I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17617

Soda Taxes, BMI and Obesity: Evidence from Seattle

James Flynn
Anja Gruber

JANUARY 2025

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17617

Soda Taxes, BMI and Obesity: Evidence from Seattle

James Flynn
Miami University and IZA

Anja Gruber
University of Colorado Boulder

JANUARY 2025

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Soda Taxes, BMI and Obesity: Evidence from Seattle*

This paper uses restricted-access data from the Behavioral Risk Factor Surveillance System Survey to assess whether the sugar-sweetened beverage (SSB) tax levied in Seattle in 2018 led to declines in body mass index (BMI) and the rate of obesity. We implement an event-study design which compares these outcomes in the treated region to those of untaxed areas. We find no evidence of divergence in trends prior to the tax, followed by large declines in both outcomes after the tax was implemented. We estimate that the tax led to a reduction of .61 BMI points and reduced the obesity rate by 4.5 percentage points. Declines were largest for individuals with lower incomes, those without a college degree, and younger people, which are all groups who tend to consume more SSBs at baseline. We address concerns that our results are driven by the COVID-19 pandemic and provide suggestive evidence that SSB taxes improved these outcomes in other SSB-taxed jurisdictions as well. Our study adds to the growing evidence that SSB taxes can improve public health, rather than only affecting prices, purchasing, or consumption of taxed beverages.

JEL Classification: H2, H3, I120, I18

Keywords: soda tax, health behavior, taxation, obesity

Corresponding author:
James Flynn
Miami University
501 E High St
Oxford
OH 45056
USA
E-mail: flynnj@miamioh.edu

* We are grateful to the many helpful comments we received from seminar participants at Ohio University and Miami University.

1. Introduction

According to the CDC more than half of all Americans aged two years and older exceed the recommended consumption of added sugars each day (CDC, 2023). The biggest source of added sugars in our diets are sugar sweetened beverages, making up for 24% of all added sugar consumed. Given the well-established correlation between SSB consumption and weight gain, obesity, type II diabetes, high blood pressure, and tooth decay, it comes at no surprise that sugar-sweetened beverage (SSB) taxes have become an increasingly popular policy instrument to improve public health. Over 40 nations have enacted SSB taxes worldwide, along with seven municipalities in the US.[1] A growing body of literature shows that these taxes have been passed through to the consumers and appear to have caused reductions in purchases and likely also in consumption of SSBs,[2] though there is evidence of both tax avoidance via cross-border shopping[3] and consumption shifting towards other unhealthy options.[4] Whether these taxes have in fact led to any health improvements is empirically still largely unanswered.

Our study addresses this question by looking at the impact of the Seattle SSB tax on BMI and obesity rates in adults. We use annual restricted-access data from the Behavior and Risk Factor Surveillance System (BRFSS) surveys from 2013-2020[5] and implement an event-study design which compares trends in Seattle and

[1] SSB taxes have been implemented in Berkeley, Oakland, Albany, and San Francisco, California, Seattle, Washington, Philadelphia, Pennsylvania, and Boulder, Colorado, as well as by the Navajo Nation.

[2] For example, Dubois, Griffith, and O'Connell (2020), Powell, Chriqui, et al. (2013), Powell and Leider (2020a), Powell, Leider, and Leger (2020), Powell and Leider (2020b), and Leider and Powell (2022) all find evidence that SSB taxes reduce purchases. Research on consumption has been more mixed, with Edmondson et al. (2021), Lee et al. (2019), Falbe et al. (2016), Cawley, Frisvold, et al. (2019), Zhong, Auchincloss, Lee, and Kanter (2018), Flynn (2023), and Flynn (2024) all finding evidence of consumption reductions and Cawley, Daly, and Thornton (2022), Silver et al. (2017), Zhong, Auchincloss, Lee, McKenna, et al. (2020) failing to find a significant effect.

[3] Bollinger and Sexton (2018), Powell, Leider, and Leger, 2020, Powell and Leider (2020a), Roberto et al. (2019), Seiler, Tuchman, and Yao (2021)

[4] Aguilar, Gutierrez, and Seira (2021), Duffey et al. (2010), Finkelstein et al. (2013), Fletcher, Frisvold, and Tefft (2010)

[5] This dataset includes observations from all five counties in the U.S. which have implemented a sugar-sweetened beverage tax, but only Seattle is sufficiently powered to estimate the impact of the tax. In the appendix, we estimate the combined effect on all treated counties, as well as each treated county individually. While the small samples in these jurisdictions prevent us from

comparison counties both before and after the tax went into effect. We find that by 2020, the Seattle SSB tax reduced the average BMI of adults in King County by 0.61 points and reduced the obesity rate by 4.5 percentage points. We find that reductions are larger for individuals with lower levels of education, younger people, and people with lower incomes – precisely the demographic groups who tend to consume more SSBs at baseline. We test the plausibility of our BMI estimates by asking what size effect we would expect to see given the SSB purchase reductions found in the existing literature. We use the 22% reduction in purchases found by Powell and Leider (2020b) and make a few important assumptions[6] and find that the Powell and Leider (2020b) paper implies a BMI reduction of .607 points, which is within 1% of our estimate of 0.612. Similarly, when we look across demographic subgroups, our estimates line up closely with the reductions implied by the Powell and Leider (2020b) estimate.

This paper builds on the literature on the health effects of soda taxes in three important ways. First, this paper is the first study to provide explicit evidence on effectiveness of SSB taxes in reducing the obesity rate in the United States. Our findings suggest that the weight loss due to the SSB tax in Seattle is coming from the upper portion of the BMI distribution, where individuals are at higher risk of developing chronic illness due to excess weight.

Second, to our knowledge this is the first paper which examines the effect of SSB taxes on the health of non-pregnant adults. Gračner, Marquez-Padilla, and Hernandez-Cortes (2022) find small reductions in BMI and obesity for girls in Mexico, while Cawley, Daly, and Thornton (2022) find no discernible change in BMI for youths in Mauritius. In the US, Flynn (2023) and Flynn (2024) find a 1-3% reduction in BMI among high school students in Philadelphia, San Francisco, and Oakland, Jones-Smith, Knox, et al. (2024) find a similar modest reduction among children in Seattle, while Jackson et al. (2023) show that SSB taxes decreased the risk of gesta-

drawing definitive conclusions, the suggestive evidence is consistent with our main results.

[6]First, we assume that Seattle residents reduced actual consumption, not just purchases, by 22%. We then convert the the 22% reduction into a weekly change in SSB consumption. Assuming that the average SSB is a 12 ounce Coca-Cola Classic, which has 150 calories, we then calculate an average annual calorie reduction which we sum over the three years the tax was in effect by 2020 and recalculate average BMI.

tional diabetes for pregnant women. We build on these findings by showing that the Seattle SSB tax led to reductions in BMI and obesity among adults in Seattle.

Finally, we demonstrate that the impact of the SSB tax on BMI and obesity varies greatly by the baseline SSB consumption of different demographic groups. Those groups which report the highest pre-tax consumption experience the greatest reduction in BMI and obesity. In fact, we show that the SSB tax is particularly effective in achieving BMI and obesity reductions for groups that are most likely to face negative health outcomes because of their baseline BMI. With the exception of Flynn (2023) and Flynn (2024) who find that BMI reductions are concentrated among female and non-white adolescents, studies on the health impacts of SSB taxes to date have have not been able to explore potential heterogeneity of public health improvements. The large sample size available in the BRFSS data provides us with the statistical power to not only measure the average treatment effect, but to estimate effects on smaller groups with relative precision.

The remainder of this paper is organized as follows. Section 2 discusses the motivation for SSB taxes and the specifics of the Seattle SSB tax. Section 3 describes the BRFSS data used in our analysis as well as the empirical approach to our study. Section 4 presents the results of our analysis and section 5 concludes.

2. Background

2.1. Motivation for Taxing SSBs

The standard motivation for so called 'sin taxes' is that without government intervention, the market presents a negative externality. A vast literature links excessive sugar consumption to negative health outcomes and serious long-term medical issues including weight gain, heart disease and high blood pressure, type II diabetes, and overall mortality.[7] Cawley and Meyerhoefer (2012) find that these negative outcomes impose significant costs on taxpayers. Using genetic weight differences to instrument for obesity, they find that obesity causes annual medical

[7] Ebbeling et al. (2012), Ruyter et al. (2012), Mozaffarian et al. (2011), Jenkins et al. (2021), Santos et al. (2012), Te Morenga et al. (2014), Xi et al. (2015), Imamura et al. (2015), Rippe and Angelopoulos (2016), Dehghan et al. (2017)

expenses to increase by almost $3,000, with 88% of the costs being born by third parties. Wang et al. (2016) estimate an external cost of 1 cent per ounce of SSB consumed, suggesting that an SSB tax of 1 cent per ounce would restore efficiency in the market for soda. Regardless of the exact external cost attribution, SSBs have become a popular target for sin taxes and are increasingly debated as a tool to both raise public revenue and positively affect the obesity epidemic in the US.

2.2. Seattle SSB Tax

The first SSB tax in the US went into effect in Berkeley, CA in 2015. Six additional cities have since implemented SSB taxes of their own. The important details of each tax are outlined in Appendix Table A.1. The Seattle SSB tax has been in effect since the beginning of 2018 and requires distributors to pay 1.75 cents per ounce of sugar-sweetened beverage product distributed within the city. This makes Seattle's tax the second highest[8] SSB tax in the country. Taxed drinks include sodas, fruit juice with added sugar, energy and sport drinks, sweetened waters, coffees and teas, as well as syrups and concentrates. Diet drinks, 100% juices, milk drinks, and powders and concentrates for mixing by the end consumer are not included.

Seattle has spent the tax revenue on a series of programs designed to expand access to nutritious food and on early childhood programs to benefit the communities most impacted by the health inequalities and chronic diseases caused by sugary beverages. The city spent approximately $20 million in 2018, $19 million in 2019, and $27 million in 2020 (SBTCAB, 2018; SBTCAB, 2019; SBTCAB, 2020; Krieger et al., 2021). About half of the money has gone to programs designed to benefit children and should therefore not impact the adult health outcomes we study. Between $9-10 million each year was spent on expanding access to health foods for low income communities. It is possible, therefore, that the health improvements we find could be partially due to improved nutrition access from these programs. It is worth pointing out, however, that programs designed to promote healthy food access have not had a great deal of success in reducing obesity (Alston, MacEwan, and Okrent, 2016; Lemmens et al., 2008) and that the scope of their potential impact is relatively limited. For example, Allcott, Lockwood, and

[8] Boulder, CO, has the highest tax at 2 cents per ounce.

Taubinsky (2019) find that exposing low income neighborhoods to the same food quality and prices available to high income neighborhoods would only reduce nutritional inequality by 10%. Therefore, we believe that any impacts on BMI and other health outcomes are likely driven by changes in SSB consumption, not by the public health investments funded by the SSB tax.

In order for a SSB tax itself to be able to impact health outcomes, the tax needs to (1) reach consumers in the form of price increases and (2) lead to reductions in consumption without consumers substituting towards other equally unhealthy options. Both of these questions have been studied extensively with regard to the Seattle tax. Using different methodologies, both Jones-Smith, Pinero Walkinshaw, et al. (2020) and Powell and Leider (2020b) find that the Seattle tax was mostly passed through. Jones-Smith, Pinero Walkinshaw, et al. (2020) perform an audit study, recording prices in over 400 retail food stores and restaurants before and after the tax went into effect. They find the tax increased prices by 1.58 cents per ounce, a pass through rate of 90%. Powell and Leider (2020b) use scanner data to assess the effect of the tax on prices paid at the counter, finding a smaller, though still substantial, pass through rate of 59%. These estimates are similar to or slightly larger than estimates of pass through rates in other SSB taxes cities.

Regarding the effect of the SSB tax on SSB purchases in Seattle, Powell and Leider (2020b) and Powell, Leider, and Oddo (2021) both use scanner data, and find reductions of 22% and 23%, respectively. Powell and Leider (2020b) find a modest 4% increase of purchases of untaxed beverages, though most of the increase is due to purchases of water, diet sodas, and unsweetened sports drinks - drinks with zero calories or very low caloric content. Powell, Leider, and Oddo (2021) also investigate potential substitution and find a 4% increase in sugar sold from untaxed beverages in the first year after the tax, but no increase by the second year, no increase in stand alone sugar sold and a 4% increase in sugar sold from sweets. Oddo, Leider, and Powell (2021) also finds a small increase (3%) in sugar sold from sweets, but no substitution towards salty snacks.

Unlike with other SSB taxes, researchers have found no evidence of cross-border shopping in Seattle, which can reduce the effectiveness of a tax for consumers who are able to shop outside of the city limits. Powell, Leider, and Oddo

(2021) found no evidence of increased volume of sales of taxed beverages in Seattle's two-mile border area. This is likely due to the fact that most of the residents of Seattle do not live close enough to a land border to be able to realistically save money by avoiding the tax. Appendix Figure A.1 displays the distance to an untaxed land border for Seattle and the other seven SSB taxed cities. Since Seattle is surrounded by water to the east and west, the only borders that residents could realistically cross in order to avoid the tax are at the southern and northern tips. These happen to also be the most sparsely populated portions of the city, as the majority of Seattleites live in the central portions of the city which are several miles to the border.

Overall, research on purchasing responses to the Seattle tax suggest a large reduction in caloric intake, with a small degree of substitution towards sugar from other sources. It is also worth pointing out that reduced sugar consumption from SSBs could lead to other health benefits beyond caloric intake, as sugar consumption can harm sleep quality (Khan et al., 2021) and make people feel lethargic (Williams et al., 2008), both of which make people less likely to exercise. Still, it is possible that consumers substituted towards other unhealthy options in ways that are not captured by the existing research. It is therefore vital to estimate the effect of the Seattle SSB tax directly on health outcomes to assess whether consumption changes translated into actual health improvements, and to better understand which groups the improvements are accruing to. If the tax is effective in targeting individuals at risk for developing chronic illnesses related to excess weight, then we should see reductions in BMI and obesity. If, on the other hand, weight reductions were coming mainly from individuals with lower baseline BMI, obesity rates are unlikely to be impacted, and the policy would likely fail to reduce healthcare costs related to chronic illnesses in the long run.

3. Methodology and Data

3.1. Data - BRFSS

Behavioral Risk Factor Surveillance Survey (BRFSS) restricted access data was obtained through the National Center for Health Statistics (NCHS) Research Data Center. Without restricted access, we would not have been able to identify which county individual respondents lived in and would not have been able to conduct this analysis. The BRFSS is the largest continuously conducted health survey globally. It collects individual data on the health-related risk behaviors, use of preventative services, and chronic health conditions of more than 400,000 individuals across all of the United States every year. Importantly for our project, the BRFSS provides information about an individual's BMI, calculated based on their height and weight, as well as an indicator variable for obesity equal to one for individuals with a BMI above 30.

There are limitations in using self-reported height and weight. For example, Flegal et al. (2019) show that the self-reported BMI variable in the BRFSS is lower than measured BMI from the National Health and Nutrition Examination (NHANES) survey. Pérez et al. (2015) also find that students tend to overestimate height and underestimate weight, but they still conclude that self-reported measurements provide a reliable proxy. Similarly, Liechty, Bi, and Qu (2016) argue that statistical adjustments can slightly improve the accuracy of self-reported measurements, but that even without adjustments the self-reported measurements are very close to the actual measured values. While self-reported measurements are imperfect, the measurement error which they introduce should only serve to attenuate our estimates.

Our data include information on the county of residence for each respondent. Table 1 displays yearly observation counts for each county with an SSB tax in the US. King County, Washington, which is where Seattle is located, has more than three times as many observations as each of the other counties, and has more total observations than all of the other counties put together. King County also has a relatively stable observation count of between 2,500 and 2,800 observations in all year except 2014 and 2014 where it has 4,000 and 3,500, respectively. All of the other treated counties have observation counts which fluctuate wildly (Philadelphia, Alameda County) or are under-powered for the purposes of this paper (San Francisco, Boulder). We therefore focus only on estimating the effects of the Seattle SSB tax, and use all observations in counties which have never implemented an SSB tax as controls. In the appendix, we run a stacked difference-in-differences specification of Cengiz et al. (2019) using all counties which have implemented an SSB tax in the U.S., as well as estimating the effect on each treated county individually. The results are largely consistent with our main analysis which focuses on Seattle, but are less conclusive due to the data issues outlined above.

As discussed in Section 2.2, focusing on Seattle provides a unique opportunity for studying the impacts of a SSB tax in a setting with high pass-through and limited cross-border shopping, making it particularly suitable in studying the potential impacts of a state or federal SSB tax. Still, while Seattle is the main population center of King County, the county also includes a number of smaller cities which are not covered by the SSB tax. Since the BRFSS does not provide more granular detail than the county of residence, this means that some untreated observations are included in our treatment groups, biasing the results towards zero.[9]

3.2. Empirical Strategy

To estimate the impact of the Seattle SSB tax on BMI and obesity we exploit an event-study design which compares the change in outcomes relative to the year of implementation (2018) in each pre- and post policy year (2013-20) in King County to the changes in US counties that do not implement a SSB tax during this time period. We thus rely on the standard difference-in-difference assumption that the trend in the outcome variable would have been similar in the treated and comparison counties in the absence of implementation of the Seattle SSB tax.

[9] The BRFSS does have an indicator for whether the resident lives in the central city of the county (which is Seattle in the case of King County), but this variable is missing for more than half of our sample. Of the observations for which we have this information, roughly two-thirds live in Seattle in any given year. We have no reason to believe that individuals with missing values are systematically more or less likely to reside in the central city and therefore assume that roughly two-thirds of the observations in King County are treated.

We estimate the following regression equations:

$$W_{ictm} = \sum_{t=2013}^{2020} \beta_t \text{SSBTax}_c + \alpha X_{ict} + \gamma_c + \delta_t + \omega_m + \epsilon_{itcm}$$

where W_{ictm} is the BMI or obesity outcome of individual i in county c, year t, and month m. β_t is our parameter of interest, and each of the β_t parameters can be interpreted as the change in the difference between weight outcomes in the treated and comparison counties in a given year t, relative to 2018. If the SSB tax was effective at improving health outcomes in Seattle, we would expect to see small and insignificant estimates for $\beta_{2013} - \beta_{2017}$ followed by negative and significant estimates. Given that the impact on weight outcomes accrues over time, the estimate for β_{2020} should be larger than for β_{2019}. X_{ict} includes a vector of individual controls, including sex, age, race, income, marital status, employment, veteran and smoker status, as well as county (γ_c), year (δ_t) and month (ω_m) fixed effects. Standard errors are clustered at the county level.

A key part of this study is the ability to assess the heterogeneity of the results by applying our regression equation to specific sub-samples. We do so by splitting the sample by family income (below and above $75K annually), by age (younger and older than 65), by sex, by educational attainment (with and without college degree), and by gender.

While we expect the Seattle SSB tax to mainly impact the BMI and obesity outcomes in 2020, this may lead to concerns that the results are in fact driven by differential impacts of the COVID-19 pandemic. While we cannot completely rule out this threat to identification, it is a worthwhile exercise to consider how COVID-19 would have had to impact individuals in King county relative to the comparison counties for any estimated impact of the SSB tax to in fact be due to the COVID-19 pandemic. Specifically, this could be the case if relatively more individuals with high BMIs passed away or moved out of King County. To address these concerns, Appendix Figure A.2 displays the 2020 COVID incidence calculated from New York Times Covid-tracker data and the out-migration rate calculated from the American Community Survey (ACS) for King County and all other counties in the US that are recorded in the ACS.

While Seattle received a great deal of attention for being the first major city to be hit by COVID (Baker and Fink, 2020), this figure highlights that King County is certainly not an outlier when it comes to cases, deaths or out-migration in 2020. One could argue that lock-downs or fears about the impacts of COVID could have led to consumption reductions of unhealthy foods or increased exercise. If such a mechanism was at play, however, it would have to be happening proportionately more in Seattle than in the rest of the country in order for it to impact our results, which seems unlikely.

Another concern could be that perhaps many overweight individuals who would otherwise have been surveyed by the BRFSS in 2020 died from COVID, leading the actual sample to look healthier than it would have in the counterfactual world where no pandemic took place. This makes some degree of sense as COVID is especially dangerous to overweight individuals. However, a quick back-of-the-envelope calculation suggests that this is unlikely to impact our results. In 2020, a total of 1,052 residents of King County died of COVID. In the same year, 2,400 residents out of a population of 2.3 million were surveyed for BRFSS. If each resident had an equal chance to be surveyed, the likelihood of any individual being contacted would be about one in a thousand. This suggests that we would only expect about one out of the 1,052 residents who died from COVID to have participated in the survey had they not died, making it vanishingly unlikely that the survey results in 2020 are skewed due to such an explanation.

4. Results

4.1. Main Specification

Figure 1 displays the main results of our analysis. In 2020, the average BMI of the treated group decreased by 0.61 points relative to 2018 when the tax was implemented, and obesity declined by 4.5 percentage points. We find no statically significant reduction in BMI or obesity in 2019, which is consistent with our expectation that weight reductions take time to materialize, even if SSB taxes immediately reduce consumption. We also find no discernible differences in the pre-trend in the outcome variables for the treated relative to the comparison group, strengthening the conclusion that the relative declines in outcomes in 2020 can be causally attributed to the implementation of the SSB tax. We interpret the relatively larger reduction in the rate of obesity as evidence that BMI reductions are concentrated within individuals with higher baseline BMIs who are near the obesity threshold.

4.2. Heterogeneous Treatment Effects

This section explores heterogeneous treatment effects across income, education, age, and gender. Figure 2 summarizes the heterogeneity that exists in baseline SSB consumption across these characteristics. This figure takes advantage of the fact that the 2016 BRFSS asked respondents a question about their SSB consumption and displays average consumption across groups. This question was removed from the survey in 2017 and therefore does not allow us to estimate the effect of the tax on consumption, but it does allow us to gain an understanding of the variation which exists in baseline consumption.

Figure 2 shows that respondents in the BRFSS survey report large differences in their average weekly SSB consumption. Individuals with lower incomes, lower levels of education, younger individuals, and men report relatively higher weekly consumption. Differences in consumption are the largest if we split the sample by years of education: Individuals with less than 12 years of education (i.e. no Highschool degree) report consuming more than twice as many (roughly 8) sugar sweetened beverages per week than individuals with 16 or more years of education (roughly 3 per week).

If the decreases in BMI and obesity discussed in section 4.1 are attributable to sugar sweetened beverage consumption reductions, we would expect to find larger improvements in the groups who consume more SSBs to begin with. Given that individuals with an annual income above $75K, people older than 65, and people with a Bachelor's degree only consume about three SSBs per week, an SSB tax might not be as effective in reducing BMI and obesity in these groups. On the other hand, for low income individuals who consume around eight SSBs per week, there is potential for serious health improvements by making SSBs more expensive. These taxes also hit low income individuals the hardest as they make up a larger share of their budget. For an individual consuming 8 SSBs per week, the tax alone could cost as much as $150 per year if they do not alter their consumption.[10]

Figures 3 repeats our main analysis with the sample split based on whether the respondent made more than $75,000 in income. Individuals making more than $75,000 show virtually no treatment effect, while those making less than $75,000 show statistically significant declines in 2020 which are larger than those from the full sample. BMI for lower-income individuals is reduced by 1.12 points in 2020, and the likelihood of obesity is reduced by 6.0 percentage points. Figure 4 repeats this exercise looking at college graduates versus non-college graduates and the results are similar. There is no clear treatment effect for college grads, while non-college grads show reductions of 1.03 BMI points and 7.0 percentage points in obesity.

Figure 5 splits the sample by age, looking the effects for individuals above and below 65. Older respondents, who consume far fewer SSBs at baseline, actually see small increases in BMI and obesity in 2020, while younger respondents see significant reductions of .71 BMI points and 5.8 percentage points in obesity. Finally, Figure 6 explores heterogeneous treatment effects by gender. In line with the relatively smaller consumption differences between men and women, we see reductions in both BMI and obesity for both groups, though the result is under powered when looking at BMI in males and obesity in females.

4.3. How do these results compare to the BMI reductions implied by other research?

This paper builds on a growing literature which has largely found that SSB taxes have led to reductions in purchases. While it makes intuitive sense that these reductions in purchases would lead directly to changes in BMI, it is not entirely obvious that this should be the case. If, for example, Seattle residents stopped buying SSBs and instead bought candy bars and potato chips, then we might not see any health benefits accrue to them. One way to test the extent to which consumers substituted towards other unhealthy items is to use the existing estimates from the literature on purchase reductions to calculate what the implied BMI reduction

[10]If they consume eight 20 ounce SSBs each week, the 1.75 cent per ounce tax would cost $2.80 per week and $145.6 annually.

would be if consumers did not substitute towards other unhealthy items at all. If the implied reductions are larger than what we find, this would suggest that some of the health benefits of the reduced SSB consumption are lost due to increased caloric intake from other sources.

This calculation provides an added benefit of testing the plausibility our estimates as being the causal effect of the SSB tax on BMI. The exercise effectively creates an 'upper bound' for the city-wide average BMI reductions that could realistically have been caused by the tax. If the purchase reduction estimates imply a much smaller effect than what we find, then it would be unrealistic to claim that the taxes fully caused the BMI reductions we document above.

We begin with the 22% decline in volume sold of taxed beverages in Seattle found by Powell and Leider, 2020b. Our goal is to take this estimate and figure out what size BMI effect we should expect to find in our data by 2020, the third year of the tax. To do this, we need to make a number of assumptions. First, we assume that pre-tax SSB consumption in Seattle was similar to the nationwide average of 4.7 SSBs per week in the 2016 BRFSS data.[11] Next, we assume that all Seattle residents reduce their consumption by 22%. This translates to a reduction in 1.03 SSBs per person. Since we do not know which SSBs each individual is consuming, we assume they are drinking 12 ounce Coca-Cola Classics, which is the most popular SSB in the United States. Each 12 ounce Coca-Cola contains 150 calories. We are therefore assuming that each Seattle resident is consuming 154.5 fewer calories each week (1.03*150=154.5). Over the first three years of the tax, this would suggest a reduction of 24,102 calories. We can then divide this by 3,500, which is the caloric equivalent of a pound, to get an estimate of the average weight loss among Seattle residents of 6.89 pounds.

Finally, in order to compare this implied reduction to our estimates, we need to account for the fact that only about two thirds of the BRFSS respondents in King County live in Seattle. We multiply our reduction of 6.89 pounds by two thirds to arrive at an average reduction of 4.56 across King County residents in the BRFSS

[11] None of the approximately 120,000 observations of the consumption variable are from King County residents, so we are unable to test whether their baseline consumption was different using this data.

data. We convert this into a BMI reduction by subtracting 4.56 off the the previous average weight in the BRFSS sample of 179.6 pounds and recalculating average BMI using the average height of five feet, seven inches. We compare the implied average BMI of 27.626 to the previous average of 28.239 to get an implied BMI reduction of .612. This amount is almost precisely equal to our actual estimate of a .610 reduction. The full calculation can be seen below:

$$E[WeightLoss] = \frac{4.7 * .22 * 150 * 52 * 3}{3500} * \frac{2}{3} = 4.56 \text{ Pounds} \tag{1}$$

We repeat this exercise for each demographic subgroup in our sample, with results from both our actual estimates (with 95% confidence intervals) as well as the implied reduction from our back of the envelope calculation displayed in Figure 7. It is important to note that since there could be heterogeneous responses to the tax among different groups, the implied estimates no longer serve as an upper bound for what we could expect to find in our data. Still, we would expect to find larger treatment effects for groups with higher baseline consumption.

There is a striking correlation between the implied reduction and our actual estimates across demographic groups. In each case, the implied estimate is included in our confidence interval. Overall, this exercise provides suggestive evidence that there was not a substantial amount of substitution towards other unhealthy foods, and also demonstrates that BMI the estimates from the previous section could realistically be attributable to the tax.

5. Conclusion

Despite a growing body of research showing that SSB taxes in the US have been effective at increasing the consumer price of targeted beverages and consequently reducing their consumption, relatively little evidence exists that these taxes have led to actual public health improvements. We build on this literature by demonstrating that both average BMI and obesity fell for adults in Seattle in the first three years following the implementation of their 2018 soda tax. We find a BMI reduction of 0.61 points and a reduction in obesity of 4.5 percentage points. These results suggest that SSB taxes can have a meaningful impact on the health outcomes of the general public, and may in fact be an effective tool to reduce the negative externality that is generated by SSB consumption.

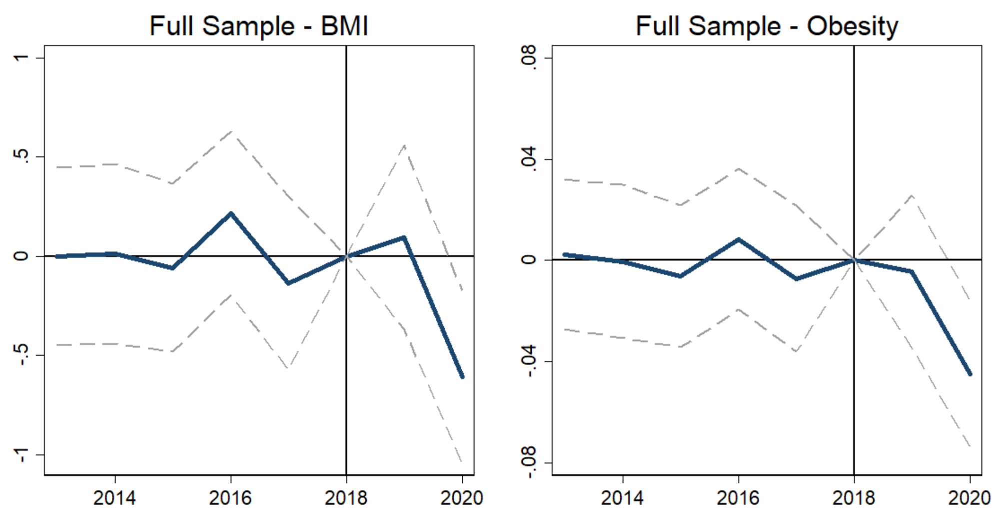
We also find that these effects are concentrated among lower income, less educated, and younger people, precisely the groups who consume more SSBs at baseline and stand to benefit more from reductions in BMI and obesity rates. We demonstrate that our results are plausibly attributable to the SSB tax by performing a back of the envelope calculation, which attempts to answer the question of what BMI reduction we should expect to find given the reductions in purchasing found in Powell and Leider, 2020b. We find that the implied BMI reduction from their work to be almost identical to our main finding. When we repeat this exercise for the various subgroups in our data, we find that the implied BMI reductions track closely with our actual findings, further suggesting that our results are plausible and that we could reasonably attribute them to the SSB tax in Seattle. While it is still too early to see whether these taxes have made a meaningful impact on other conditions like type II diabetes and heart disease, our findings lead us to speculate that future research may be able to uncover similar improvements in these outcomes. The findings and conclusions in this paper are those of the authors and do not necessarily represent the views of the Research Data Center, the National Center for Health Statistics, or the Centers for Disease Control and Prevention.

Table 1 — Observation Counts for SSB Taxes Counties - BRFSS 2013-2020

Year	King County	Philadelphia	Alameda County.	San Francisco	Boulder
2013	2,700	1,400	250	450	600
2014	2,600	1,100	150	350	600
2015	4,000	600	250	450	600
2016	3,500	600	250	450	750
2017	2,800	650	200	400	650
2018	2,500	700	150	400	600
2019	2,500	900	250	450	600
2020	2,400	600	80	150	650
Total	23,000	6,550	1,580	3,100	5,050

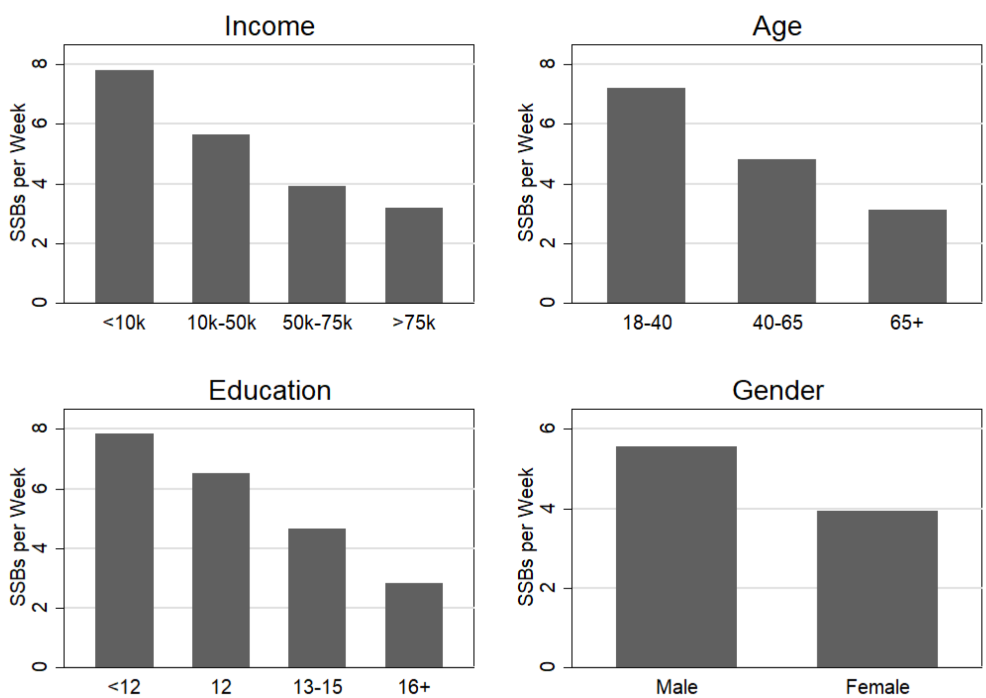
Note: This table displays observation counts in the Behavioral Risk Factor Surveillance System Survey (BRFSS) for each of the five SSB tax treated counties in each year from 2013 to 2020.

Figure 1 — The Effect of Seattle's Sugar-Sweetened Beverage Tax on BMI and Obesity: BRFSS 2013-2020



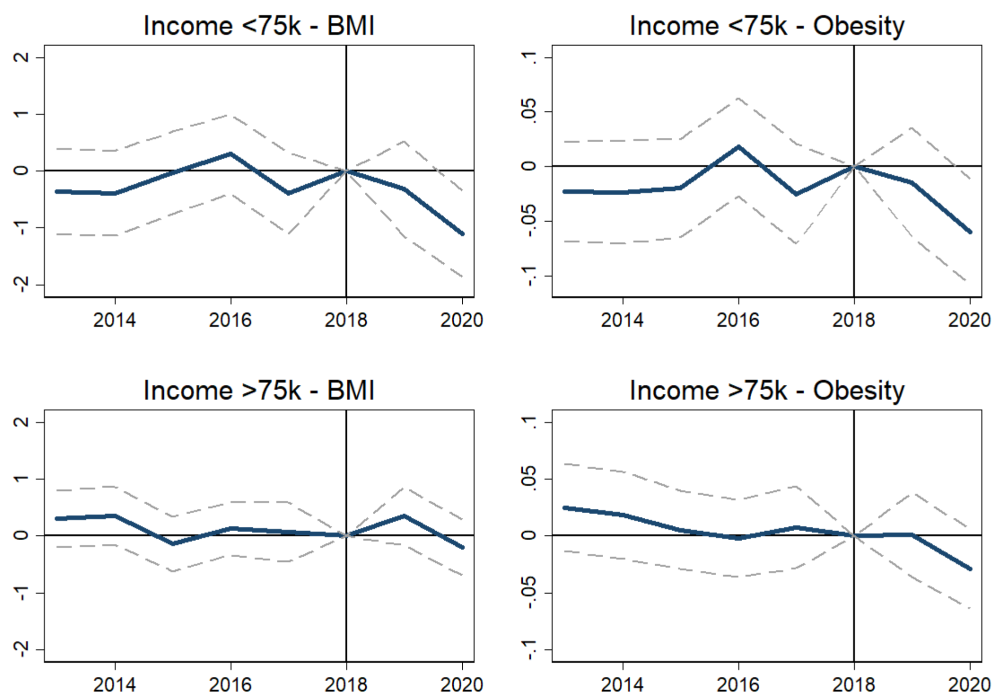
Note: Figure 1 shows the point estimates and 95% confidence intervals for the event-study design comparing the difference in outcomes in each year relative to 2018 in King County and comparison counties using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure 2 — Average Weekly SSB Consumption by Education, Marital Status, Education, and Age - BRFSS 2016



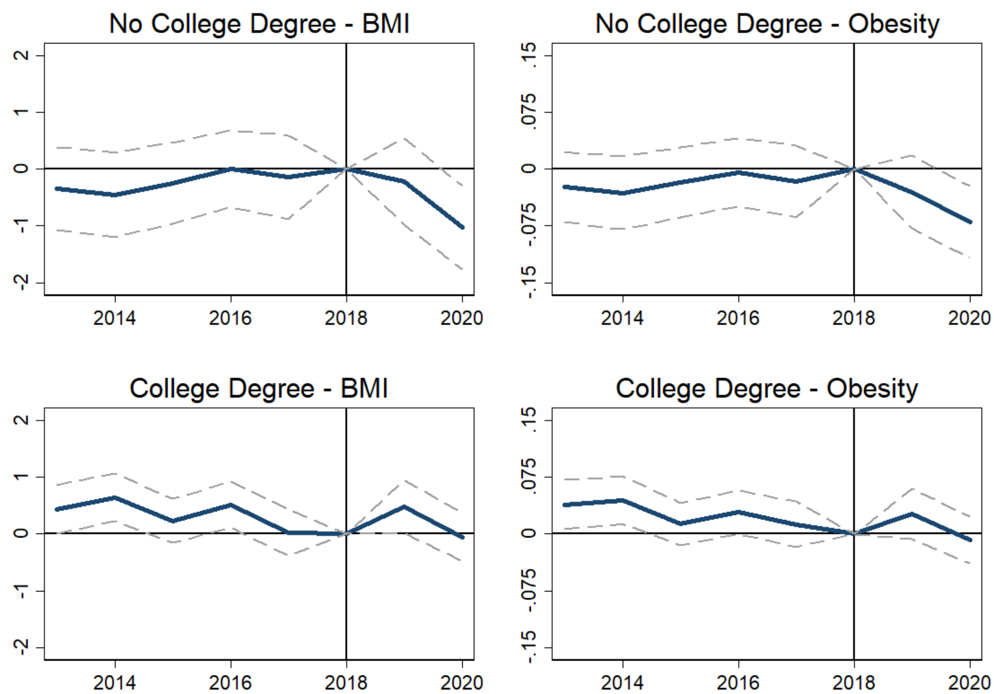
Note: Figure 2 displays average weekly SSB consumption for different groups, estimated using data from the 2016 BRFSS survey. The top left graph displays average SSB consumption by income, the top right displays SSB consumption by age group, the bottom left displays SSB consumption by education attainment (in completed years), and the bottom right displays SSB consumption by age group.

Figure 3 — The Effect of Seattle's Sugar-Sweetened Beverage Tax on BMI and Obesity, Incomes Above and Below 75k and Non-College Graduates and College Graduates: BRFSS 2013-2020



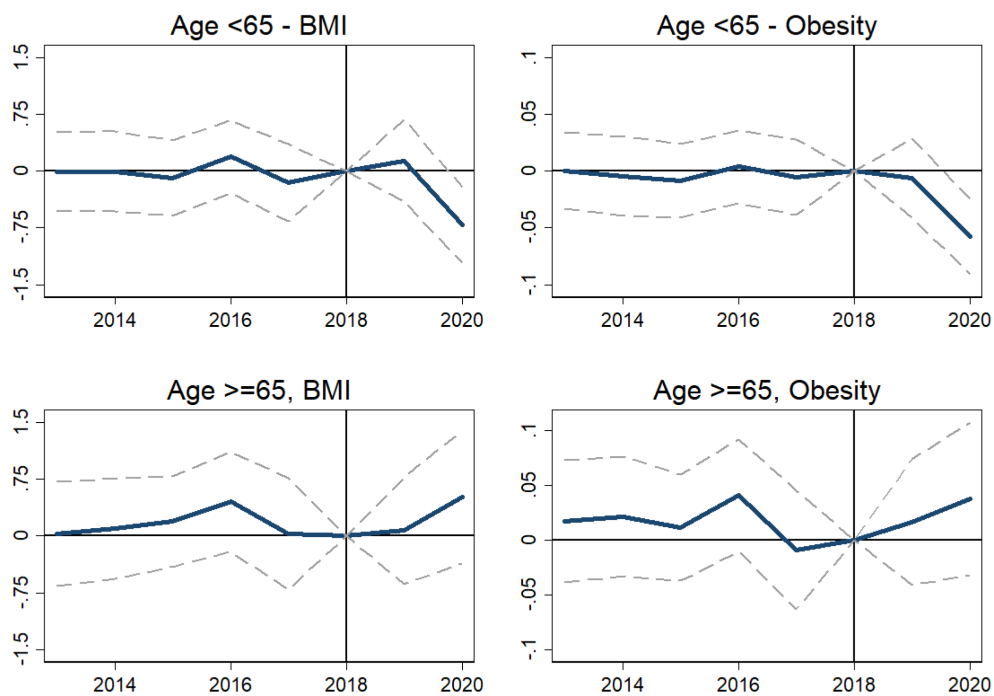
Note: Figure 3 shows the point estimates and 95% confidence intervals for the event-study design comparing the difference in outcomes in each year relative to 2018 in King County and comparison counties using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure 4 — The Effect of Seattle's Sugar-Sweetened Beverage Tax on BMI and Obesity, Incomes Above and Below 75k and Non-College Graduates and College Graduates: BRFSS 2013-2020



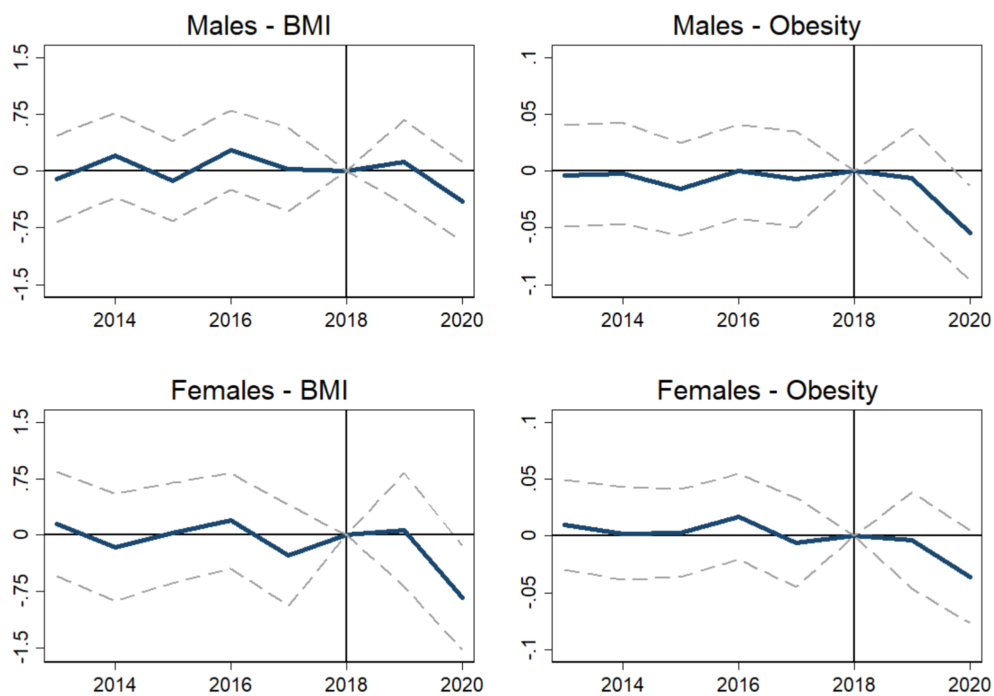
Note: Figure 4 shows the point estimates and 95% confidence intervals for the event-study design comparing the difference in outcomes in each year relative to 2018 in King County and comparison counties using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure 5 — The Effect of Seattle's Sugar-Sweetened Beverage Tax on BMI and Obesity, by Age above and below 65 and by Gender: BRFSS 2013-2020



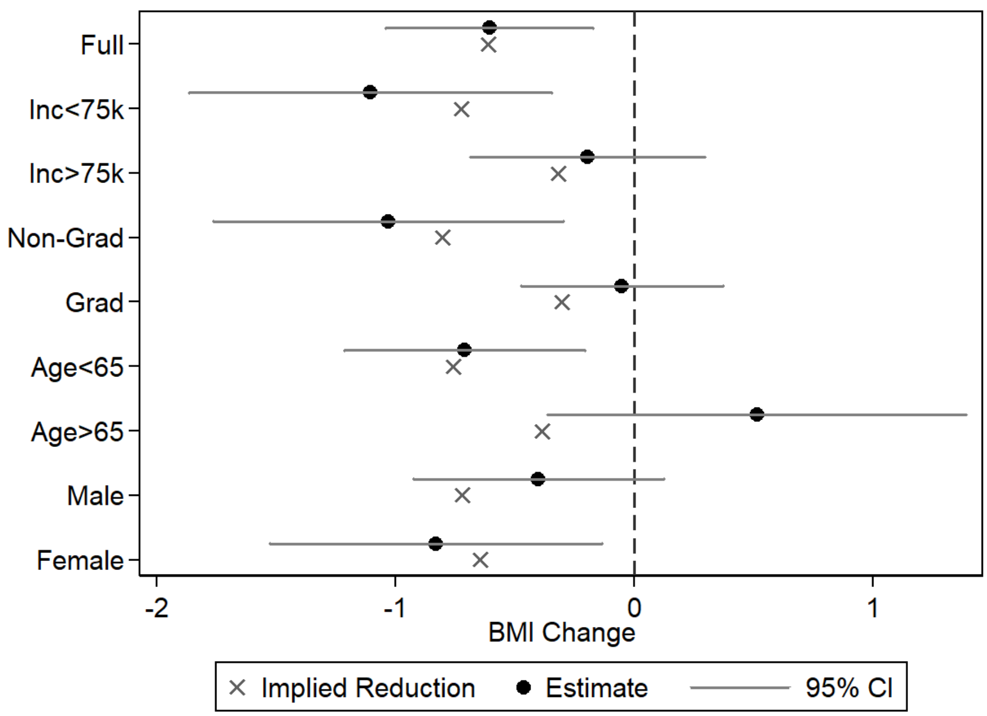
Note: Figure 5 shows the point estimates and 95% confidence intervals for the event-study design comparing the difference in outcomes in each year relative to 2018 in King County and comparison counties using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure 6 — The Effect of Seattle's Sugar-Sweetened Beverage Tax on BMI and Obesity, by Age above and below 65 and by Gender: BRFSS 2013-2020



Note: Figure 6 shows the point estimates and 95% confidence intervals for the event-study design comparing the difference in outcomes in each year relative to 2018 in King County and comparison counties using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure 7 — Comparison of our Event-Study Estimates for 2020 with the Implied BMI Reduction from Powell and Leider, 2020b



Note: Figure 7 compares the implied reductions based on the estimate of a 22% reduction in SSB purchases from Powell and Leider, 2020b, with our actual estimates using data from the Behavioral Risk Factor Surveillance System Survey (BRFSS). We calculate the implied estimate for each group by taking their baseline SSB consumption and assuming each group reduced consumption by 22%. We multiply this reduction by two thirds, which is the likelihood that a King County resident in the BRFSS data resides in Seattle and is therefore impacted by the tax. We then multiply implied SSB consumption reduction by the caloric content of a 12 ounce Coca-Cola (150 calories) and calculate the weight they would be expected to lose over the three years the soda tax was in effect from 2018-2020. Finally, we subtract the calculated weight loss from the group's average weight prior to the SSB tax and recalculate their implied BMI.

References

Aguilar, Arturo, Emilio Gutierrez, and Enrique Seira (2021). "The effectiveness of sin food taxes: Evidence from Mexico". In: *Journal of Health Economics* 77, p. 102455. ISSN: 0167-6296.

Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky (May 2019). "Regressive Sin Taxes, with an Application to the Optimal Soda Tax*". In: *The Quarterly Journal of Economics* 134.3, pp. 1557–1626. ISSN: 0033-5533.

Alston, Julian M, Joanna P MacEwan, and Abigail M Okrent (2016). "The economics of obesity and related policy". In: *Annual Review of Resource Economics* 8, pp. 443–465.

Baker, Michael and Sheri Fink (Apr. 2020). "COVID-19 Arrived in Seattle. Where It Went From There Stunned the Scientists." In: *The New York Times*.

Bollinger, Bryan and Steven E. Sexton (2018). "Local Excise Taxes, Sticky Prices, and Spillovers: Evidence from Berkeley's Soda Tax". In: *Political Economy: Fiscal Policies and Behavior of Economic Agents eJournal*.

Cawley, John, Michael Daly, and Rebecca Thornton (2022). "The effect of beverage taxes on youth consumption and body mass index: Evidence from Mauritius". In: *Health Economics* 31.6, pp. 1033–1045.

Cawley, John, David Frisvold, et al. (2019). "The impact of the Philadelphia beverage tax on purchases and consumption by adults and children". In: *Journal of Health Economics* 67, p. 102225. ISSN: 0167-6296.

Cawley, John and Chad Meyerhoefer (2012). "The medical care costs of obesity: An instrumental variables approach". In: *Journal of Health Economics* 31.1, pp. 219–230. ISSN: 0167-6296.

CDC (Mar. 2023).

Cengiz, Doruk et al. (May 2019). "The Effect of Minimum Wages on Low-Wage Jobs*". In: *The Quarterly Journal of Economics* 134.3, pp. 1405–1454. ISSN: 0033-5533.

Dehghan, Mahshid et al. (2017). "Associations of fats and carbohydrate intake with cardiovascular disease and mortality in 18 countries from five continents (PURE): a prospective cohort study". In: *The Lancet* 390.10107, pp. 2050–2062.

Dubois, Pierre, Rachel Griffith, and Martin O'Connell (Nov. 2020). "How Well Targeted Are Soda Taxes?" In: *American Economic Review* 110.11, pp. 3661–3704.

Duffey, Kiyah J. et al. (Mar. 2010). "Food Price and Diet and Health Outcomes: 20 Years of the CARDIA Study". In: *Archives of Internal Medicine* 170.5, pp. 420–426. ISSN: 0003-9926.

Ebbeling, Cara B. et al. (June 2012). "Effects of Dietary Composition on Energy Expenditure During Weight-Loss Maintenance". In: *JAMA* 307.24, pp. 2627–2634. ISSN: 0098-7484.

Edmondson, Emma K. et al. (Dec. 2021). "Association of a Sweetened Beverage Tax With Soda Consumption in High School Students". In: *JAMA Pediatrics* 175.12, pp. 1261–1268. ISSN: 2168-6203.

Falbe, Jennifer et al. (2016). "Impact of the Berkeley Excise Tax on Sugar-Sweetened Beverage Consumption". In: *American Journal of Public Health* 106.10. PMID: 27552267, pp. 1865–1871.

Finkelstein, EA et al. (Jan. 2013). "Implications of a sugar-sweetened beverage (SSB) tax when substitutions to non-beverage items are considered". In: *Journal of Health Economics* 32, pp. 219–39.

Flegal, Katherine M et al. (2019). "Comparisons of self-reported and measured height and weight, BMI, and obesity prevalence from national surveys: 1999-2016". In: *Obesity* 27.10, pp. 1711–1719.

Fletcher, Jason, David Frisvold, and Nathan Tefft (2010). "The effects of soft drink taxes on child and adolescent consumption and weight outcomes". In: *Journal of Public Economics* 94.11-12, pp. 967–974.

Flynn, James (2023). "Do sugar-sweetened beverage taxes improve public health for high school aged adolescents?" In: *Health Economics* 32.1, pp. 47–64.

— (2024). "Soda taxes, consumption, and health outcomes for high school students". In: *Economics Letters* 234, p. 111507. ISSN: 0165-1765.

Goodman-Bacon, Andrew (2021). "Difference-in-differences with variation in treatment timing". In: *Journal of Econometrics* 225.2. Themed Issue: Treatment Effect 1, pp. 254–277. ISSN: 0304-4076.

Gračner, Tadeja, Fernanda Marquez-Padilla, and Danae Hernandez-Cortes (Feb. 2022). “Changes in Weight-Related Outcomes Among Adolescents Following Consumer Price Increases of Taxed Sugar-Sweetened Beverages”. In: *JAMA Pediatrics* 176.2, pp. 150–158. ISSN: 2168-6203.
Imamura, Fumiaki et al. (2015). “Consumption of sugar sweetened beverages, artificially sweetened beverages, and fruit juice and incidence of type 2 diabetes: systematic review, meta-analysis, and estimation of population attributable fraction”. In: *BMJ* 351.
Jackson, KE et al. (2023). “Sweetened Beverage Taxes and Perinatal Health: A Quasi-Experimental Study.” In: *Am J Prev Med.* 25.
Jenkins, David J.A. et al. (2021). “Glycemic Index, Glycemic Load, and Cardiovascular Disease and Mortality”. In: *New England Journal of Medicine* 384.14. PMID: 33626252, pp. 1312–1322.
Jones-Smith, Jessica C., Melissa A. Knox, et al. (May 2024). “Sweetened Beverage Tax Implementation and Change in Body Mass Index Among Children in Seattle”. In: *JAMA Network Open* 7.5, e2413644–e2413644. ISSN: 2574-3805.
Jones-Smith, Jessica C., Lina Pinero Walkinshaw, et al. (2020). “Impact of a sweetened beverage tax on beverage prices in Seattle, WA”. In: *Economics Human Biology* 39, p. 100917. ISSN: 1570-677X.
Khan, A et al. (2021). “Association of carbonated soft drink and fast food intake with stress-related sleep disturbance among adolescents: A global perspective from 64 countries.” In: *EClinicalMedicine.*
Krieger, James et al. (2021). “How sugar-sweetened beverage tax revenues are being used in the United States”. In: *Preventive Medicine Reports* 23, p. 101388.
Lee, Matthew M. et al. (2019). “Sugar-Sweetened Beverage Consumption 3 Years After the Berkeley, California, Sugar-Sweetened Beverage Tax”. In: *American Journal of Public Health* 109.4. PMID: 30789776, pp. 637–639.
Leider, Julien and Powell (2022). “Longer-term impacts of the Oakland, California, sugar-sweetened beverage tax on prices and volume sold at two-years post-tax”. In: *Social Science Medicine* 292, p. 114537. ISSN: 0277-9536.
Lemmens, Valery Eduard Petronius Paulus et al. (2008). “A systematic review of the evidence regarding efficacy of obesity prevention interventions among adults”. In: *Obesity reviews* 9.5, pp. 446–455.
Liechty, JM, X Bi, and A. Qu (2016). “Feasibility and validity of a statistical adjustment to reduce self-report bias of height and weight in wave 1 of the Add Health study.” In: *BMC Med Res Methodol.* 16(1).
Mozaffarian, Dariush et al. (2011). “Changes in Diet and Lifestyle and Long-Term Weight Gain in Women and Men”. In: *New England Journal of Medicine* 364.25. PMID: 21696306, pp. 2392–2404.
Oddo, Vanessa M, Julien Leider, and Lisa M Powell (2021). “The Impact of Seattle’s Sugar-Sweetened Beverage Tax on Substitution to Sweets and Salty Snacks”. In: *The Journal of Nutrition* 151.10, pp. 3232–3239. ISSN: 0022-3166.
Pérez, A. et al. (2015). “Measuring the bias, precision, accuracy, and validity of self-reported height and weight in assessing overweight and obesity status among adolescents using a surveillance system.” In: *Int J Behav Nutr Phys Act* 2.
Powell, J Chriqui, et al. (2013). “Assessing the potential effectiveness of food and beverage taxes and subsidies for improving public health: a systematic review of prices, demand and body weight outcomes”. In: *Obesity Reviews* 14.2, pp. 110–128.
Powell and Julien Leider (Dec. 2020a). “Evaluation of Changes in Beverage Prices and Volume Sold Following the Implementation and Repeal of a Sweetened Beverage Tax in Cook County, Illinois”. In: *JAMA Network Open* 3.12, e2031083–e2031083. ISSN: 2574-3805.
Powell, Lisa and Julien Leider (2020b). “The impact of Seattle’s Sweetened Beverage Tax on beverage prices and volume sold”. In: *Economics Human Biology* 37, p. 100856. ISSN: 1570-677X.
Powell, Lisa, Julien Leider, and Pierre Leger (2020). “The Impact of a Sweetened Beverage Tax on Beverage Volume Sold in Cook County, Illinois, and Its Border Area”. In: *Annals of Internal Medicine* 172.6. PMID: 32092766, pp. 390–397.
Powell, Lisa M., Julien Leider, and Vanessa M. Oddo (Nov. 2021). “Evaluation of Changes in Grams of Sugar Sold After the Implementation of the Seattle Sweetened Beverage Tax”. In: *JAMA Network Open* 4.11, e2132271–e2132271. ISSN: 2574-3805.
Rippe, James M. and Theodore J. Angelopoulos (2016). “Relationship between Added Sugars Consumption and Chronic Disease Risk Factors: Current Understanding”. In: *Nutrients* 8.11. ISSN: 2072-6643.

Roberto, Christina A. et al. (May 2019). “Association of a Beverage Tax on Sugar-Sweetened and Artificially Sweetened Beverages With Changes in Beverage Prices and Sales at Chain Retailers in a Large Urban Setting”. In: *JAMA* 321.18, pp. 1799–1810. ISSN: 0098-7484.

Ruyter, Janne C. de et al. (2012). “A Trial of Sugar-free or Sugar-Sweetened Beverages and Body Weight in Children”. In: *New England Journal of Medicine* 367.15. PMID: 22998340, pp. 1397–1406.

Santos, F. L. et al. (2012). “Systematic review and meta-analysis of clinical trials of the effects of low carbohydrate diets on cardiovascular risk factors”. In: *Obesity Reviews* 13.11, pp. 1048–1066.

SBTCAB (2018). “2018 Annual Report - Seattle’s Sweetened Beverage Tax”. In: *Sweetened Beverage Tax Community Advisory Board.*

— (2019). “2019 Annual Report - Seattle’s Sweetened Beverage Tax”. In: *Sweetened Beverage Tax Community Advisory Board.*

— (2020). “2020 Annual Report - Seattle’s Sweetened Beverage Tax”. In: *Sweetened Beverage Tax Community Advisory Board.*

Seiler, Stephan, Anna Tuchman, and Song Yao (2021). “The Impact of Soda Taxes: Pass-Through, Tax Avoidance, and Nutritional Effects”. In: *Journal of Marketing Research* 58.1, pp. 22–49.

Silver, L. et al. (2017). “Changes in prices, sales, consumer spending, and beverage consumption one year after a tax on sugar-sweetened beverages in Berkeley, California, US: A before-and-after study”. In: *PLoS Medicine* 14.

Te Morenga, Lisa A et al. (May 2014). “Dietary sugars and cardiometabolic risk: systematic review and meta-analyses of randomized controlled trials of the effects on blood pressure and lipids”. In: *The American Journal of Clinical Nutrition* 100.1, pp. 65–79. ISSN: 0002-9165.

Wang, Xuanwen et al. (2016). “Occupational Medicine & Health Affairs”. In.

Williams, RH et al. (2008). “Adaptive sugar sensors in hypothalamic feeding circuits.” In: *Proceedings of the National Academy of Sciences.*

Xi, Bo et al. (2015). “Sugar-sweetened beverages and risk of hypertension and CVD: a dose–response meta-analysis”. In: *British Journal of Nutrition* 113.5, pp. 709–717.

Zhong, Yichen, Amy H Auchincloss, Brian K Lee, and Genevieve P Kanter (2018). “The Short-Term Impacts of the Philadelphia Beverage Tax on Beverage Consumption.” In: *Am J Prev Med.*

Zhong, Yichen, Amy H. Auchincloss, Brian K. Lee, Ryan M. McKenna, et al. (2020). “Sugar-Sweetened and Diet Beverage Consumption in Philadelphia One Year after the Beverage Tax”. In: *International Journal of Environmental Research and Public Health* 17.4. ISSN: 1660-4601.

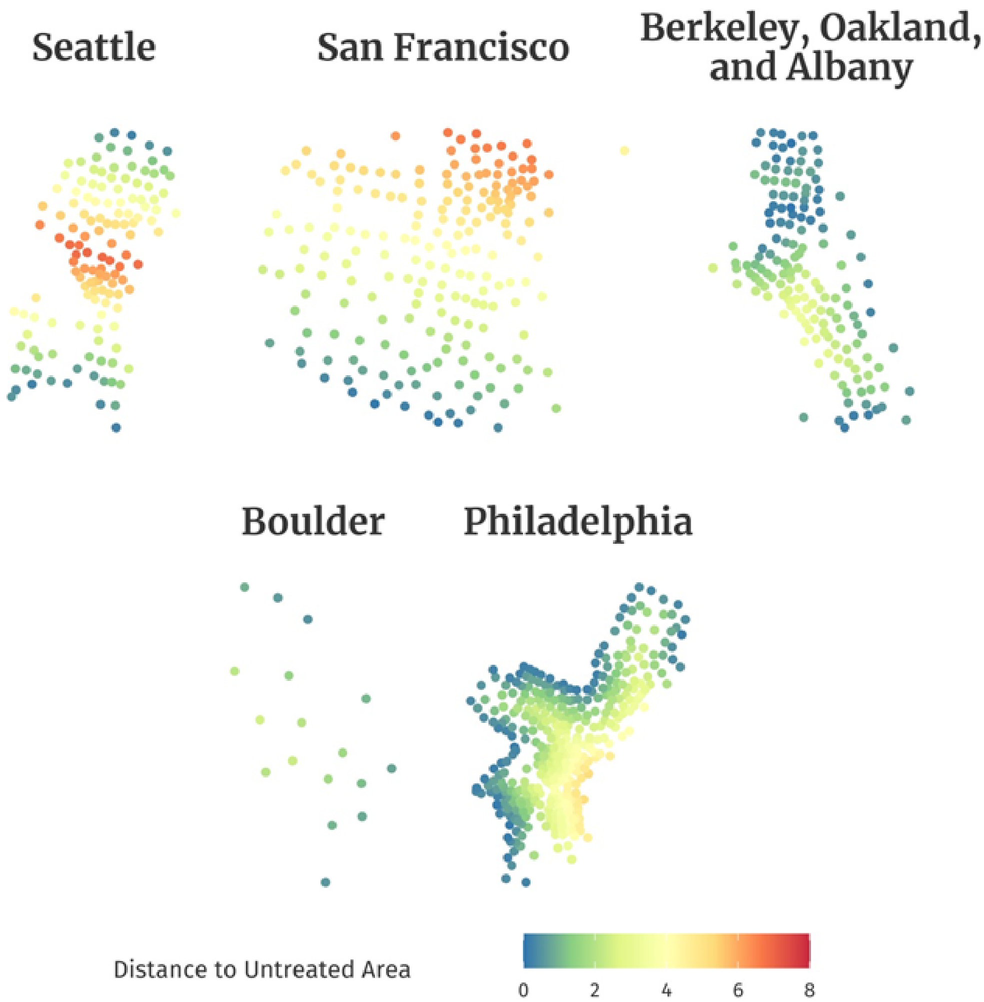
A. Online Appendix (Not for Publication)

Table A.1 — Important Details for Sugar-Sweetened Beverage Taxes in the US

City	Approval Date	Effective Date	Cents per Oz.	Diet Drinks Taxed?
Berkeley	Nov. 2014	Jan 1, 2015	1	No
Philadelphia	June 2016	Jan 1, 2017	1.5	Yes
Oakland	Nov. 2016	July 1, 2017	1	No
Albany	Nov. 2016	April 1, 2017	1	No
San Francisco	Nov. 2016	Jan. 1, 2018	1	No
Boulder	Nov. 2016	July 1, 2017	2	No
Seattle	June 2017	Jan. 1, 2018	1.75	No

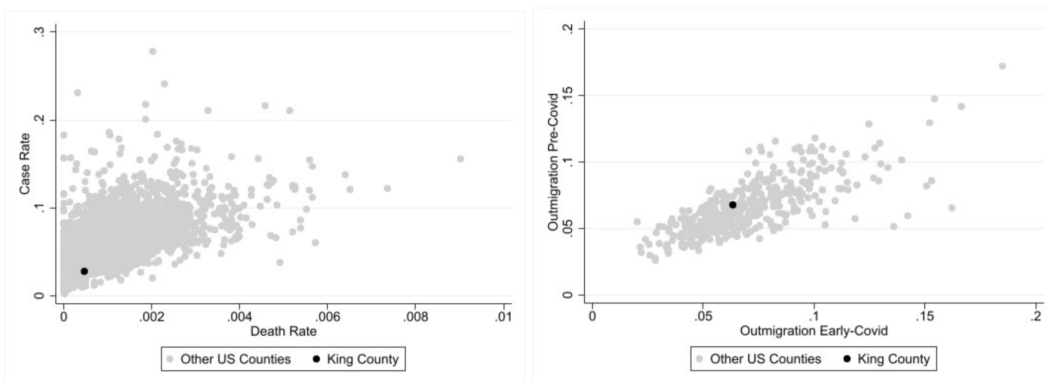
Note: This table displays the relevant details for each SSB tax that remains in place in the United States. For each tax, the table includes the city where the tax was levied, the date it was approved, the date it went into effect, the cost of the tax in cents per ounce of liquid, and an indicator for whether diet drinks are taxed.

Figure A.1 — Distance to Untaxed Land Border for each Census Tract in SSB Taxed Cities in the US



Note: This figure displays all of the census tracts in the seven American cities with a sugar sweetened beverage tax. The color of each census tract represents the distance from the centroid of that census tract to an untaxed land border.

Figure A.2 — COVID-19 Incidence and Impact on Migration in King County



Note: The left panel of this figure shows the case and death rate of COVID-19 in 2020 for King County and all other counties in the US, calculated from NYT Covid-tracker data divided by 2020 county-level census counts. The right panel shows the pre-COVID average percentage of adults leaving the county in the following year from 2013-2018, and the early-Covid percentage of adults leaving the county within a year in 2019 for King county and all other counties in the US that are large enough to be identified in the American Community Survey (ACS).

B. Estimating the Effect of SSB Taxes Across Treated Counties

In this section, we estimate the effect of sugar-sweetened beverage taxes on all treated counties in the US. In the main paper, we focused on Seattle because only King County, WA, had enough observations to pick up a treatment effect. Here we expand our analysis to include the other counties as well, in order to demonstrate that the results in other treated counties are consistent with our main findings, if slightly noisier and less reliable.

We begin by combining all treated counties into a single regression and implementing the 'stacked differences-in-differences' estimator of Cengiz et al. (2019). Here, in order to address the issues that can arise with staggered treatment timing (Goodman-Bacon, 2021), we create separate 'stacks' for each group that received treatment in a given year. Each stack contains the treated observations from that year as well as all of the never-treated observations, with the observations treated in different periods omitted. This results in three stacks, with one treated in 2015, one in 2017, and one in 2018. The stacks are then appended onto one another and we run the standard two-way fixed effect event-study specification, with an additional fixed effect for each stack. The results for the full set of treated observations is displayed in Figure B.1. In the graph on the left of the figure, BMI is the dependent variable, while an indicator for obesity status is the dependent variable on the right.

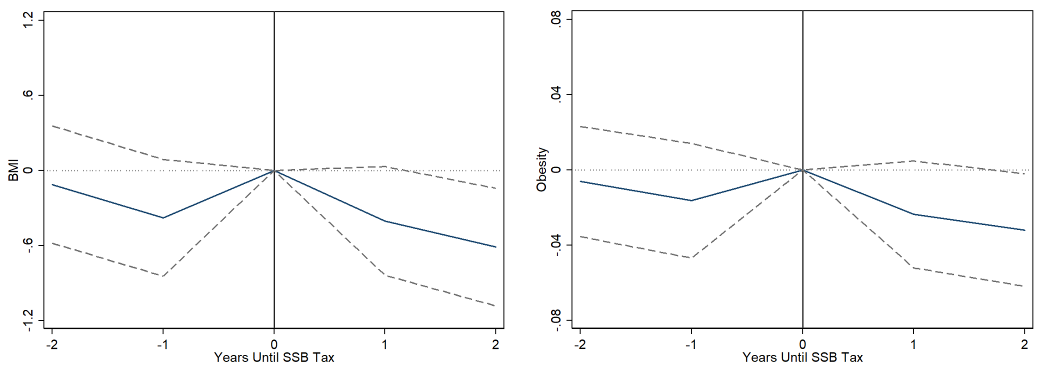
In both cases, we see economically meaningful, statistically significant declines in the second year after the tax goes into effect. There is a reduction of .61 BMI points (p-value=.005) and a reduction in the likelihood of obesity of 3.2 percentage points (p-value=.018). In both cases, the pre-treatment leads are insignificant, but they are also negative are not statistically significantly different than the post-treatment lags, raising concerns about whether the reduction in year two is entirely driven by a causal effect of the policy, or could be partially driven by a reversion to the mean.

Figures B.2 and B.3 display individual event-study estimates for each treated county in the US, aside from King County, WA, which was analyzed in the main portion of the paper. The top left graph displays Alameda County, CA, which includes Oakland, Berkeley, and Albany, CA, each of which enacted a tax during our sample window. As evident in Table 1, there are never more than 300 observations in any given year from Alameda County, so it is perhaps unsurprising that the confidence intervals are so large and imprecise.

Philadelphia, Boulder, and San Francisco all show some evidence of reductions following the taxes, though again statistical power is an issue. Philadelphia displays a significant reduction in BMI in the second year after the tax, but there are also negative and significant estimates on the pretreatment leads as well. Among the treated counties, Philadelphia had the largest variance in the number of observations per year, fluctuating from a high of over 1,400 in 2013 to just 600 in 2015 and 2016, so it is possible that the noisy pre-treatment estimates are due to these swings in sample size.

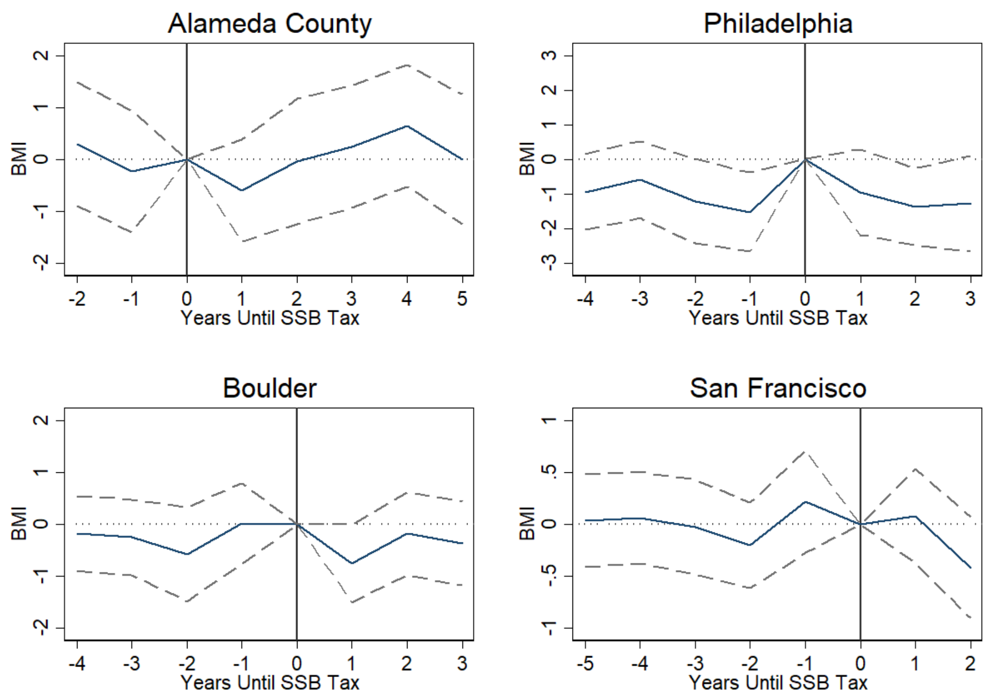
The event-study estimates for both San Francisco and Boulder show suggestive evidence of a treatment effect on both outcomes, with small and insignificant estimates on all of the pretreatment leads, followed by negative but insignificant estimates on the post-treatment lags as well. For both, the point estimates on the post-treatment reductions are larger in magnitude than any of the pretreatment leads, but again they are underpowered to find a compelling treatment effect. Taken together, the results from including observations from the other treated counties in the US are largely consistent with our main estimates, though they are more noisily estimated and slightly more difficult to interpret.

Figure B.1 — Stacked DiD Estimates of the Effect of Sugar-Sweetened Beverage Taxes on BMI and Obesity



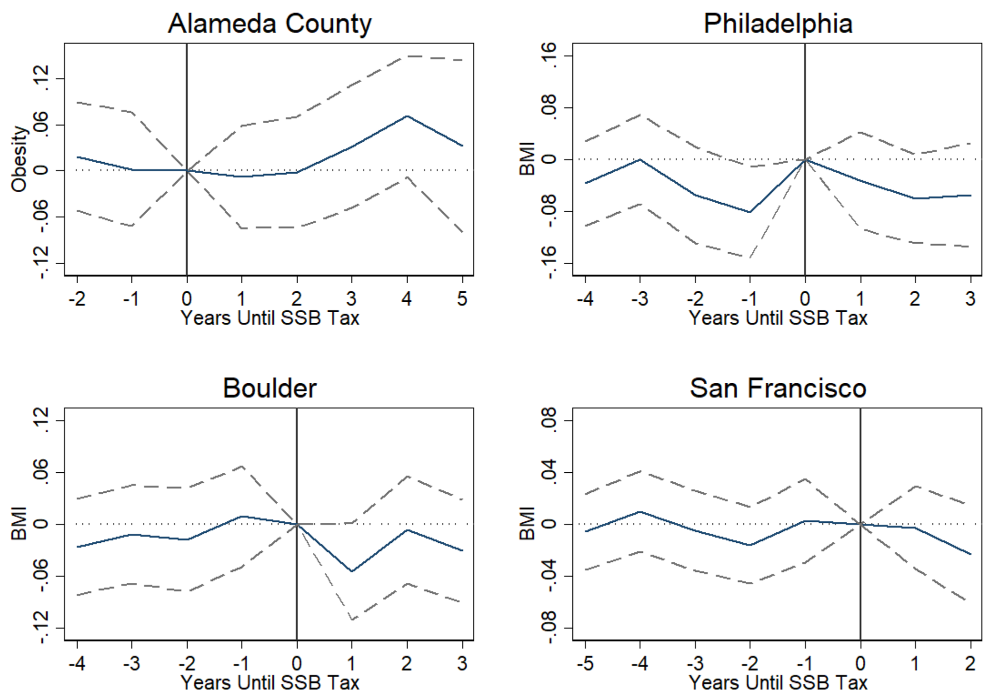
Note: This figure displays point estimates and 95% confidence intervals for the event-study design estimating the effect of a sugar-sweetened beverage tax on both BMI and the rate of obesity using data from the 2013-2020 BRFSS surveys. These specifications implement the 'stacked difference-in-differences' method of Cengiz et al. (2019). All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure B.2 — Event-Study Estimates of the Effect of Sugar-Sweetened Beverage Taxes on BMI in Each of the Treated Counties in the United States, Apart from King County, WA



Note: This figure displays point estimates and 95% confidence intervals for the event-study design estimating the effect of a sugar-sweetened beverage tax on BMI for each of the treated counties in the US apart from King County, WA, using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.

Figure B.3 — Event-Study Estimates of the Effect of Sugar-Sweetened Beverage Taxes on the rate of obesity in Each of the Treated Counties in the United States, Apart from King County, WA



Note: This figure displays point estimates and 95% confidence intervals for the event-study design estimating the effect of a sugar-sweetened beverage tax on the rate of obesity for each of the treated counties in the US apart from King County, WA, using data from the 2013-2020 BRFSS surveys. All regressions include year, month, and county fixed effects as well as a vector of individual controls. Standard errors are clustered at the county level.