Evaluation of changes in prices and purchases following implementation of sugar-sweetened beverage taxes across the United States

Scott Kaplan, United States Naval Academy
(with Justin White, Sanjay Basu, Kristine Madsen, Sofia Villas-Boas, and Dean Schillinger)

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Introduction

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- There is also economic rationale for implementing SSB taxes.
  - → Reduce medical costs of obesity and diabetes borne by others.
    - Cawley & Meyerhofer (2012) estimate 88% of obesity-related medical costs are paid by 3rd party payers.
  - → Correct internalities from diet choices (Allcott et al., 2019).
  - → Policymakers are drawn to the revenue stream.

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  - → Correct internalities from diet choices (Allcott et al., 2019).
  - → Policymakers are drawn to the revenue stream.
- Currently implemented in 9 US jurisdictions and 50+ countries.

Introduction

- Previous studies have examined the impact of SSB taxes on prices, consumption, and health outcomes.
  - → Economic outcomes: Han and Powell 2013; Cawley et al. 2019; Taylor et al. 2019; Teng et al. 2019; Powell and Leider 2020; Cawley et al. 2020a; Cawley et al. 2020b; Powell et al. 2021; Cawley et al. 2021; Andreyeva et al. 2022; Barker et al. 2022; White et al. 2023.
  - → Health outcomes: Wang et al. 2012; Dietary Guidelines Advisory Committee 2015; Long et al. 2015; Wilde et al. 2019; Lee et al. 2020; Jackson et al. 2023.
- Despite the abundance of research on the effectiveness of SSB taxes, two primary gaps exist in the literature.
  1) Nearly all U.S-based studies of SSB taxes analyzed a single taxed city.
  2) These studies generally use conventional DID approaches, which may suffer from unforeseen bias (De Chaisemartin and d'Haultfoeuille 2020).

Introduction

- Our study uses (i) retail sales data from five taxed cities and (ii) the recently developed *augmented synthetic control* (ASC) model to estimate the composite effect of SSB taxes in the US on SSB prices and volume purchased.
  - → Critical for understanding the generalizability of SSB tax impacts on different localities featuring heterogeneous characteristics.
  - → Complementary to existing estimates from individual localities.
  - → Better inform the potential effectiveness of a state or nationwide tax, especially considering recent efforts to preempt local SSB taxes.

Data & Research Setting

Data Disclaimer: All estimates and analyses in this presentation are by the authors and not by The Nielsen Company. Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Retail Scanner Data (from The Nielsen Company)

- Product-week-store observations from 90+ retail chains across the US.
  - → Observe # of units sold and average shelf price for each observation.
- Store locations identified at the 3-digit zip code level (871 total 3-digit zips).
- Our study period: January 1, 2012 – December 31, 2019.
- We examine beverage products, supplemented with nutritional and general product information from *Label Insight* and hand-coded sources.
  - → Allowed us to classify individual beverage products (each with a unique UPC) as SSBs or not based on tax regulations.
  - → 5,500 UPCs considered SSBs.
- Analysis uses data aggregated to the 3-digit zip code-by-month level.

Summary of Taxed and Untaxed Jurisdictions

Table 1: Descriptive Statistics of 3-Digit Zip Codes

	3-Digit Zip Code						
	941 (SF)	946 (Oak.)	191 (Phil.)	803 (Boul.)	981 (Sea.)	Borders	Donors
Number of 3-Digit Zips	1	1	1	1	1	13	279
Number of Stores	103	41	213	26	113	1,340	24,502
Date Tax Implemented	1/1/18	7/1/17	1/1/17	7/1/17	1/1/18	---	---
# Months (in Data) Pre-Tax	72	66	60	66	72	---	---
# Months (in Data) Post-Tax	24	30	36	30	24	---	---
$/Ounce	0.01	0.01	0.015	0.02	0.0175	---	---

▸ Coverage

- Borders: All immediately adjacent 3-digit zip codes to each treated zip code.
- Donors: All 3-digit zip codes with a "% Urban" value within one standard deviation (0.35) of the mean urbanicity of the five treated localities (0.98).
- Omit Berkeley, CA and Albany, CA (947) because they were taxed at different times and could not be separately identified.
- Omit areas with sales taxes (Washington, DC and Navajo Nation).

Empirical Approach & Validation

Overview of SC Method & Recent Advances

- Began with Abadie and Gardeazabal (2003) and Abadie et al. (2010).
  - → Balanced panel, exposure to binary treatment.
  - → Single treated unit, many donor units.
  - → Creation of a single "synthetic" unit based on pre-treatment outcomes and observable, time-invariant covariates.
  - → Emphasizes transparent achievement of parallel trends assumption.

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  - → Both can accommodate multiple treated units.
  1) Staggered adoption: Multiple treated units treated at different times.
  2) Bias correction: Introduces an outcome model that is used to determine (and correct) bias as a result of a relatively poor pretreatment fit between the treated and synthetic units.
- Estimate using the *augsynth* package in `R`.

Inference: The Placebo Method

- For inference, we use an in-space placebo estimation procedure (Abadie, Diamond, and Hainmueller 2010; 2015).
- One-by-one, we "treat" each donor pool unit to generate a placebo estimate.
- To generate p-values, we compute the RMSPE in the post-tax vs. pre-tax period for the treated unit estimate ($s = 0$) and each of the placebo unit estimates ($s = 1, ..., S$), and rank them from largest to smallest.

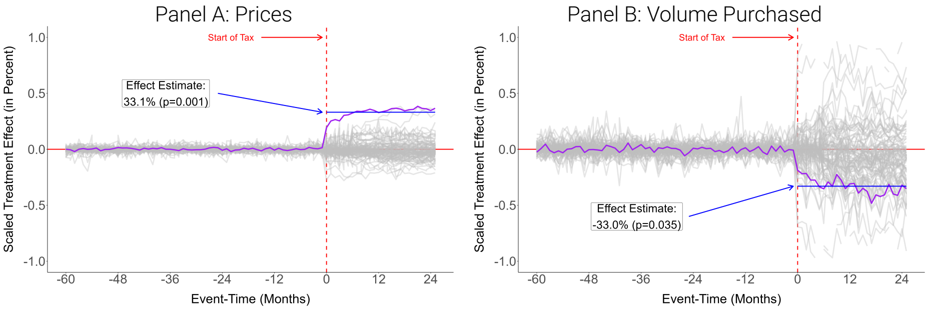
$$RMSPE_s = \frac{\hat{\tau}^2_{post,s}}{\hat{\tau}^2_{pre,s}}$$

$$p_{RMSPE} = \sum_{s=1}^{S} \frac{\mathbb{1}[RMSPE_s \geq RMSPE_0]}{S+1}$$

- While the SCM delivers less biased estimates than DID approaches, they also generate less statistical power (O'Neill et al. 2016).

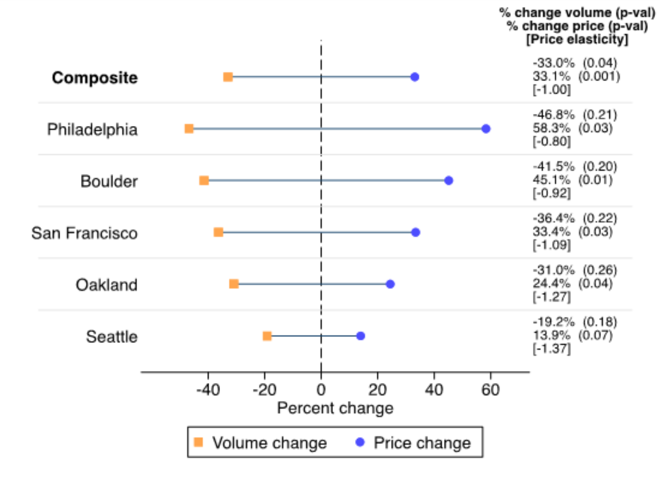
Results

Figure 1: Bias-Corrected Synthetic Control Estimates for Composite Changes in Prices and Volume Purchased



- Bolded purple line represents the composite treated unit.
- Light gray lines represent a sample of in-space placebo estimates.
  - → 100 randomly selected "pruned" placebo estimates depicted on graph.

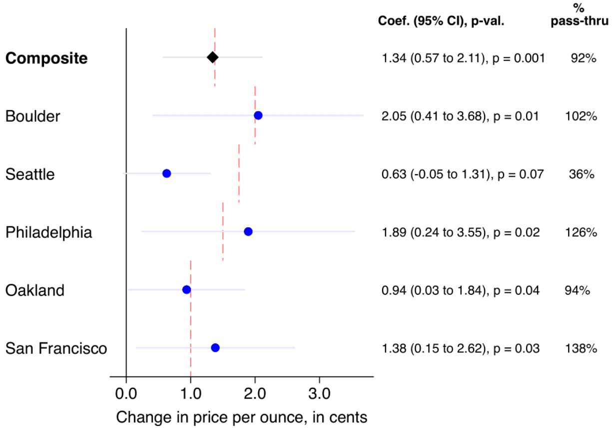
Figure 2: Composite and Individual Locality Demand Elasticity Estimates



- Demand elasticity of -1.00 suggests moderate demand responsiveness.
- Individual taxed city elasticities were relatively consistent, ranging from -0.80 (Philadelphia) to -1.37 (Seattle).

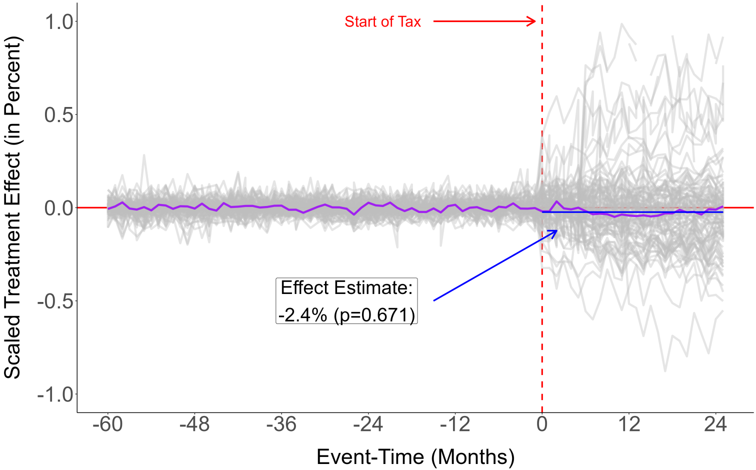
Robustness

Figure 3: Composite and Individual Locality Price Pass-Through



- Composite estimate of pass-thru to consumers was 1.3 cents/ounce (92%).

Figure 4: Composite Changes in Volume Purchased of SSBs in Border Areas



- No evidence of offsetting purchases via cross-border shopping.

▸ Individual City Results

Conclusion

Potential Limitations

1) Scanner data only identifies purchasing behavior, not direct consumption.

2) The scanner data does not cover all volume sales in each zip code.

   → Coverage "backed out" from local tax revenues.

   → Unequal coverage across treatment and control localities should not cause unintended bias, since the ASC approach generates a reliable counterfactual from the existing sample of donor zip codes.

3) Only observe posted shelf prices, which may underestimate pass-through.

4) The scanner data is primarily composed of sales from large chain stores.

   → Similar estimates have been found in settings studying independent stores (Bleich et al. 2020).

5) The five treated localities are not fully representative of the US population.

   → Our findings may not fully generalize (especially to less urban populations).

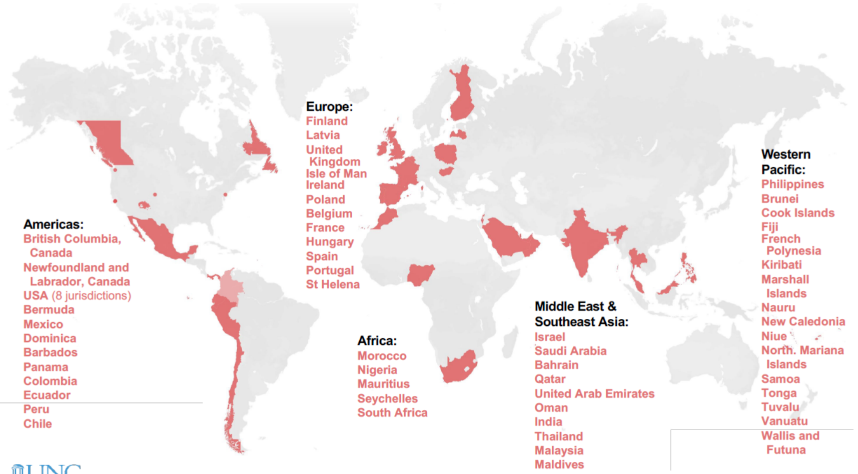
Conclusion

- Our estimates compared with previous literature (Andreyeva et al. 2022).
  - → Slightly higher pass-through (92% vs. 82%)
  - → Substantially more consumption reduction (33% vs. 15%)
  - → Moderately less demand responsiveness (ϵ_D = -1.00 vs. ϵ_D = -1.59)
  - → Less cross-border shopping than some studies (Cawley et al. 2019).
- Modest discrepancies may reflect differences in:
  - → Geographic areas of comparators.
  - → Store sample composition.
  - → Greater accounting of confounders compared with prior DID studies.
- Studies have found a 15-20% increase (decrease) in prices (consumption):
  - → Generates significant health benefits (Long et al. 2015; Wilde et al. 2019).
  - → Gives rise to large societal cost-savings (Lee et al. 2020; White et al. 2023).
- States have begun preempting local SSB taxes (Crosbie et al. 2021).
  - → Our study helps informs potential effectiveness at a coarser geographic level.

Thanks!

skaplan@usna.edu

Sugary Drink Taxes around the World



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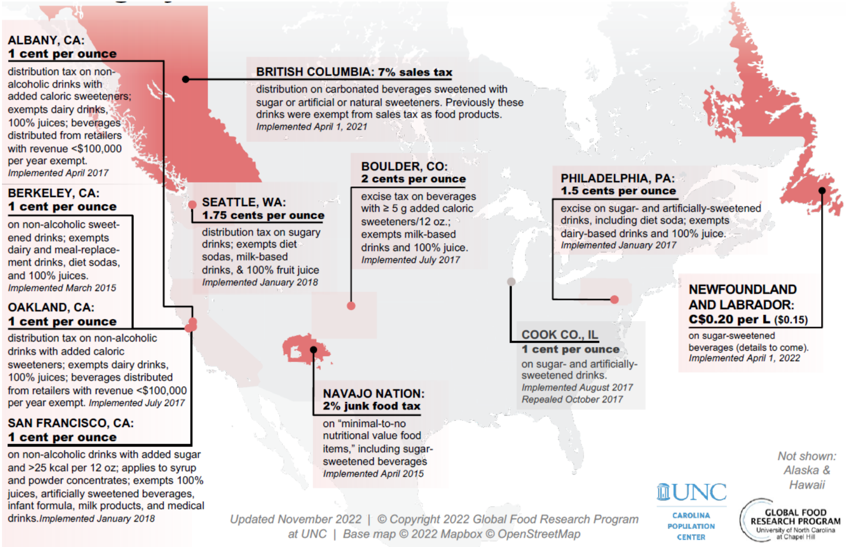
Sugary Drink Taxes in the USA and Canada



(Washington, DC implemented a 2 pp. increase in sales tax on sugary drinks in 2019)

Total Coverage of SSB Ounces Sold

Table A.1: Total Coverage of SSB Ounces Sold in Matched Nielsen Retail Scanner Data

City (first complete fiscal year of SSB tax)	**Tax Revenue** ($000's)	**Tax** ($/Ounce)	**Total SSB Sales** (1000s of Ounces)	**SSB Sales of Nielsen UPCs** (1000s of Ounces)	**Coverage (%)**
Boulder (2018)	$4,868	$.02	243,400	50,781	20.86%
Oakland (Jul 2017–Jun 2018)	$11,076	$.01	1,107,600	171,850	15.52%
Philadelphia (Jul 2017–Jun 2018)	$77,421	$.015	5,161,400	240,146	4.65%
San Francisco (Jul 2018–Jun 2019)	$16,098	$.01	1,609,800	287,089	17.83%
Seattle (2018)	$22,254	$.0175	1,271,657	404,600	31.82%
Composite	$131,717	$.0145	9,083,931	1,154,468	12.71%

Note: Tax revenues taken from Krieger et al. (2021). Coverage estimates use the first fiscal year of each city's respective tax implementation. Lower coverage in Philadelphia is in part due to the exclusion of artificially sweetened beverages in our analysis. The tax amount for the Composite geographic unit is the unweighted average of the tax amounts across the five taxed cities.

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Arkhangelsky et al. 2021 (Figure 1)

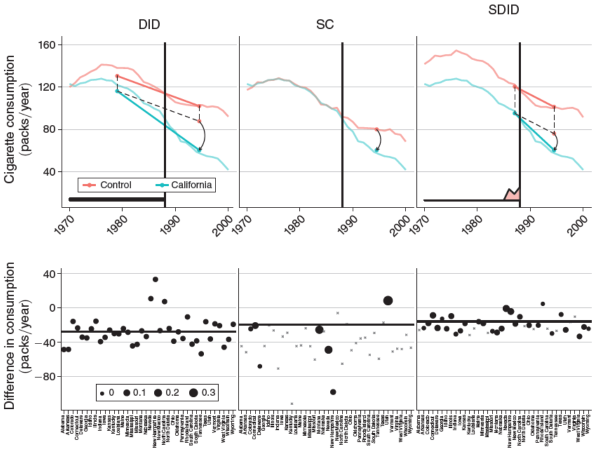

FIGURE 1. A COMPARISON BETWEEN DID, SC, AND SDID ESTIMATES FOR THE EFFECT OF CALIFORNIA PROPOSITION 99 ON PER-CAPITA ANNUAL CIGARETTE CONSUMPTION (IN PACKS/YEAR)

Math

- Estimated effect is indicated by the arrow in the top row.

DID vs. SCM vs. SDID (Arkhangelsky et al. 2021)

DID

$$(\hat{\tau}^{did}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \right\}$$

SCM

$$(\hat{\tau}^{sc}, \hat{\mu}, \hat{\beta}) = \underset{\tau,\mu,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sdid} \right\}$$

SDID

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{\operatorname{argmin}} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{sdid} \hat{\lambda}_t^{sdid} \right\}$$

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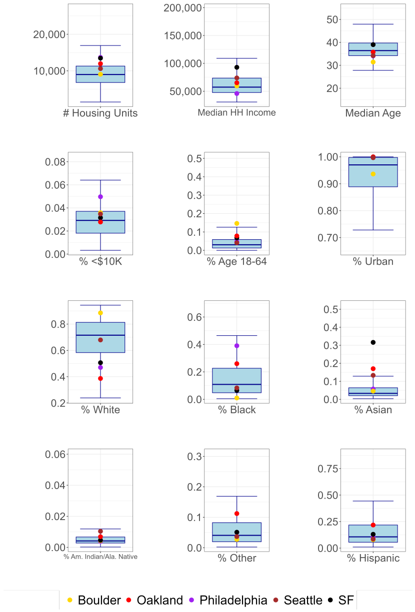
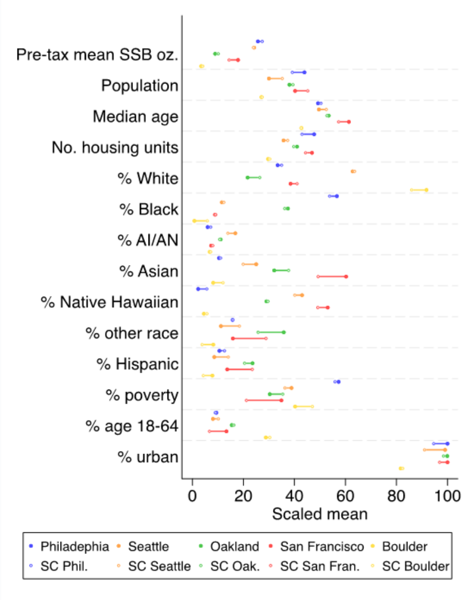
Figure: Overlap of Census Sociodemographic Characteristics Between each Taxed City and Donor Pool of Control Zip Codes



- Most characteristics of taxed cities fall within IQR of distribution.
- Justification for use as reliable SCM covariates.

Figure: Comparing Treated and Synthetic Values of Prognostic Factors from the Analysis of SSB Volume Purchased



- Most comparisons within five index points.
- No comparisons differed by more than 14 index points.
- Comparisons were similar in the price analysis.

TWFE Results

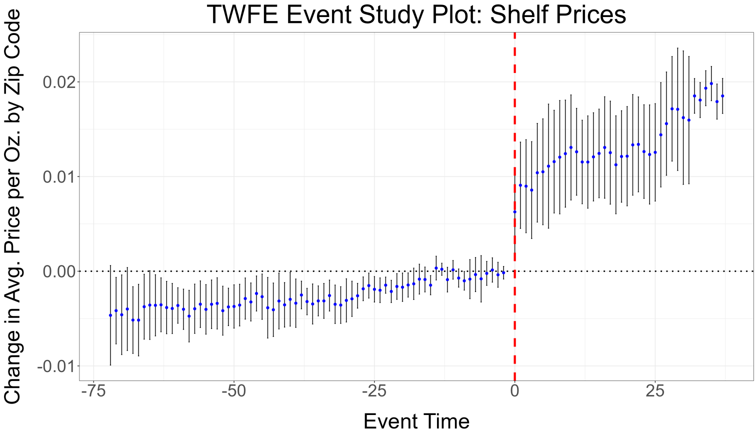
$$Y_{it} = \beta Tax_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

	Dependent variable:		
	Total Oz.	Avg. Price per Oz.	Total Oz.
Treatment * Post	$-11{,}612{,}405.0^{**}$	0.0147^{***}	$-2{,}681{,}965.0^{*}$
	(3,549,033.0)	(0.0029)	(1,177,461.0)
Analysis Type	Volume (Taxed)	Prices	Volume (Borders)
Dep. Var. Pretreatment Mean	27,850,700	0.041	42,345,118
Month-Year FE	X	X	X
Zip Code FE	X	X	X
Clustered Robust SEs (Zip Code)	X	X	X
Observations	27,832	27,832	36,162
R^2	0.9450	0.8470	0.9400
% Change	-41.7	35.9	-6.3
% Change (ASC Results)	-33.1	33.0	-2.4
% Difference from ASC	26.0	8.8	162.5

$^{*}p<0.05$ $^{**}p<0.01$ $^{***}p<0.001$

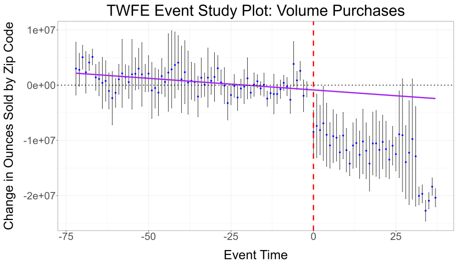
- TWFE appears to overestimate changes in volume purchased and prices.

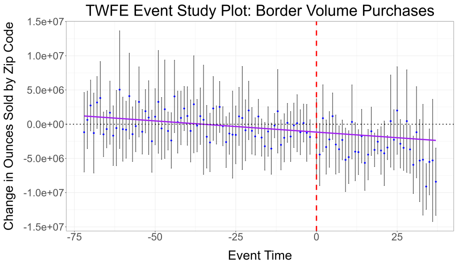
TWFE Results: Prices



- Treated zips trending down relative to control zips in pre-policy period.
  $\rightarrow$ upward biased treatment effect.

TWFE Results: Volume Purchases

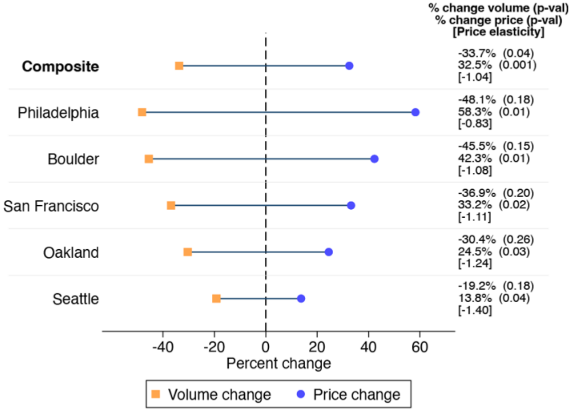




- Purple line represents best-fit line through pre-policy coefficients.
- Despite parallel trends appearing to be (mostly) satisfied, there is a clear downward trend in the pre-policy coefficients.
  - → downward biased treatment effect.
- Roth (2022) and Rambachan and Roth (2023) suggest that pre-trends tests may be ineffective in avoiding biases from violations of parallel trends (and can even exacerbate biases).

Robustness (Urbanicity > 0.85)

Figure A.2: Composite and Individual Locality Demand Elasticity Estimates



Note: This plot shows the % change in volume sold (in ounces) and % change in price for the bias-corrected synthetic control staggered adoption composite analysis, and the same information for bias-corrected synthetic control analyses of each of the five treated localities individually. Price elasticities of demand are provided in brackets, and p-values for each estimation are provided in parentheses.

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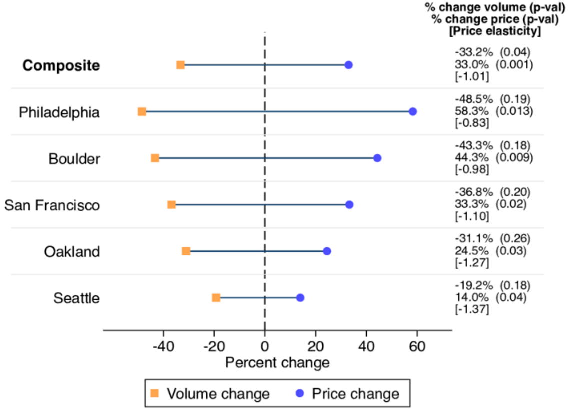
Robustness (Urbanicity > 0.9)

Figure A.3: Composite and Individual Locality Demand Elasticity Estimates



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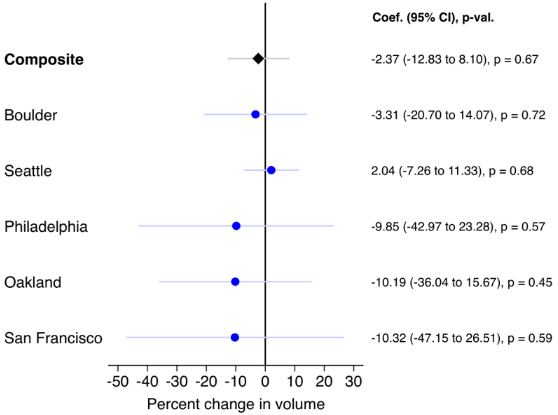
Volume Purchase Changes for Individual City Borders

Figure A.1: Changes in Volume Sales in Adjacent Border Zip Codes



Note: Coefficient estimates represent the % change in SSB purchases in immediately adjacent border localities to each treated locality, and all borders in the composite estimation. Lightly shaded horizontal lines through each coefficient indicate 95% confidence intervals. Corresponding 95% confidence intervals and p-values are indicated next to each coefficient.

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