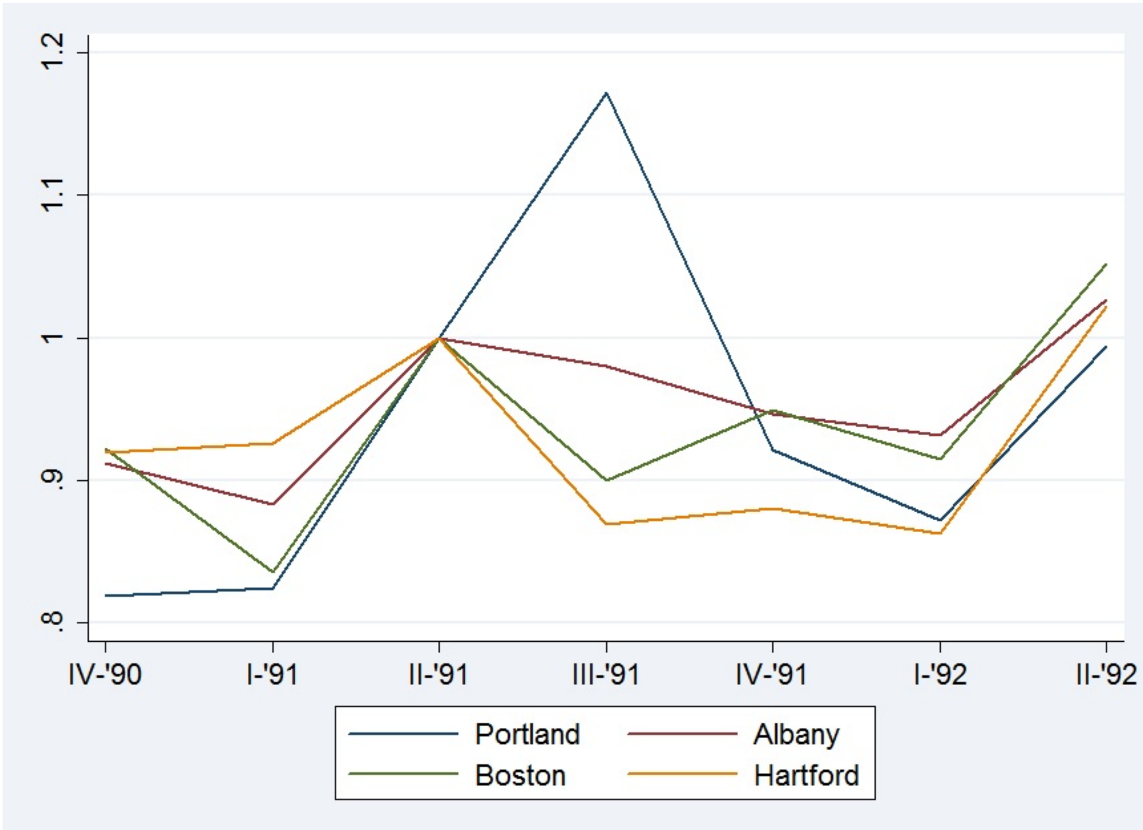
2.4.1 Descriptive Evidence

A crucial requirement for the reliability of difference-in-difference estimators is that the control units should share a common trend with the treatment units. Since this condition is largely difficult to ensure in non-lab environments, it is important to check how plausible this assumption is. We do this by graphically comparing the evolution of the outcome variable of main interest (volume sales) in both the treatment city as well as in the control cities.

Figures 2.3 and 2.4 depict, for each city, the quarterly series of total volume sales. These volume sales are computed using the selected brands reported in Tables 1.1 and 1.2 (similar graphs are obtained if all brands are included). The time period spans from the fourth quarter of 1990 to the second quarter of 1992, and from the second quarter of 2002 to the fourth quarter of 2003, respectively. To facilitate comparability, total volume sales are normalized by using volume sales in the fourth quarter of 1990 (data set A) and volume sales in the fourth quarter of 2002 (data set B) as the base period.

We observe an unusually large peak in total volume sales for Portland in the third quarter in 1991. This peak only occurs in Portland and we are unsure about its cause. This peak may be a reason to doubt the appropriateness of the control cities as one would expect control cities to mimic volume changes in the treatment city. However, one would be particularly worried about this if such disparity between control and treatment cities is also observed in other quarters (especially those preceding the tax increase). The graph obtained by excluding that specific quarter (Figure 2.5) suggests that the Portland volume sales peak appears to be an isolated event that occurred in

Figure 2.3. CSD total volume sales* (y-axis) per city (different lines) and quarter (x-axis), IRI Infoscan Data, Oct 1990 – June 1992

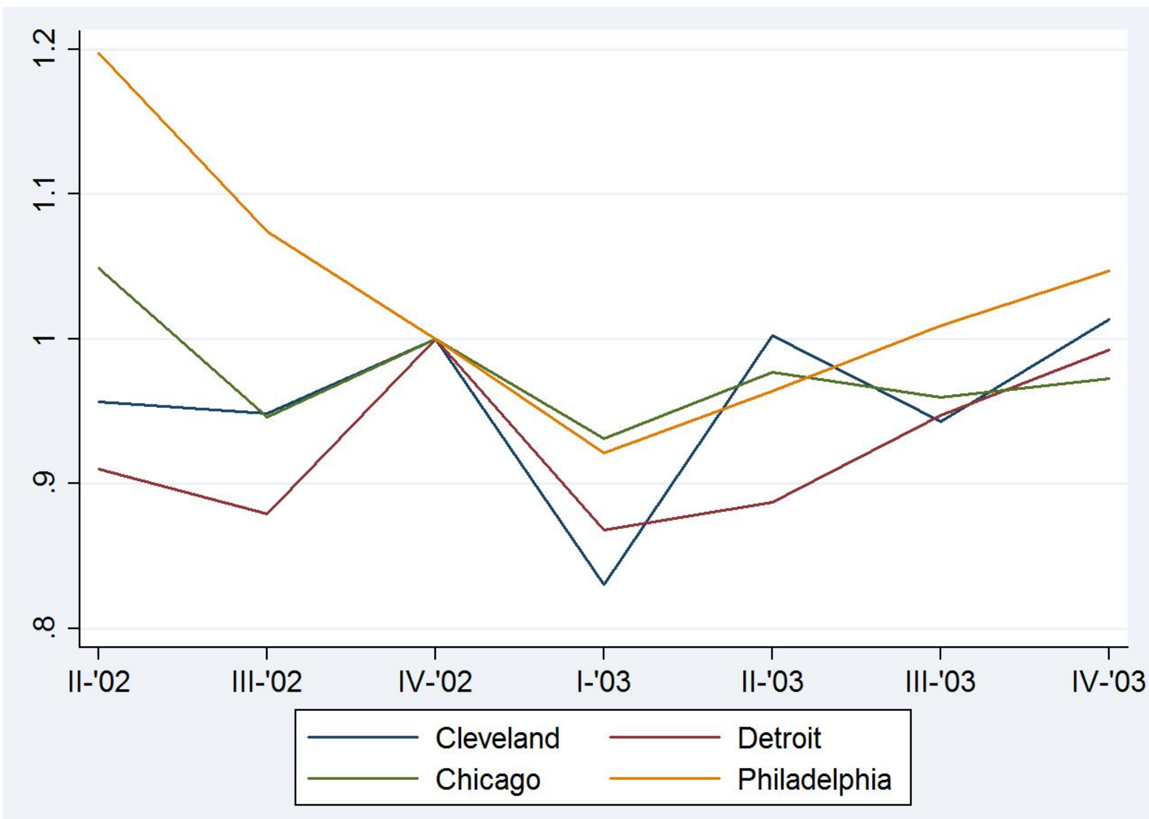


*Total volume sales have been normalized using the 2^{nd} quarter of 1991 as base period.

the summer of 1991[7] since volume trends seem to be reasonably similar across cities once this quarter is removed from the graph. Due to this seemingly isolated disparity in trends, we exclude the third quarter in 1991 from our analysis. We note that, in any case, this choice will allow us to err on the conservative side when estimating the effect of the tax on consumption (i.e. including the spike in volume sales registered in the third quarter of 1991 in the regressions below leads to a positive effect of con-

[7]After checking that no transcription errors or other data mistakes were reported in our data set, we checked whether this event was due to an unusually warm summer in Portland with respect to other cities. Data from NOAA's Satellite and Information Service (http://www.nesdis.noaa.gov/) suggests that this was not the case: the July-September average temperatures in 1990, 1991 and 1992 for our study were, respectively: 62.6°F, 61.6°F, 60.2°F (ME); 66.8°F, 66.5°F, 64.5°F (MA); 64.7°F, 65.1°F, 62.8°F (NY); 68.2°F, 68.1°F, 65.7°F (CT).

Figure 2.4. CSD total volume sales* (y-axis) per city (different lines) and quarter (x-axis), IRI Infoscan Data, Apr 2002 – Dec 2003

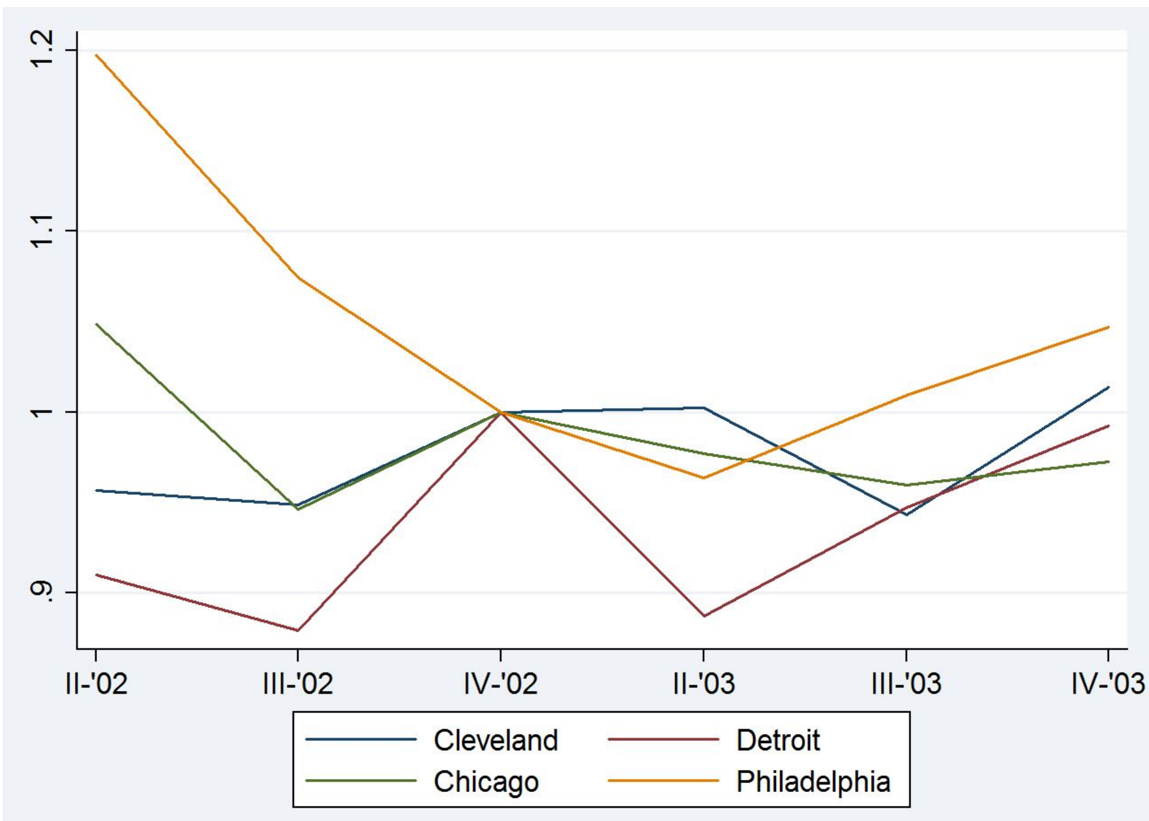


*Total volume sales have been normalized using the 4^{th} quarter of 2002 as base period.

Figure 2.5. CSD total volume sales* (y-axis) per city (different lines) and quarter (x-axis), IRI Infoscan Data, Oct 1990 – June 1992, 3^{rd} *quarter 1991 excluded*

*Total volume sales have been normalized using the 2^{nd} quarter of 1991 as base period.

Figure 2.6. CSD total volume sales* (y-axis) per city (different lines) and quarter (x-axis), IRI Infoscan Data, Apr 2002 – Dec 2003, 1^{st} *quarter 2003 excluded*



*Total volume sales have been normalized using the 4^{th} quarter of 2002 as base period.

sumption by the tax increase, an unlikely scenario). In order to maintain consistency in the analysis of the two data sets, we also removed from the analysis in the second event the quarter when the tax was enacted (Figure 2.6).

Figure 2.5 shows reasonably similar volume trends between the treatment city and the control cities in the period prior to the imposition of the soft drinks tax, adding confidence to our empirical approach. Moreover, and consistent with the demographic information, Albany's volume trend seems to more closely resemble that of Portland. Any significant changes in trends (between Portland and its controls) in the period after the tax increase can be used to infer what the effect of the tax on consumption might have been. Following the imposition of the tax, all cities show a negative trend in volume sales; further, it appears as if Portland's downward trend (especially when compared with the most reliable control, Albany) might be somewhat more pronounced. While this "graphical" evidence suggests that the tax might have curbed soft drinks consumption in Maine, our overall initial assessment is that such effect might not be substantial.

Similar comments can be made when interpreting the graph in Figure 2.4. Clearly, the control city that better represents volume sales trend in Cleveland (treatment city), before the tax was applied, is Detroit. However, the other cities also show a similar trend, although a larger volume level can be observed in Philadelphia and Chicago with respect to Cleveland and Detroit. From the volume sales trend shown in the graph, Philadelphia appears to be the least appropriate control city for Cleveland. Notwithstanding, given the limited number of control cities, we decided to keep Philadelphia in the analysis and proceed with caution when considering results when using Philadelphia as a control city. As opposed to the first event, in this second event, the effect of the tax cannot be visualized based on graphical inspection.

2.4.2 Regression Results

Tables 2.5 and 2.6 show the DIDM results for volume sales as well as for price. As opposed to the "total volume sales" variable in Figure 2.3 through 2.6 (which is the sum of volume sales over all brands in a city-quarter pair), "volume sales" in this analysis is measured at the brand level. We define the before period as the three quarters preceding the tax change (i.e. fourth quarter of 1990 through second quarter of 1991 for data set A; second quarter of 2002 through fourth quarter of 2002 for data set B) and the after period as the three quarters after the change due to the tax (i.e. fourth quarter of 1991 through second quarter of 1992 for data set A; second quarter of 2003 through fourth quarter of 2003 for data set B). Because the matching estimator requires one observation in each the post- and pre-treatment periods, we aggregate quarters by taking the mean of the variable (volume or price) over the quarters considered (for both the before or the after period) and perform the test on the difference of the logs of these mean values (see equation 1.1). Results are not sensitive to this method of aggregation. Specifically, our conclusions remain unchanged if we report results on quarter by quarter comparisons, which we will discuss later. For robustness purposes, we compute the DIDM estimator for all possible sets of control cities. That is, we consider the case in which we use all 3 control cities in the estimator, as well as cases when we include a pair of cities, or just one city.

The parameter estimates can be (roughly) interpreted as the percentage variation of the variable of interest (in the treatment city) with respect to the control city (using the three quarters after the tax was enacted as the after period and the three quarters before the tax enactment as the before period).[8] We observe from the results in Table 2.5 that there is no statistically significant change in either price or volume

[8]Strictly speaking, because we are using the difference of the variable in natural *log* format, the percentage change in the variable is given by $e^{\hat{\alpha}_{DIDM}} - 1$, where $\hat{\alpha}_{DIDM}$ is the $DIDM$ estimate reported in Table 2.5 and 2.6. For small enough $\hat{\alpha}_{DIDM}$ (as is the case here), $\hat{\alpha}_{DIDM}$ is a good approximation of $e^{\hat{\alpha}_{DIDM}} - 1$.

Table 2.5. DIDM Results for Volume and Price, Portland as treatment city and Albany, Hartford and Boston as control cities

Date	**IV'90-II'91 vs. IV'91-II'92**	
	Volume change (s.e.)	Price change (s.e.)
Control city (#obs)		
All control cities (96)	-0.02 (0.04)	0.00 (0.01)
Albany-Boston (72)	-0.04 (0.04)	0.00 (0.01)
Albany-Hartford (72)	0.00 (0.05)	0.00 (0.01)
Hartford-Boston (72)	-0.02 (0.04)	0.01 (0.01)
Albany (48)	-0.02 (0.05)	-0.01 (0.01)
Boston (48)	-0.06 (0.04)	0.02 (0.01)
Hartford (48)	0.01 (0.06)	0.00 (0.02)

Notes: Pre-tax period is fourth quarter of 1990 through second quarter of 1991; post-tax period is fourth quarter of 1991 through second quarter of 1992. The specification uses the mean volume (and mean price) over the pre-tax and the post-tax periods, respectively.

Table 2.6. DIDM Results for Volume and Price, Cleveland as treatment city and Chicago, Detroit and Philadelphia as control cities

Date	**II'02-IV'02 vs. II'03-IV'03**	
	Volume change (s.e.)	Price change (s.e.)
Control city (#obs)		
All control cities (120)	-0.02 (0.04)	0.08*** (0.02)
Chicago-Detroit (90)	-0.04 (0.04)	0.10*** (0.02)
Chicago-Philadelphia (90)	0.00 (0.05)	0.08*** (0.02)
Detroit- Philadelphia (90)	-0.02 (0.04)	0.05*** (0.02)
Chicago (60)	-0.02 (0.05)	0.13*** (0.02)
Detroit (60)	-0.06 (0.04)	0.07*** (0.02)
Philadelphia (60)	0.01 (0.06)	0.04** (0.02)

Notes: Level of significance: ***=1%; **=5%. Pre-tax period is second quarter of 2002 through fourth quarter of 2002; post-tax period is second quarter of 2003 through fourth quarter of 2003. The specification uses the mean volume (and mean price) over the pre-tax and the post-tax periods, respectively.

Table 2.7. DIDM results for Volume and Price change, Portland as treatment city and Albany-Hartford-Boston as control [quarter by quarter comparisons instead of aggregate comparisons]

	Volume change (s.e.)		**Price change (s.e.)**	
Date	**Control cities (# obs.)**			
	Albany (48)	Hartford - Boston - Albany (96)	Albany (48)	Hartford - Boston - Albany (96)
IV'90 v. IV'91	-0.01 (0.17)	0.07 (0.09)	-0.03 (0.02)	0.01 (0.01)
IV'90 v. I '92	0.02 (0.16)	-0.01 (0.09)	-0.07** (0.02)	0.02 (0.02)
IV'90 v. II '92	-0.08 (0.17)	-0.08 (0.09)	0.00 (0.03)	-0.01 (0.02)
I'91 v. IV'9	-0.09 (0.14)	0.02 (0.07)	-0.03 (0.02)	0.00 (0.01)
I'91 v. I'92	-0.07 (0.13)	-0.10 (0.08)	-0.07** (0.03)	0.01 (0.02)
I'91 v. II'92	-0.06 (0.12)	-0.13 (0.08)	0.00 (0.03)	0.00 (0.02)
II'91 v. IV'91	0.02 (0.05)	0.02 (0.04)	-0.03 (0.02)	0.01 (0.01)
II'91 v. I'92	0.05 (0.11)	-0.07 (0.09)	0.00 (0.03)	0.02 (0.03)
II'91 v. II'92	-0.04 (0.10)	-0.04 (0.07)	0.06* (0.03)	0.02 (0.02)

Notes: Significance level: **=5%. Standard errors are calculated using the formula provided by Abadie and Imbens (2008) for nearest neighbor matching estimator

Table 2.8. DIDM results for Volume and Price change, Cleveland as treatment city and Chicago-Detroit-Philadelphia as control [quarter by quarter comparisons instead of aggregate comparisons]

	Volume change (s.e.)		**Price change (s.e.)**	
Date	**Control cities (# obs.)**			
	Detroit (60)	Chicago - Detroit - Philadelphia (120)	Detroit (60)	Chicago - Detroit - Philadelphia (120)
II'02 v. II'03	0.09 (0.06)	0.12* (0.06)	0.00 (0.04)	0.00 (0.03)
II'02 v. III'03	0.04 (0.07)	0.07 (0.07)	0.19*** (0.03)	0.18*** (0.03)
II'02 v. IV'03	0.03 (0.08)	0.01 (0.07)	0.14*** (0.03)	0.21*** (0.03)
III'02 v. II'03	0.01 (0.06)	0.07 (0.06)	0.05 (0.03)	0.04 (0.03)
III'02 v. III'03	-0.03 (0.07)	0.02 (0.06)	0.11*** (0.02)	0.10*** (0.02)
III'02 v. IV'03	0.00 (0.08)	-0.04 (0.07)	0.06** (0.03)	0.13*** (0.03)
IV'02 v. II'03	0.05 (0.05)	0.08* (0.05)	0.00 (0.03)	-0.03 (0.02)
IV'02 v. III'03	0.00 (0.06)	0.04 (0.06)	0.04 (0.03)	0.02 (0.03)
IV'02 v. IV'03	0.03 (0.05)	-0.02 (0.04)	0.00 (0.03)	0.05** (0.02)

Notes: Significance level: ***=1%, **=5%, *=10%. Standard errors are calculated using the formula provided by Abadie and Imbens (2008) for nearest neighbor matching estimator for the first event. The price estimates imply that firms in Portland did not react in any systematic way as a consequence of the imposition of the tax and that the tax was fully passed through to consumers.

While the lack of a significant effect on volume sales is confirmed in the second experiment (Table 2.6), we notice significant increases in the average price for Cleveland with respect to the control cities. In order to analyze in closer detail the observed price increases, we ran DIDM regressions quarter by quarter (for completeness, we do this for both events). For brevity, we report the results of the regressions where we consider all control cities and the most reliable control city in the group. As shown in Table 2.7, except for a 7% decrease with respect to Albany between the second quarter of 1991 and the same quarter of 1992, no other significant changes can be highlighted for Portland before and after the tax was applied (recall that the tax was enacted during the third quarter of 1991).

Table 2.9. DID Results for Volume and Price, Portland as treatment city and Albany, Hartford and Boston as control cities

Date	**IV'90-II'91 vs. IV'91-II'92**	
	Volume change (s.e.)	Price change (s.e.)
Control city (#obs)		
All control cities (576)	-0.04 (0.03)	0.00 (0.01)
Albany-Boston (432)	-0.07 (0.05)	0.00 (0.01)
Albany-Hartford (432)	-0.02 (0.04)	-0.01 (0.01)
Hartford-Boston (432)	-0.03 (0.04)	0.01 (0.01)
Albany (288)	-0.07 (0.09)	-0.01 (0.01)
Boston (288)	-0.07 (0.04)	0.01 (0.01)
Hartford (288)	0.02 (0.06)	0.00 (0.02)

Notes: Pre-tax period is fourth quarter of 1990 through second quarter of 1991; post-tax period is fourth quarter of 1991 through second quarter of 1992. Standard errors (in parenthesis) are clustered at the brand level.

On the other hand, results shown in Table 1.8 highlight that in the quarter following the tax increase (the 2^{nd} quarter of 2003), tax-exclusive prices did not experience

Table 2.10. DID Results for Volume and Price, Cleveland as treatment city and Chicago, Detroit and Philadelphia as control cities

Date	**II'02-IV'02 vs. II'03-IV'03**	
	Volume change (s.e.)	Price change (s.e.)
Control city (#obs)		
All control cities (720)	0.01 (0.04)	0.08*** (0.01)
Chicago-Detroit (540)	-0.02 (0.04)	0.10*** (0.01)
Chicago-Philadelphia (540)	0.02 (0.04)	0.08*** (0.01)
Detroit- Philadelphia (540)	0.04 (0.05)	0.05*** (0.01)
Chicago (360)	-0.04 (0.03)	0.12*** (0.01)
Detroit (360)	0.00 (0.06)	0.07*** (0.01)
Philadelphia (360)	0.09 (0.07)	0.04*** (0.02)

Notes: Significance level: ***=1%; **=5%. Notes: Pre-tax period is second quarter of 2002 through fourth quarter of 2002; post-tax period is second quarter of 2003 through fourth quarter of 2003. Standard errors (in parenthesis) are clustered at the brand level.

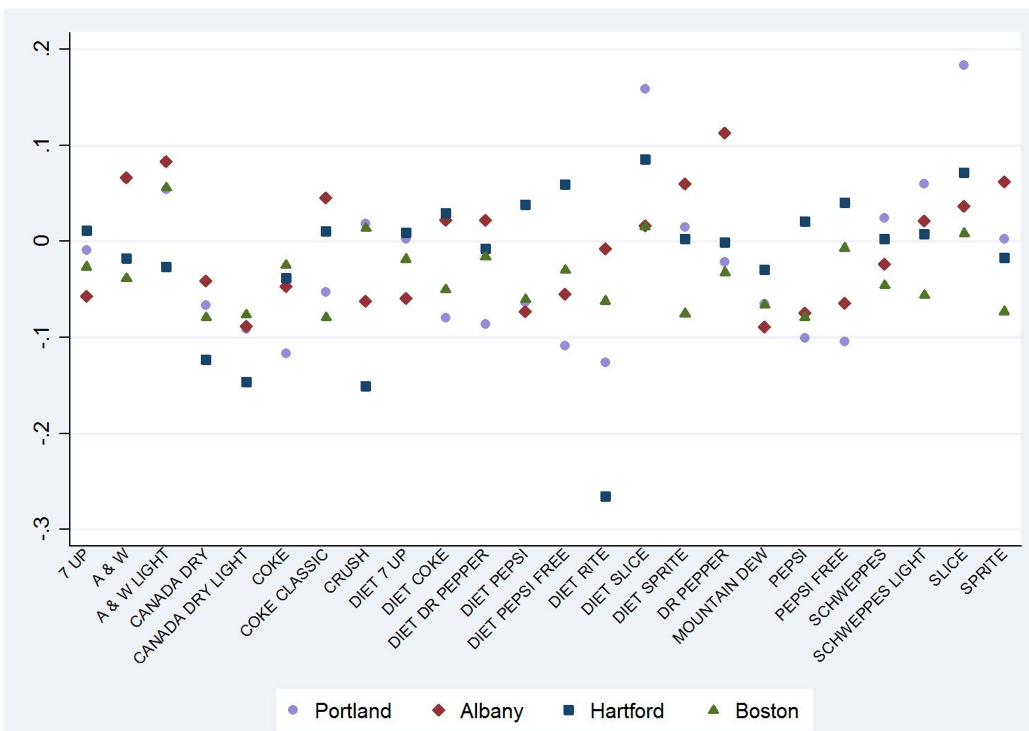
a significant change (recall that the tax was applied at the beginning on the first quarter in 2003). However, this is not true for the following quarters. In fact, the later the after tax periods, the higher are the price changes registered in Cleveland. In other words, the quarter by quarter comparisons suggest that the price increase that we observe in Cleveland is likely to be linked to Cleveland-specific events occurring after the tax imposition. Surprisingly, nevertheless, the registered price increases appear not to have affected soda consumption.[9]

Tables 2.9 and 2.10 present the results for the standard DID regressions, which we use as a robustness test for our DIDM estimates. The DID estimator is applied on the log of volume and price, respectively; the reported coefficient corresponds to $\hat{\alpha}_{DID}$ in equation 1.2. Standard errors (in parenthesis) are clustered at the brand level. Clustering at the company level does not alter our results. In all cases, signifi-

[9]Of course, price movements can be caused by both supply and demand shifts. Hence, a higher price (and no volume change) may reflect, for instance, a upward movement in both supply and demand

cance levels are the same as those obtained in our DIDM regressions. We choose to report brand-level clustering because clustered errors are valid only for a sufficiently large number of clusters, ideally more than 20-25 (Cameron et al., 2008). As in the DIDM analysis, we consider two independent variables: the natural logarithm of volume sales and the natural logarithm of price. We make the same comparisons among cities as in the DIDM analysis. The DID regressions confirm DIDM results.

Figure 2.7. Change in Volume sales by Brand and City (log (Mean Volume sales IV'91-II'92/Mean Volume sales IV'90-II'91))



To further understand whether there are particular patterns in price and volume changes at the brand level, we visually inspect price and volume changes for each brand in our data set. Figures 2.7, 2.8, 2.9 and 2.10 show, respectively, the change in price and the change in volume for each brand-city pair (Figures 2.7 and 2.9 correspond to data set A and Figures 2.8 and 2.10 correspond to data set B). In the figures, brands appear on the horizontal axis, while cities are depicted by markers. These figures not only highlight the importance of using a control in measuring the

Figure 2.8. Change in Volume sales by Brand and City (log (Mean Volume sales II'02-IV'02/Mean Volume sales II'03-IV'03))

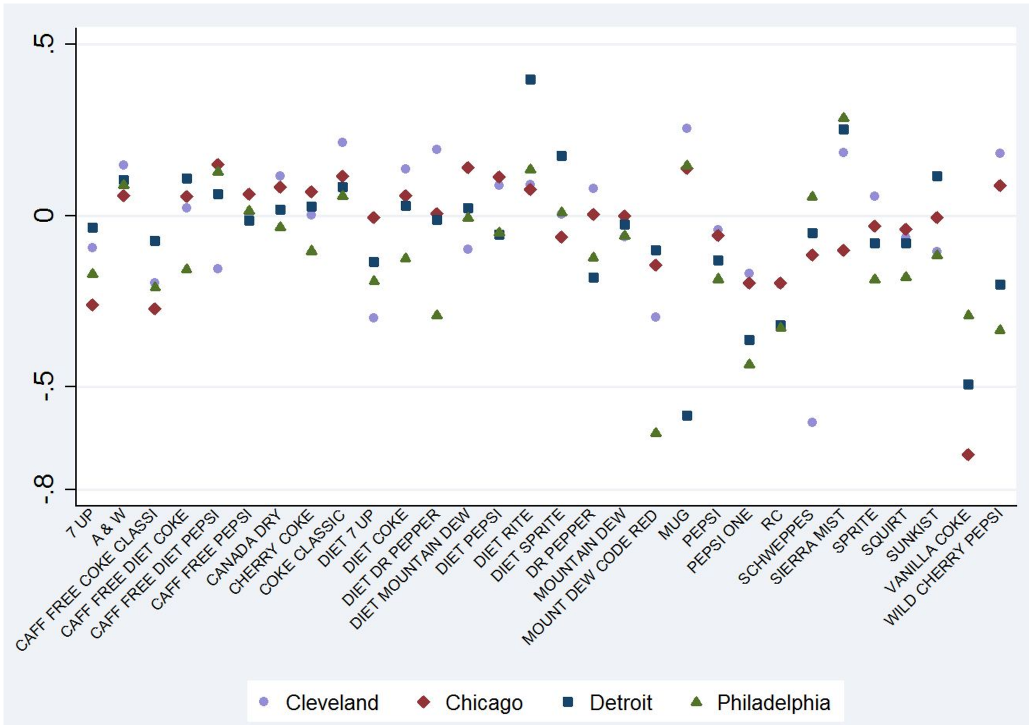


Figure 2.9. Change in Price by Brand and City (log (Mean Price IV'91-II'92/Mean Price IV'90-II'91))

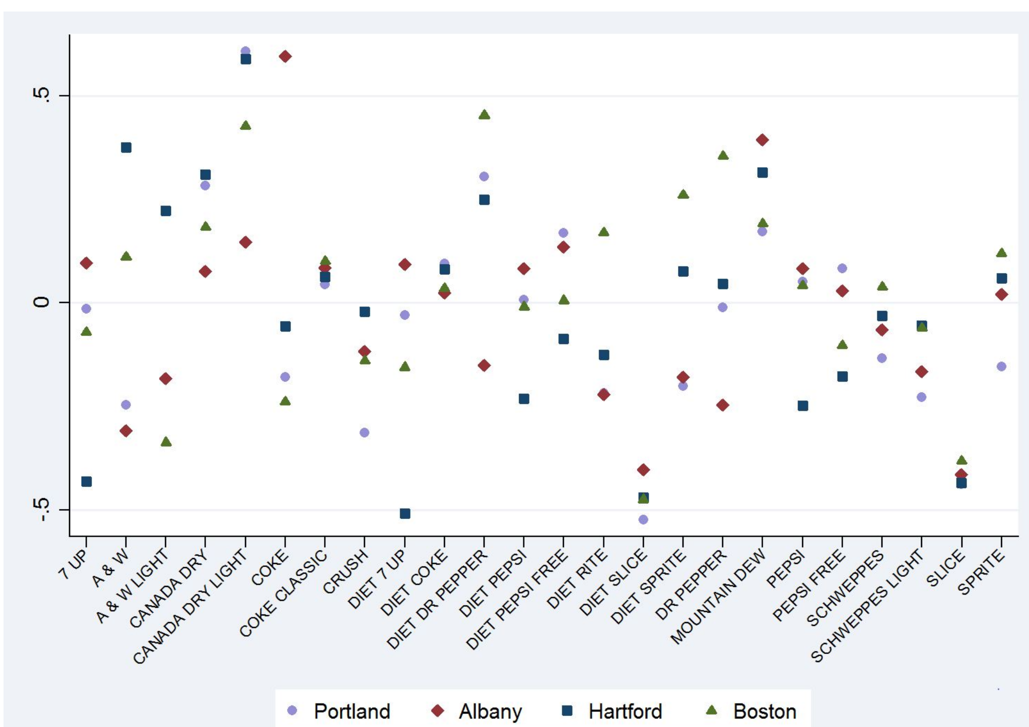
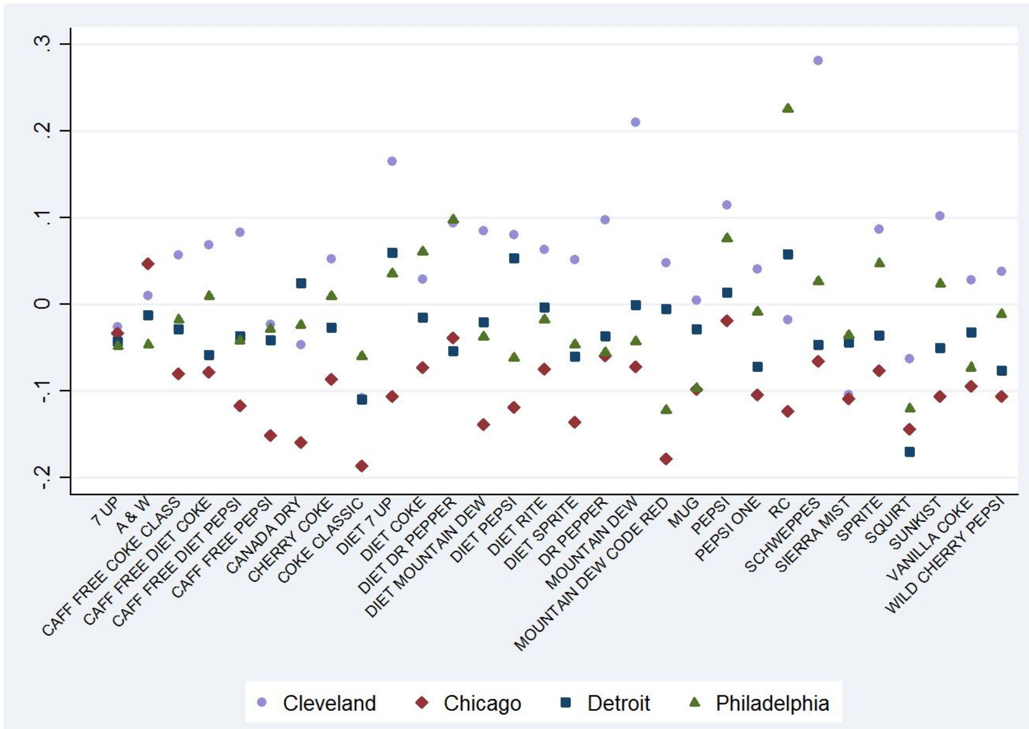


Figure 2.10. Change in Price by Brand and City (log (Mean Price II'02-IV'02/Mean Price II'03-IV'03))



desired effect, but they are also consistent with the econometric results. For the Portland event, there is no clear pattern suggesting a sizable effect of the tax increase in either volume or prices at the brand-level. In the Cleveland event, we notice from Figure 2.10 a clear increase in price for virtually all brands in our sample, which is reflected in the econometric results.

2.5 Conclusion

In this chapter we show the results of DIDM and standard DID estimations, with the aim of uncovering the effect that the imposition of a soft drinks sales tax might have had on brand-level consumption and prices. Results suggest that the 5.5% sales tax that Maine applied to soft drinks in July of 1991 did not cause a generalized impact on volume sales at either the aggregate or the disaggregate (brand) level. Subsequently, using a more recent data set (2001-2006), we identified a similar tax event, which occurred in 2003, and we implemented a similar analysis. This allowed us to verify whether the effect of this type of tax has changed over time. This is particularly important given consumers' greater awareness about the relationship between obesity and soda consumption. As in 1991, we found that the 2003 application of a sales tax on soft drinks in Ohio did not affect the consumption in a significant way. In fact, we find that after the tax is applied, there is an overall increase in the tax-exclusive price in the treatment city that does not translate in a decrease in consumption either. Our results are robust to several alternative specifications.

While our main finding is consistent with the generalized conclusion in the literature that demand for soft drinks is inelastic, it casts some doubt about whether one should use price elasticities to form counterfactuals for how consumers might react to tax increases. Specifically, we find that such counterfactuals might be optimistic as they predict an actual reduction in consumption. The fact that the tax is not displayed on the shelf (where many consumers might base their purchasing decisions) may help explain why a tax does not cause a reduction in consumption in our data. One caveat of our study regarding Maine is that the tax was also applied to other high-calorie foods (snacks and pastries), so there is not much room for a possible substitution effect away from soda and towards other sources of sugar. This could partly explain the insignificant impact on soft drinks consumption in our *quasi*-experiment. However, this concern is not present in the second part of the study, given that the Ohio tax was soda specific.[10] Still, our results raise interesting questions about the role of substitute categories when a commodity is taxed. For example, if the impact on soft drink consumption in our study had been statistically significant and the tax had been applied only on soft drinks, a reduction in consumption could have reflected a switch towards higher consumption of other sugary products (and not necessarily

[10]Candies, pudding/gelatin, sugar and sugar substitutes or snacks were considered food by Ohio Legislation and therefore sales tax exempted. http://tax.ohio.gov/

the reduction in sugar intake intended by policy makers).

While we only look at two isolated instances of a tax increase, our results may have broader implications as the tax applied in Maine and Ohio are very close to the mean sales tax applied to soft drinks (currently enforced in 33 states), which is 5.2% (Brownell et al., 2009).Also, because our data for price excludes the tax, we can directly test whether firms reacted in their pricing decisions. Our results suggest that the price increase due to the tax was , by and large, entirely passed through to the consumer. This finding may be informative for future researchers in suggesting a likely pass-through rate for a tax increase when one needs to be assumed for counterfactual purposes.

Our results show the taxes in Maine and Ohio did not significantly decrease consumption. Therefore, these taxes have the effects of raising tax revenues for the states. While this added tax revenue should, in principle, be reinvested in programs and campaigns to promote a healthier consumption of food, in most of the cases the revenue from the "snack-taxes" has become part of the general treasury, as occurred in Maine (Jacobson and Brownell, 2000). Because the objective of the policy is to curb consumption for consumers who are less likely to give up consumption of soda, discussion of any proposal of special "soda taxes" should take into account that even substantial price increases from soda companies have minimal effects on volume sales. In sum, our study indicates that if the objective of the studied taxes was to influence behavior through a higher tax-inclusive price for unhealthy foods (by inducing consumers to consume fewer high calorie drinks) the result of the tax imposition will be disappointing for policy makers. On the other hand, if the objective of the studied taxes was to raise states' revenues and use the additional resources to engage in other strategies to address the obesity problem, then soda taxes might have been quite successful.

Finally, we note one methodological point. While our matching mechanism is simple and intuitive, we are not aware of other studies that have applied this approach. We think that this could be a particularly useful technique in work that investigates the effect of a policy (or other environment changes) that is homogenously applied to a differentiated commodity.

CHAPTER 3

SODA SALES TAXES: WHO PAYS MORE? A STUDY ON CONSUMPTION BY DEMOGRAPHICS

3.1 Introduction

Sales taxes have been demonstrated to be regressive (Wang, 2012; Lin et al., 2010; Chouinard et al., 2007). In particular, it has been found that soda taxes generate a welfare loss not homogeneously distributed across households of different income levels, with poorer consumers being more affected by such taxes. In fact, poor households appear to be heavier consumers of regular soda; further these households may have a lower price elasticity for regular than for diet soda. As a consequence, poor households pay, in proportion to their income level, more in tax than rich households (Wang, 2012). The nature of the data in our previous study did not allow us to separate the effects among different types of consumers; specifically, we found that the "average" effect on consumption of a 5% soft drink sales tax is not significantly different from zero. Yet, there is the possibility that heterogeneous effects of taxation exist, namely, that there are households that reduce their consumption when a tax is applied while others do not.

In this chapter, we examine whether the impact of the tax is different for different population groups. For this purpose, we use one of the IRI scanner panel data sets (2001-2006). The original data set is disaggregated at the supermarket-level, with each supermarket belonging to a different (identifiable) city area (neighborhood), defined by a census tract. The location of each supermarket allows us to match sales data to demographic census tract data from 2000.

The method we apply is described in the next section (3.2). Section 3.3 describes the data while section 3.3 reports the results of the study. Concluding remarks are presented in section 3.4.

3.2 Method

As in the second event studied in Chapter 2, sales data collected by scanner devices in Cleveland (Ohio), Detroit (Michigan), Chicago (Illinois) and Philadelphia (Pennsylvania) are used. In this chapter we focus our attention on whether the 5% soda sales tax had a differential effect on different population groups. Recall that the sales tax was levied in Ohio in January 2003, and that it applied exclusively to soft drinks. The available data limit our comparison to consumption across cities (rather than across entire states). The data, provided by Information Resources Inc. (IRI), come from a sample of supermarkets in the largest metropolitan areas in the U.S. The data set includes brand-level sales information for the periods 2001-2006. More details on characteristics of the data set are provided in section 2.3.

We performed a cluster analysis in order to group supermarkets according to some demographics of the area where they are located. This grouping allows us to apply the DIDM analysis to each population sub-groups separately. Cluster analysis is a statistical method of multidimensional analysis that allows a complex phenomenon to be described by constructing categories or types of elements from a plurality of primary measures. In other words, it classifies observations into groups (clusters) such that elements/observations within a group are relatively homogeneous among themselves but heterogeneous with respect to elements/observations in another groups, on the basis of a defined set of variables. In this study, the diversity measure (that is, the measure of heterogeneity between elements) used for the classification of observations, is the Euclidean distance. The clustering procedure is agglomerative, that is, it starts from n clusters and decreases progressively towards one cluster. The agglomeration criterion used here is known as the Ward's method, which computes the sum of squared distances within clusters and aggregates clusters with the minimum increase in the overall sum of squares. Parsing the classification tree (the graphical summary of the cluster solution) to determine the number of clusters, is a subjective process. The classification tree is called dendrogram. The method suggests that efficient cuts of the dendrogram correspond to sudden jumps between distance values. In our case this process identified three clusters. The separation of supermarkets into three clusters highlights some substantial differences among the three groups according to selected demographics and, at the same time, provides an interpretable representation.

Specifically, the variables we chose to base the clustering criteria are: level of education (% of population whose level of education is inferior to the 9^{th} grade; % of population who have attained a BS Degree); racial composition of the neighborhood (% of Black, % Hispanic and % White population); income variables (% of population below the poverty line; % of the population whose income is above \$200 thousand); % of unemployed population.

The resulting clustering procedure suggests that supermarkets in cluster 2 and cluster 3 are very different from each other in terms of education, income level and rate of unemployment. Specifically, cluster 2 represents wealthier neighborhoods while cluster 3 represents poorer/less educated areas. Conversely, cluster 1 includes areas whose demographics lie in a “middle zone”; that is, neither in cluster 2 nor in cluster 3.

We separately applied a difference-in-difference matching estimator (DIDM) on supermarket sales data in each of the three clusters (see Chapter 2 for a description of the method). For this experiment we used weekly data on sales and prices (for each supermarket) and considered an 8-week period of time before and after the tax application (total of 16 weeks).

3.3 Description of the data

The data set we employed contains store sales data on carbonated beverage sales and pricing spanning 5 years (2001-2006) of weekly data and 47 IRIs metropolitan areas (we refer to a metropolitan area as a "city" henceforth).[1] Data are available at the store level for each chain. More details on this data set are provided in Chapter 2 (specifically, in the description of data set B). In this study, we consider the 30 brands (commercial names of the product) characterized by larger market share (Table 2.2).

As in Chapter 2, we used 4 cities for the analyses: Cleveland (OH), Chicago (IL), Detroit (MI), Philadelphia (PA). We focus our analyses on 16 weeks: last 8 weeks of 2002 and the first 8 weeks of 2003. This decision is determined mainly by the fact that not all the supermarkets have been consistently registered weekly in each city; therefore the set of supermarkets appearing each week varies over time. To preserve consistency in this analysis, we analyze the same set of supermarkets over time; this choice greatly reduced the number of weeks we could consider (hence our choice of 16). Prolonging the number of weeks would have significantly reduced the number of supermarkets for the analysis. We selected brands that were present in all quarters and in all cities in our study; this procedure allows us to have a balanced panel (necessary for our matching procedure). In Table 2.2 we report the selected brands with the corresponding parent companies, as well as the number of observations. The 30 brands in Table 2.2 account for the 83% of the overall total volume sales in the selected supermarkets over all city-quarter pairs. The availability of supermarkets location data allows us to identify the census tract to which each supermarket belongs. We then pull demographic information for the identified census tracts and match it to the selected supermarkets.

The availability of the census tract per each supermarket allowed us to exploit the

[1] IRIs metropolitan area definitions are similar to those used by the Bureau of Labor Statistics.

richness of data from the 2000 Census, thereby making our cluster analysis feasible.[2] In Table 3.1 we report summary statistics of the selected demographic variables for each of the three groups that resulted from the cluster analysis. The choice of these demographic variables was based on socioeconomic factors that, at the aggregate level, are thought to have a stronger correlation with obesity (Sobal and Stunkard, 1989; Rosmond and Bjrntorp, 1999; Sodjinou et al., 2008; Wang, 2012). For instance, unemployment is a social condition that may lead to increased inactivity and, as a consequence, to body weight gain. Given that this classification is done at the census tract level, rather than the individual level, some potentially important characteristics could not be considered (i.e. gender), for lack of enough variability across the census tracts.

3.4 Results

The cluster analysis yielded three groups of supermarkets. Every supermarket is located in a different census tract. This analysis allowed us to group (both treatment and control supermarkets) with respect to their similarity given by selected demographic variables. Results are shown in Table 3.1.

The most evident differences are between Cluster 2 and Cluster 3. We notice that Cluster 2 is composed of areas characterized by a high level of education, where part of the population has a relatively higher income and a relatively low rate of unemployment is registered. Conversely, Cluster 3 is composed of areas characterized by a low

[2] According to the definition from the United States Census Bureau: *"Census tracts are small, relatively permanent statistical subdivisions of a county. Census tracts are delineated for most metropolitan areas and other densely populated counties by local census statistical areas committees following Census Bureau guidelines [...]. Census tracts usually have between 2,500 and 8,000 persons and, when first delineated, are designed to be homogeneous with respect to population characteristics, economic status, and living conditions. Census tracts do not cross county boundaries. The spatial size of census tracts varies widely depending on the density of settlement. Census tract boundaries are delineated with the intention of being maintained over a long time so that statistical comparisons can be made from census to census."*. http://www.census.gov/

Table 3.1. Descriptive statistics* of clustering variables by Cluster of census tracts

Cluster	%<9th Grade	%BS Degree	% Black	% Hisp.	% White	%Below Pov Line	%Inc.> $200k	% Unemp
1	3.8, 2.4	20, 2.6	10, 21	2.7, 2.7	84, 21	7, 12	0.6, 0.5	4, 2
2	**1.8**, 0.7	**30**, 3.6	6, 7	1, 0.3	87.5, 9	**1.5**, 3	**2.4**, 1	**2**, 1
3	**5.4**, 2.3	**9**, 3.2	9, 19	3, 3	83, 19	**18**, 29	**0**, 0.3	**6**, 0.2

*Mean, standard deviation

education level, high poverty within the population, and high unemployment rate. Racial composition is similar among the three clusters of supermarkets identified.

Table 3.2. DIDM Results for Volume and Price, Cleveland as treatment city and Chicago, Detroit and Philadelphia as control cities

Date	**Nov 1 '02- Dec 31 '02 vs. Jen 1 '03 - Feb 28 '03**	
	Volume change (s.e.)*	Price change (s.e.)*
All clusters (#obs)	-0.06 (0.05)	0.01 (0.01)
Cluster 1 (150)	-0.14 (0.08)	0.02 (0.02)
Cluster 2 (150)	-0.07 (0.10)	0.00 (0.03)
Cluster 3 (90)	0.04 (0.09)	-0.05 (0.03)

*Standard errors are calculated using the formula provided by Abadie and Imbens (2008) for nearest neighbor matching estimator

In Table 3.2 we report the results from the DIDM estimation by cluster. No significant change in either volume or price was observed after the tax was applied. But we do notice that wealthier areas (Clusters 1 and 2) have a negative coefficient, which is in line with our expectations. For the Cluster 3, the change is positive, but only marginally so, and may in part be due to the small (but insignificant) decrease in price.

3.5 Concluding remarks

The results shown in this chapter are in line with those found in Chapter 2. Further, we found that (for the data available) the impact of the tax might have had a homogeneous statistically insignificant effect on different demographic groups.

According to the findings from this study, however, this tax did not discourage soda consumption in lower income areas, which are characterized by higher obesity incidence. On the other hand, we obtained a negative coefficient for the cluster characterized by higher income and higher level of education. The sign of this coefficient, even though the estimate is statically insignificant, seems to confirm that the demand elasticity might be higher (in absolute value) for higher income consumers (Andreyeva et al., 2011; Finkelstein et al., 2010). This may be explained by a greater level of information awareness by people in this cluster regarding the detrimental effects of sugar consumption.

More work is needed to reveal who, among soda consumers, is more likely to actually respond to pricing policies. In fact, if the more educated and moderate consumers were the ones more likely to react to a tax, it seems unlikely that a strategy of combating soda consumption (and obesity) via taxation would be effective. Small sales taxes, indeed, would not change the behavior of those people causing the externalities. There is currently very little research on this aspect (Block and Willett, 2011).

CHAPTER 4

HETEROGENEOUS BEHAVIOR AND STORABILITY IN SOFT DRINK CONSUMPTION: USING A DYNAMIC DEMAND MODEL TO EVALUATE POLICY INTERVENTIONS TO CURB OBESITY

4.1 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 (Lustig et al., 2012). 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).

As discussed in the previous chapters, 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. One of the arguments frequently used to justify soda taxes is the success obtained by cigarette taxes in decreasing cigarette consumption (Block and Willett, 2011). However, cigarettes and soda are different in a number of ways. First, cigarette taxes are often designed to cause significant price increases (e.g., in New York State cigarette sales taxes amount to 57% of the price per pack). High taxation levels might not be possible or justifiable for soft drinks given that, as opposed to cigarettes, moderate soda consumption is

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

considered safe. A second difference with cigarettes is that soda has many substitutes (Block and Willett, 2011). Lastly, the ubiquitous presence of temporary price reductions (sale periods) in virtually all soda products, allows consumers to take advantage of such discounts by buying (and storing) large quantities for future consumption (a situation that is not present in the market for cigarettes).

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, 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; 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 epidemic (West, 2001). In the case of soft drinks, which contain high levels of both sugar and caffeine, the addictive potential may be compounded making them possibly more addictive than foods or drinks containing only one of the two ingredients. In summary, the presence of these elements may have an important impact on both the purchase frequency as well as the volume bought (and consumed), compared to what one would observe in healthier food products.

A central component of the social problem is the fact that there are households purchasing extremely large quantities of soda (who are therefore more exposed to obesity and to several health problems caused by soft drink ingredients)[2], while other consumers consume the product in moderate quantities.[3] There can be several reasons for high consumption levels. Brand loyalty and addiction are possible explanations; the relative unwillingness to abandon consumption by these consumers (who are, as already stated, more vulnerable to obesity) make simple taxing policies less likely to be effective for this segment of the population. Further, as noted above, soda, as opposed to other taxed goods (e.g. cigarettes), is frequently subject to temporary price reductions allowing soda consumers (especially those that consume large quantities) to dodge the price increase by stockpiling this storable good while on promotion.[4]

In this research we estimate a model of demand for soft drinks that takes into account the unique characteristics of this market that we have just described. Specifically, the model allows for the possibility that some consumers buy larger quantities of soda during sale periods in order to store the product for future consumption (when prices are higher); we call this feature of behavior "sale-sensitivity". Further, our model takes into consideration product differentiation (i.e. we model demand at the brand level), which allows us to calculate and account for substitution patterns across brands. Finally, we are able to estimate whether and how price sensitivity and storability sensitivity vary across populations with differing degrees of obesity incidence (we call this feature "consumer heterogeneity").[5]

Prior research that accounts for both storability and product differentiation of soft

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[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)

[4]In general, one should expect that producers of addictive products will offer (at least temporarily) attractive prices in order to entice people to initiate consumption.

[5]In the analysis we study other possible sources of consumer heterogeneity. Specifically, we consider whether sensitivity parameters (storability and price) depend on the level of other demographic characteristics such as low income, race, rural areas and low education.

drinks (Hendel and Nevo, 2013; Wang, 2012), has shown that a dynamic model of consumer inventory behavior is necessary to estimate accurate price sensitivity parameters, and that more realistic substitution patterns for differentiated products are obtained by including consumer heterogeneity in the model. Following the dynamic model of Hendel and Nevo (2013) we identify the percentage of consumers that are *storers* (consumers that stockpile purchases) versus those that are not and estimate their respective price elasticity parameters. We then extend the model to study whether and how the fraction of *storers* as well as their price sensitivity in a geographic area depends on the percentage of obese individuals in that area. To fulfill this objective, we match store-level soft drinks sales data to county-level obesity rates (and other demographic data), and take these data to the estimation of our dynamic demand model. Results from this study suggest that populations characterized by higher rates of obesity, despite being less price-sensitive for soda, are more inclined to store (i.e. are more "sale-sensitive"). This result may appear counterintuitive at first. However, by allowing for storing behavior, it is entirely possible that some consumers that are less sensitive to the overall price of soda are also those that buy large quantities during sale periods in order to avoid having to purchase at high prices when the sale expires.[6]

In the second part of our empirical analysis, we illustrate the policy usefulness of our model. Specifically, we use our demand estimates to simulate how consumers would react (i.e. how soda purchases would change) when prices of products are affected by two possible policy interventions: a) a ban on temporary price reductions (i.e. sales), and b) a sales tax on all soda products (diet and regular).The first intervention, albeit not considered before by policy makers, is motivated by the results

[6]To better illustrate this possibility it is useful to highlight the casual observation that smokers (by and large characterized by low price sensitivity) are frequently seen buying (often numerous) cigarette cartons at airports' duty free shops to benefit from discounted prices.

of our model (i.e. sale sensitivity being more prevalent in populations with higher obesity incidence). The second intervention has been proposed (and implemented in several states).

Results indicate that the former intervention, even though it implies a smaller average price increase than that resulting from a sales tax, would be more effective in reducing overall soft drink consumption. This finding highlights the crucial role that sale sensitivity has in this market: restricting consumers' ability to switch purchases from high price periods to (temporary) low price periods (i.e. the first intervention) can magnify the effect of a price increase on consumption reduction. While in both interventions consumption reduction is larger in areas with higher obesity incidence, this relationship is more pronounced when temporary price reductions are banned. Thus, a ban on temporary price reductions would be more effective in reducing both overall consumption as well as consumption by populations that are at a greater health risk. The main take away from this chapter is that using a more realistic model when carrying out counterfactual analysis can be crucial.

The rest of this chapter is organized as follows. Section 4.2 reviews the previous literature. Section 4.3 develops the theoretical framework, the model and the methodology applied. Section 4.4 presents the demand estimation results and the policy simulations. Finally, section 5 concludes.

4.2 Previous Literature

A number of studies have estimated the price elasticity of demand for soda in order to predict the decrease in consumption that would result from the price increase caused by taxation. One review of prior work on demand estimates for food products reports that own-price elasticity for soda and other beverages ranges between -0.8 and -1 (Andreyeva et al., 2011). However, a more recent review of empirical studies suggests that soft drink consumption is more price sensitive than what previously reported (Powell et al., 2013). 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. In addition to the still debated effect on consumption, some studies 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).

Some authors suggest that while small soda taxes are not likely to decrease BMI significantly, larger taxes might have a measurable effect on weight, and that these taxes should determine at least a 20% price increase (i.e., one penny-per-once) (Powell and Chaloupka, 2009; Powell et al., 2014). Nevertheless, Fletcher et al. (2013) suggest caution in enacting "big" soft drink taxes with the purpose of reducing obesity since large taxes may have different effects than the small taxes presently in place. Specifically, for hefty taxes to be effective, these would need to shift consumption toward healthy/healthier drinks (such as water and low-calorie beverages), something that currently small taxes appear not be doing (Fletcher et al., 2013). These considerations imply that in order to observe a price-induced decrease in the obesity rate, it would be necessary to tax several, if not many, food and beverage groups. For instance, Miao et al. (2013) estimate excess calories and welfare loss assuming that taxes are imposed on both added sugar and solid fat. They use a demand system that accounts for both the within-food group substitution as well as the substitution across food groups (which most studies do not take into account). Their simulations of taxes on added sugars and solid fat show that the tax impact on consumption patterns in the literature is understated and that the induced welfare loss is thus overstated when not allowing for the substitution possibilities toward leaner and lighter versions of the taxed items (Miao et al., 2013). According to these studies, hence, taxing policies should be applied to added sugar and fatty food concurrently, other than only on soda, to avoid shifting consumption towards other unhealthy categories, otherwise the positive effect of unhealthy consumption reduction of taxed products may be dampened.

Zhen et al. (2011), using homescan panel data, estimate the demand for sugary nonalcoholic beverages. By applying a dynamic extension of the almost ideal demand system, they find evidence of habit formation and argue that, because of this behavioral feature, consumers are more likely to respond to taxes in the long run than in the short run. Patel (2012) similar in flavor to what we do in this chapter, accounts for obesity rates and demographic characteristics in the context of a static model of demand and preferences for soda. Patels estimates suggest that consumers with higher body weight tend to be less price-sensitive and prefer diet sodas. In Patels 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 concludes that, given the static nature of his demand estimation, his estimates of price sensitivity are likely overstated.

While our results confirm Patels findings that high obesity rates are associated to lower (in absolute value) own price elasticities, our model does account for dynamics (i.e. forward looking behavior of consumers when they face a temporary price reduction), and thus provide more reliable demand elasticity estimates (Hendel and Nevo, 2006, 2013). Indeed, as conjectured by 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, 2012). In addition, by explicitly considering temporary price reductions and the stockpiling behavior in our model, we do not overstate moves to 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 notes that if obese consumers engage in stockpiling more than non-obese consumers, this would lead to an over-statement of his obese-specific price-sensitivity estimates. Indeed, 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 will be overstated.

Hendel and Nevo (2013), develop a dynamic demand model that allows the researcher to determine from the data the fraction of soda consumers that are $storers$ as well as those that are $non-storers$. The authors use their model to study intertemporal price discrimination of storable goods. Hendel and Nevo use their model and estimates 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 discount price by buying large quantities while on sale thereby significantly reducing their purchase needs during high price (i.e. non-sale) periods ($storers$). The remaining consumers are assumed to buy about the same volume regardless of whether the product is on sale or not ($non-storers$). The existence of these two consumer types in the market justifies, according to Hendel and Nevo, why optimal pricing involves discounts. Unlike our work, however, Hendel and Nevo do not distinguish sale-sensitivity from price-sensitivity and, instead, impose the assumption that more price sensitive consumers are the ones who store (and vice versa). We relax this assumption and show that this extension of Hendel and Nevo's model is important in our application as sale-sensitive populations (i.e. those with a higher obesity rate) actually have a lower price sensitivity. Importantly, our results suggest that this more flexible modeling approach can play a crucial role in the results and policy simulations.

4.3 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 (2013) (H&N,

henceforth) since their model allows us to handle the demand dynamics (generated by product storability) in a relatively simple way.

Let consumer h's utility function at time t be:

$$U_{ht}(\mathbf{q}, m) \equiv U(\mathbf{q}, m) \tag{4.1}$$

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 ($\mathbf{q}_t$).

As in H&N, we 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 assume that rational consumers will store just enough soda to last between one sale and another, because they know the price history and they can anticipate soda price up to T ahead (perfect foresight), so they can minimize storage costs. This assumption leads to simple dynamics, whereby stockpiling is only done exactly when inventory runs out. The model allows for the incorporation of stockpiling behavior by assuming that the population is made up by two types of consumers: $storers$ (S) and $non-storers$ (NS).

$Non-storers$ are those consumers that buy during both sale and non-sale periods only to satisfy current consumption needs; that is, these consumers do not buy "extra" (i.e. stockpile) when there is a sale period. Conversely, storers' purchase decisions are dynamic in the sense that on any given time period they determine purchases based on whether: a) they have inventory from prior periods, b) the current price is a sale price or not, and c) the anticipated future prices and consumption needs (below we provide more details on how this is operationalized). Because H&N's model is suited for aggregate data (i.e. data that aggregates, for each product, across the purchases made of all consumers) the estimation routine's output consists of, among other things, an estimate of the fraction of consumers in the population that are $non-storers$

(ω^{NS}).[7] The fraction of *storers* is recovered via the identity $\omega^S = 1 - \omega^{NS}$. To simplify notation, we henceforth only refer to ω^{NS} and denote it as ω.[8] We consider the fraction $1 - \omega$ as a measure of the population's sensitivity to sales.

We extend H&N's model by allowing the incorporation of demographic variables with the objective of testing and accounting for consumer heterogeneity. In particular, we allow price coefficients and the (non-) storability parameter (ω) to vary by the population's obesity incidence (% of population with $BMI \geq 30$) and other demographic variables recognized by the literature as predictors of obesity. This extension allows us to incorporate consumer heterogeneity in a model of aggregate data.

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

$$\text{Max} \sum_{t=0}^{R} \mathbb{E}\left[u_t^S(\mathbf{q}_t, m_t)\right] \tag{4.2}$$

s.t.

$$0 \leq \sum_{t=0}^{R} [(y_t - (\mathbf{p}_t' \mathbf{x}_t + m_t)] \quad \text{(Budget Constraint), and} \tag{4.3}$$

$$\mathbf{q}_t \leq \mathbf{x}_t + \sum_{\tau=0}^{t-1} (\mathbf{x}_\tau - \mathbf{q}_\tau - \mathbf{e}_\tau) \quad \text{(Inventory Constraint)} \tag{4.4}$$

where $\mathbf{x}_t$ is the vector of purchases and $\mathbf{e}_\tau$ is the vector of unused units that expire in period τ. Equation (4.4) thus allows for the possibility that current consumption ($\mathbf{q}_t$) might be satisfied by either current purchases ($\mathbf{x}_t$) or past purchases ($\mathbf{x}_\tau$ where $\tau > t$, up to T preceding periods), or both. A direct implication of this inter-period

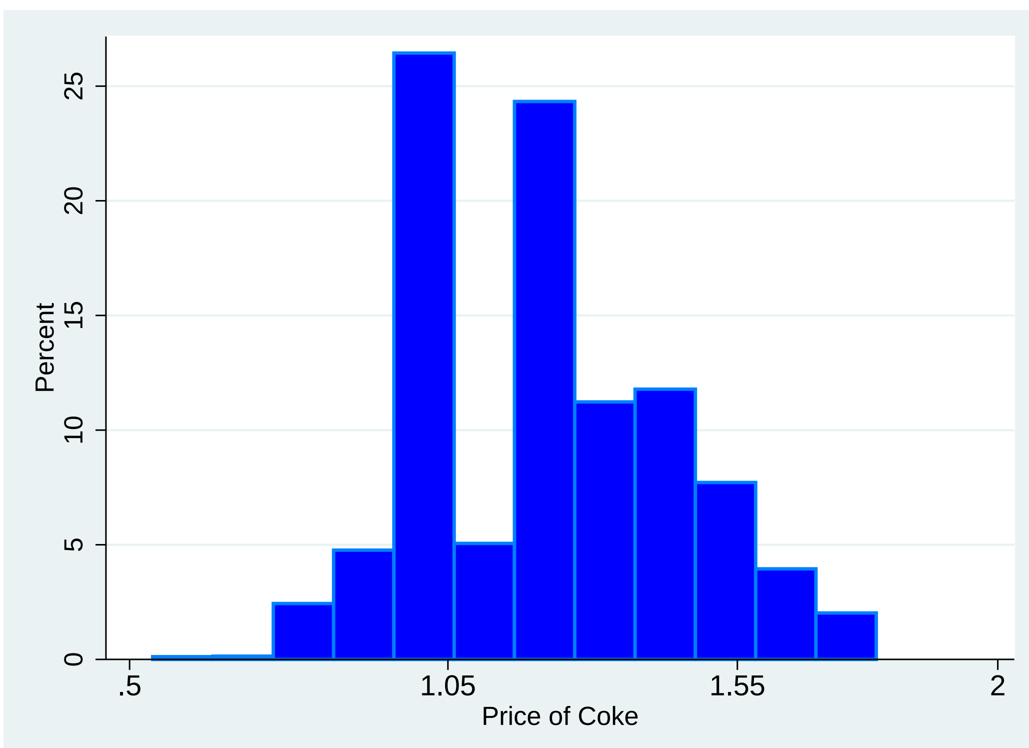
[7]As noted by H&N, an important advantage of using an aggregate model is its computational tractability.

[8]When refering to the fraction of storers we will use $1 - \omega$.

relationship, 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 what H&N denote effective price; that is, the price of the currently consumed product at the price at which it was purchased. Intuitively, if there was a sale in any of the preceding T periods, then current consumption's effective price would be such sale price (and not the current market price); otherwise the current price is the market price (we later formalize the definition of an effective price). An attractive feature of this assumption is that, by replacing current prices with effective prices, the dynamic problem collapses to a static one thereby making estimation straightforward.

The definition of the threshold that determines whether a price is low enough to qualify as a sale price is guided by the empirical distribution of prices observed in our data. As in H&N, we detect two modal values in the price distribution (Figure 4.1). The lower modal value is consistently equal or below \$1.05 (across chains, stores

Figure 4.1. Distribution of the price of Coke across all stores in 2006



and cities), therefore we selected this value as the threshold for determining a sale period and the corresponding effective price for each brand in each period.[9] Let's define a sale period (s) as the period when (p_{jt}) is a sale price, and a non-sale period (n) otherwise.[10] In a given period, *storers*' purchases may not coincide with current consumption; the reason for this is that this type of consumers, as indicated earlier, respond to sale periods by stockpiling. 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. Consequently, the dynamic optimization problem for *storers* becomes a system of static optimization problems since *storers* solve their optimization problem T periods in advance by buying what they need when the price is a sale price. In the 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* period, 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 $T + 1$ periods is a sale period, no price replacement is operated.

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:

$$\mathbf{q}_t^S = Q_t^S(\mathbf{p}_t^{ef}) \tag{4.5}$$

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

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[9] We performed sensitivity analyses with different (albeit marginally so) alternative cutoff prices. Our qualitative results and conclusions are robust to these variations.

[10] To avoid confusion with the notation between the type of period (n and s) and the type of consumer (i.e. S and NS for *storers* and *non − storers*, respectively), we use lowercase for the former and capital letters for the latter.

$$X_{jt}(\mathbf{p}_{t-T},...,\mathbf{p}_{t+T}) = Q_{jt}^{NS}(\mathbf{p}_t) + X_{jt}^{S}(\mathbf{p}_{t-T},...,\mathbf{p}_{t+T}) \tag{4.6}$$

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: consumers know 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 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. Intuitively, identification between *storers* and *non−storers* is straightforward: if the data reveal that much more is being purchased during sale periods (compared to periods when prices where high) then the fraction of *storers* that would rationalize this data pattern ought to be higher. To formally define the total quantity purchased in the market (by both *storers* and *non−storers*), let's consider the case of $T = 1$. In this case, *storers*' behavior can be predicted by defining four types of periods: a sale period preceded by a non-sale period (ns), a non-sale period preceded by a sale period (sn), two consecutive sale periods (ss) and two consecutive non-sale periods (nn). Considering each type of period defined above and assuming perfect foresight, product aggregate purchases, as defined in equation 4.6, need to be scaled up and down in the following way:

$$X_j(\mathbf{p}_{t-1},\mathbf{p}_t,\mathbf{p}_{t+1}) = \begin{cases} \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)Q_{jt}(p_{jt},p_{-jt}), & nn \\ \omega Q_j(p_{jt},p_{-jt}), & sn \\ \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)(Q_{jt}(p_{jt},p_{-jt}) & \\ +Q_{jt}(p_{jt},p_{-jt+1})), & ns \\ \omega Q_j(p_{jt},p_{-jt}) + (1-\omega)Q_{jt}(p_{jt},p_{-jt+1}), & ss \end{cases} \tag{4.7}$$

Where $Q_j(.)$ is the static demand for $storers$ and $non-storers$, and ω is the fraction of $non-storers$. Notice that effective prices for product j in equation 4.7 are used to scale up or down current purchases of $storers$ (i.e. they do not enter as an argument in the demand function q_{jt}). Thus, once the regimes are determined (and the corresponding scaling process is done), current purchases are function of current prices.

Specifically, the aggregated demand for $storers$ and $non-storers$ in every regime is determined in the following way. For $non-storers$ demand and consumption always 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[11]; 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 discount (sale-period), for both $t-1$ as well as t consumption. 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 is satisfied by their purchase in $t-1$.

In addition to scaling $storers$' demand depending on the type of period, the dynamics are incorporated by updating p_{-jt+1} with p^{ef}_{-jt+1} (not shown in equation 4.7 to preserve simplicity). 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 is 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 substitute products (through the inclusion of rival products'

[11] 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 illustrate how the demand is scaled in the different regimes.

effective prices). In fact, using contemporaneous prices for substitute products would generate a bias in the estimated cross-price effect.

4.4 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:

$$x_{jst} = Q_{jst}^{NS}(p_{jst}, \mathbf{p}_{-jst}) + \sum_{\tau=0}^{T} Q_{jst+\tau}^{S}(p_{jst}, \mathbf{p}_{-js,t+\tau})\mathbf{1}\left[p_{jst} = \mathbf{p}_{js,t+\tau}^{ef}\right] \tag{4.8}$$

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 4.7, one or both of the components of the demand for $storers$ can be zero, depending on the sale/non-sale regime. The regime is determined by the argument of the indicator function[$\bullet$]. Recall that for product j, in all cases actual prices are used (i.e. j's prices dictate the regime, are never changed). We assume that the demand for product j at store s in week t is log-linear:

$$logQ_{jst}^{h} = \omega^{h}\alpha_{js} - \beta_{j}^{h}p_{jst} + \sum_{j\neq i}\gamma_{ji}^{h}p_{ist} + \epsilon_{jst}, \quad j,i = 1,...,n \quad h = S, NS \tag{4.9}$$

where, ω^h is a parameter that allows for different intercept depending on the consumer type (recall that we simplified notation earlier by setting $\omega = \omega^{NS}$ and $\omega^{S} = 1 - \omega$). Fixed effects (α_{js}) are included to account for product-store specific effects.

We augment the model by interacting the obesity rate[12] with the fraction of non-storers in the population as well as with the own-price coefficient:

$$\omega = \omega_1 + \omega_2 * \textit{obesity-rate} \tag{4.10}$$

[12] In an alternative specification we consider and explain later, we use consider several obesity predictors (i.e. demographic variables known to be related to obesity rates) in lieu of the obesity rate.

$$\beta_j^h = \beta_{1j}^h + \beta_{2j}^h * \textit{obesity-rate} \tag{4.11}$$

To operationalize the inclusion of store-brand specific effects, we re-write equation 4.9, for each type of consumer, as:

$$Q_{jst}^{NS}(p_{jst}, \mathbf{p}_{-jst}) = \omega e^{\alpha_{sj}} e^{(-\beta_j^{NS} p_{jst} + \sum_{j \neq i} \gamma_{ji}^{NS} p_{ist})} + e^{\varepsilon_{jst}} \tag{4.12}$$

$$Q_{jst+\tau}^{S}(p_{jst}, \mathbf{p}_{-js,t+\tau}^{ef}) = (1-\omega) e^{\alpha_{sj}} e^{(-\beta_j^{S} p_{jst} + \sum_{j \neq i} \gamma_{ji}^{S} p_{is,t+\tau}^{ef})} + e^{\varepsilon_{js,t+\tau}} \tag{4.13}$$

$$x_{jst} = e^{\alpha_{sj}} (Q_{jst}^{NS*} + \sum_{\tau=0}^{T} Q_{jst+\tau}^{S*}$$

where

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

and

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

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

$$\log x_{jst} - \overline{\log x_{jst}} = \log(Q_{jst}^{NS*} + \sum_{\tau=0}^{T} Q_{jst+\tau}^{S*}) - \overline{\log(Q_{jst}^{NS*} + \sum_{\tau=0}^{T} Q_{jst+\tau}^{S*})} \tag{4.14}$$

Finally we assume that the error term, let's call it μ, enters 4.14 in an additively separable fashion (not displayed) and that $E(\mu \mid \mathbf{p}_{t-T}, ..., \mathbf{p}_{t+T}) = 0$. These assumptions allow us to carry out estimation of 4.14 via nonlinear least squares.

4.5 Data

As in chapter 2 and 3, we use data collected by IRI's sample of supermarkets across the U.S. This data set contains store-level information on volume sales and prices for carbonated beverages during the 2001-2006 period. Data consist of weekly observations and include 47 metropolitan areas as per IRI's definitions.[13] Recall that data are are disaggregated at the store level for each supermarket chain. IRI only includes chains and not independent stores, and the observations are drawn from IRI's national sample of stores. 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 the container itself (e.g. can vs. bottle; see Bronnenberg et al., 2008).

We choose data from 2006 for our analysis since this is the most recent year available. Supermarkets for which there are missing observations for any of the products considered in the analysis are dropped. Further, we only retain stores that show a clear break in the price distribution (as discussed earlier and illustrated in Figure 4.1), so as to allow us to objectively and consistently define the threshold for separating sale from non-sale periods (as required by the model). This procedure leaves us with 181 stores located across 33 states.

The size we choose is the 2-liter bottle, which is the most popular size in our data set (33% market share). To make the dynamic problem tractable, while the data we take to estimation account for the whole 2-liter bottle market, we only account for dynamics for the two most popular brands. The reason for this is that the nature of the dynamic problem requires us to search for and define sale and non-sale periods for each specific brand. This procedure is burdensome as it requires us to use weekly

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

prices in all store-week combinations to establish those stores in which there is a consistent threshold price that can objectively separate sale from non-sale periods. Doing this for numerous brands not only would increase the computational burden but would significantly reduce the number of stores that we can keep in order to maintain consistency in the threshold definition. We do not consider this feature to be critical for our qualitative conclusions; if anything, we believe that future analyses that can incorporate the dynamic effects of more brands would make our results stronger as the effect of stockpiling would be greater than we are currently able to measure.

The brands we focus on are regular Coke and regular Pepsi. These two brands have the leading market shares in our data set. They represent 12% and 10% of total volume total sales (across all brand-size-presentations in the data set), respectively, and each company's 2-liter bottle presentation accounts for approximately 4% of the whole soft drinks market. To account for the whole 2-liter bottle market for carbonated beverages, we include all other brands in the estimation procedure by aggregating all the remaining brands (in 2-liter bottle presentation) in two categories: composite regular brand and composite diet brand (depending on whether a brand is "regular" or "diet", respectively).[14] We compute the total units sold for each of the two composite brands by summing over all the units sold (in each week-supermarket pair) across all brands belonging to each of the two categories. The average weekly unit price (in a supermarket-week pair) of a composite brand is given by the total dollar sales across all brands in each composite category, divided by the total units sold in that category. Descriptive statistics of the data used (Coke and Pepsi) are reported in Table 4.1.

To implement our modeling approach, we complement the IRI store-level data with both obesity incidence data (% of people with $BMI \geq 30$) as well as demographic

[14]the diet versions of Coke and Pepsi are included in the composite diet brand

Table 4.1. Descriptive statistics IRI dataset for Coke and Pepsi

Variable	Mean	Std
Price Coke	1.21	0.22
Price Pepsi	1.17	0.21
Units sold Coke	165.67	189.86
Units sold Pepsi	144.03	226.31
Sale Coke†	0.33	0.47
Sale Pepsi†	0.37	0.48

Note: 9231 observations per brand. A sale (discount period) occurs when the price drops to $1.05 or below. †Fraction of weeks the brand was on sale in 2006.

indicators, both at the county level. Obesity rates are obtained from CDC's Behavioral Risk Factor Surveillance System (BRFSS) in 2006 (Figure 4.2). 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.[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 2005 estimate (and so on). Estimates are 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 are 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 is then used to adjust the rates by age.[16]

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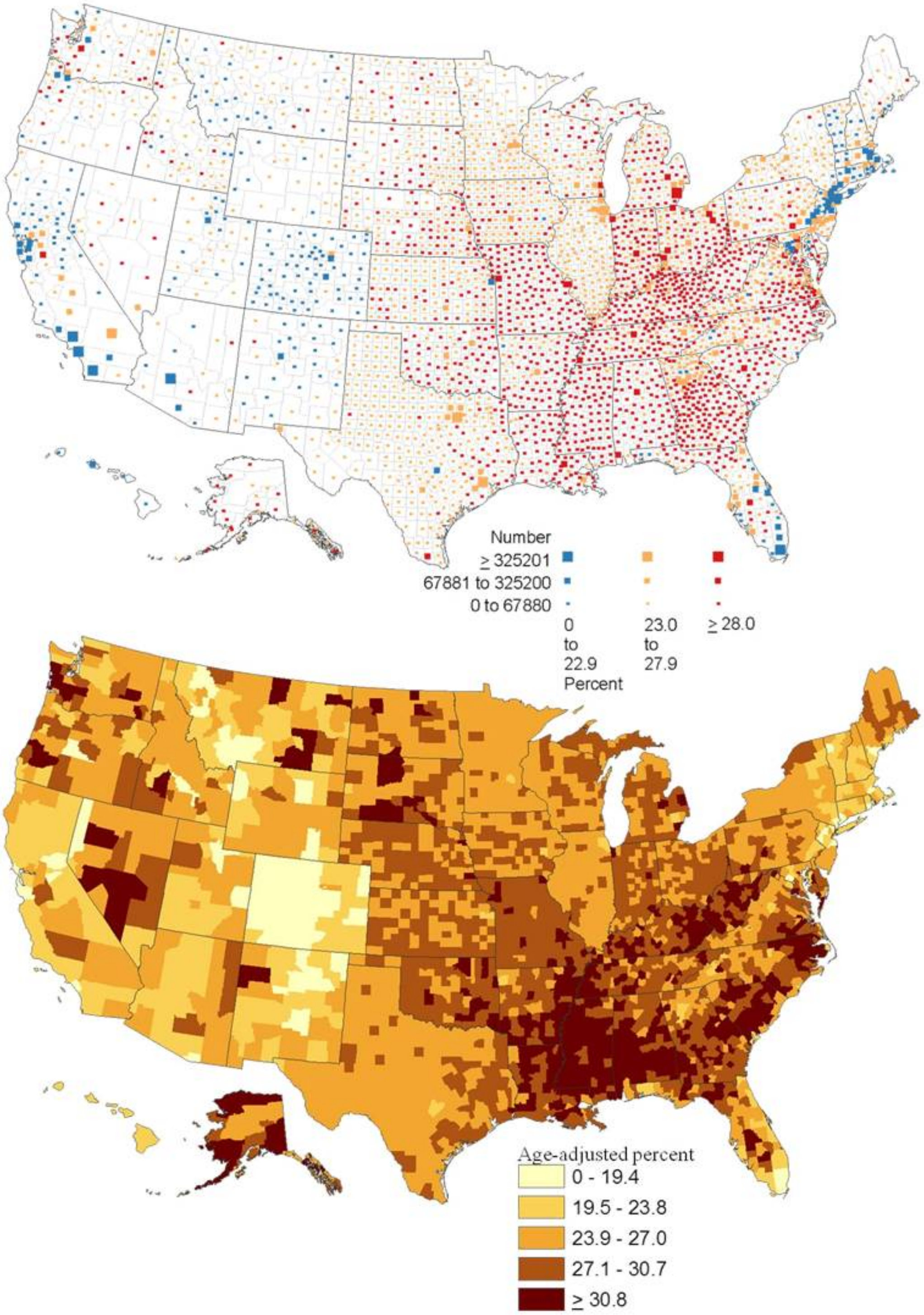
[15]Body mass index formula: $BMI = weight(kg)/height^2(m)$. It was derived from self-report of height and weight.

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

Figure 4.2. County-level Estimates of Obesity among Adults aged $\geq$ 20 years: United States 2006



Source: www.cdc.gov/diabetes

Note: from top to bottom, these maps show estimates of the number and percentage, and the age-adjusted percentage of adults who were obese in 2006, respectively.

Data on demographic characteristics [17] in our data were retrieved from the American Community Survey (ACS).[18] Annual data on age, gender, race, income, education, disabilities, etc. are released at different geographic levels (region, division, state, county, census tract, zip-code, etc). To keep consistency with the level of dissagregation at which obesity data is observed, we use county level data in our analysis. This survey, administered by the U.S. Census Bureau, is sent to approximately 250,000 addresses monthly (3 million per year). The survey 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.

The selection of demographic characteristics from the survey datasets for our analysis is based on socioeconomic factors that, at the aggregate level, are thought to have a strong correlation with obesity (i.e. commonly known as "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 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 Table 4.2. 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 a high school diploma or less; and the percentage of rural population. Selected demographic characteristics and their distribution characteris-

[17] 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.

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

tics for the counties studied in this chapter are displayed in Table 4.3. Finally, we match IRI data to both obesity rates and demographic characteristics data using the geographical information of the location of each store in our dataset. In several cases, we have more than one store in a given county.

Table 4.2. 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. The coefficients are all significant at 1% or better.

Table 4.3. Distribution of obesity rate and obesity predictors

Variable	Mean	Std	Min	I Quartile	Median	III Quartile	Max
% Obesity	25.08	3.22	17.10	22.70	25.10	27.50	40.10
% of Households received food stamps	6.54	3.18	1.81	4.21	6.36	8.10	21.02
% African-American Population	12.96	13.19	0.57	2.93	8.58	20.41	64.19
% Attained High School Diploma or less	41.56	8.67	21.60	35.10	41.30	48.00	63.70
% Rural Population†	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 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.

4.6 Results

Demand estimation results are reported in Tables 4.4, 4.5 and 4.6. All results, unless otherwise specified, are significant at 5% or better. As stated earlier, the unit of analysis is 2-liter bottles. Results in all tables are based on regressions that use the (log) quantity of (regular) Coke or Pepsi (or a modified version of it as per equation 4.14), sold in a week-store pair, as the dependent variable. The right-hand side variables include own-price, cross-price as well as the prices of the two composite brands (for brevity, we do not report coefficients for prices of the composite brands). We run regressions for the two composite brands, but do not present results as their value is limited since dynamics are not incorporated in those equations.[19] All results in Tables 4.4, 4.5 and 4.6 are obtained via least squares and all the regressions include

[19]The results from these regressions (as well as those of the coefficients of prices of the composite brands in the Coke and Pepsi equations) play an important in our policy simulations below, however. They are useful to capture the substitution across products resulting from the policy interventions we consider.

store-week fixed effects.[20] Table 4.4 presents the estimated coefficients from static models. Columns 3 and 6 display estimates of whether the presence of a(current and/or past) sale had an impact on current purchases. Columns 4 and 7 display the coefficients on the interaction of own-price and the current-period sale dummy with the rate of obesity.

Table 4.4. Static model estimates of the demand function

	Coke			**Pepsi**		
	I	II	III	I	II	III
Own Price	-1.84	-1.46	-1.81	-1.87	-1.39	-2.08
	(0.02)	(0.03)	(0.12)	(0.02)	(0.03)	(0.12)
Cross Price	0.34	0.31	0.31	0.65	0.56	0.57
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$Sale_t$		0.25			0.28	
		(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.

Own- and cross-price coefficients have the expected signs and are all statistically significant. We notice that a sale in the current period has a positive effect on the quantity demanded, as expected, and that sales in preceding periods (weeks) consistently alternate in sign. This result suggests that the relevant storage period is one week ($T = 1$), which is what we use in our the estimation of the dynamic version

[20]Regressions for the static model (Table 4.4) are estimated separately (via linear least squares). Estimates for the dynamic model are obtained via estimation of a simultaneous equations system, and a non-linear least square procedure is used.

of the model. We observe, consistent with our expectations, that both coefficients are positive suggesting that price sensitivity is lower in areas where the population has a higher rate of obesity.

Table 4.5 and 4.6 present the results from dynamic models, where we distinguish fractions of the population as *storers* and $non-storers$, and identify the fraction of the population that corresponds to each type. Table 4.5 considers specifications with the rate of obesity as the interaction variable, whereas Table 4.6 considers specifications where the interactions involve demographic variables. In Table 4.5, specification I provides estimates obtained by imposing two restrictions. The first restriction concerns the cross-price coefficient: substitution coefficients (Coke versus Pepsi and Pepsi versus Coke) are symmetric for *storers* as well as for $non-storers$. We relax this restriction in specification II. We notice that the unrestricted cross-price coefficients are roughly the average of the unrestricted ones. Thus, to preserve parsimony, we keep the restriction of specification I in subsequent regressions. The second restriction imposes the fraction of $non-storers$ (ω) to be the same for both brands; since the two products are close substitutes and the population is the same, we maintain this constraint throughout.

Specification III shows the results of a model that considers the potential impact of the rate of obesity on the non-storing population. We observe that, as the rate of obesity increases, the fraction of $non-storers$ decreases and that this effect is statistically significant. The fraction of $non-storers$ is 58% and 59%, respectively, for the specifications that do not include the interaction with the rate of obesity (I and II). The parameter ω represents the relative intercept of the demand for $non-storers$. By separating the effect of obesity on the intercept ω (specification III), we find that the percentage of non-storing population effectively decreases with greater rates of obesity. Specifically, the percentage of $non-storers$ in the area with the highest rate of obesity in our data set (40.1%), would be as low as 52%, whereas ω would be

Table 4.5. Dynamic model estimates of the demand function (I)

	Specification:									
	I		II		III		IV		V	
	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi	Coke	Pepsi
Own Price	-1.66	-1.77	-1.69	-1.75	-1.67	-1.78	-1.67	-1.78	-1.56	-1.99
non-storers	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.09)	(0.09)
Own Price non-storers *									$0.00^{\dagger}$	$0.01^{\dagger}$
%obesity									(0.01)	(0.01)
Cross Price	0.40		0.30	0.49	0.40		0.40		0.40	
non-storers	(0.01)		(0.02)	(0.02)	(0.01)		(0.01)		(0.01)	
Own Price	-2.24	-2.29	-2.34	-2.25	-2.22	-2.28	-3.10	-2.89	-2.25	-2.30
storers	(0.12)	(0.12)	(0.14)	(0.14)	(0.12)	(0.12)	(0.37)	(0.34)	(0.12)	(0.12)
Own Price storers *							0.03	0.02		
%obesity							(0.01)	(0.01)		
Cross Price	-0.58		-0.63	-0.49	-0.59		-0.60		-0.58	
storers	(0.10)		(0.12)	(0.12)	(0.09)		(0.09)		(0.09)	
ω	0.58		0.59				0.59		0.59	
	(0.09)		(0.04)				(0.04)		(0.04)	
ω_1					0.76					
					(0.07)					
ω_2 * %obesity					-0.006					
					(0.002)					

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

as high as 66% in the area with the lowest rate of obesity. In specification IV, we report the results of a specification that considers the impact of the rate of obesity on the own-price elasticity for $storers$. 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 (in absolute terms). Specification V allows us to evaluate the impact of the rate of obesity on the own-price elasticity for $non-storers$, which is not statistically different from zero.

We observe that the results from static and dynamic models are similar, but there are some important differences. By comparing columns 2 and 5 in Table 4.4 with the results in Table 4.5, column 1, notice that own-price coefficients are lower (in absolute terms) if we consider demand dynamics. This confirms results in the previous literature that show how failure to account for inter-temporal substitution and storability can lead to an overestimate of the own-price elasticity and of the effect of taxes on consumption (Wang, 2012; Hendel and Nevo, 2013). We also notice that the own-price sensitivity for both brands is higher for *storers* than for $non-storers$.

In both the restricted and unrestricted versions (specifications I and II), the cross-price coefficient for *storers* is negative and statistically significant; the explanation for this seemingly at odds with economic theory result is that in a dynamic setting two products can be *intertemporal* complements.[21] In a static setting, if the price of Coke goes down today, the quantity demanded for Pepsi should also go down. However, in a dynamic setting purchases depend on both current as well as future prices and consumption. Coke and Pepsi infrequently go on sale in the same week. Instead, both products tend to alternate sale weeks (see Figure 5.1 and Table 5.1 for data that supports this pattern). To explain this intertemporal complementarity,

[21] This negative cross-price coefficient result is robust to several alternative specifications (not reported). These include, among others, relaxing the constraint of symmetric cross price elasticities and limiting the estimation to several data sub-samples.

assume that one given week is a sale period for Pepsi and a non-sale period for Coke, while, vice-versa, the previous week was a sale period for Coke and non-sale period for Pepsi. In the current week storers would buy less Pepsi because they purchased more Coke in the previous week, therefore they already have some soda in their stock (recall that consumers are assumed to minimize storage costs). In a situation like the one just described, it turns out that as the price of Coke goes up (from last period to this period), demand for Pepsi goes down, consistent with a negative cross-price coefficient. In general, when demand dynamics are considered, it is quite frequent that substitute products in the short run become complements in the long run (Chavas, 2013).

Table 4.6 displays results from the dynamic models that include demographic variables known to be obesity predictors. Recall that the selected obesity predictors are: the percentage of households that received food stamps, the percentage of African-American population, the percentage of population that attained a high school diploma or less, and the percentage of rural population. For each of these variables, we consider two specifications. These specifications are identical to II and III in Table 4.5 except that we replace the obesity rate with one of the demographic variables, one at a time (i.e. first four regressions correspond to the first demographic variable considered, etc.).

Results are similar to the ones from models using the percentage of obesity, consistent with the high correlation between the selected demographic variables and obesity rates. In particular, the obesity predictor that yields (the comparatively) largest effect on the fraction of $non - storers$ is the percentage of households that received food stamps. Households that received food stamps[22] are located in lower income

[22]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 therefore households can use SNAP benefits to buy them (http://www.fns.usda.gov/snap/retailers/eligible.htm)

Table 4.6. Dynamic model 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	-1.78	-1.67	-1.78	-1.67	-1.78	-1.67	-1.78	-1.66	-1.76	-1.66	-1.77	-1.66	-1.77	-1.67	-1.77
non-storers	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Cross Price	0.40		0.41		0.40		0.44		0.39		0.39		0.40		0.39	
non-storers	(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)	
Own Price	-2.47	-2.42	-2.24	-2.31	-2.24	-2.21	-2.22	-2.28	-3.47	-3.22	-2.24	-2.30	-2.31	-2.40	-2.23	-2.28
storers	(0.15)	(0.15)	(0.12)	(0.12)	(0.13)	(0.13)	(0.14)	(0.14)	(0.26)	(0.23)	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)
Own Price S *	0.03	0.02			0.001	0.005			0.03	0.02			0.004	0.007		
obes. pred.	(0.01)	(0.01)			(0.003)	(0.004)			(0.00)	(0.00)			(0.003)	(0.003)		
Cross Price	-0.61		-0.64		-0.59		-0.57		-0.41		-0.58		-0.56		-0.54	
storers	(0.09)		(0.09)		(0.10)		(0.09)		(0.08)		(0.09)		(0.09)		(0.09)	
ω	0.58				0.57				0.60				0.60			
	(0.04)				(0.05)				(0.04)				(0.04)			
ω_1			0.64				0.59				0.59				0.62	
			(0.09)				(0.05)				(0.06)				(0.04)	
ω_2 *			-0.01				-0.0001†				-0.005				-0.001	
obes. pred.			(0.00)				(0.0006)				(0.00)				(0.000)	

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

Table 4.7. Predicted percentages of storing population

Rate and demographic variable considered:	% Storers Mean	Min	I Quartile	Median	III Quartile	Max
% Obesity	39	34	38	39	41	48
% of Households received food stamps	43	38	40	42	44	57
% African-American† Population	42	41	41	42	43	47
% Attained High School Diploma or less	62	53	58	62	65	73
% Rural Population	39	38	38	39	40	45

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

brackets; thus, it is not surprising that higher values for this variable result in greater sale sensitivity (and thus a higher inclination to store). The impact of the percentage of African-American population was found to be small and not statistically significant. In Table 4.7 we report a summary of the estimated distributions of the fraction of $storers$, using the results of the models that consider the interaction of ω with the obesity rate and with the obesity predictors.

4.7 Policy Simulations

In this section we examine policy implications of our estimates. Specifically, we conduct simulations to examine how consumers consumption of the selected soda products might be affected by the following policy scenarios:

1. A 5.2% soda sales tax (current average sales tax for soda in the U.S.) applied to all products (i.e. Coke, Pepsi, diet composite good and regular composite good).

2. A ban on temporary price reductions (TPRs).

For this exercise we used the estimated coefficients obtained from the specifications III and IV reported in Table 4.5 (including the unreported cross-price coefficients for the two composite brands in Coke and Pepsi equations). In addition, the simulation takes into account the change in quantity that the two composite goods would experience from such interventions; to do this, we use the (unreported) regression results from the two composite brand regressions in the simulation. To compute the percent variations in quantity demanded predicted for scenario 1, we increase all prices (including those of the composite brands) by 5.2%. For scenario 2, we only increase sale prices of Coke and Pepsi (recall: all prices less or equal to \$1.05) and keep regular prices at their current levels.[23] Specifically, we shifted all (Coke and Pepsi) sale prices by an amount equal to the price increase needed so that the minimum sale price observed in the data (prior to the simulation) would be equal to \$1.05 (i.e. would no longer be a sale price). This procedure yields an average price increase of 2% for Coke and 3% for Pepsi, which is significantly smaller (roughly 50% less) than the overall price increase that results from the first scenario. Our simulation exercise output is the total annual quantity that would be predicted (demanded) in each scenario. We bootstrap the predicted post-policy consumption predictions 1,000 times using the distribution of our estimated coefficients (while keeping store-brand fixed effects constant across draws) All results from our bootstrap computations are significant at the five percent level.

Results from our counterfactual analyses are reported in Table 4.8 as percentage changes in consumption relative to the annual purchases registered in 2006 across all store-week pairs in our data. Specification III refers to the results from model specification III (Table 4.5), where we let the coefficient ω (fraction of non-storing population) be a function of the obesity rate; specification IV refers to model speci-

[23]We cannot increase sale prices of composite brands as it is unfeasible to model the dynamics of composite brands with our model (see section 4.2 for details).

fication IV (Table 4.5), where we considered the impact of the rate of obesity on the own price elasticity for *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 in scenario 1. The most likely explanation for this result is that the effect of a price increase when a tax is imposed (scenario 1) is mitigated by the presence of temporary discounts. In other words, while there is a price increase associated in both scenarios considered, the price increase in scenario 2 is targeted to periods when a significant portion of the population used to stockpile. These results highlight the critical importance of stockpiling behavior in the effectiveness (in this case ineffectiveness) of policies that would impose a price increase across the board without taking into consideration the existence of temporary price reductions by firms.

Simulation results from both specifications (III and IV) indicate that the reduction in quantity (in both scenarios) is larger as the obesity rate increases; however, this effect is greater in specification III (which considers the interaction of the obesity rate with ω) than in specification IV (which considers the interaction of the obesity rate with *storers*' own-price coefficient). This finding suggests that the role of sale sensitivity in populations with higher obesity incidence is more crucial than the role played by price sensitivity.

Notice that, under scenario 1 (which implies a 5.2% price increase), when the maximum rate of obesity is considered, quantity demanded is predicted to decrease by 1.54% and by 1.47%, for specification III and IV, respectively. Under scenario 2 (TPRs banned), the quantity decrease is predicted to be much larger in areas with high obesity rates (2.66%, for specification III and 2.42% for specification IV).

Table 4.9 displays the elasticities implied by the two policy scenarios we consider. We observe that the current average sales tax (5.2%) implies very low demand elasticities; in other words, soda consumers are predicted to reduce their consumption

Table 4.8. Quantity demanded variations under two policy scenarios

		Obesity Rate being considered (%)					
Policy		Mean	Min	I Quartile	Median	III Quartile	Max
Scenario:		25.08	17.10	22.70	25.10	27.50	40.10
		% Quantity Change[2] (95% Confidence Interval)					
	Specific. III	-1.448	-1.409	-1.436	-1.448	-1.461	-1.542
Sales Tax		(-1.451 -1.446)	(-1.412 -1.406)	(-1.439 -1.433)	(-1.451 -1.446)	(-1.464 -1.459)	(-1.546 -1.538)
	Specific. IV	-1.452	-1.432	-1.446	-1.452	-1.457	-1.472
		(-1.454 -1.449)	(-1.435 -1.429)	(-1.449 -1.443)	(-1.454 -1.449)	(-1.460 -1.454)	(-1.475 -1.470)
TPR^1	Specific. III	-2.455	-2.367	-2.427	-2.455	-2.484	-2.663
Banned		(-2.458 -2.452)	(-2.370 -2.363)	(-2.430 -2.424)	(-2.458 -2.452)	(-2.487 -2.481)	(-2.669 -2.656)
	Specific. IV	-2.458	-2.456	-2.459	-2.458	-2.457	-2.423
		(-2.462 -2.455)	(-2.459 -2.453)	(-2.462 -2.456)	(-2.462 -2.455)	(-2.460 -2.454)	(-2.427 -2.419)

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.
[2]Percentage changes in consumption relative to the annual purchases registered in 2006 across all store-week pairs.
95% Confidence Intervals computed via bootstrap simulations.

Table 4.9. Demand elasticities corresponding to the % change in quantity demanded predicted for the two policy scenarios considered

		Obesity Rate being considered (%)					
Policy		Mean	Min	I Quartile	Median	III Quartile	Max
Scenario:		25.08	17.10	22.70	25.10	27.50	40.10
		Elasticities:					
Sales Tax	Specific. II	-0.278	-0.270	-0.276	-0.278	-0.281	-0.300
	Specific. III	-0.279	-0.275	-0.278	-0.279	-0.280	-0.283
TPR^1 Banned	Specific. II	-0.982	-0.947	-0.971	-0.982	-0.993	-1.065
	Specific. III	-0.983	-0.982	-0.983	-0.983	-0.983	-0.969

Note: [1]Temporary Price Reduction.

only by a negligible amount after a 5.2% sales tax applies. On the other hand, a ban on temporary price reductions (about 2.5% price increase) implies demand elasticities that are approximately three times larger than those seen in the first scenario. In sum, limiting the magnitude of discounts would have a comparatively higher impact than increasing soda prices via taxes, largely because fewer consumers would be able to store.

4.8 Discussion and concluding remarks

In this research we investigate the role of dynamics and obesity on the demand for soda . The main feature of our dynamic model is that it accounts for storing behavior (i.e. consumers' propensity to stockpile during periods of temporary low prices). Also, our specification of the model allows us to determine whether price sensitivity and sale sensitivity of soda consumers varies across populations with different obesity incidence. We find that a substantial fraction of the population stockpiles during temporary price reductions in order to avoid paying higher prices when prices go back up to normal levels. Further, our results suggest that higher-BMI consumers, despite being less price-sensitive, are more inclined to store (i.e. more sale-sensitive).

These findings suggest that lower price-sensitivity for high BMI consumers may not necessarily translate into substantial differences in quantity decreases across different obesity rates as a result of a policy intervention that increases the price of the product (e.g. a soda tax).

We translate our results to policy implications by computing the potential decrease in quantity demanded that would be observed after a sales tax is imposed. In addition, we consider a counterfactual where price discounts (sales) would be substantially limited. Our estimates indicate that a price increase due to a tax would fail to yield large reductions in total quantity demanded. The main explanation for this result is that consumer's ability to stockpile during sale periods (which will persist even if taxes are increased) would neutralize the effect of the tax. Conversely, our research suggests that a policy intervention restricting the magnitude temporary price reductions would be significantly more successful by a ratio of 3 to 1 (than the current level of taxation) in reducing soda consumption.

Stockpiling behavior (or sale sensitivity) 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 retrospective study that compares the effect of these taxes on soda consumption in jurisdictions where the taxes were enacted versus nearby locations not affected by the tax increase (see Chapters 2 and 3). In addition, our results suggest that a ban on temporary price reductions would be more effective in reducing the consumption of high BMI consumers. The reason is that, according to our estimates, consumers in areas with higher obesity rates are more inclined to store than in other regions.

One behavioral factor that our counterfactual analysis does not take into consideration is the fact that sales taxes are not very salient (i.e., they do not show on the shelf price) and as a consequence consumers are less likely to respond to them than to a price increase of the same magnitude that is included in the shelf price (see, for example, Feldman and Ruffle (2014)). This feature may further limit the effectiveness of sales taxes if the goal of the policy is to reduce soda consumption, rather than to increase the tax revenue of the state (see Chapter 2 and 3).

Our predictions, while consistent with the main results from previous studies (i.e., Patel, 2012), highlight the importance of considering the demand dynamics when studying soda consumers' behavior. As opposed to previous studies that 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. Further, to the best of our knowledge, no previous research has studied whether discount responsiveness varies across populations that have different rates of obesity incidence. Nevertheless, more research is needed to establish what policy (or combination of policies) would more effectively curb obesity (e.g., ban of obesogenic/addictive ingredients, advertising, large sizes, etc.). The main take away from this chapter is that policies that are targeted in a way that they focus on crucial features of the market are likely to be more effective than across the board policies that affect all features of the market with the same intensity.

CHAPTER 5

DO SODA MANUFACTURERS RUN SALES MORE FREQUENTLY IN AREAS WITH HIGH OBESITY RATES?

5.1 Introduction

In this Chapter we examine companies' conduct in terms of temporary price reductions (TPRs), to verify whether sales and discounts regimes are randomly set or they follow certain patterns. Our investigations are confined to Coke and Pepsi, which are the market leader brands. Specifically, first, we analyze whether Coke and Pepsi compete on sales (i.e., set the sale periods on the same week) or coordinate (i.e., avoid to set the sale period on the same week). Second, we analyze whether the frequencies of discount periods for these two companies are systematically related with obesity rates or obesity predictors.

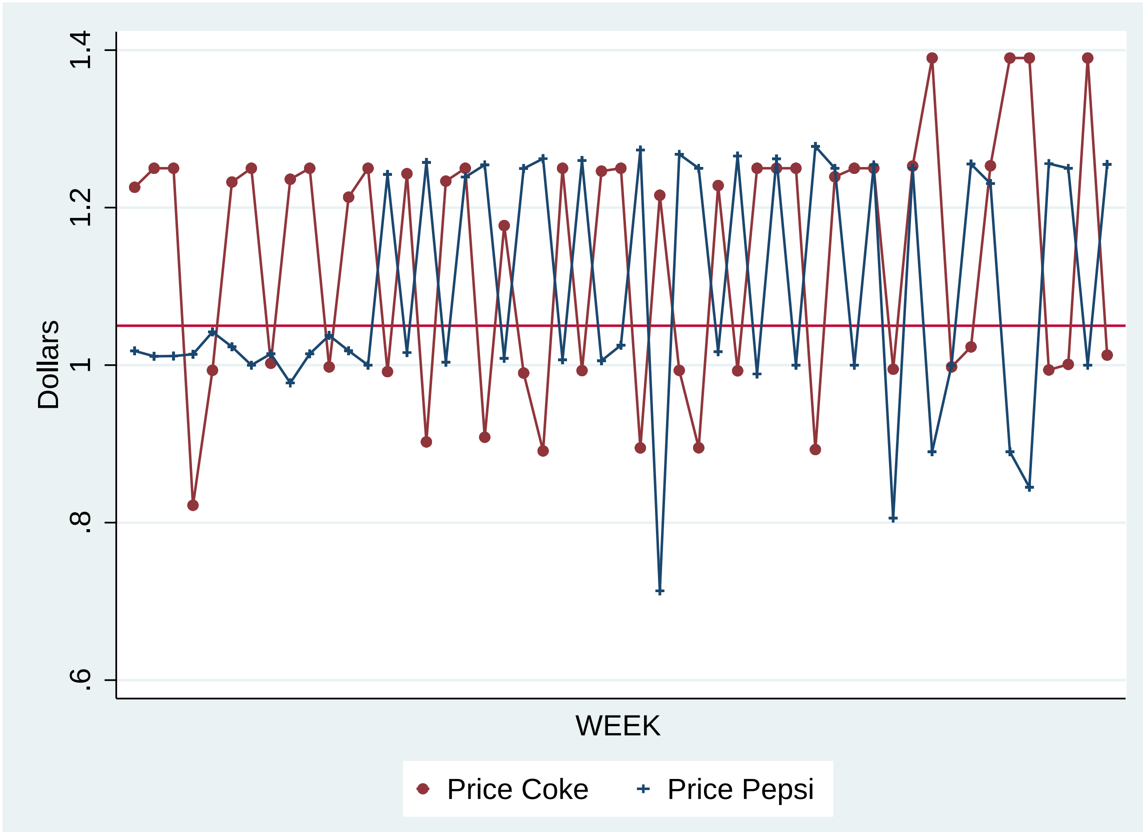
In Chapter 4 we show that populations characterized by a high rate of obesity are more prone to make their soda purchases during a discount period (or sale week). This knowledge leads us to investigate whether soda companies exploit the described attitude of obese consumers, leveraging their ability to set the price, to sell more soda where the rate of obesity is already high. Additionally, we look at the price trend for each supermarket in the attempt to explain the negative sign of the cross price elasticities reported in Tables 4.5 and 4.6. We notice, as explained below, not only that Coke and Pepsi seem to cooperate in setting their discount periods, but also a high price volatility. As mentioned in Chapter 4, in general, one should expect that producers of addictive products will offer (at least temporarily) attractive prices in order to entice people to initiate consumption. In light of these considerations, in this Chapter we take a closer look at the manufacturers' TPRs conduct.

5.2 Companies' conduct in terms of temporary price reductions

For the following analyses we use 2006 IRI data on soda prices and volumes described in Chapter 3 and 4. Also, we use obesity data derived from CDC's Behavioral Risk Factor Surveillance System (BRFSS) in 2006, as described in Chapter 4. First, we plot Coke and Pepsi weekly price trends for each supermarket in the sample. We observe that prices of Coke and Pepsi tend to follow opposite trends consistently, and that discount periods appear to alternate weekly (see Figure 5.1 for an example of a typical yearly price trend). Table 5.1 compares mean non-sale prices (across all supermarkets in the sample) 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 5.1). Conversely, when the two brands are both on non-sale regime, the mean price is not statistically different from zero. 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 might possibly be engaging in collusive behavior, or sale-coordination (in the sense that weeks during which both brands are on sale occur much less frequently than chance would predict).

In addition, we investigate the often cited claim that soda companies are to blame for the obesity epidemic as they might be more likely to disproportionately target temporary price reductions in areas where the obesity rate is higher. According to our results from the dynamic models in Chapter 4, areas characterized by a higher

Figure 5.1. Typical supermarket yearly price trend for Coke and Pepsi in 2006



Note: example of price trend in one supermarket. The reference line denotes the sale price threshold ($1.05).

Table 5.1. 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.

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 obtain results from county-level regressions of an index of sale intensity (frequency of temporary price reductions) on the rate of obesity. We repeat the same procedure using the obesity predictor variables discussed in Chapter 4 (recall: % of Households received food stamps; % African-American Population; % Attained High School Diploma or less; % Rural Population). As in Chapter 4, a sale price is defined as any price below the $1.05 threshold. Results from these regressions show no statistical evidence of an association between county obesity rates (or obesity predictors) and sale intensity, for either brand (Table 5.2).

$$Sale = \begin{cases} 1 & \text{if sale} \\ 0 & \text{otherwise} \end{cases} \tag{5.1}$$

$$Index_{ji} = \sum_t \left(Sale_{jit} \frac{Vol_{jit}}{TotVol_{ji}} \right), \quad j = Coke, Pepsi \quad i = County \quad t = Week \tag{5.2}$$

Table 5.2. Results from regressions of a sale index for Coke and Pepsi on the rate of obesity and obesity predictors

	Dep. Variable:	Sale index Coke	Sale index Pepsi
	Indep. Variables:		
Regression 1	% Obesity	0.00	-0.01
		(0.00)	(0.01)
	Const.	0.38	0.75
		(0.13)	(0.24)
	R^2	0.00	0.00
Regression 2	% of Households received food stamps	0.00	-0.01
		(0.00)	(0.00)
	Const.	0.52	0.62
		(0.04)	(0.04)
	R^2	0.00	0.00
Regression 3	% African-American Population	0.00	0.00
		(0.00)	(0.00)
	Const.	0.51	0.57
		(0.02)	(0.02)
	R^2	0.00	0.00
Regression 4	% Attained High School Diploma or less	0.00	0.00
		(0.00)	(0.00)
	Const.	0.34	0.43
		(0.08)	(0.09)
	R^2	0.03	0.02
Regression 5	% Rural Population	0.00	0.00
		(0.00)	(0.00)
	Const.	0.46	0.55
		(0.02)	(0.02)
	R^2	0.08	0.00

Note: sample size of 126 counties. Standard errors in parentheses.

5.3 Concluding remarks

Chapter 5 presents the results of analyses aimed at investigating strategic conducts of soda companies concerning timing and frequency of temporary price reductions. We find statistical evidence suggestive of a cooperative behavior between Coke and Pepsi manufactures in terms of the timing of decisions for when their respective products go on sale. They appear to offer discounts on alternate weeks, which suggests that firms may be avoiding price competition. While this strategy is certainly enacted to maximize the volume sold for both brands, the quantification of this cooperation gain, as well as the consumers' gain (or loss) remain open questions.

Further, we investigate the often cited claim that soda companies disproportionately target large-volume soda consumers (i.e., more likely to be obese) with more frequent temporary price reductions offered in areas where the obesity rate is higher. This claim is based on the marketing principle that is less expensive and more efficient to retain existing customers than to acquire new ones. However, results from our analyses do not show statistical evidence that the described behavior is enacted by Coke and Pepsi manufactures.

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