Price Elasticities of Demand For Soda and Salty Snacks

by

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(Under the Direction of Chen Zhen)

Abstract

Due to the growing rates of obesity and the high consumption of sugar-sweetened beverages (SSBs), several US municipalities have implemented large excise taxes on SSBs. One tenet of demand theory is the downward-sloping demand curve. As the SSB price is raised by a tax, SSB quantity demanded is expected to decline. However, there is a concern that consumers may substitute other untaxed unhealthy foods for SSBs. In this study, we investigate the potential for this unintended consequence using retail scanner data on carbonated soft drinks and salty snacks.

Index words: Price Index, Price Elasticity, Obesity, Soda, Salty Snacks

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Chapter 1

Introduction

1.1 Background

Obesity has grown at an alarming rate in children, adolescents, and adults not only in the United States but also in the rest of the world. Figure 1.1 [27] shows the obesity growth statistics for adults and youth from 1999 to 2017 in the United States reported by CDC. A large body of research [32, 31] has linked increased body weight to diseases such as heart disease, liver and gall bladder disease, stroke and cancers. In addition to its serious health consequences, obesity has real economic costs that affect all of us. From National League of Cities reported, the estimated annual health care costs of obesity-related illnesses are a staggering \$190.2 billion or nearly 21% of annual medical spending in the United States. Figure 1.2 shows the geographical distribution of obesity in the United States. States colored in dark red on the map have the highest obesity prevalence. One important risk factor for obesity is the heavy consumption of SSBs including but not limited to carbonated soft drinks (i.e., soda). There is a significant literature associating obesity with SSBs consumption. Gibson and Sigrid [25] re-examined the evidence from epidemiological studies and interventions. The authors searched papers Medline, Cochrane reviews, Google scholar and through cross-references and identified forty-four original studies (twenty-three cross-sectional, seventeen prospective and four intervention) in adults and children, as well as six reviews. These were critically examined for methodology, results and interpretation. Approximately half the cross-sectional and prospective studies found a statistically significant association between SSBs consumption and BMI, weight, adiposity or weight gain in at least one subgroup. Most studies suggest that the effect of SSBs is generally small except in susceptible individuals or at high levels of intake. Giammattei et al. [24] found that school students' BMI is significantly associated with the hours of television watched per evening and daily soft drink consumption. Apovian and Caroline [2] found that people with stable consumption patterns had no difference in weight gain, but weight gain over a 4-year period among women who also highly increased their sugar-sweetened soda consumption. In addition to soft drinks, some work also tried to characterize additional eating habits among obese people. [12] and [36] found that salty snacks are also one of the major sources of fat. In [19], positive relationship is found between obesity and snacking frequency, especially among women. Snacks were positively related to energy intake, irrespective of physical activity. Sweet, fatty food groups were associated with snacking and contributed considerably to energy intake. Thus, they suggest snacking needs to be considered in obesity treatment, prevention and general dietary recommendations(Forslund et al.).

1.2 Research Question

The increasing burden of diet-related noncommunicable diseases has prompted policymakers and researchers to explore broad-based approaches to improving diets. One way to address the issue is to change the relative prices of regular soda through carefully designed tax or subsidy policies. As shown in table 1.1, the list of countries already implemented soda tax or plan to, has grown rapidly. With these policies gaining popularity, the effectiveness of these

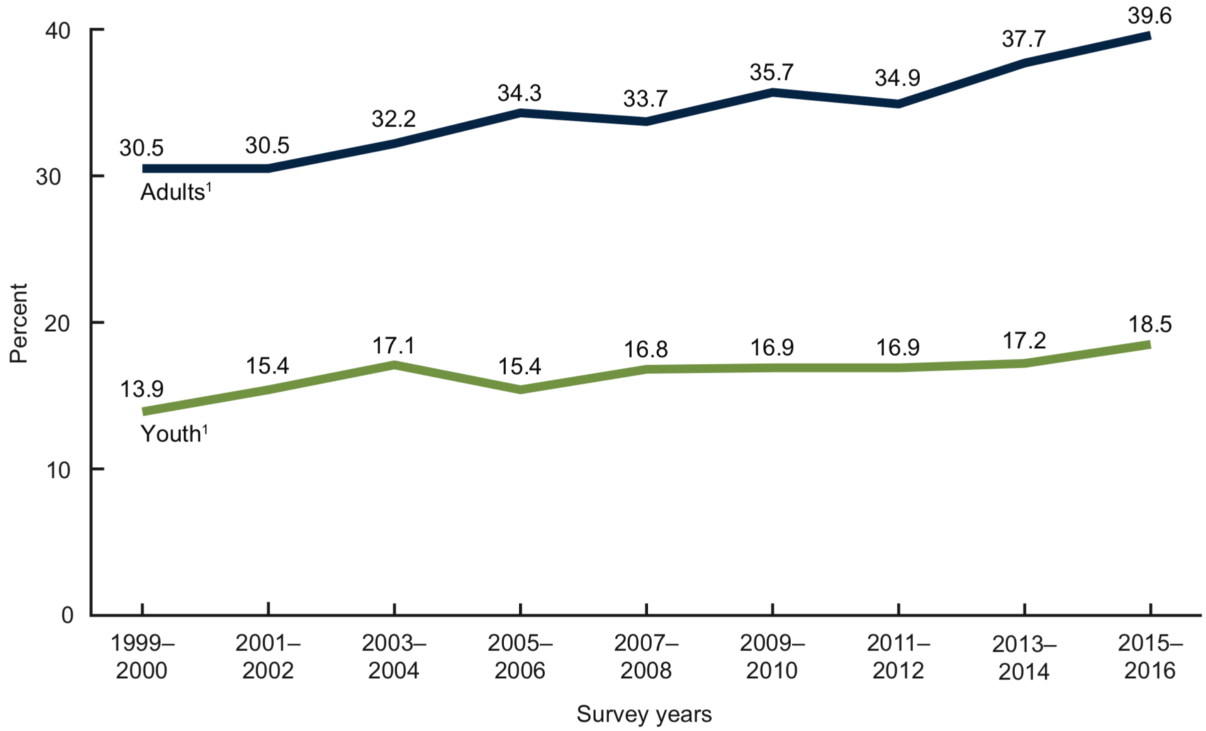

Figure 1.1: Obesity Growth in Adults and Youth (Note: Adults is equal or greater than 20 years old, Youth is below 20 years old)
Source: https://www.cdc.gov/nchs/products/databriefs/db288.htm

policies became a hot research area. Berkeley, California used to be a large soda consumption city in the United States, the sales data indicated a 9% decline in the purchase of taxed soda [45]. In Mexico, after adding approximately 10% tax on SSBs, the demand for sweetened beverages dropped 6-9% in the first two years [48]. Although the policy seems to be working in the sense that the consumption of soda is decreasing, whether these taxes have resulted in weight reduction is less clear.

Nakhimovsky and Feigl [37] claims that although SSBs tax reduced net energy intake by enough to prevent further growth in obesity prevalence, but not to reduce population weight permanently. Even with decreased consumption of soda, the weight of the current population

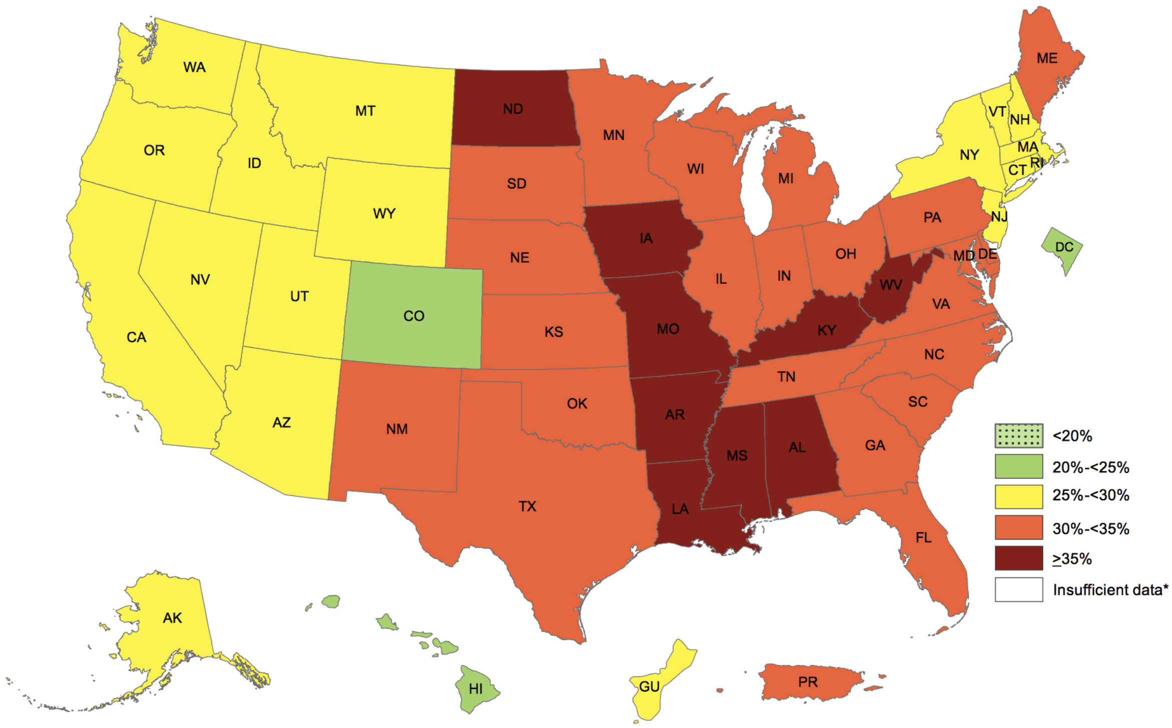

Figure 1.2: Obesity distribution in United States 2018
Source: https://www.cdc.gov/obesity/data/adult.html

does not change a lot [50]. The soda tax not only reduced calorie intake but also increased the price of soda relative to other foods. The change in relative prices may cause customers to purchase substitute products for soda which also have high calories. Salty snack is one of the potential substitute product categories. Besides caloric soda, salty snacks may also help to fuel the obesity epidemic.

This thesis aims to reveal the relationship between soda and salty snacks. If the two product categories are substitutes, we expect some of the reduction in soda calories due to a soda tax to be offset by an increase in salty snack consumption.

Table 1.1: Planned and recently implemented soda taxes.

Location	Date	Details
Planned South Africa	April 2018	Tax on sugary beverages at a rate of 2.1c per g of sugar in each 100ml beyond 4g/100ml.
United Kingdom	April 2018	Tax rates are £0.18/L for drinks containing 5–8g of sugar/100 ml and £0.24 for drinks containing > 8g of sugar/100 ml; revenues earmarked for school sports and educational programs.
Ireland	April 2018	Tax rates will are €0.2/L for drinks containing 5–8 g of sugar/100 ml and €0.3 for drinks containing > 8g of sugar/100 ml.
Seattle (US)	January 2018	1.75-cent tax on distributors of sodas, sports drinks, energy drinks and other sweet drinks.
San Francisco (US)	January 2018	1-cent per fluid ounce excise tax on the distribution of sugar-sweetened beverages.
Delayed Estonia	Intended January 2018; delayed	Two-tiered levy on producers of sugary beverages. Tax rates are €0.1/L for drinks containing artificial sweeteners, juices with no added sugar or added sugar up to 8g/100 ml; €0.3/L for drinks with > 8g of sugar/100 ml. To allow for reformulation the €0.3 rate was initially set with a threshold of 10g of sugar/100 ml (2018), then 9g (2019) and 8g by 2020.
Implemented United Arab Emirates	October 2017	An excise tax of 50% on carbonated drinks and 100% on energy drinks.
Thailand	September 2017	Drinks divided into five categories based on sugar content per 100g: below 6g, 6–10g, more than 10–14g, more than 14–18g and more than 18g.
Cook County, IL (US)	August 2017	1-cent per ounce tax on sugar-sweetened beverages sold at retail in the County.
Boulder, CO (US)	July 2017	2-cent per fluid ounce of sugar-sweetened beverage product excise tax on the distributors of the beverages.

Continued on next page

Table 1.1 – continued from previous page

Location	Date	Details
Oakland, CA (US)	July 2017	1-cent per fluid ounce excise tax on the distribution of sugar-sweetened beverages containing at least 2 kcal/ounce.
Saudi Arabia	June 2017	An excise tax of 50% on carbonated drinks and 100% on energy drinks.
Albany, CA (US)	April 2017	1-cent per fluid ounce excise tax on the distribution of sugar-sweetened beverages.
Catalonia (Spain)	April 2017	€0.08/L for drinks with 5–8 g of sugar per 100 ml, €0.12 for drinks with > 8 g of sugar per 100 ml.
Brunei	April 2017	Excise duty of (∼.28/L) of SSBs with > 6g of total sugar per 100 ml.
Portugal	February 2017	Drinks with < 8g of sugar/100 ml are taxed at €8.2 per 100 L, and drinks with > 8g of sugar/100 ml are taxed at €16.46 per 100 L.
Philadelphia (US)	January 2017	1.5-cent-per-ounce tax on soda and other sweetened beverages, including diet drinks, sports, drinks, and juices.
Dominica	September 2015	10% excise tax to drinks with high sugar content.
Barbados	September 2015	10% excise tax on sugar sweetened beverages.
Mauritius	October 2016	Excise tax of ∼$0.08 per 100 g of sugar content in beverages containing sugar, including juices, milk based beverages and soft drinks.
Belgium	January 2016	Excise tax (€0.068/L) on all non-alcoholic beverages with added sugar or sweeteners.
Berkley, CA (US)	January 2015	1-cent per fluid ounce excise tax on the distribution of sugar-sweetened beverages.
Chile	January 2015	Two-tiered ad-valorem tax on sweetened beverages. An existing 13% tax rate was increased to 18% for high-sugar drinks (>$ 6.25g of sugar/100 ml) and reduced to 10% for drinks below the threshold.

Source: Cornelsen, L. and Smith, R.D., 2018. Soda taxes–four questions economists need to address. Food Policy, 74, pp.138-142.

Chapter 2

Related Work

In this paper, we are going to use three different regression models to analyze the price elasticity among four different categories. This chapter introduces some basic knowledge that will be used in the following chapters and some previous similar works.

2.1 Price Index

Consumers adjust their purchase mix in response to relative price changes. As the purchase mix changes, so does the level of utility. To measure the cost of living holding the standard of living constant, we use price indexes to measure user cost at the food/beverage category level. Unlike unit values, which conflate differences in product quality with market price variation, price indexes compare the same product's price cross different time periods, we use the price index to eliminate this difference. Laspeyres price index is proposed by German economist Étienne Laspeyres in 1871 to measure current prices in relation to the selected base period. The formula for Laspeyres price index is equation 2.1, p_t is the price in period t, q_0 is the base quantity, p_0 is the price at base period. Paasche price index is another method to control for quality changes over time due to changes in product mix. Equation 2.2 is the

Paasche index formula, it's really similar to the Laspeyres index. However, in Paasche the weight q_0 changes to q_t which is the contemporaneous quantity. By using contemporaneous quantities as weights, the Paasche index fully incorporates substitution. However, because the changes in product mix, utility is not fixed. So neither Laspeyres nor Passche can be considered a cost of living index, which requires standard of living (i.e., utility) be fixed.

Compared to a cost of living index, Laspeyres-based indices have an upward bias and Paasche-based indices have a downward bias. Thus, Fisher [16] proposed fisher ideal price index which expressed in equation 2.3 is calculated by taking geometric mean of P_l and P_p. This 'ideal' price index lies between Laspeyres and Paasche [53].

$$P_L = \frac{\sum (p_t \cdot q_0)}{\sum (p_0 \cdot q_0)} \tag{2.1}$$

$$P_P = \frac{\sum (p_t \cdot q_t)}{\sum (p_0 \cdot q_t)} \tag{2.2}$$

$$P_F = \sqrt{P_L \times P_P} \tag{2.3}$$

2.2 Price Elasticity

There are lots of research on calculating price elasticities for soda tax. Finkelstein et al. [15] estimated the changes in energy, fat and sodium purchases resulting from a tax on SSBs. By using the 2006 Homescan panel, they analyzed the effect of increasing soda tax by 20% on body weight. Also, they account for substitutions between SSBs and 12 major food categories. They found that the tax would result in a decrease in store-bought energy of 24.3 kcal per day per person, which would translate into an average weight loss of 1.6 pounds during the first year and a cumulated weight loss of 2.9 pounds in the long run. Zhen et al. [54] estimated an approximate EASI incomplete demand system containing 23 packaged food and beverage categories and a composite numéraire good to analyze the effect of soda tax. Their preferred demand specification predicts that almost half of the reduction in SSB calories caused by an increase in SSB prices is compensated for by an increase in calories from other foods. They further found that a potential substitutes of an SSB price increase is sodium and fat intake. Specifically, an increase in the price of SSBs of 1.5 cent per ounce,is expected to reduce per capita daily calorie intake by 13.2kcal for the low-income population and 5.6 kcal for the high-income population. Fletcher, Frisvold and Tefft investigated the potential for soft drink taxes to combat rising levels of adolescent obesity through a reduction in consumption. They used state soft drink sales and excised tax information between 1988 and 2006. From their regression model's results that a one percentage point increase in the soft drink tax rate reduces the amount of calories consumed by soda by nearly 8 calories, which is about 6 percent of the sample mean. This reduction in calories is likely not caused by a switch to diet soft drinks as there is a 22 gram decrease in soft drink consumption from a one percentage point increase in the soft drink tax rate, which is also about 6 percent of the sample mean. Thus, their initial findings suggest that increasing the taxes on soft drinks will lead to reductions in soft drink consumption by children and adolescents [17]. Dharmasena, Senarath and Capps Jr, Oral [11] estimated the own-price and cross-price elasticities using a linearized Quadratic AIDS model for 10 non-alcoholic beverages: isotonics, regular soft drinks, diet soft drinks, high-fat milk, low-fat milk, fruit drinks, fruit juices, bottled water, coffee and tea. They found that consumption of isotonics, regular soft drinks and fruit drinks, the set of SSBs, is negatively impacted by the proposed tax, while the consumption of fruit juices, low-fat milk, coffee, and tea is positively affected. Diversion ratios are provided identifying where the volumes of the SSBs are directed as a result of the tax policy. The reduction in the body weight as a result of a 20% tax on SSBs is estimated to be between 1.54 and 2.55 lb per year. However, not considering demand interrelationships would result in higher weight loss. Unequivocally, it is necessary to consider interrelationships among non-alcoholic beverages in assessing the effect of the tax

SSBs may be the single largest driver of the obesity epidemic. A recent meta-analysis found that the intake of sugared beverages is associated with increased body weight, poor nutrition, and displacement of more healthful beverages; increasing consumption increases the risk for obesity and diabetes; the strongest effects are seen in studies with the best methods; and some studies show that reduced intake of soft drinks improves health [51, 9]. Many researchers aim to understand how price changes affect the demand for various foods. In order to improve diets by shifting food prices. In [13, 21, 28], experimental research in both laboratory and intervention settings shows that lowering the price of healthier foods and raising the price of less healthy alternatives shift purchases toward healthier food options. The [13] study tests the influence of price changes on mother's purchases of high-energy-density (HED) and low-energy-density (LED) foods for their families through the use of a laboratory analog method. Mothers are generally responsible for the quality and quantity of the foods that are brought into the household, which in turn affect the family's eating habits. Modifying the purchasing patterns of mothers can affect the entire family and can aid in the treatment and prevention of pediatric obesity. Totally, this study finds 47 mothers between the ages of 25 and 50 y participants. Participants were recruited from an existing family database, through flyers posted around the University of Buffalo campuses, and through direct mailings. All participants at least have one child, responsible for the primary grocery shopping for the family. Mothers required to complete 3 trials that varied price (75%, 100%, and 125% of reference price) for each of 2 income conditions ($15/person and $30/person) in a counterbalanced order. This provided the opportunity to assess whether price had a differential influence on purchases based on available resources. The incomes studied were based on values that were equally lower or higher than a reference value of approximately $22.50, which was computed based on the minimum amount of money that would be needed to eat a balanced diet for the LED foods offered for purchase in this experiment. The results show the expected own-price elasticity for HED and LED foods, ie, as the price goes up, purchases go down. These data along with other laboratory [14] and field research [23, 22, 29, 43, 49] suggest that one way to increase the purchase of healthy foods is to reduce the price of these foods. Conversely, purchases of less healthy foods will decrease as their price increases.

Gortmaker, Steven and Long, Michael and Wang, Y Claire also interested in how taxes can be used to promote public health. Especially their research area is the health impacts of SSBs consumption, how food and beverage prices affect consumption and related weight outcomes, and the potential impact of both large and small SSBs taxes. Their results suggest that 1) substantial consumption of SSBs can be detrimental to overall health and may contribute to higher obesity rates among youth. A growing but mixed body of research indicates that an increase in SSBs consumption is associated with increases in caloric intake, weight gain, obesity and a variety of other negative health consequences among children, teens and adults [26, 18, 51, 34]. Increased consumption of SSBs in adults has been linked with higher rates of type 2 diabetes, and a school-based intervention that lowered SSBs consumption among Native American adolescents significantly reduced plasma insulin levels, a risk factor for type 2 diabetes [44, 42]. SSBs intake is associated with an inadequate intake of several important nutrients, including calcium, iron, folate, and vitamin A [20, 6, 33, 30]. 2) As prices of unhealthy foods and beverages increase, consumption of them decreases. Numerous studies demonstrate that changes in the relative prices of foods and beverages lead to changes in how much people consume them [1, 52, 41]. Several of these studies have estimated that a 10 percent increase in the price of SSBs could reduce consumption of them by 8 percent to 11 percent [7, 5]. 3) As relative prices of unhealthy foods increase, compared with the prices of healthy foods, weight levels decrease. A small but growing body of national research indicates that higher prices of unhealthy foods and beverages versus healthy ones are associated with reductions in BMI and the prevalence of overweight and obesity [4, 40, 35, 46, 47, 39, 10, 38].

Chapter 3

Data

3.1 IRI Academic Dataset

The dataset used in this project is produced by IRI [8], consist of retail data and household data collected from 2008 to 2012. We only use the retail data at the store level from 2008 to 2011, contain the sales at the Universal Product Code(UPC) level by store by week. The store-level dataset has 32.2 billion records. This dataset is composed of many different pieces. The following introduces the different data we need for our project.

Store Level Scanner Data. IRI dataset contains sales data for several food categories, such as soda, frozen pizza, frozen soup, salty snacks, and milk, etc. Since our project only focuses on two food categories which are soda and salty snacks, we choose the 4-year retail scanner dataset at the store level for these two categories. In this dataset, we have sales data with unique store code, UPC, product quantity, product price and purchased week.

Product Information. To further divide soda into regular soda and diet soda, salty snacks to potato chips and other salty snacks we have to find the description of each product at the UPC level. We use the product description dataset, extract the description and merge it to store-level scanner data. According to the description, we separate data into four different categories: (1) diet soda, (2) regular soda, (3) potato chips, (4) other salty snacks.

Store Information. Our project also needs geographic information and chain information for each store. We further matched the store level dataset with the store chain and location. For each IRI_KEY we have the chain information and the location information with county level.

3.2 Census Data

In order to get the population of each county, we collect the census data for different years in the United States online and map the county's population to our store level dataset. Then the dependent variable q is calculated from $\frac{Q_{s,t}^{(i)}}{pop_{c,y}}$, $Q_{s,t}^{(i)}$ is the sales quantity for category i (i = 1,2,3,4) at store s and quarter week t, $pop_{c,y}$ is the population at county c and year y, the county c contains the store s and the quarter week t is in year y.

3.3 Data Description

After combining all the data mentioned above, we got the final version of the dataset. Table 3.1 describes the dataset, IRI_KEY is the unique code for each store, the QW record the time information for 4 years at the quarter week level. In total, we have over 150 million records, 52-time periods, 4 categories, and 2109 unique stores. The largest category of our data is other salty snacks which contain pretzel, other chips popcorn, etc. The potato chips only contain potato chips. The diet soda includes diet soda, zero soda, and less calorie soda. The regular soda includes regular soda and mid-level calorie soda.

Table 3.1: Unique Value Count for Variables

Category	IRI_KEY	QW	County	Number of Observations
Diet Soda	2109	52	688	34,490,995
Regular Soda	2109	52	688	47,669,493
Potato Chips	2109	52	688	20,837,726
Other Salty Snacks	2109	52	688	53,791,312

Chapter 4

Method

This section describes the different demand models we used in this paper. First of all, we discuss how we calculate the price index for each category.

4.1 Fisher Ideal Price Index

We use the Fisher Ideal price index to enable the panel price comparisons in this paper. An entity is a unique combination of store and time, we use Quarter Week (approximately 4 weeks) as the time measurement. The price indexes are obtained from comparing entity j with base 0. Totally, we have 52 quarter weeks for 4 years and 2109 unique stores and around 90,000 unique entities.

4.2 Demand Models

4.2.1 Two Way Fixed Effects

Our first approach, equation 4.1, is a two way fixed effects linear regression. In this regression model, the dependent variable here represents the log of quantity demand for category i per person which is mentioned in section 3.2. $P_{s,t}^{(k)}$ is the Fisher Ideal price index for category k (k= 1, 2, 3, 4) at store s and quarter week t. γ_t is the time fixed effects that eliminates the impacts vary by quarter week and year, ϕ_s is the store fixed effects control for permanent differences between different stores. $\epsilon_{r,t}^{(i)}$ is the error term.

$$\log(q_{s,t}^{(i)}) = \alpha_{s,t}^{(i)} + \sum_{k=1}^{4} \beta_k \cdot P_{s,t}^{(k)} + \gamma_t + \phi_s + \epsilon_{s,t}^{(i)} \tag{4.1}$$

In this demand model, we mainly focus on the interpretation of the $\beta_{(k)}$ which quantify the change of demand for category i based on the change of the price for category k. For example, when i is equal to 1 (diet soda), k could be 1 (diet soda), 2 (regular soda), 3 (potato chips) or 4 (other salty snacks). $\beta_{(1)}$ can use to calculate the own-price elasticity of diet soda, $100\beta_{(1)}$ is the percentage change in demand of diet soda at store s and quarter week t resulting from a unit change in price of diet soda at store s and quarter week t. $\beta_{(1)}$ can use to calculate the cross-price elasticity of diet soda demand, $100\beta_{(2)}$ is the percentage change in demand of diet soda at store s and quarter week t resulting from a unit change in the price of regular soda at store s and quarter week t, same for potato chips and other salty snacks.

This model is implemented in Stata, with xtreg command. Before using the xtreg, we have to use the xtest command to set the fixed effects, in our case, we set QW and IRI_KEY variables. Xtreg fits regression models to panel data. In particular, xtreg with the be option fits fixed-effects models by using the fe option(by using the within regression estimator).

4.2.2 2SLS with Two Way Fixed Effects Model

In our project, the dependent variable is determined by the independent variables, and some of the independent variables may, in turn, be determined by the dependent variable (i.e., reverse causality) or with the dependent variable by some omitted factors (i.e., simultaneity).

For example, the decreased demand for diet soda may cause the price of diet soda to go down and the price for regular soda goes up. This violates the OLS assumption which is the explanatory variables are distributed independently from the stochastic disturbance term. If this independence assumption is violated, then, the least square estimators are not only biased but also inconsistent.

In order to solve this endogenous problem, we use two-stage least squares model which is to use instrument variables $\frac{1}{S}\sum_{s=0}^{S} P_{r,t}^{(k)}$ for the endogenous variable $P_{s,t}^{(k)}$ in the equation 4.1. $P_{s,t}^{(k)}$ is the price index for category k (k = 1, 2, 3, 4) at store s and quarter week t. $\frac{1}{S}\sum_{s=0}^{S} P_{r,t}^{(k)}$ is the instruments variable we choose which is the average of $P_{r,t}^{(k)}$ from all other stores r of the same chain as s but in a different county from s. This IV is used to remove the effect of county and QW-specific demand shock on $P_{s,t}^{(k)}$. $\hat{P}_{s,t}^{(k)}$ is the fitted price based on OLS regression of the endogenous $P(k)_s$, t on the two-way fixed effects and IVs.

This 2SLS with two way fixed effects model is implemented in Stata, with Xtivreg command. Before use Xtivreg, we have to use xtest command to set the fixed effects. Xtivreg offers five different estimators for fitting panel-data models in which some of the right-hand-side covariates are endogenous. These estimators are two-stage least-squares generalizations of simple panel-data estimators for exogenous variables. Xtivreg with the fe option uses the two-stage least-squares within estimator.

4.2.3 Dynamic Model

The third model of our method is the dynamic model. By adding one time period lag of the dependent variable on the right side of the equation 4.2:

$$\log(q_{s,t}^{(i)}) = \alpha_{r,t}^{(i)} + \sum_{k=1}^{4} \beta_k \cdot \hat{P}_{s,t}^{(k)} + \gamma_t + \phi_r + \theta_i(\log(q_{s,t-1}^{(i)})) + \epsilon_{r,t}^{(i)} \tag{4.2}$$

After adding the lag of the dependent variable, our model is able to portray the time path of the dependent variable in relation to its past value. The coefficient θ_i can explain the change of demand per person for category i at this quarter week caused by the demand of last quarter week.

One of the major reasons why we choose this dynamic model is the purchase dynamics of customers. As a result of the force of habits, current-period consumption may be positively correlated with consumption of the last period. Conversely, as a result of inventory holding (i.e., stockpiling), they may buy a lot last quarter and then store it at home, which led to a decline in the purchasing power of this quarter. Thus, by adding the lag of dependent variable, θ_i can describe whether customers purchase pattern is habits or inventory holding.

In this equation, the β_k can be used to calculate the short-run price elasticity, and together with θ_i, to calculate the long-run price elasticity. In the long run steady state, $q_{s,t}^{(i)}$ is equal to $q_{s,t-1}^{(i)}$, so the long-run own-price elasticity is equal to β_i multiply the sample mean of the instrumented price index for category i, then divide by $(1 - \theta_i)$.

We use xtabond estimator in Stata which is designed for the linear dynamic panel-data model include lags of the dependent variable as covariates and contains unobserved panel-level effects, fixed and random. Treats the model as a system of equations, one for each period. By construction, the unobserved panel-level effects are correlated with the lagged dependent variables, making standard estimators inconsistent.[3].

Chapter 5

Results

5.1 Results for Two Way Fixed Effects

Table 5.1, table 5.2, table 5.3 and table 5.4 shows the results for our first approach aimed at four different food categories. Table 5.1 is the results for diet soda, the dependent variable is the log of quantity demand per person of diet soda. If we increase the price of diet soda by one unit, we'd expect the demand to decrease by 70.97%. The own-price elasticity is negative, multiply the coefficient and mean of $P^1_{r,t}$ is -0.7643 which is the own-price elasticity of diet soda. If we change the price of diet soda by 1%, the demand for diet soda will change by -0.76%. The coefficient of regular soda is -0.29 when the price of regular soda changes by one unit the demand for diet soda change by -29.01%. After multiplying the average of $P^2_{r,t}$ and coefficient, we get -0.3166 which is the cross-price elasticity. The negative sign indicates that diet soda and regular soda are complement goods. Potato chips are also the complement goods for diet soda, the coefficient is -0.0413. If the price of potato chips changes by 1 unit, the demand for diet soda will change by -4.1%. The other salty snacks is substitute goods for diet soda, the cross-price elasticity is positive, the coefficient is 0.042321. All of the p-values is smaller than 0.05 which means that the results are statistically significant at the 0.05 significance level.

Table 5.1: Results of Two Way Fixed Effects Model for Diet Soda

	Coef	Std. Err.	t	$P>\|t\|$	[95% Conf. Interval]
P_{diet}	-.7097253	.0306383	-23.16	0.000	-.7697762, -.6496744
$P_{regular}$	-.2901005	.0321658	-9.02	0.000	-.3531452, -.2270557
P_{pc}	-.0413781	.0102874	-4.02	0.000	-.0615413, -.0212148
P_{oss}	.042321	.014384	-2.94	0.003	.0141285, .0705135
IRI_KEY	0 (omitted)				
QW	-8.11e-06	9.37e-07	-8.65	0.000	-9.94e-06, -6.27e-06
$cons$	-3.91284	.0170418	-229.60	0.000	-3.946242, 3.879438
$sigma\_u$	1.8875399				
$sigma\_e$	.18450667				
rho	.99053541				

Table 5.2 shows the results of two way fixed effects model when the dependent variable is the demand for regular soda. The coefficients tell us that the own-price elasticity of regular soda is negative. The coefficient is -1.249, if the price of regular soda increase by one unit, the demand for itself will decrease by 124.9%. The coefficient for the price index of diet soda is 0.198, we can calculate the cross-price elasticity is 0.2132. When the price of diet soda changes by 1%, we expect the demand for regular soda to increase 0.21%. In this case, diet soda and regular soda are substitute products. The potato chips and regular soda are complement goods, the cross-price elasticity is -0.87, is negative. The other salty snacks is substitute goods with regular soda, if one unit increased in price index of other salty snacks, the demand for regular soda will increase 12.6%. All of these estimators' p-values are 0.000, these coefficients are statistically significant at 0.05 significance level.

The following table 5.3 shows the results for two way fixed effects model when the left side of the equation is the demand for potato chips. As shown in the table, the estimators for the price index of diet soda and regular soda are not significant at the 0.05 significance level. We can only analyze the coefficients for the price indexes of potato chips and other salty

Table 5.2: Results of Two Way Fixed Effects Model for Regular Soda

	Coef	Std. Err.	t	$P>\|t\|$	[95% Conf. Interval]
P_{diet}	.1980645	.0311642	6.36	0.000	.1369828, .2591461
$P_{regular}$	-1.248657	.0327179	-38.16	0.000	-1.312784, -1.18453
P_{pc}	-.0806062	.010464	-7.70	0.000	-.1011156, -.0600968
P_{oss}	.1262649	.0146309	8.63	0.000	.0975885, .1549412
IRI_KEY	0 (omitted)				
QW	2.33e-07	9.53e-07	0.24	0.807	-1.63e-06, 2.10e-06
$cons$	-3.410572	.0173343	-196.75	0.000	-3.444547, -3.376597
$sigma\_u$	1.7900578				
$sigma\_e$	.18767361				
rho	.98912762				

snacks. The potato chips have negative own-price elasticity with -1.178 coefficient. Other salty snacks has positive estimator, 0.045. The cross-price elasticity is 0.04778, if the price of other salty snacks changes by 1%, the demand for potato chips will increase by 0.05%. Thus, other salty snacks are substitute goods for potato chips.

Table 5.3: Results of Two Way Fixed Effects Model for Potato Chips

	Coef	Std. Err.	t	$P>\|t\|$	[95% Conf. Interval]
P_{diet}	.0234957	.0363358	0.65	0.518	-.0477222, .0947136
$P_{regular}$	-.047976	.0381473	-1.26	0.209	-.1227445, .0267924
P_{pc}	-1.178068	.0122005	-96.56	0.000	-1.201981, -1.154155
P_{oss}	.0450084	.0170588	2.64	0.000	.0115733, .0784436
IRI_KEY	0 (omitted)				
QW	.0000774	1.11e-06	69.70	0.000	.0000752, .0000796
$cons$	-4.491705	.0202108	-222.24	0.000	-4.531318, -4.452091
$sigma\_u$	1.9341824				
$sigma\_e$	.21881728				
rho	.98736297				

Table 5.4 is the result of the relationship between the demand for other salty snacks and the price indexes of the other three categories. The results show that the other salty snacks has negative own-price elasticity. The estimator for the price index of diet soda is 0.205,

the calculated cross-price elasticity is 0.221. Regular soda has positive cross-price elasticity with 1.069 positive coefficient. Potato chips' price index has a positive relationship with the demand for other salty snacks, they are substitute products. The coefficients of the price index for regular soda and potato chips are relatively large which has greater effects on demand of other salty snacks.

Table 5.4: Results of Two Way Fixed Effects Model for Other Salty Snacks

	Coef	Std. Err.	t	$P>\|t\|$	[95% Conf. Interval]
P_{diet}	.2053998	.0650518	3.16	0.002	.0778986, .3329009
$P_{regular}$	1.069137	.068295	15.65	0.000	.9352795, 1.202995
P_{pc}	1.121827	.0218424	51.36	0.000	1.079016, 1.164638
P_{oss}	-3.102208	.0305403	101.58	0.000	-3.162067, -3.042349
IRI_KEY	0 (omitted)				
QW	.0002449	1.99e-06	123.14	0.000	.000241,.0002488
$cons$	-4.603266	.0361834	-127.22	0.000	-4.674185,-4.532347
$sigma\_u$	1.8020062				
$sigma\_e$	.39174797				
rho	.954872				

5.2 Results for 2SLS with Two Way Fixed Effects Model

The following four tables show the results for two way fixed effects model with added instrument variables. The first table, table 5.5, shows that diet soda has negative own-price elasticity. The estimator for the price index of regular soda is 3.346964, the calculated cross-price elasticity is 3.6542. If the price of regular soda increase by 1%, the demand for diet soda will increase 3.65%. According to this result, regular soda and diet soda are substitute goods. The p-value for potato chips is grater than 0.05, the results is insignificant. Other salty snacks have negative coefficient, is the complement products for diet soda.

Table 5.6 shows that regular soda has negative own-price elasticity. The coefficient for the price of diet soda is 1.072404, if the price of diet soda increase by 1 unit, the demand for regular soda will increase by 107.24%, they are substitute products. The potato chips is the

Table 5.5: Results of 2SLS with Two Way Fixed Effects Model for Diet Soda

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$\hat{P}_{diet}$	-3.871895	.2816384	-13.75	0.000	-4.423896, -3.319894
$\hat{P}_{regular}$	3.346964	.3063973	10.92	0.000	2.746436, 3.947491
$\hat{P}_{pc}$	.108316	.0969095	1.12	0.264	-.0816231, .2982551
$\hat{P}_{oss}$	-.1468328	.06056	-2.42	0.015	-.2655281, -.0281374
IRI_KEY	0 (omitted)				
QW	-.0000245	1.58e-06	-15.54	0.000	-.0000276,-.0000214
$cons$	-4.420873	.0779952	-56.68	0.000	-4.573741,-4.268006
$sigma\_u$	1.9070398				
$sigma\_e$	.19887514				
rho	.98924169				

substitute products for regular soda, the cross-price elasticity is 1.055. Other salty snacks have negative cross-price elasticity of demanding, if the price of other salty snacks increase will cause the demand for regular soda decrease. All estimators are statistically significant in the results of this model.

Table 5.6: Results of 2SLS with Two Way Fixed Effects Model for Regular Soda

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$\hat{P}_{diet}$	1.072404	.2730859	3.93	0.000	.5371653, 1.607642
$\hat{P}_{regular}$	-2.021313	.297093	-6.80	0.000	-2.603604, -1.439021
$\hat{P}_{pc}$	.9763181	.0939666	10.39	0.000	.7921469, 1.160489
$\hat{P}_{oss}$	-.4876707	.058721	-8.30	0.000	-.6027617, -.3725797
IRI_KEY	0 (omitted)				
QW	-2.09e-07	1.53e-06	-0.14	0.891	-3.20e-06,2.79e-06
$cons$	-3.970985	.0756267	-52.51	0.000	-4.119211,-3.822759
$sigma\_u$	1.7963067				
$sigma\_e$	.19283592				
rho	.98860699				

Table 5.7 shows the results when we regress the demand for potato chips on explanatory variables. According to the table, potato chips have a negative own-price coefficient at -2.749819. The positive sign of diet soda shows that they are substitute goods. The price

of regular soda has a negative relationship with the demand for potato chips, if the regular soda's price increase one unit, the demand for potato chips decreases 146.95%.

Table 5.7: Results 2SLS with Two Way Fixed Effects Model for Potato Chips

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$\hat{P}_{diet}$	2.089014	.3798273	5.50	0.000	1.344566, 2.833462
$\hat{P}_{regular}$	-1.469503	.3491347	-4.21	0.000	-2.153794, -.7852112
$\hat{P}_{pc}$	-2.749819	.0750735	-36.63	0.000	-2.89696, -2.602677
$\hat{P}_{oss}$	1.670743	.1201344	13.91	0.000	1.435284, 1.906202
IRI_KEY	0 (omitted)				
QW	.0000635	1.95e-06	32.51	0.000	.0000597,.0000673
$cons$	-5.233628	.0966872	-54.13	0.000	-5.423131,-5.044124
$sigma\_u$	1.9404221				
$sigma\_e$	.24653678				
rho	.98411393				

According to table 5.8, the coefficient of other salty snacks is not statistically significant. Price index of diet soda has a positive relationship with other salty snacks, on the contrary, the regular soda and potato chips have a negative sign with demand for other salty snacks. Regular soda and potato chips are complement products with other salty snacks.

Table 5.8: Results of 2SLS with Two Way Fixed Effects Model for Other Salty Snacks

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$\hat{P}_{diet}$	6.516366	.6894585	9.45	0.000	5.165052, 7.86768
$\hat{P}_{regular}$	-3.232725	.6337456	-5.10	0.000	-4.474843, -1.990606
$\hat{P}_{pc}$	-5.763569	.2180667	-26.43	0.000	-6.190972, -5.336166
$\hat{P}_{oss}$	-.1329421	.1362727	-0.98	0.329	-.4000317, .1341475
IRI_KEY	0 (omitted)				
QW	.0001859	3.55e-06	52.44	0.000	.000179,.0001929
$cons$	-2.618261	.1755055	-14.92	0.000	-2.962245,-2.274276
$sigma\_u$	1.7662329				
$sigma\_e$	.44751091				
rho	.93967609				

5.3 Results for Dynamic Model

The following four tables show the results for the dynamic model. $L1$. denotes the lag of the dependent variable which is the quantity demand in last quarter week. Table 5.9, shows the results of dynamic model for diet soda. In the short run, own-price elasticity of diet soda is negative, the coefficient is relatively large, the price of diet soda has a great impact on the demand for itself. The demand of last quarter week has a positive coefficient which means that the demand for this quarter week will increase along with the demand of last quarter week increase. The coefficient for the price index of regular soda is positive. We expected diet and regular soda to be substitutes. This means the dynamic model may be preferred to the static models. Same for the other salty snack which also has a positive relationship with the demand for diet soda. Potato chips have a negative coefficient, they are complementary products. All of the estimators are statistically significant at the 0.05 significance level.

In the long run, we assume that the $q_{s,t}^{(i)}$ is equal to the $q_{s,t-1}^{(i)}$. To calculate the long-run price elasticity, multiply the coefficient with average for the price of category i and divide by $(1-\theta)$. The long-run own-price elasticity of diet soda is -2.65 $(-2.388112 * 1.077008/(1 - 0.0318286))$, cross-price elasticity of regular soda is 1.52. Similarly, the long-run cross-price elasticity of potato chips is -0.36, for other salty snacks is 1.64. Either in the long run or short run, the diet soda is substitute products with regular soda and other salty snacks. Potato chips are complementary goods with diet soda.

Table 5.10 shows the dynamic model results regarding the demand for regular soda. All of the estimators are statistically significant at 0.95 confidence interval. In the short run, own-price elasticity of regular soda is -1.56516, is negative, the price of itself has the largest impact on the demand of itself compare with other categories' price.

$L1$ has a statistically significant positive value, implies that current-period consumption of regular soda is positively correlated with consumption of the last period. The coefficient

Table 5.9: Results of Dynamic Model for Diet Soda

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$L1.$	.0318286	.0065875	4.83	0.000	.0189172, .0447399
$\hat{P}_{diet}$	-2.388112	.0687659	-34.73	0.000	-2.52289, -2.253333
$\hat{P}_{regular}$	1.345961	.0869341	15.48	0.000	1.175574, 1.516349
$\hat{P}_{pc}$	-.3238521	.1376585	-2.35	0.019	-.5936577, -.0540465
$\hat{P}_{oss}$	1.498121	.2571362	5.83	0.000	.9941436, 2.002099
IRI_KEY	0 (omitted)				
QW	...	...	...	...	...
$cons$	-5.053429	.2498838	-20.22	0.000	-5.543192, -4.563666

for potato chips is negative, diet soda and other salty snacks are positive. Diet soda is substitute products with regular soda, this conclusion is as same as the table 5.9. The Other salty snacks is also substitute products with regular soda. In the long run, since the θ is smaller than 1, to calculate the long-run price elasticity, the denominator is 1 minus θ which is smaller than 1. Thus, all of the absolute value of long-run price elasticity should greater than the short run's price elasticity. The relationship between different categories is the same as the short run's. In the long run the impact of other categories' prices on the demand for regular soda should be greater than the effect caused in the short run.

Table 5.10: Results of Dynamic Model for Regular Soda

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$L1.$	.0546824	.0066762	8.19	0.000	.0415972, .0677676
$\hat{P}_{diet}$	.4720148	.0873971	5.40	0.000	.3007197, .6433098
$\hat{P}_{regular}$	-1.56516	.0690725	-22.66	0.000	-1.700539, -1.42978
$\hat{P}_{pc}$	-.4550235	.1394726	-3.26	0.001	-.7283847, -.1816623
$\hat{P}_{oss}$	1.470913	.2638795	5.57	0.000	.9537189 , 1.988108
IRI_KEY	0 (omitted)				
QW	...	...	...	...	...
$cons$	-4.261897	.2542728	-16.76	0.000	-4.760263, -3.763531

In table 5.11, the results for demanding for potato chips. The coefficient of regular soda is not significant at 0.95 confidence interval, other estimators are statistically significant. In the short run, negative own-price elasticity is found, has a great influence on the demand of itself. The lag of demand has a positive relationship with the current demand. In the long run and short run cross-price elasticity of diet soda is negative, it is complementary category with potato chips, this results is as same as the table 5.9. The other salty snacks are substitute products with potato chips. In the short run, the price elasticity of diet soda is -0.38, potato chips are -7.69, other salty snacks are 7.75. In the long run the price elasticity of diet soda is -0.47, potato chips are -9.25, other salty snacks are 9.33.

Table 5.11: Results of Dynamic Model for Potato Chips

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$L1.$	.1686444	.006663	25.31	0.000	.1555852, .1817035
$\hat{P}_{diet}$	-.3534408	.0782226	-4.52	0.000.	-.5067543, -.2001273
$\hat{P}_{regular}$	.1629223	.0993925	1.64	0.101	-.0318834, .357728
$\hat{P}_{pc}$	-7.116333	.1560884	-45.59	0.000	-7.422261, -6.810406
$\hat{P}_{oss}$	7.304296	.2930392	24.93	0.000	6.72995, 7.878643
IRI_KEY	0 (omitted)				
QW	...	...	...	...	...
$cons$	-4.632112	.2852085	-16.24	0.000	-5.191111, -4.073114

The last table presents the results for other salty snacks category. The demand of the last time period is positive, the large z-score also implies that $L1$ explains a lot for the dependent variable. In the short run, the price elasticity of potato chips is 0.51, other salty snacks is -7.29. We expected downward sloping demand for other salty snack. This finding suggest the dynamic model is better than the static model. In the long run, the price elasticity of potato chips is 0.84, other salty snacks is -11.84. Generally, the long-run impact of price on the demand for other salty snacks is greater than the short-run. Negative own-price elasticity is also found for the other salty snacks. The potato chips are substitute products with the other salty snacks, this result is as same as the table 5.11. However, p-value for both diet soda and regular soda are statistically non-significant at 0.05 level.

Table 5.12: Results of Dynamic Model for Other Salty Snacks

	Coef	Std. Err.	z	$P>\|z\|$	[95% Conf. Interval]
$L1.$	.3839932	.0062543	61.40	0.000	.371735, .3962513
$\hat{P}_{diet}$	-.0717468	.0769518	-0.93	0.351	-.2225696, .0790761
$\hat{P}_{regular}$	-.1826128	.0976491	-1.87	0.061	-.3740015, .0087759
$\hat{P}_{pc}$	.4767126	.1545619	3.08	0.002	.1737769, .7796484
$\hat{P}_{oss}$	-6.866706	.2944832	-23.32	0.000	-7.443883, -6.28953
IRI_KEY	0 (omitted)				
QW	...	...	...	...	...
$cons$	4.088471	.280576	14.57	0.000	3.538552, 4.638389

Chapter 6

Discuss and Conclusion

Taxes on soda are being imposed in several cities. Proponents assume that quantity demand for such drinks is highly responsive to own-price so that taxes will help deal with problems like obesity. The price elasticities of demand reported by applied economists over many decades likely contribute to this view. Although it's correct, we cannot ignore that implying the soda tax might cause substitute consuming behavior among customers, which may offset the benefit of tax policy. Thus, not only own-price elasticities are essential but also cross-price elasticities between the demand for regular soda and other unhealthy food prices are important for the policymaker.

In this paper, we show that there are substitutes for regular soda that are equally or more unhealthy. We estimated three different models of demand and found the dynamic model to be the preferred specification. This dynamic model is more comprehensive by adding fixed effects to control time effects and store effects, instrument variables for solving the endogenous problem of demand equation and lag variable of demand to explain the purchase dynamic of customers. The following are the main findings based on the dynamic model: 1) all products' own-price elasticities are negative and most of them are larger in magnitude than their cross-price elasticities; 2) diet soda and regular soda are substitutes;

3) regular soda and other salty snacks are substitutes; 4) diet soda and other salty snacks are substitutes; 5) diet soda and potato chips are complements; 6) regular soda potato chips are complements; 7) other salty snacks and potato chips are substitutes; 8) long-run price elasticities are larger than the short-run elasticities. Among these results, the relationships between diet and regular soda, regular soda, and salty snacks are important to our research question. As the conjecture we mentioned at the beginning of the paper, our results proved that after adding the tax to regular soda customers may substitute to purchase more other salty snacks. In addition, diet soda is also a substitute for regular soda. Thus, taxing sugar-sweetened beverages alone may not be enough for controlling obesity in the United States, policymakers may need to explore policies that make healthier foods more affordable in general than unhealthy foods. Because we only have store-level sales data for this analysis, can't look at heterogeneity in price elasticities across consumer segments. Also, the purchase elasticity analyzed in our paper may be different from the effect of price changes on consumption.

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