

# Can Pigouvian taxes reduce pigging out? The Effect of Philadelphia's Sweetened Beverage Tax on Obesity and Diabetes

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## **Abstract:**

This study evaluates the impact of Philadelphia's 2017 beverage tax on obesity and diabetes rates using Synthetic Control and Difference-in-Differences methods. While the policy reduced consumption in prior research, downstream health effects remain unclear. The synthetic control model for obesity demonstrates a strong pre-treatment fit ( $MSPE = 0.0015$ ) and reveals no post-treatment divergence. A Difference-in-Differences model estimates a 1.9 percentage point reduction in obesity, with weak credibility. Diabetes models, for both approaches, show null results or poor pre-treatment fit. These findings suggest that the short-run effects of the beverage tax on chronic health outcomes are limited.

## **1. Introduction**

In June 2016, the Philadelphia City Council voted on a sweetened beverage tax, a cornerstone policy of the new Mayor, Jim Kenney. This proposal attracted significant outside attention: the beverage lobby spent over \$10 million in opposition. Proponents like New York Billionaire Michael Bloomberg spent millions in support.<sup>1</sup> It even became a wedge issue in the 2016 Democratic presidential primary.<sup>2</sup> People phonebanked, and media campaigns were dominated by dire warnings and sweet promises.

A 1.5¢/oz excise tax was passed. Philadelphians now pay 1.5¢ more per oz of sugary liquid. All sweetened beverages are taxed at the same rate, regardless of sugar density, including diet beverages. This

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<sup>1</sup> [The Beverage Lobby Spent \\$10.6 Million to Kill the Soda Tax — and Failed | Philly Mag 2016](#)

<sup>2</sup> [Bernie Sanders Op-Ed: A Soda Tax Would Hurt Philly's Low-Income Families | Philly Mag 2016](#)

comes out to approximately 18¢ per can of soda, or \$1 for a two-liter bottle, on top of the normal price. While a 1.5¢/oz tax is high (San Francisco charges 1¢/oz)<sup>3</sup>, it is significantly lower than the 3¢/oz initially proposed. Mayor Kenney’s office argued that it would generate “sweet health rewards”<sup>4</sup> for Philadelphia, estimating it would save 350 lives. They claimed the beverage tax would prevent 968 diabetes cases annually, and 14,000 obesity cases over ten years.<sup>5</sup>

From 2017 to the beginning of 2024, the Philadelphia Beverage Tax raised \$518 million in revenue, or \$73 million annually, on average. The largest beneficiary of this revenue was Philadelphia Pre-K, paying for 5,250 slots at \$10,000 each.<sup>6</sup> Other recipients include community schools and Rebuild Philadelphia, an urban revitalization program.<sup>7</sup>

This creates tension between the public health and revenue goals; any programs funded are funded by consumption. Reduced consumption due to taxation could reduce tax revenue if consumption drops faster than projected. On one hand, the decline in consumption is desirable from a public health standpoint. On the other hand, promised programs might not get funded.

## **2. Literature**

A beverage tax is a Pigouvian tax. The key assumption is that sweetened beverages have negative externalities associated with their consumption, a cost not reflected in the price. Numerous studies have shown sugar consumption is associated with obesity and diabetes (Huang et. al 2023). Increased rates of obesity and diabetes lead to significant negative health impacts. (MacEwan, Chiu et. al 2023) The estimated economic cost of diabetes nationally was estimated at \$413 billion in 2022. (Parker, Lin et. al 2024) These costs are absorbed not just by the drinkers of sugary drinks, but by the entire economy and health system supporting them. The Pigouvian tax aims to capture this externality, by charging consumers for the costs associated with their consumption. According to theory, the higher taxed price will reduce

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<sup>3</sup> [Sugary Drinks Tax | San Francisco Treasurer and Tax Collector](#)

<sup>4</sup> [ICYMI: Philly's Soda Tax Will Bring Sweet Health Rewards: Harvard Study | Philadelphia.gov 2016](#)

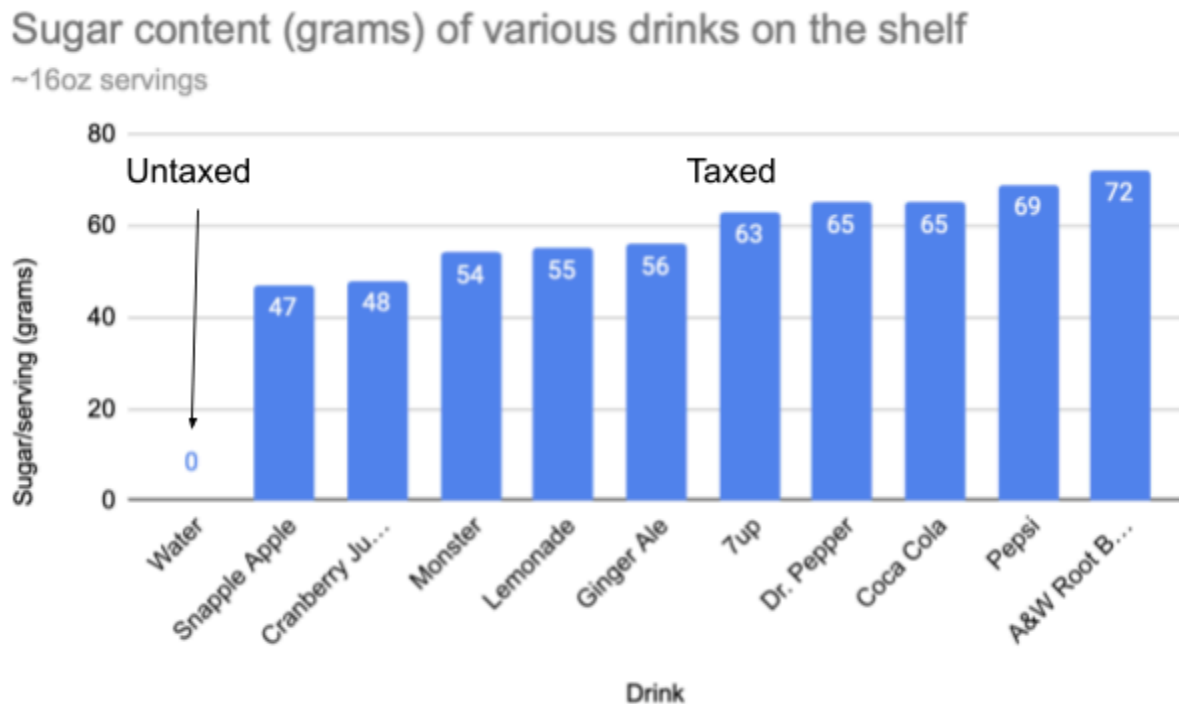
<sup>5</sup> [BRIEF: COST-EFFECTIVENESS OF A SUGAR-SWEETENED AND DIET BEVERAGE EXCISE TAX IN PHILADELPHIA, PA | Clear Choices 2016](#)

<sup>6</sup> [Philadelphia Beverage Tax Eclipses \\$500 Million in Revenue | Office of the Philadelphia Controller. 2024](#)

<sup>7</sup> [Controller's Office Releases Philadelphia Beverage Tax Revenue and Expenditures | 2018](#)

the negative externalities by encouraging consumer substitution; consumers will balk at a price reflecting the true (harmful) consumption costs, and be more likely to choose healthier untaxed alternatives such as water.

Figure 1.



Data: sugar content of various drinks in a census conducted at the Foggy Bottom CVS.

According to a 2013 CDC Report based on the National Health and Nutrition Survey, Americans received around 13% of their daily calories from added sugar. Of that 13%, only 33% of the added sugar was consumed in beverage form, the rest from food.<sup>8</sup>

There is strong evidence Philadelphia's beverage tax alters purchasing behavior. Based on sales data from large retailers, prices of taxed beverages increased by an average of 1.02¢/oz in the two years after the policy was implemented, suggesting 68% of the 1.5¢/oz tax was passed on to consumers. This translates to a 29% price increase. (Petimar, Gibson et. al 2022) Another study suggests that taxed beverage prices may have increased by as much as 1.55¢/oz (Cawley, Frivsold et. al. 2019).

<sup>8</sup> [Consumption of Added Sugars Among U.S. Adults, 2005–2010 | CDC 2013](#)

Petimar et. al. found a 50% reduction in sales of taxed beverages in Philadelphia. Sales of these beverages increased by 16% in stores bordering Philadelphia county lines, suggesting many consumers now travel further to avoid the tax. They found no change in the consumption of high-calorie foods and alcohol and little change in consumption of untaxed beverages. They also discovered a 34% increase in consumption of non-taxed beverage concentrates—some consumers may be evading the tax by mixing their own drinks.

Philadelphia adults showed a 31% decline in soda consumption associated with the tax, with no discernable impact on youth, aside from youth who frequently consumed soda, who reduced consumption. African Americans saw slightly greater drops in sugar consumption due to the policy (Cawley, Frivsold et. al. 2019).

On the other hand, this overall drop in daily sugar consumption was marginal: adult consumption decreased by 5.9 grams of sugar or 23.6 calories. This is only 1.2% of the FDA-recommended daily intake for a 35-year-old woman living a moderate lifestyle (2,000 calories)<sup>9</sup> (Cawley, Frivsold et. al. 2019). The authors calculate a sustained daily reduction of 23.6 calories would be associated with a 2-pound reduction in weight.

Empirical studies on the effects of sweetened beverage taxes on obesity and other health indicators are rare; most analyses rely on modeling. In a global systematic review of 18 eligible studies on sugary beverage taxes, 16 showed reduced consumption. Twelve relied on modeling. Thirteen studies examined obesity. High-income countries showed 0.99-2.7% reductions in obesity when a 10-20% excise tax was applied. The reviewers warned the models may overestimate the effect of the policy, but concluded beverage taxes could be effective at obesity reduction, although more empirical research is necessary. (Itria, Borges et. al 2021)

There is even less literature focusing on diabetes. In California, sweetened beverage excise taxes had no statistically significant effect on hemoglobin A1C levels (blood sugar tests), or diabetes incidence

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<sup>9</sup> [Do you know how many calories you need? | FDA.Gov](https://www.fda.gov/food/healthy-eating-tips/2015/08/04/do-you-know-how-many-calories-you-need)

in patients with prediabetes in the 4 years following the implementation of excise taxes in certain areas.  
(Lee, Sidell et. al 2024)

While extensive literature covers the impact of the Philadelphia beverage tax on consumption, less research has focused on public health effects. This study aims to fill this gap by examining whether or not the beverage tax has reduced the incidence of chronic conditions such as obesity and diabetes in Philadelphia.

### 3. Data

As the City of Philadelphia is coterminous with Philadelphia County, I was able to access health data at that unit. This analysis relied on county-level data from the Behavioral Risk Factor Surveillance System (BRFSS), CDC Diabetes Surveillance System, and the U.S. Census, ranging from 2004-2021. My dependent variables were Obesity and Diabetes rates, and my control variables were median age, income per capita, and a poor health metric, which represents the percent of the population reporting poor health in the BRFSS. I constructed a control basket drawing from 9 of the 15 densest counties in the United States. The District of Columbia and San Francisco metropolitan areas were excluded from the analysis, as both implemented policies targeting sweetened beverage sales. San Juan was also excluded. The final basket included 6 New York Metropolitan area counties, as well as Boston and Baltimore.

#### Summary Statistics:

*Table 1.*

Treatment	Pre/Post 2017	Obesity (Mean)	Obesity (S.D.)	Diabetes (Mean)	Diabetes (S.D.)	(n)
Control	Pre	0.241	0.048	0.09	0.02	104
Control	Post	0.260	0.056	0.10	0.02	40
Philadelphia	Pre	0.296	0.017	0.10	0.01	13

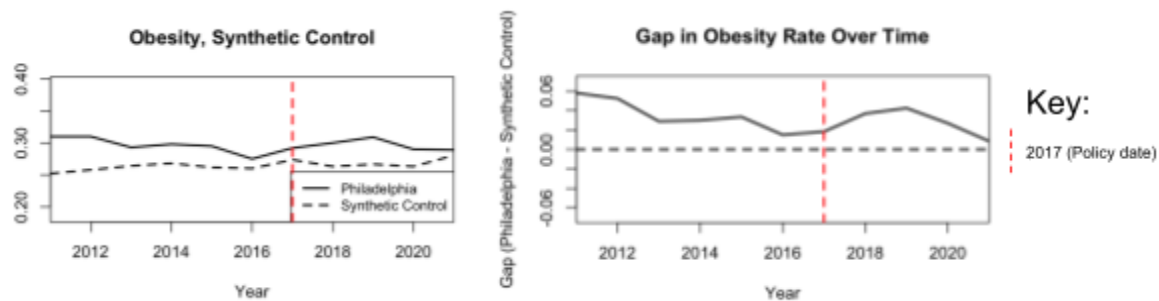
Philadelphia	Post	0.296	0.008	0.11	0.00	5
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#### 4. Models

To model the causal impact of the beverage tax, I used a synthetic control model. A synthetic control manufactures a weighted average control, aimed at replicating Philadelphia's pre-trends. I modeled the effect of the beverage tax on both obesity and diabetes. I constructed my synthetic controls using the control basket of 8 urban counties, per capita income, median age, and a health indicator representing the percentage of people in the county reporting poor health in the BRFSS survey from 2011-2021.

##### Synthetic Control: Obesity

*Figures 2 & 3.*



*Data: CDC Diabetes Surveillance System, BRFSS, U.S. Census, County Health Indicators*

For obesity, the pre-treatment control runs below Philadelphia, on a similar trend. There is no divergence between Philadelphia's obesity rate and the control after treatment, suggesting the beverage tax had no discernible impact on obesity.

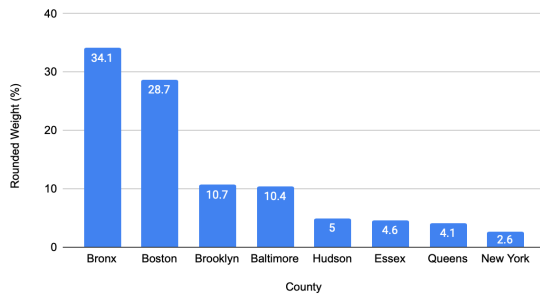
**Mean Squared Prediction Error:** 0.001522994

This MSPE indicates a close pre-trend fit, which strongly supports the validity of this synthetic control model. Given a low MSPE and no divergence, I find no evidence of an effect on obesity.

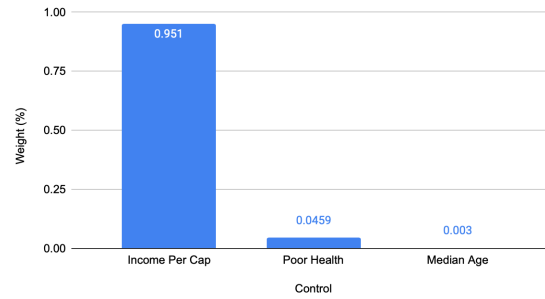
**Model Weights:** Obesity Synthetic Control

*Figures 4 & 5.*

Location Weights (Obesity Synthetic Control)



Controls (Obesity Synthetic Model)

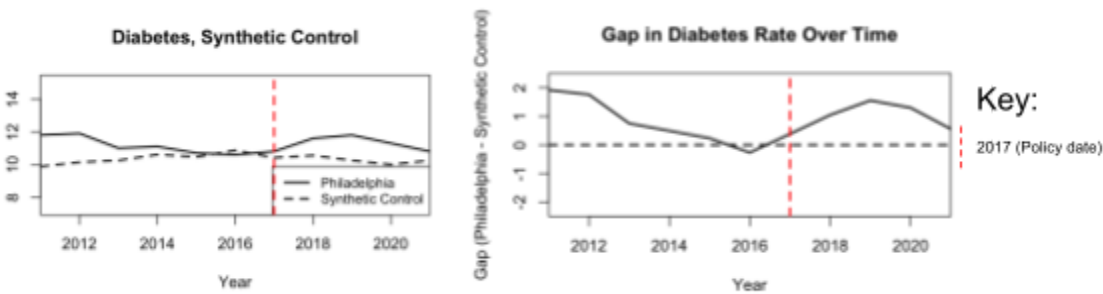


84% of the model's location weight comes from the Bronx, Boston, Brooklyn, and Baltimore.

Income per capita contributes over 95% of the predictor weight.

### Synthetic Control: Diabetes

Figures 6 & 7.



Data: CDC Diabetes Surveillance System, BRFSS, U.S. Census, County Health Indicators

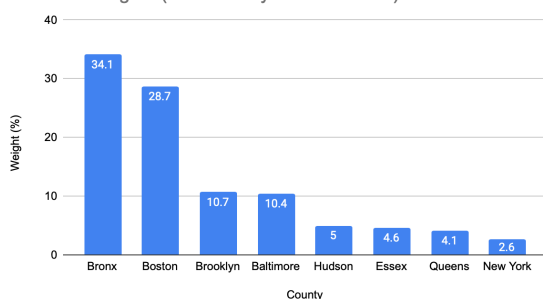
**Mean Squared Prediction Error: 1.289401**

The Diabetes Synthetic Control MSPE is very high, which suggests the synthetic control was unable to match Philadelphia's diabetes pre-trends. This means the synthetic control does not provide a valid counterfactual for causal inference on diabetes in Philadelphia, preventing reliable inference on diabetes.

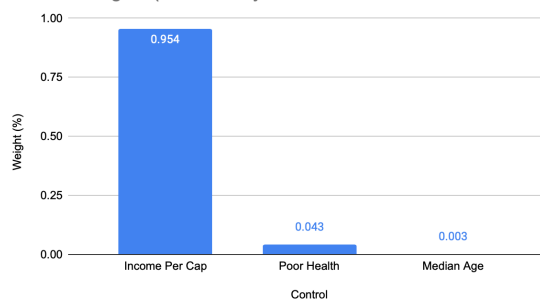
### Model Weights: Diabetes Synthetic Control

Figures 8 & 9.

Location Weights (Diabetes Synthetic Control)



Control Weights (Diabetes Synthetic Model)



The diabetes synthetic control model weights are almost identical to the ones in the obesity synthetic control.

As the effects of the beverage tax may be staggered from the implementation date, I performed an event study, to analyze the dynamic policy effects over time. Event studies are similar to Difference-in-Differences models, however they contain an event time factor. This enables me to determine whether the policy took time to take effect.

### Interaction effects: year and time factor

Figure 10.

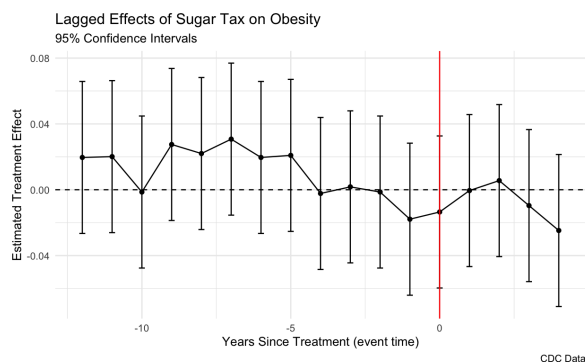


Figure 10 shows estimated treatment effects for each year relative to treatment. All error bars are relatively wide, crossing zero. This means the annual treatment effect for each year is indistinguishable from zero at an  $\alpha=0.05$  level. This suggests variations in individual time factor effects in Philadelphia may be due to volatility and pre-trends. As the pre-treatment effects are statistically not different from zero, the parallel pre-trend assumption is strengthened. Any post-treatment drop would suggest a policy effect. No significant drop can be observed here.



The point estimates do not consistently dip below zero until 2019. Because of this, I also ran a two-year lag Difference-in-Differences model, achieving similar results. A weakness of these results is the small size of my post-treatment sample, which ends in 2021.

## 5. Robustness

### Difference in Differences:

I conducted Difference-in-Differences analyses using the following formulae:

1.  $ObesityRatio_{it} = \beta_0 + \beta_1(timePeriod_t) + \beta_2(treatment_i) + \beta_3(timePeriod_t \times treatment_i) + \mu_i + \tau_t + \varepsilon_{it}$
2.  $DiabetesRatio_{it} = \beta_0 + \beta_1(timePeriod_t) + \beta_2(treatment_i) + \beta_3(timePeriod_t \times treatment_i) + \mu_i + \tau_t + \varepsilon_{it}$

Where:

- $ObesityRatio_{it}$  represents the ratio of people in each region with obesity.
- $DiabetesRatio_{it}$  represents the ratio of people in each region with diabetes.
- $timePeriod_t$  is a time dummy representing whether or not the sugar tax has occurred (before/after 2017).
- $treatment_i$  represents whether data falls in Philadelphia, or in the control group.
- $timePeriod_t \times treatment_i$  is the interaction term, which represents the effect of the sweetened beverage tax in Philadelphia.
- $\mu_i$  represents entity-fixed effects.
- $\tau_t$  represents time-fixed effects.
- $\varepsilon_{it}$  is the error term.

I also ran a regression with the policy date set to 2019, in order to model a two-year lag, as a change in sugar consumption might have a delayed effect on chronic conditions.

Values are in ratio form. These Difference-in-Difference regressions should not be taken as strong causal evidence, due to violations of the parallel pre-trend rule.

### Regression Outputs

Table 2.

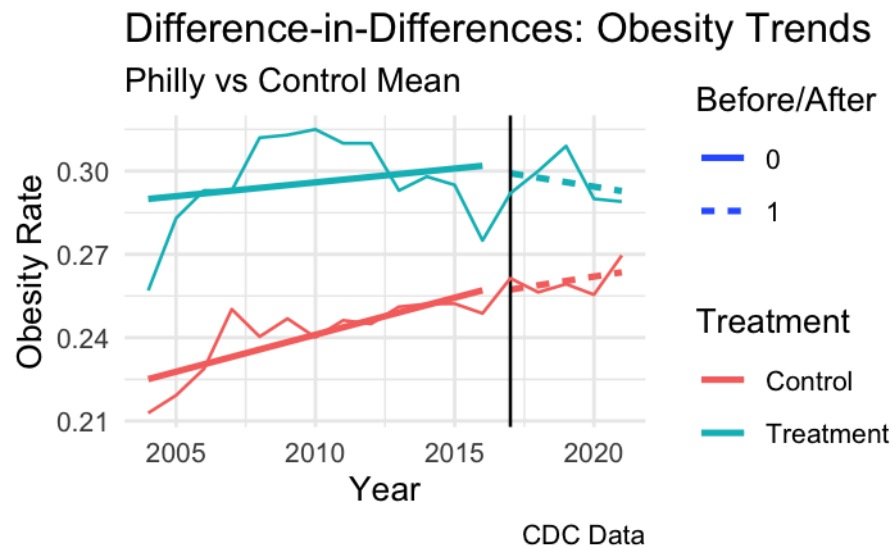
	Model 1: Obesity (Robust SE)	Model 2: Obesity (2 year lag) (Robust SE)	Model 3: Diabetes (Robust SE)	Model 4: Diabetes (2 year lag) (Robust SE)
(Intercept)	0.291*** (0.008)	0.291*** (0.008)	0.096*** (0.002)	0.096*** (0.002)
Before/After	0.056*** (0.007)	0.056*** (0.006)	0.023*** (0.003)	0.023*** (0.003)
Location (Control)	-0.025** (0.009)	-0.027** (0.010)	-0.008*** (0.001)	-0.008*** (0.001)
Interaction Effect	-0.019** (0.007)	-0.018* (0.009)	0.001 (0.002)	0.002 (0.002)
Entity FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

The Difference-in-Differences model estimated a statistically significant 1.9 percentage point decline in obesity with robust SE. The effect of the policy with a two-year lag was similar, with a 1.8 p.p. decline. This result is likely driven by the downward trend in Philadelphia's obesity rate leading up to 2017.

There was no statistically significant effect of the policy on diabetes rates relative to the control cities. Given the limited post-policy sample size (5 years), the results of the Differences-in-Difference should be interpreted with caution. This is doubly true of the lagged model.

Figure 11.



The assertion that the Philadelphia sugar tax caused a decline in obesity is weakened by non-parallel pre-trends. The obesity rate in Philadelphia is volatile and is in decline leading up to 2017. In other words, the 2 percentage point decline in obesity may be due to volatility not present in the controls, therefore the Difference-in-Differences methodology could be invalid.

## 6. Discussion

### Summary of Results:

Table 3.

Outcome	Method	Result	Credibility
Obesity	DiD	-1.9 p.p. decline***	Weak
Obesity	Synthetic Control	No post-treatment gap	Strong
Diabetes	DiD	Null	Weak
Diabetes	Synthetic Control	Poor pre-fit	Unreliable

This study attempts to evaluate whether Philadelphia's 2017 beverage tax reduced obesity and diabetes in the years following implementation. While prior research has shown a reduction in the consumption of sweetened beverages in Philadelphia, the extent to which that has contributed to improved health outcomes remains unclear.

Using a synthetic control method, I constructed a counterfactual Philadelphia based on a weighted combination of comparable cities. The model fit the pre-treatment obesity trend closely (MSPE = 0.0015), and no divergence emerged after the tax—suggesting no detectable short-term effect on obesity. A Difference-in-Differences model estimates a 1.9 percentage point decline in obesity, but this result is undermined by pre-existing downward trends and higher volatility in Philadelphia's data. Diabetes models, in both approaches, yielded null results or suffered from poor pre-treatment fit.

Several explanations are possible. First, obesity and diabetes are delayed outcomes which may require more time to react to consumers' behavioral changes. Second, the geographic scope of the tax may limit its reach, as consumers can cross city boundaries or substitute for untaxed sugary products. (Petimar et. al 2022) Third, the reduction in soda consumption may not represent a large enough portion of Philadelphian's calorie intake to have a notable effect. (Cawley, Frivsold et. al 2019)

These findings do not imply beverage taxes are ineffective in principle. Previous research shows clear reductions in sugary drink consumption following such taxes, and policymakers may still view them as valuable tools for raising revenue or nudging behavior. However, expectations about their health effects should be modest. Taxes on sugar-sweetened beverages may be necessary but are not sufficient for preventing chronic health conditions like obesity and diabetes alone.

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