Distribution Agreement

Signature:

_______________________________ _______________

Simon Ramirez-Garces Date

Impact of Soft Drink Prices on Obesity Levels: Evidence for the U.S.

By

Simon Ramirez-Garces
Master of Arts

Economics

Sara Markowitz, Ph.D.
Advisor

David Jacho-Chavez, Ph.D.
Committee Member

Ian McCarthy, Ph.D.
Committee Member

Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

Impact of Soft Drink Prices on Obesity Levels: Evidence for the U.S.

By

Simon Ramirez-Garces
M.Sc., EAFIT University, 2016

Advisor: Sara Markowitz, Ph.D.

An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory
University in partial fulfillment of the requirements for the
degree of Master of Arts
in Economics
2019

Abstract

Impact of Soft Drink Prices on Obesity Levels: Evidence for the U.S.
By Simon Ramirez-Garces

Soft drinks consumption has been widely linked to overweight and obesity, especially in developed countries. In this paper I study the effect of changes in soft drink prices on overweight and obesity for the United States from 2011 to 2018. Using data from the Cost of Living Index (COLI) by the Council for Community and Economic Research (C2ER), the unemployment rate from the Bureau of Labor Statistics (BLS), and eight waves of the BRFSS by the Centers for Disease Control and Prevention (CDC), I estimate two-way fixed effect OLS and linear probability models. I calculate two different types of effects: the average impact of soft drink prices on BMI and the effect of soft drink prices within different categories of income by including interactions between prices and levels of income. Results suggest that higher soft drink prices have a significant effect on reducing BMI. However, on average, prices do not affect the probability to become obese or overweight. Furthermore, I find that the impact of soft drink prices on different categories of income is heterogeneous; individuals with distinct levels of income are affected differently by changes in prices of soft drinks.

Impact of Soft Drink Prices on Obesity Levels: Evidence for the U.S.

By

Simon Ramirez-Garces,
M.Sc., EAFIT University, 2016

Advisor: Sara Markowitz, Ph.D.

A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory
University in partial fulfillment of the requirements for the
degree of Master of Arts
in Economics
2019

Contents

1 Introduction

Obesity has almost tripled worldwide since 1975 [World Health Organization, 2019]. The increase in body mass index (BMI) across populations around the world has been considered of "epidemic proportions" by the World Health Organization (WHO). For the year 2016, almost 2 billion adults were overweight and around 35% of those were considered obese [World Health Organization, 2000, 2018]. Furthermore, this issue is even worse if only the developed world is considered; being overweight is one of the top five risk factors that contribute to the burden of disease in these countries [World Health Organization, 2002; Bleich et al., 2008]. In the United States, for instance, there is a significantly increasing trend in obesity. From 1999 to 2016 the prevalence of obesity in adults went from 30.5 to 39.6 and in youth from 13.9 to 18.5 in the same period of time [Hales et al., 2017]. And although the average prevalence of obesity in the U. S. decreased in 2018 for the first time in many years, many states still increased their obesity rate that year[1].

Soft drinks have been pointed out as an important source of sugar and are thought as one major cause for increasing overweight [Basu et al., 2013]. Vartanian et al. [2007] find clear associations between sugar-sweetened beverages (SSBs) intake and body weight. These beverages are usually considered as an unnecessary risk for health. On the one hand, they are often referred to as only contributing "empty calories" since their nutritional value is frequently very low. On the other hand, is argued that these drinks can be easily substituted with easy-to-access and healthier alternatives such as milk, tea, or even water [Blakely T, 2014].

With this in mind, it is relevant to analyze how soft drink prices affects the U.S. population's BMI. This paper contributes to the current literature in at least two ways: first, it provides evidence on the impact of soft drink prices on obesity levels. And second, it further examines the effect of changes in soft drink prices on obesity levels making emphasis on possible heterogeneous effects for different categories of income. Both of which have relevance for public policy design (*e.g.* soda taxes). The rest of this paper is organized as follows: In section 2, I present a brief literature review on the current state of research on the impact of taxes and prices on obesity. In section 3, I describe the data including some details about the sources and variables used. Additionally, some descriptive statistics are posed. In section 4 I explain the methodology I use to estimate both average effect of soft drink prices on BMI and possible heterogeneous effect of those prices on the various income categories. The most important results of these estimations are presented in section 5. Finally, in section 6, conclusions are stated including some limitations of this work and future research recommendations are mentioned.

[1] According to data from the Behavioral Risk Factor Surveillance System (BRFSS)

2 Literature review

In developed countries, health behaviors are particularly important [Cawley and Ruhm, 2012]. Cutler et al. [2003], argue that the increase in weight by all demographic groups increase is a result that comes mainly from an increased in food consumption, instead of the reduction of exercise. Since 1975, Americans have been eating a lot more. Increasing rates of overweight, which often leads to obesity, is problematic at various levels. According to an overwhelmingly amount of evidence, being obese increases the risk of suffering illnesses such as cardiovascular disease, type 2 diabetes, cancer, high blood pressure, breathing problems and others. From an economic point of view, there is a clear link between overweight and a higher medical spending [Finkelstein et al., 2009]. Economically speaking, there are at least 4 ways in which obesity and overweight can negatively affect a person: 1. Direct medical costs: increased risk of multiple conditions raise the cost of diagnosis and corresponding treatment. 2. Cost in productivity: there are a few channels through which productivity can suffer as a consequence of excess weight. Two of these are absenteeism –not attending the job– and presenteeism –lower productivity at the workplace– 3. Higher transportation costs: more people with obesity means more or larger vehicles are required to transport the same number of commuters with two different kind of effects. There is a direct impact on the cost but also an indirect cost given by the greenhouse gas emissions that can be considered a negative externality; and 4. Human capital costs which gain importance as the levels of overweight are present in younger people, in age of attending schools, college or university. There are several channels through which higher levels of obesity may lead to higher costs in terms of human capital acquisition; obesity has been shown to correlate with school attendance, for example [Hammond and Levine, 2010].

2.1 The effect of soft drinks taxes and prices on overweight and obesity levels

Throughout the last few years, as this topic has gained interest among researchers and policy makers, several papers have considered the matter and present reviews of literature, all with different levels of detail and specificity[2]. In this subsection, some of the studies on the impact of taxes to soft drinks on overweight and obesity are briefly discussed.

One recurring trend in the literature is estimation using the Almost Ideal Demand Systems (AIDS). Dharmasena and Capps JR [2012], for instance, study both intended and unintended effects of tax on SSBs to combat obesity in the United States. Direct effects, meaning those which are related only to the use of own-price elasticities and indirect effects, meaning those related to the use of cross-price elasticities. Total

[2]See James and Kerr [2005]; Hammond and Levine [2010]; Escobar et al. [2013]; Wright et al. [2017]; Allcott et al. [2019]; Cawley et al. [2019c].

effects include both. The authors make a linear approximation to the Quadratic AIDS or also know as QUAIDS model to capture interrelationships among 10 non-alcoholic beverage categories. Using data from 1998 to 2003, they conclude that tax interventions do reduce the consumption of SSBs, but this is partially offset by an increase of fruit juices and coffee. In such a case, an unintended effect of the tax is raising the consumption of coffee and fruit juices, that may be a source of sugar. Lin et al. [2011] also consider the problem using AIDS, making emphasis in the comparison between the static and the dynamic approaches. They evaluate the impact of taxing SSBs on health and economic outcomes for the U.S. with data from 1998 to 2007. One of the main conclusions is that static models, although still widely used in the literature, understate the contraction of calories intake required for weight loss. In other words, the dynamic model predicts a much smaller reduction in body weight compared to the static model.

Fletcher et al. [2010a] and Fletcher et al. [2010b] apply a methodology traditionally used for estimating the effect of taxation on tobacco consumption to calculate taxes effects on soft drinks. Using data for the U.S. Fletcher et al. [2010a] use a two-way fixed effects OLS to estimate the effect of state soft drink tax rates on different weight outcomes. They include state-specific time trends to control for potential unobserved characteristics within states and over time. The authors conclude that, although taxation lead to a fall in consumption, the behavioral changes due to tax imposition is not large enough to have an effect on population weight, given the current magnitudes of the tax on soft drinks. According to the researchers, if soft drinks taxes are raised to be comparable to those of tobacco, there might be a non negligible impact on population weight. Fletcher et al. [2010b] identify impacts of soft drink tax rates from changes in the tax rate within states over time. Conclusions suggest that the taxes on soft drink, as they are being implemented in the time of the study, decrease adolescents and children consumption. Fletcher et al. [2014] on the other hand, find virtually no evidence of non-linear or threshold effects by using difference-in-difference and synthetic control methods.

For the relationship between taxes and consumption, Sturm et al. [2010] use a gamma regression with a log link and for the relationship between taxes and BMI, the authors use OLS. Surprisingly enough, within the boundaries of their analysis, soda consumption was not affected by increasing the differential tax on this product. They conclude that soda taxes, if relatively small, might impact more through the dedication of the generated revenues to some sort of obesity prevention program than directly by the impact on consumption. Precisely, Jacobson and Brownell [2000] propose the use of revenues from the collection of taxes on foods of low nutritional value to fund health promotion programs. Cawley et al. [2019a] use longitudinal data to estimate the effects of the 1.5 cents per ounce beverage tax in Philadelphia (PA, U.S.) on sales and consumption. The authors find reduction in purchases in Philadelphia with corresponding increases outside the city. Another important result is that the tax reduced the frequency of soda consumption by adults in around 30%. Finkelstein et al. [2010] use models of multivariate regression to find the link between prices and calories purchased. They estimate two-part marginal effects models including logistic regression and reach the conclusion that large taxes on soft drinks have effects on weight outcomes, especially for household of middle income. Wang et al. [2012] modeled the health benefits that a proposed tax would induce. Along with Brownell et al. [2009], Brownell and Frieden [2009] and Smith et al. [2010], they find that a tax on SSBs would effectively lower the adverse health effects among adults. [Cawley et al., 2019b] analyze data from the four largest U.S. cities to examine the impact of SSB taxes on households' purchases of beverages. The authors find that the impact is relatively small in magnitude, but consistent with a reduction in individual consumption and weight.

There has also been some studies on the effect of soft drinks prices on BMI and other health outcomes, Goryakin et al. [2017] for example, analyzes the relationship of SSBs' sales and prices with BMI, overweight, obesity and diabetes. The authors use a data set from 78 countries between 1999 and 2014 to apply a panel data approach controlling for both time effects, and country-level fixed effects. Interestingly, they find significant effects on some health outcomes only in the low and lower-middle income countries. However it is suggested that individual level studies are still needed to understand the impact of prices and the sales of soft drinks BMI, overweight, obesity and diabetes. Wendt and Todd [2011] present an individual-level study to address the effect of food and drinks intake on children weight for the U.S. with data from 1998 to 2007. They use fixed-effects regression and quantile regression in their analysis. They find that lower prices for soda likely led to increases in children's BMI. The estimated effects are small, but statistically significant.

In this paper I try to advance the literature by evaluating the impact of soft drink prices on BMI. According to the estimations by Fletcher et al. [2010a], the effects of taxing soft drinks on BMI are significant, but rather small. They argue, however, that the tax rate of soft drinks is a small proportion of price. In this paper, I use price instead of taxes to see how the magnitude of the estimated effect changes when tax is replaced by price. The idea is checking a different specification and since the proportion of taxes with respect to prices is small, taking a look a prices as variable of interest, might lead to a better understanding of the problem.

3 Data

The data used in this paper comes from three sources: The Cost of Living Index (COLI) by the Council for Community and Economic Research (C2ER), the Behavioral Risk Factor Surveillance System (BRFSS) by the Centers for Disease Control and Prevention (CDC) and the Bureau of Labor Statistics (BLS). I merge these in a dataset that has annual information for the eight years, from 2011 to 2018. This period of time is chosen due to a change of methodology in one of the data sources. The BRFSS, introduced some changes for the 2011 wave, which make difficult to make comparisons with previous years. I end up with a total of 2,894,674 observations for 50 states with 2018 as the most recent year included.

3.1 Soft Drink Prices

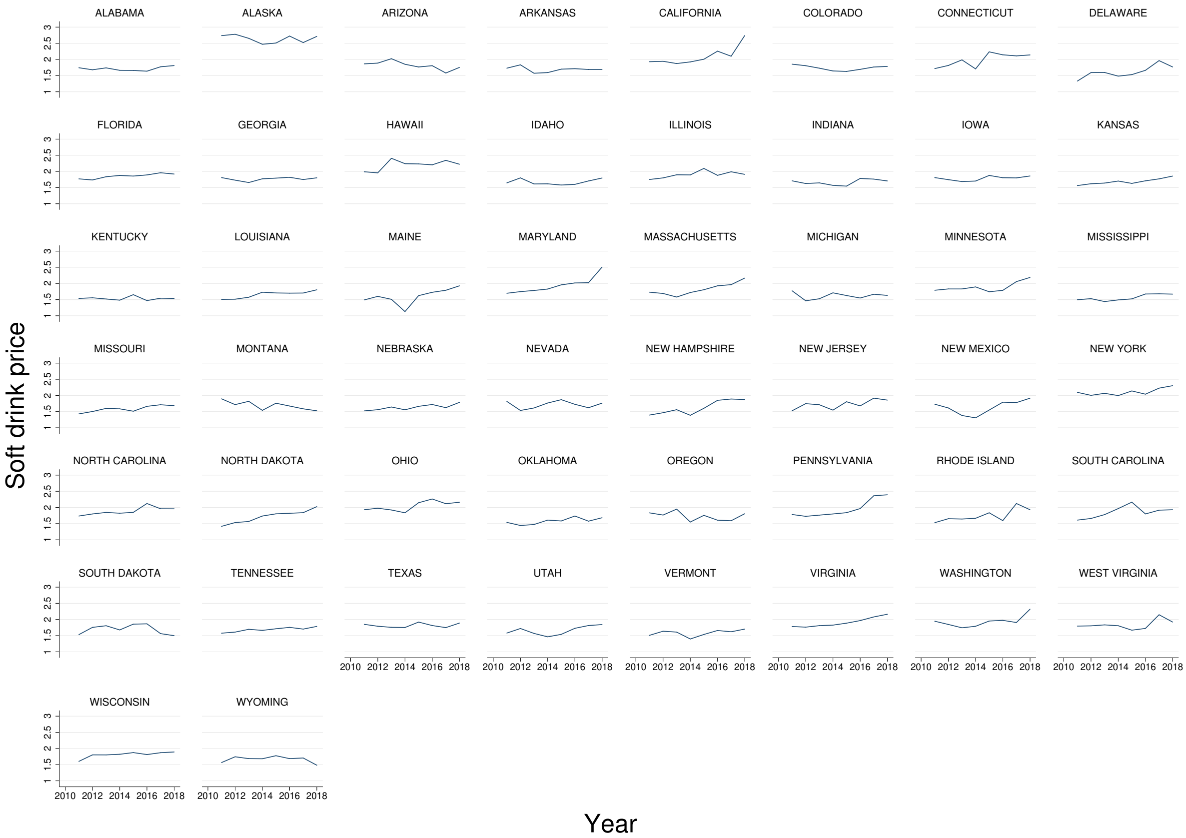
The COLI is published since 1968 by the Council for Community and Economic Research. It's frequency of publication is quarterly and contains data on over 60 goods and services. The information is available for metropolitan statistical areas (MSA) and counties. The COLI is divided into six categories (i.e. food, housing, utilities, transportation, health care, and miscellaneous goods and services). In this paper, I am interested in the variable that accounts for the price of soft drinks. I proxy soft drink prices with a variable available in the COLI whose description is "2 liter Coca Cola, excluding any deposit".I use the higher value from the available metropolitan statistical areas of each state as the state's soft drink price in each year. This allow me to follow the prices of soft drinks for all states during 8 years. Figure 1 presents the evolution of soft drink prices for each state. As can be seen, prices have different behaviors in different states; Some states have had stable prices and other have had relatively higher variation for the analyzed time period. This will be important for the estimation strategy.

3.2 Individual data

In order to calculate the relationship between prices and obesity levels, I include information from the BRFSS. The Behavioral Risk Factor Surveillance System provides information on U.S. residents regarding their health-related risk behaviors and health conditions. It gathers data from all states and conducts more than 400,000 adult interviews year per year. According to the CDC, it is the largest continuously conducted health survey system in the world. Some interesting features of the BRFSS particularly important for this paper are the following: it is an individual-level survey that contains detailed information on individuals. For instance, BMI, race, state, income category, marital status among others. In 1 I present how the population is distributed by income categories. Some definitions and basic descriptive statistics can be found in Tables 2 and 3. The BRFSS has a large sample size that is representative for the U.S.

Figure 2 shows two overlapped histograms, one for people with *low income* (in green) and other for people with *high income* (in red). Where histograms overlap, the color is brown. This is a simple, yet interesting figure. In short, individuals with higher income have a more concentrated distribution of BMI. In other words, distribution of people with an income lower than the median, have thicker tales in comparison. More people

Figure 1: Soft drink prices by state



suffer from extreme BMI, in both directions: underweight and on the other end underweight and obese.

4 Methodology

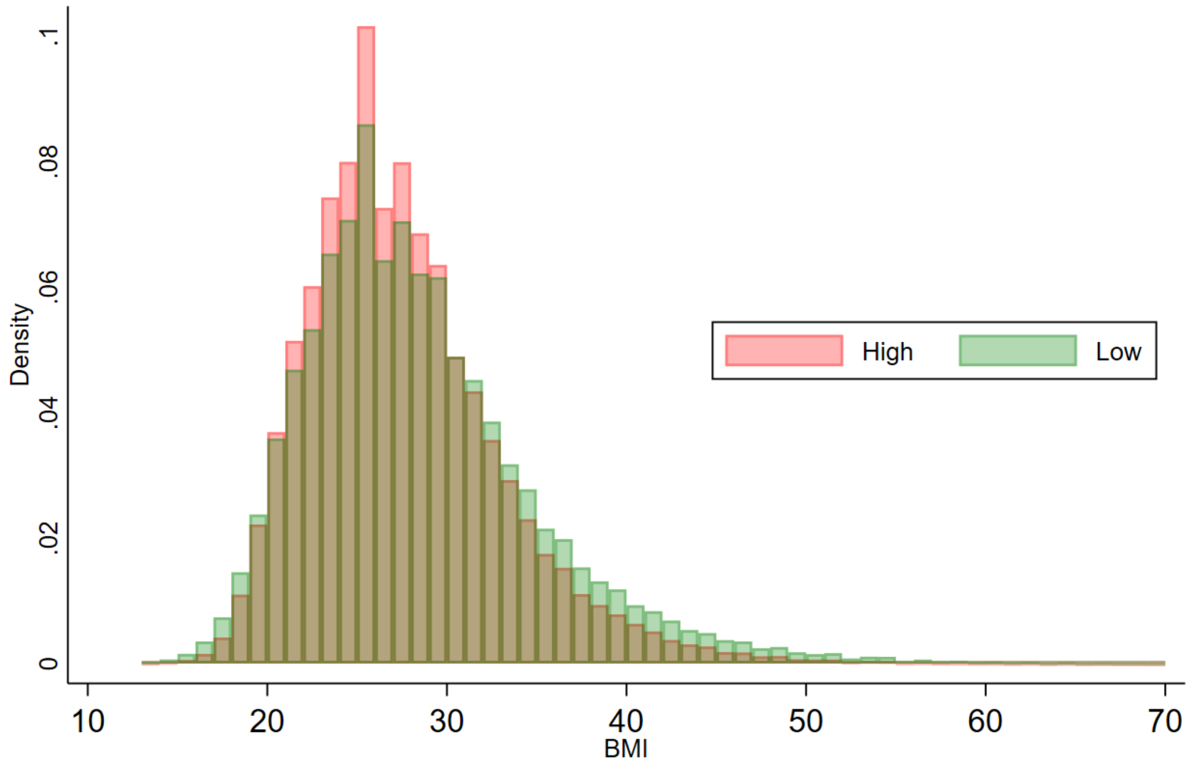
I first estimate the effect of soft drink prices on obesity levels measured as BMI[3]. For this purpose, I follow the method by Fletcher et al. [2010a] who used a two-way fixed effect ordinary least squares. For this approach, it is important to satisfy 1) Multiple observations per state, 2) BMI varying within states over time, and 3) Taking into account the potential bias coming from unobservables predicting variations in both soft drink prices and BMI levels. With these in mind, I estimate the following equation:

$$B_{ist} = \varphi_1' X_{ist} + \varphi_2 U_{s,t-1} + \beta P_{st} + \alpha_s + \delta_t + \epsilon_{ist} \tag{1}$$

Where B_{ist} is the body mass index for individual i in state s at year t. X_{ist} is a vector of controls that

[3]BMI is defined as a person's weight in kilograms divided by the square of its height in meters. $BMI = \frac{weight(kg)}{(height(m))^2}$

Figure 2: BMI by Income



Notes: "High" and "Low" refer to individuals above and below the median of Income, respectively.

Table 1: Categories of income

Category	Income level	Frequency	Percent	Cum.
1	<10,000	143,450	4.96	4.96
2	10,000 - 14,999	162,784	5.62	10.58
3	15,000 - 19,999	219,594	7.59	18.17
4	20,000 - 24,999	271,453	9.38	27.54
5	25,000 - 34,999	324,215	11.20	38.74
6	35,000 - 49,999	423,048	14.61	53.36
7	50,000 - 74,999	466,285	16.11	69.47
8	>75,000	883,845	30.53	100
	Total	2,894,674	100	

Table 2: Variable definitions

Variable	Definition
BMI	Body mass index.
Obese	Dummy equal to one if BMI ≥ 30.
Overweight	Dummy equal to one if BMI ≥ 25 & BMI < 30.
Underweight	Dummy equal to one if BMI < 18.5.
Sex	Dummy equal to one if male.
Age	Age in years (truncated by source at 80 years old).
Black	Dummy equal to one if race is Black.
Hispanic	Dummy equal to one if race is Hispanic.
White	Dummy equal to one if race is White.
HS grad	Dummy equal to one if max level of education is graduated from high school.
C grad	Dummy equal to one if max level of education is graduated from college or above.
Married	Dummy equal if married.
Income	Category of income. (8 different categories)*
Unemployment rate	State's Unemployment rate.
Price	Price of 2-liter Coca Cola, excluding any deposit.

*See table 1

vary individually and through state and time. $U_{s,t-1}$ is the average unemployment rate for a state in the previous year. P_{st} is the natural logarithm of price of soft drinks that do not vary across individuals, β is the parameter of interest and measures the effect of soft drink prices on BMI by contrasting individuals in a state who face soft drink prices that change over time. α_s and δ_t represents the state and time (year) fixed effects respectively.

To further explore the impact of soft drink prices on BMI, I follow income-based differences found in previous literature. With this in mind, I estimate the soft drink price effect on BMI for different categories of income. To do this, instead of including P_{st} as in equation (1), I create a set of dummy variables, each for every category of income and include these as an interaction with the P_{st}. The equation can be written as:

$$B_{ist} = \varphi_1' X_{ist} + \varphi_2 U_{s,t-1} + \sum_{u=1}^{8} \beta_u P_{st} * I_{u,ist} + \alpha_s + \delta_t + \epsilon_{ist} \tag{2}$$

Where $\sum_{u=1}^{8} \beta_u P_{st} * I_{u,ist}$ are the eight interactions terms. β_u, $u = 1, 2, ..., 8$ are the parameters of interest. These interaction terms will reflect the effect of soft drink prices on BMI for each category of income. When estimating equations 1 and 2 I use heteroskedasticity-robust standard errors to allow for clustering within states. To check if I have enough variation in the prices of soft drinks within states and overtime, I run the

Table 3: Descriptive Statistics

	Means by income categories								
	1	2	3	4	5	6	7	8	All
BMI	28.98	28.98	28.62	28.40	28.23	28.20	28.06	27.36	28.06
	(7.679)	(7.314)	(6.897)	(6.552)	(6.252)	(5.997)	(5.780)	(5.312)	(6.122)
Obese	0.367	0.366	0.345	0.330	0.317	0.314	0.303	0.255	0.304
	(0.482)	(0.482)	(0.475)	(0.470)	(0.465)	(0.464)	(0.460)	(0.436)	(0.460)
Overweight	0.294	0.316	0.330	0.344	0.358	0.370	0.379	0.390	0.364
	(0.455)	(0.465)	(0.470)	(0.475)	(0.479)	(0.483)	(0.485)	(0.488)	(0.481)
Underweight	0.0303	0.0256	0.0232	0.0199	0.0168	0.0133	0.0111	0.0106	0.0154
	(0.172)	(0.158)	(0.151)	(0.140)	(0.129)	(0.115)	(0.105)	(0.103)	(0.123)
Sex	0.350	0.352	0.371	0.393	0.418	0.456	0.474	0.512	0.448
	(0.477)	(0.478)	(0.483)	(0.488)	(0.493)	(0.498)	(0.499)	(0.500)	(0.497)
Age	52.04	58.12	56.96	57.21	57.34	56.03	54.25	52.20	54.82
	(17.39)	(17.29)	(18.39)	(18.38)	(18.01)	(17.11)	(15.93)	(14.31)	(16.63)
Black	0.182	0.130	0.132	0.101	0.0895	0.0709	0.0562	0.0406	0.0777
	(0.386)	(0.337)	(0.339)	(0.301)	(0.286)	(0.257)	(0.230)	(0.197)	(0.268)
Hispanic	0.126	0.107	0.111	0.0944	0.0781	0.0576	0.0433	0.0352	0.0645
	(0.332)	(0.309)	(0.314)	(0.292)	(0.268)	(0.233)	(0.204)	(0.184)	(0.246)
White	0.583	0.684	0.680	0.739	0.770	0.815	0.848	0.868	0.795
	(0.493)	(0.465)	(0.467)	(0.439)	(0.421)	(0.388)	(0.359)	(0.338)	(0.404)
HS grad	0.379	0.404	0.422	0.412	0.373	0.310	0.231	0.131	0.276
	(0.485)	(0.491)	(0.494)	(0.492)	(0.484)	(0.462)	(0.421)	(0.337)	(0.447)
C grad	0.115	0.116	0.128	0.168	0.226	0.322	0.441	0.635	0.375
	(0.319)	(0.320)	(0.334)	(0.374)	(0.418)	(0.467)	(0.497)	(0.482)	(0.484)
Married	0.138	0.163	0.249	0.343	0.414	0.528	0.641	0.792	0.536
	(0.345)	(0.370)	(0.433)	(0.475)	(0.493)	(0.499)	(0.480)	(0.406)	(0.499)
Obs	143,450	162,784	219,594	271,453	324,215	423,048	466,285	883,845	2,894,674

Standard deviations in parentheses

regression: $P_{st} = \pi_1 \alpha_s + \pi_2 \delta_t + \mu$ and find an R^2 of 0.74. This result can be compared with the threshold of 0.9 beyond which the variation would not be sufficient [Carpenter and Cook, 2008]. From this, I conclude the variable of prices I am using has enough variation to be appropriate for the estimations of equations (1) and (2).

While keeping the same structure of the two equations presented above, I also estimate two linear probability models to further examine the effect of soft drink prices on weight. This is a different approach to calculate the impact of soft drink prices on BMI. Rather than intensity, these estimations are useful for analyzing the propensity of becoming obese (or overweight, depending on the specification). The dependent variables used in each of the specifications are shown in 4.

Table 4: Three probability models

			Dependent variables		
BMI Classification	Obs	%	*LPM1*	*LPM2*	*LPM3*
Underweight	44,657	1.54	–	–	–
Normal weight	917,132	31.68	0	0	–
Overweight	1,053,130	36.38	1	0	0
Obese	879.755	30.39	1	1	1

LPM1 is used for (7.1) and (8.1). *LPM2* is used for (7.2) and (8.2). *LPM3* is used for (7.3) and (8.3). "–" means individuals part of that category are omitted for that variable.

5 Results

In this section I present four different tables. In tables 5 and 6 I present results from estimating equations (1) and (2) respectively, these two tables are relevant to measure the intensity of the impact of soft drink prices on obesity levels. The dependent variable is the BMI and the variable of interest *price* is in logs for ease of interpretation; I have run these regressions with prices without logs and the results are similar. In tables 7 and 8 I present linear probability models, these are relevant to measure the effect of soft drink prices on the probability of becoming obese or overweight (depending on the specification). In all four tables, estimations include fixed effects by year and state. Particular details of each are described below.

5.1 BMI as dependent variable

In this subsection I present results for the two-way fixed effect OLS. In table 5, I present the results from estimating equation (1). Columns (5.1) and (5.2) include the variable *price* in period t and columns (5.3) and (5.4) include the variable *price* lagged one period, in $t-1$. Lagging the price would capture the effect behind the idea that a price this year might affect the outcome variable next year. The reader can see the effects of several controls on BMI; as shown, basically all controls have significant effects on the dependent variable.The coefficients of interest in this table are the first two rows. The effect of price is negative in all cases, however not necessarily statistically different from zero. Current price affects BMI significantly but lagged price does not seem to have any effect on current BMI. With a 95% confidence level, a 1% increase in soft drink prices reduces, on average, the BMI by around 0.19. The coefficients for the categories of income are rather interesting: having an income between $\$10,000$ and $\$14,999$ affects the BMI positively in comparison with those having less than $\$10,000$. For the category of income between $\$15,000$ and $\$19,999$, although the magnitude is smaller, the sign of the effect changes. This negative sign is preserved for the rest of the categories, however the magnitude of the coefficient –in absolute value– increases for each higher category. For instance, having an income greater than $\$75,000$ reduces, on average, the BMI by 1.38 in comparison with with those having less than $\$10,000$.

In table 6, I present results from equation (2). As mentioned in the methodology section, the purpose of this exercise is to examine the effect of changes in soft drink price on BMI, for each category of income. The only difference between (6.1) and (6.2) is the inclusion of the lagged unemployment rate. Differences between both specification are fairly small; discrepancies in magnitude and even more in significance are quite marginal. In short, the inclusion of the lagged unemployment rate does not make much of a difference. Taking a look at the estimated coefficients, one can note that the effect of a soft drink price change has a stronger effect for people in the first category of income (Income $< \$10,000$). This is the effect of the interaction of price of soft drink and individuals with an income of less than $\$10,000$. According to my estimations, a 1% increase in soft drink prices, lowers the BMI of those in the first category of income by around 0.82. Interestingly, this effect start decreasing as the income category increases. This trend continues until, for categories 6, 7 and 8, the effect vanishes and estimated coefficients are no longer significant even at the 10% confidence level. One of the lessons that can be learned here is that looking at the average effect of change in soft drink price on BMI does not tell the whole story, and actually misses an important point: soft drink prices do affect BMI, but not only that. They do so by affecting every category of income in a different manner. The richer an individual is, the less impact he or she perceives from a change in soft drink prices on his or her BMI.

Table 5: Effect of soft drink prices on BMI.

	(5.1)	(5.2)	(5.3)	(5.4)
Log of price	-0.158*	-0.188**		
	(0.094)	(0.078)		
Log of price$_{t-1}$			-0.096	-0.128
			(0.099)	(0.094)
Unemployment rate$_{t-1}$		0.047***		0.047***
		(0.010)		(0.010)
Sex	0.633***	0.634***	0.634***	0.634***
	(0.047)	(0.047)	(0.047)	(0.047)
Age	0.390***	0.390***	0.390***	0.390***
	(0.005)	(0.005)	(0.005)	(0.005)
Married	0.139***	0.139***	0.139***	0.139***
	(0.025)	(0.025)	(0.025)	(0.025)
Income between 10,000 and 14,999	0.198***	0.198***	0.200***	0.201***
	(0.032)	(0.032)	(0.032)	(0.032)
Income between 15,000 and 19,999	-0.089***	-0.089***	-0.088***	-0.088***
	(0.030)	(0.030)	(0.030)	(0.030)
Income between 20,000 and 24,999	-0.231***	-0.230***	-0.230***	-0.229***
	(0.030)	(0.030)	(0.030)	(0.030)
Income between 25,000 and 34,999	-0.391***	-0.390***	-0.392***	-0.391***
	(0.034)	(0.034)	(0.034)	(0.034)
Income between 35,000 and 49,999	-0.480***	-0.479***	-0.480***	-0.479***
	(0.030)	(0.031)	(0.031)	(0.031)
Income between 50,000 and 74,999	-0.678***	-0.677***	-0.677***	-0.677***
	(0.040)	(0.040)	(0.040)	(0.040)
Income greater than 75,000	-1.385***	-1.384***	-1.385***	-1.384***
	(0.053)	(0.053)	(0.053)	(0.053)
HS grad	-0.048**	-0.048**	-0.047**	-0.047**
	(0.022)	(0.022)	(0.022)	(0.022)
C grad	-0.975***	-0.974***	-0.974***	-0.974***
	(0.038)	(0.038)	(0.038)	(0.038)
Observations	2,894,674	2,894,674	2,889,874	2,889,874
R-squared	0.058	0.058	0.058	0.058

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Variables Age squared, White, Black and Hispanic also included as controls. Fixed effects of year and state are included in all estimations.

Table 6: Effect of soft drink prices on BMI by category of income.

	(6.1)	(6.2)
Interactions of price and income categories		
Income <10,000	-0.811***	-0.831***
	(0.266)	(0.250)
Income 10,000 - 14,999	-0.613**	-0.637**
	(0.264)	(0.254)
Income 15,000 - 19,999	-0.563***	-0.590***
	(0.210)	(0.197)
Income 20,000 - 24,999	-0.438***	-0.469***
	(0.157)	(0.144)
Income 25,000 - 34,999	-0.308**	-0.338**
	(0.147)	(0.145)
Income 35,000 - 49,999	-0.126	-0.158
	(0.103)	(0.097)
Income 50.000 - 74,999	0.072	0.040
	(0.118)	(0.109)
Income >75,000	0.101	0.071
	(0.175)	(0.169)
Unemployment rate$_{t-1}$		0.046***
		(0.010)
Constant	19.710***	19.285***
	(0.289)	(0.329)
Observations	2,894,674	2,894,674
R-squared	0.058	0.058

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Variables Sex, Age, Age squared, Black, Hispanic, White, HS grad, C grad, Married and Income also included but not displayed in table. Fixed effects of year and state are included in all estimations. Dependent variables in both (6.1) and (6.2) is BMI.

5.2 Linear Probability Models

In this subsection, I present the results for the linear probability models. The logic of the results of the models in tables 7 and 8 are somehow similar to those presented below in tables 5 and 6, respectively. However there are some major differences that are worth noting.

In table 7, models (7.1), (7.2) and (7.3) are estimated. These models do not include the whole sample, the reason behind this is that in terms of probability, the factors causing going from one classification of BMI to a different one, might be conditional on the category. For example, going from overweight to obese might have very different causes than going from underweight to normal weight. By restricting the sample I try to better narrow the problem with the trade off that the results of the estimations might be not so general. (7.1) and (7.2) omit people that have a BMI classified as underweight. (7.3) omit both those who have a BMI classified as underweight and also those with normal weight; so it only considers two categories: Obese (in which the outcome variable takes the value of one) and overweight (in which the outcome variable takes the value of zero)

There are a few results worth mentioning from table 7. To start, I will mention a couple of things about the education variables. The difference in magnitude and significance between high school and college graduates is rather interesting. The former is insignificant in two out of three specifications with the effect only on the probability of going from overweight to obese –column (7.3)–. The later, has a much stronger effect regardless the specification: individuals with a college degree are less likely to be higher in the BMI classification by around 6% with respect to individuals with no formal education (the magnitude varies). For the income set of dummies, I obtain different levels of significance, magnitude of the coefficient and even signs for different specifications. For model (7.1), for instance, belonging to any category of income from 2 to 7 impacts positively the probability of becoming overweight or obese –relatively compared to category 1–; for category 8, however, the sign of the marginal effect changes from negative to positive. Furthermore, belonging to the category with income greater than $\$75,000$ lowers the probability of being overweight or obese with respect to individuals in the first category of income (*i.e.* less than $\$10,000$). All of this, taking into account that underweight people are not included; although, recall only around 1.5% of the sample is underweight.

In (7.2) estimations are more in line with what was expected. Excluding category of income number 2, belonging to any other category of income, decreases the probability of being obese. These coefficients are all statistically significant at 99% and the higher the category of income, the higher effect with respect to the base category of an income of less than $\$10,000$. In (7.3) the situation is very similar, with two differences: the first, belonging to the category of income between $10,000$ and $14,999$ is not significant anymore. And second, all other marginal effects have a greater magnitude compared to those in (7.2) while the significance at 1% does not change for any of them. One of the most striking result from table 7 is the fact that soft drink price does not have a significant effect on any of the outcome variables in (7.1), (7.2) or (7.3). In other words, according to my results, soft drink price is important for explaining the magnitude of BMI, but not different from zero when explaining the probability of being obese or overweight.

Meanwhile table 7 is analogous to table to 5, table 8 is analogous to 6. The fundamental difference being that table 8 present linear probability models for the three dependent variables mentioned in tables 4 and 7. Interactions terms between income categories and soft drink prices have a less clear and consistent trend in these three linear probability specification relatively to the results from table 6. For the specification (8.1), almost all coefficients are negative for the interaction terms (category of income 7 and 8 are not, but neither statistically significant) and they do reduce in magnitude from category 2 and on, so the differentiated effect of price for different categories of income is still present here. In (8.1) and (8.2) less interactions terms are significant but even in those cases I found prices being important with significant differences for some categories of income. Categories of income 1 and 3 being impacted the most by the price change in soft drinks.

6 Conclusions

In this paper I have estimated the effect of soft drink prices on BMI using data from the C2ER, the CDC and the BLS for the U.S. during the years 2011 to 2018. I follow a similar methodological approach as Fletcher et al. [2010a], but I use prices of soft drinks instead of taxes to perform the estimations. By doing so, I find evidence on the negative and statistically significant impact of soft drink price on BMI, but an effect of soft drink price on the probability of obesity and overweight that was indistinguishable from zero. Another important finding is that the price of soft drinks affects BMI, obesity and overweight in different degrees depending on individuals' categories of income.

Although direct comparison might not be possible due to the difference in variables, time frames and details in methodology, my results are in line with the authors'. Soft drink prices –taxes on soft drink in their case– have a negative, significant and relatively small effect on BMI. For Fletcher et al. [2010a], "an increase in the state soft drink tax rate of 1 percentage point leads to a decrease in BMI of 0.003 points". In my case, a 1% increase in soft drink price, leads to a decrease of BMI of 0.18. Magnitudes are very different, but again, this results are far from being directly comparable. For the probability models –and this is an important difference between my results and the results by Fletcher et al. [2010a]–, I do not find evidence in favor of the hypotheses that soft drink prices increases lead to an average decrease in overweight or obesity,

Table 7: Linear probability models.

	(7.1)	(7.2)	(7.3)
Dep. variable:	Overweight or obese	Obese	Obese
Sample omitted:	Underweight	Underweight	Underweight & Normal weight
Log of price$_t$	-0.008	-0.009	-0.008
	(0.005)	(0.006)	(0.007)
Unemployment rate$_{t-1}$	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Age	0.025***	0.023***	0.019***
	(0.011)	(0.009)	(0.007)
HS grad	0.002	-0.002	-0.004***
	(0.001)	(0.001)	(0.001)
C grad	-0.068***	-0.068***	-0.056***
	(0.003)	(0.002)	(0.002)
Married	0.023***	0.007***	-0.002
	(0.002)	(0.002)	(0.002)
Income 10,000 - 14,999	0.020***	0.011***	0.001
	(0.002)	(0.002)	(0.002)
Income 15,000 - 19,999	0.015***	-0.007***	-0.020***
	(0.002)	(0.002)	(0.002)
Income 20,000 - 24,999	0.013***	-0.018***	-0.034***
	(0.002)	(0.002)	(0.002)
Income 25,000 - 34,999	0.010***	-0.030***	-0.051***
	(0.002)	(0.002)	(0.002)
Income 35,000 - 49,999	0.014***	-0.036***	-0.062***
	(0.002)	(0.002)	(0.002)
Income 50.000 - 74,999	0.009***	-0.050***	-0.078***
	(0.002)	(0.002)	(0.002)
Income >75,000	-0.029***	-0.096***	-0.122***
	(0.003)	(0.003)	(0.003)
Constant	-0.038**	-0.195***	0.137***
	(0.016)	(0.016)	(0.014)
Observations	2,850,017	2,850,017	1,932,885
R-squared	0.055	0.039	0.033

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Variables Sex, White, Black, Hispanic and Age squared also included as controls. Fixed effects of year and state are included in all estimations. For (7.1) dependent variable is a dummy equal to one if individual is overweight or obese. For (7.2) and (7.3) dependent variable is obese, all three omitting the category underweight. "Income $< 10,000$" is the base category for income.

Table 8: Linear probability models: Interactions.

	(8.1)	(8.2)	(8.3)
Dep. variable:	Overweight or obese	Obese	Obese
Sample omitted:	Underweight	Underweight	Underweight & Normal weight
Interactions of price and income categories			
Income <10,000	-0.030	-0.039**	-0.033**
	(0.019)	(0.017)	(0.014)
Income 10,000 - 14,999	-0.035**	-0.027	-0.012
	(0.014)	(0.016)	(0.017)
Income 15,000 - 19,999	-0.030**	-0.031**	-0.021
	(0.014)	(0.014)	(0.017)
Income 20,000 - 24,999	-0.016**	-0.034***	-0.036***
	(0.008)	(0.010)	(0.013)
Income 25,000 - 34,999	-0.013	-0.013	-0.008
	(0.012)	(0.009)	(0.010)
Income 35,000 - 49,999	-0.018**	-0.003	0.008
	(0.007)	(0.008)	(0.010)
Income 50.000 - 74,999	0.004	0.004	0.002
	(0.006)	(0.009)	(0.010)
Income >75,000	0.007	0.001	-0.004
	(0.013)	(0.011)	(0.010)
Unemployment rate$_{t-1}$	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Constant	-0.026	-0.178***	0.152***
	(0.022)	(0.021)	(0.017)
Observations	2,850,017	2,850,017	1,932,885
R-squared	0.055	0.039	0.033

*Notes:**** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Variables White, Black, Hispanic and Age squared also included as controls. Fixed effects of year and state are included in all estimations. For (8.1) dependent variable is a dummy equal to one if individual is overweight or obese. For (8.2) and (8.3) dependent variable is obese, all three omitting the category underweight. "Income $< 10,000$" is the base category for income.

but there is an effect on low income individuals.

When considering the differentiated effect of soft drink price by level of income, methodology used by Fletcher et al. [2010a] and the methodology used in this paper are very different, so comparisons might be even more complicated. They find the soft drink tax rate affects more strongly the behavior of individuals in the tails of the distribution. On the other hand, I find that soft drink prices affect BMI significantly different as a function of the income category. The impact of soft drink price on BMI is stronger for low categories of income and it reduces as the level of income increases, until it completely vanishes for the three richest categories (income greater than $\$35,000$).

There are a few drawbacks of this work. “Soft drinks” are much more than 2-liter bottles of coca cola. Unfortunately, due to data availability, I only use this indicator in my estimations. This might be problematic in various ways. I don’t take into account the behavior of prices of direct substitutes like Pepsi, sweetened juices or even the same Coca cola in different sizes or types of bottles. When a bottle of 2-liter Coca cola price goes up, consumers might substitute their consumption for a different good (or the same good in a different size or container) to a certain degree. Nevertheless, I still think that the exercise presented in this paper is valuable. Coca cola is a major player in the soft drink industry and it is reasonable to think that the price of coca cola and its competitors might be somehow correlated. Including competitors, considering substitutes and complements, and working with county level data could lead to interesting results that would enrich the findings of this work. Finally, although the repeated cross section data I work with is rich and useful, ideally a panel dataset where following the same individuals over time is possible, would be even better research purposes. It would allow to better tackle the genetic component of obesity.

References

Allcott, H., Lockwood, B., and Taubinsky, D. (2019). Should we tax sugar-sweetened beverages? an overview of theory and evidence. *Journal of Economic Perspectives*, 33:202–227.

Basu, S., McKee, M., Galea, G., and Stuckler, D. (2013). Relationship of soft drink consumption to global overweight, obesity, and diabetes: a cross-national analysis of 75 countries. *American journal of public health*, 103 11:2071–7.

Blakely T, Wilson N, K.-B. B. (2014). Taxes on sugar-sweetened beverages to curb future obesity and diabetes epidemics. *PLoS Med*, 11(1):285–295.

Bleich, S. N., Cutler, D., Murray, C., and Adams, A. (2008). Why is the developed world obese? *Annual Review of Public Health*, 29(1):273–295. PMID: 18173389.

Brownell, K. D., Farley, T., Willett, W. C., Popkin, B. M., Chaloupka, F. J., Thompson, J. W., and Ludwig, D. S. (2009). The public health and economic benefits of taxing sugar-sweetened beverages. *New England Journal of Medicine*, 361(16):1599–1605. PMID: 19759377.

Brownell, K. D. and Frieden, T. R. (2009). Ounces of prevention — the public policy case for taxes on sugared beverages. *New England Journal of Medicine*, 360(18):1805–1808. PMID: 19357400.

Carpenter, C. and Cook, P. (2008). Cigarette taxes and youth smoking: New evidence from national, state, & local youth risk behavior surveys. *Journal of health economics*, 27:287–99.

Cawley, J., Frisvold, D., Hill, A., and Jones, D. (2019a). The impact of the philadelphia beverage tax on purchases and consumption by adults and children. *Journal of Health Economics*, 67:102225.

Cawley, J., Frisvold, D., and Jones, D. (2019b). The impact of sugar-sweetened beverage taxes on purchases: Evidence from four city-level taxes in the u.s. Working Paper 26393, National Bureau of Economic Research.

Cawley, J. and Ruhm, C. (2012). The economics of risky health behaviors. *Handbook of Health Economics*, 2:95–199.

Cawley, J., Thow, A. M., Wen, K., and Frisvold, D. (2019c). The economics of taxes on sugar-sweetened beverages: A review of the effects on prices, sales, cross-border shopping, and consumption. *Annual Review of Nutrition*, 39(1):317–338. PMID: 31116649.

Cutler, D. M., Glaeser, E. L., and Shapiro, J. M. (2003). Why have americans become more obese? *Journal of Economic Perspectives*, 17(3):93–118.

Dharmasena, S. and Capps JR, O. (2012). Intended and unintended consequences of a proposed national tax on sugar-sweetened beverages to combat the u.s. obesity problem. *Health Economics*, 21(6):669–694.

Escobar, M., Veerman, J., Tollman, S., Bertram, M., and Hofman, K. (2013). Evidence that a tax on sugar sweetened beverages reduces the obesity rate: A meta-analysis. *BMC public health*, 13:1072.

Finkelstein, E. A., Trogdon, J. G., Cohen, J. W., and Dietz, W. (2009). Annual medical spending attributable to obesity: Payer-and service-specific estimates. *Health Affairs*, 28(Supplement 1):w822–w831.

Finkelstein, E. A., Zhen, C., Nonnemaker, J., and Todd, J. E. (2010). Impact of Targeted Beverage Taxes on Higher- and Lower-Income Households. *JAMA Internal Medicine*, 170(22):2028–2034.

Fletcher, J., Frisvold, D., and Tefft, N. (2010a). Can soft drink taxes reduce population weight? *Contemporary Economic Policy*, 28(1):23–35.

Fletcher, J., Frisvold, D., and Tefft, N. (2014). Non-linear effects of soda taxes on consumption and weight outcomes. *Health Economics*, 24.

Fletcher, J. M., Frisvold, D. E., and Tefft, N. (2010b). The effects of soft drink taxes on child and adolescent consumption and weight outcomes. *Journal of Public Economics*, 94(11):967 – 974.

Goryakin, Y., Monsivais, P., and Suhrcke, M. (2017). Soft drink prices, sales, body mass index and diabetes: Evidence from a panel of low-, middle- and high-income countries. *Food Policy*, 73:88 – 94.

Hales, C. M., Carroll, M. D., Fryar, C. D., and Ogden, C. L. (2017). Prevalence of obesity among adults and youth: United states, 2015–2016. Data Brief 288, Centers for Disease Control and Prevention, Geneva.

Hammond, R. A. and Levine, R. (2010). The economic impact of obesity in the united states. *Diabetes, Metabolic Syndrome and Obesity: Targets and Therapy*, 3:285–295.

Jacobson, M. and Brownell, K. (2000). Small taxes on soft drinks and snack foods to promote health. *American journal of public health*, 90:854–7.

James, J. and Kerr, D. (2005). Prevention of childhood obesity by reducing soft drinks. *International journal of obesity (2005)*, 29 Suppl 2:S54–7.

Lin, B.-H., Smith, T. A., Lee, J.-Y., and Hall, K. D. (2011). Measuring weight outcomes for obesity intervention strategies: The case of a sugar-sweetened beverage tax. *Economics and Human Biology*, 9(4):329 – 341.

Smith, T., Lin, B.-H., and Lee, J.-Y. (2010). Taxing caloric sweetened beverages: Potential effects on beverage consumption, calorie intake, and obesity. *Economic Research Report*, 100.

Sturm, R., Powell, L., Chriqui, J., and Chaloupka, F. (2010). Soda taxes, soft drink consumption, and children's body mass index. *Health affairs (Project Hope)*, 29:1052–8.

Vartanian, L. R., Schwartz, M. B., and Brownell, K. D. (2007). Effects of soft drink consumption on nutrition and health: A systematic review and meta-analysis. *American Journal of Public Health*, 97(4):667–675. PMID: 17329656.

Wang, Y. C., Coxson, P., Shen, Y.-M., Goldman, L., and Bibbins-Domingo, K. (2012). A penny-per-ounce tax on sugar-sweetened beverages would cut health and cost burdens of diabetes. *Health Affairs*, 31(1):199–207. PMID: 22232111.

Wendt, M. and Todd, J. E. (2011). The effect of food and beverage prices on children's weights. Economic Research Report 118, U. S. Department of Agriculture, Washington D.C.

World Health Organization (2000). Obesity: Preventing and managing the global epidemic. Technical Report 894, WHO.

World Health Organization (2002). The world health report. Technical report, WHO, Geneva.

World Health Organization (2018). *Obesity and Overweight, Facts Sheet.* `https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight`.

World Health Organization (2019). Fact sheet: Obesity and overweight. `https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight`.

Wright, A., Smith, K., and Hellowell, M. (2017). Policy lessons from health taxes: A systematic review of empirical studies. *BMC Public Health*, 17.