Synthetic Control

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Outline

1. Motivation - Case Study
   - The Case Study DAG
   - Problem with our usual methods
   - The Synthetic Control Solution
2. Synthetic Control Details
   - Framing with Potential Outcomes
   - Synthetic California
   - Inference
   - Summary

Synthetic Control – Summary

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- Constructs a synthetic comparison unit by weighting control units to match pre-treatment outcomes
- Credibility comes from strong pre-treatment fit
- Treatment effect is the difference between the treated unit and its synthetic control after treatment

Housekeeping

- Throughout the slide deck you will see "Q", which indicates a question to you, the reader
- You will also see "A", which indicates the associated answer
- It is generally most efficient to learn this material through active participation. Whenever you encounter a "Q", be sure to try and develop your answer before turning the page to the provided "A" answer
- I recommend reading through these slides before engaging in associated coding exercises
- This slide deck is part of a broader curriculum in causal estimation and inference
- Suggested pre-requisite: OVB, Potential Outcomes

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Case Study - Cigarette Taxes



Image created with Bing Image Creator

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- Prop.99 was a large-scale tobacco control program that increased cigarette excise tax by 25 cents per pack
- The (partial) intent of the program was to curb consumer demand for cigarettes
- The program went into effect Jan1989
- The following is based upon the work of Abadie, Diamond, and Hainmueller (2010)

Data

- California
- Annual data
- 1970-2000
- Cigarette sales are available for the state on an aggregate basis each year (e.g. per capita cigarette sales in 1980 were 120 packs)
- We also have controls on an aggregate basis such as GDP per capita, demographics, retail price of cigarettes, and beer consumption

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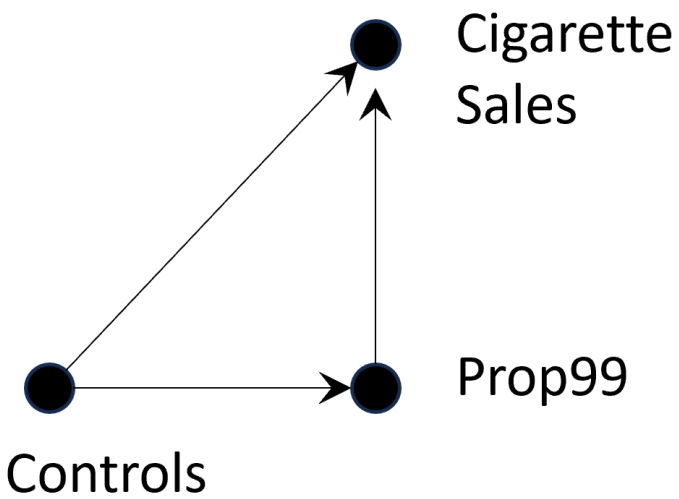
Causal Path

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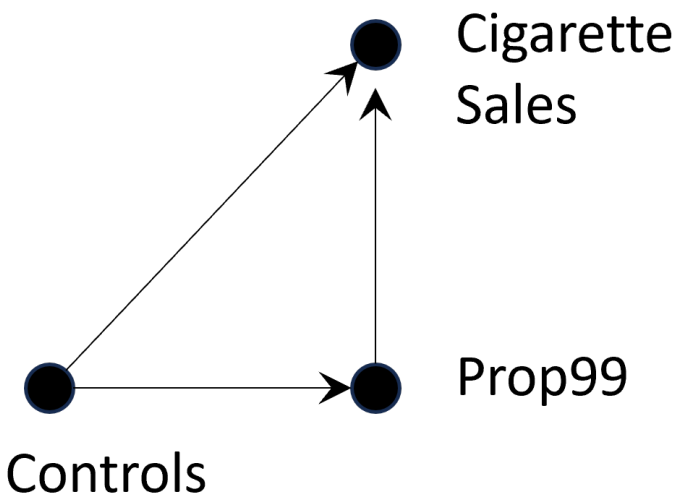
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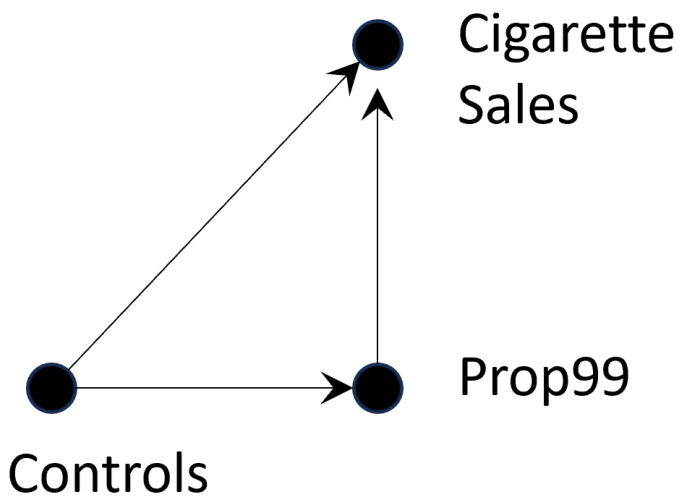


- Outcome:

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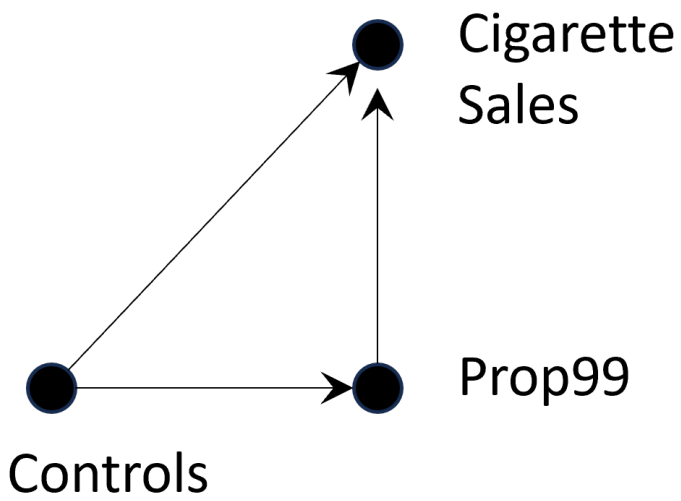


- Outcome: Cigarette sales

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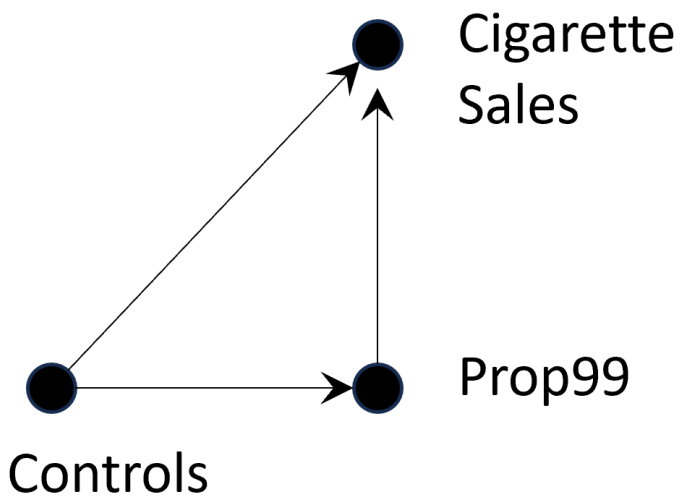


- Outcome: Cigarette sales
- Treatment:

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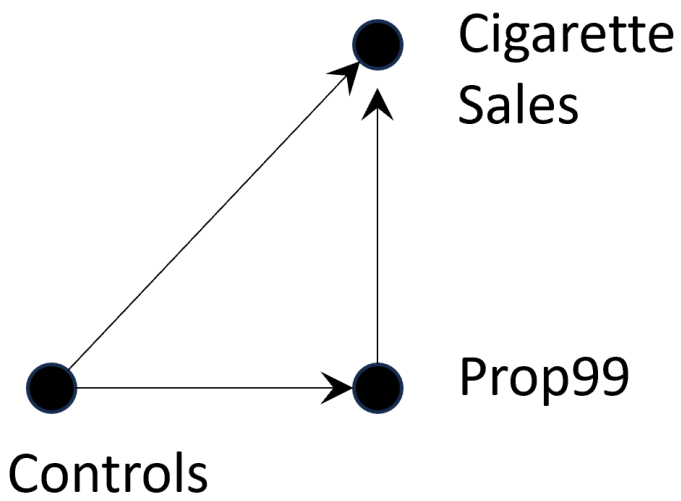


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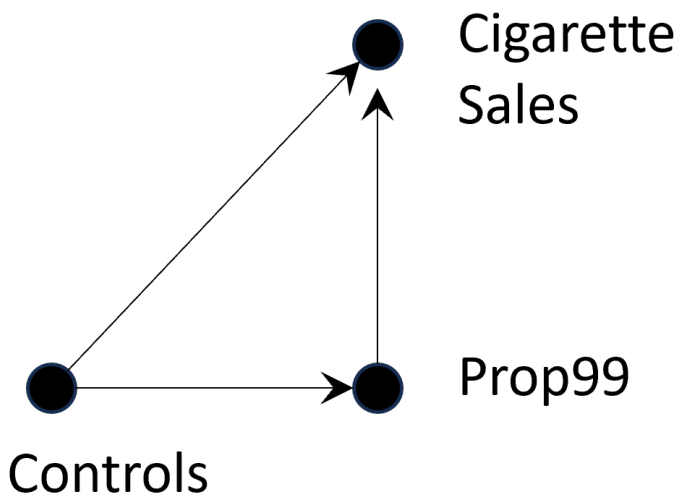


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- Outcome: Cigarette sales
- Treatment: Prop.99
- Treatment Effect: Impact of Prop.99 on cigarette sales

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A: All of our observations pertain to the treated group (California)

Q: So why not compare California before and after Prop.99 (e.g. 1988 and 1989)?
A: California might look different in 1989 than 1988 for reasons other than Prop.99. We might be capturing a time effect as well as a Prop.99 effect.

Extending the Dataset

- California
- Annual data
- 1970-2000
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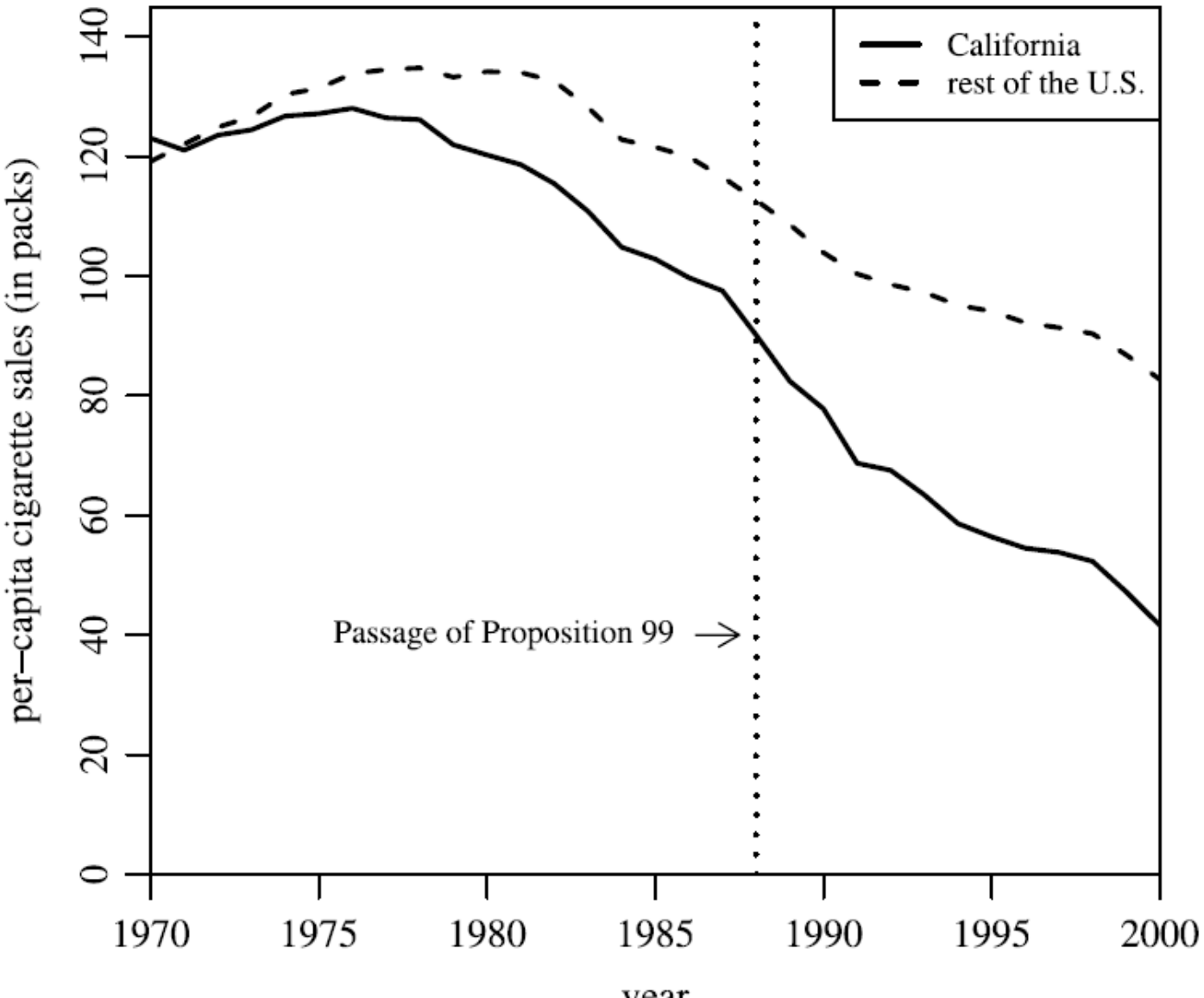
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- We also have controls on an aggregate basis such as GDP per capita, demographics, retail price of cigarettes, and beer consumption
- Cigarette sales data for all other states
- Controls for all other states
- We will assume that California is the ONLY state with cigarette taxes at that time.

California is Different

There isn't a single perfect control for California. Even the average of the other states differs from California.



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- Synthetic California $= .1\text{Nevada} + .7\text{New York} + .2\text{Florida}$

The weightings and choice of states above are purely for example.

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- Use Synthetic California as the control group.

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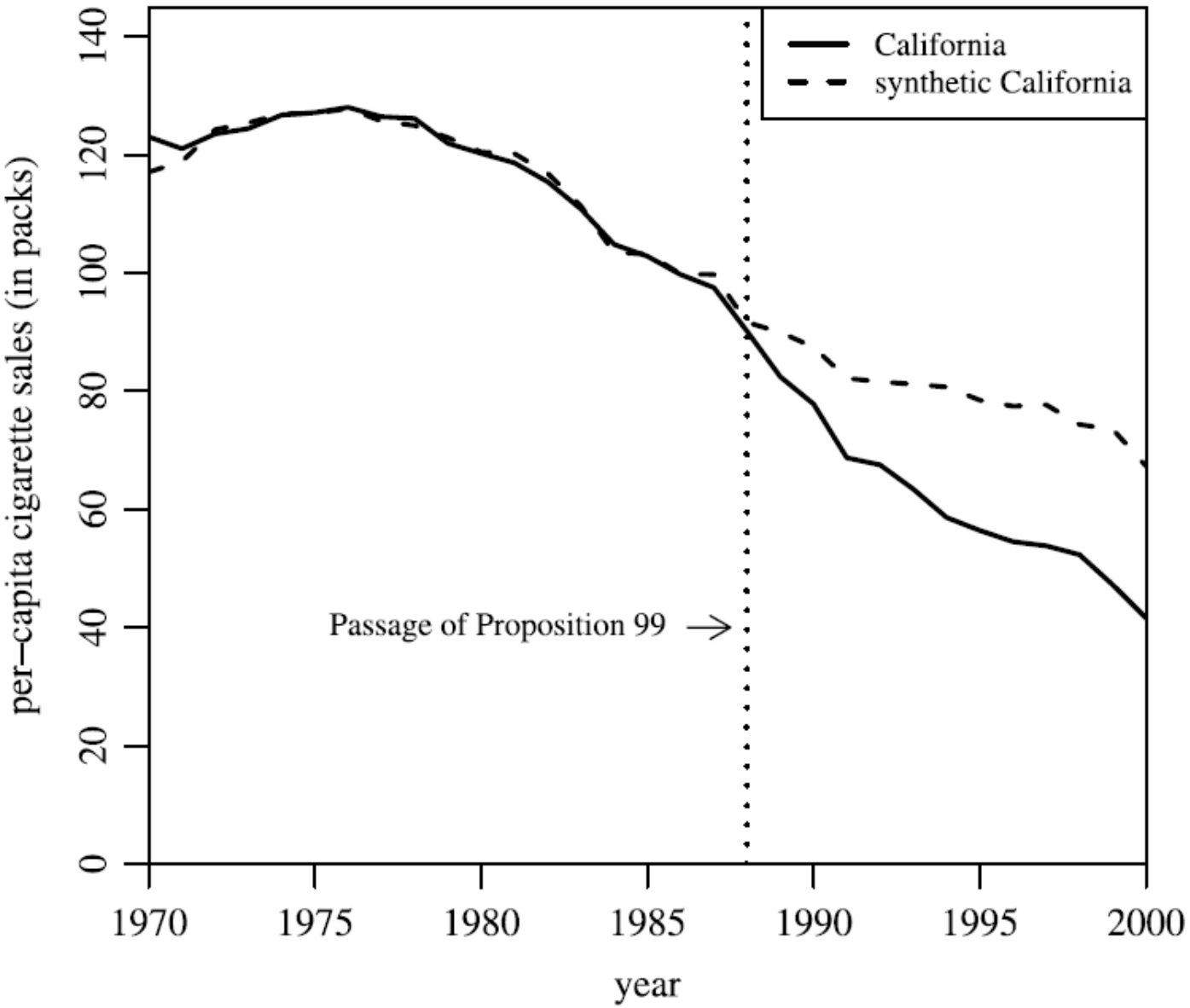
  The weightings and choice of states above are purely for example.
- Use Synthetic California as the control group.
- Remember that California was the only state that made this change, so all other states are potentially suitable control candidates.

Use other states to infer California without Prop.99

TE=(California - Synthetic California) after Prop.99

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Consider 2 States [California (CA) and North Carolina (NC)], 2 years [1988, 1989], and two potential outcomes [Tax, No Tax].

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- $D_i = 1$ as CA, and 0 as NC
- $D_t = 1$ as 1989 and 0 as 1988
- $Y_{1,i,t}$ as cig. sales for State i in year t with taxes, and $Y_{0,i,t}$ without taxes

Q: What is the meaning of $(Y_{1i}|D_i = 1, D_t = 1)$?

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Q: What is the meaning of $(Y_{1i}|D_i = 1, D_t = 1)$?
A: The expected cigarette sales in CA in 1989 under the potential outcome of having taxes.

Simplifying Notation

The Potential Outcomes notation is cumbersome even in a 2x2 panel setting. Thankfully, we can simplify.

$$(Y_{1i}|D_i = 1, D_t = 1) =$$
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ATT

Q: What is the meaning of ATT in our case?

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Q: Which piece of ATT is not observable?
A: The second piece is unobserved $Y^{CA}_{NoTax,t}$ (i.e. cigarette sales in CA for years 1989 and later if Prop.99 never went into law).

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Q: Which piece of ATT is not observable?
A: The second piece is unobserved $Y^{CA}_{NoTax,t}$ (i.e. cigarette sales in CA for years 1989 and later if Prop.99 never went into law). Our goal is to estimate this unobserved potential outcome.

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Creating a Synthetic CA

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A: Synthetic Control creates a pseudo version of California as a proxy for the unobserved potential outcome.

$$\widehat{ATT}_t = Y^{CA}_{Tax,t} - Y^{SynthCA}_{NoTax,t}$$

Forming Synthetic California

$$\widehat{ATT}_t = Y^{CA}_{Tax,t} - \sum_{s=1}^{50} w_s Y^s_{NoTax,t} \ \forall t >= 1989$$

where s denotes each State other than California. Note that the authors have data on Washington DC and so we have 50 "States" other than California.

Notice that if none of the States in our sample, other than CA, had cigarette taxes during any point of our sample, we could write $Y^s_{NoTax,t} = Y^s_t$.

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Q: What is the meaning of w_s?
A: The w^s is the importance (i.e. weight) of State s in creating the Synthetic California.

Choosing Optimal State Weights

- The weights can be chosen in myriad ways (equal, population weighted, etc..)

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Then the optimal weights are the solution to

$$w^* = argmin(X^{CA} - \sum_{s=1}^{50} w_s X^s)^2$$

such that w sum to 1 and are all non-negative. We typically optimize over the central tendency of the covariate X observed over time.

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Q: How interpret v_k?

A: The importance of predictor k for determining the optimal weights.

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Notice that w_s is a function of V. Once V^* is found, we can plug these optimal predictor importance weights into Equation (1) to find the State weights w_s^*.

Optimization Difficulties

Q: Which comes first, w or v? (trick question)

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A: They are jointly estimated. w is a function of v, and v is a function of w. We have a "bi-level" optimization. Albalate, Bel, and Mazaira-Font (2021) warn about numerical instabilities in solving such problems, so caution should be taken.

Choosing Proper Control States

Q: Weight=0 is not the same as excluding a State (as indicated by the -). Why might the authors have excluded some States?

State	Weight	State	Weight
Alabama	0	Montana	0.199
Alaska	–	Nebraska	0
Arizona	–	Nevada	0.234
Arkansas	0	New Hampshire	0
Colorado	0.164	New Jersey	–
Connecticut	0.069	New Mexico	0
Delaware	0	New York	–
District of Columbia	–	North Carolina	0
Florida	–	North Dakota	0
Georgia	0	Ohio	0
Hawaii	–	Oklahoma	0
Idaho	0	Oregon	–
Illinois	0	Pennsylvania	0
Indiana	0	Rhode Island	0
Iowa	0	South Carolina	0
Kansas	0	South Dakota	0
Kentucky	0	Tennessee	0
Louisiana	0	Texas	0
Maine	0	Utah	0.334
Maryland	–	Vermont	0
Massachusetts	–	Virginia	0
Michigan	–	Washington	–
Minnesota	0	West Virginia	0
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These States won't serve as suitable controls to represent California without Prop.99 after 1989.

Outline

1. Motivation - Case Study
   - The Case Study DAG
   - Problem with our usual methods
   - The Synthetic Control Solution
2. Synthetic Control Details
   - Framing with Potential Outcomes
   - Synthetic California
   - Inference
   - Summary

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- But in our case we only have a single treated unit (California), so typical hypothesis tests don't work
- Instead, the authors use a "placebo" approach.

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4. Repeat steps 1,2,3 for every State
5. Construct histogram of $\frac{MSPE_{s,t\geq 1989}}{MSPE_{s,t<1989}}$
6. Use quantiles of MSPE ratio as the density to compute p-value of test statistic.

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MSPE for Placebo Inference

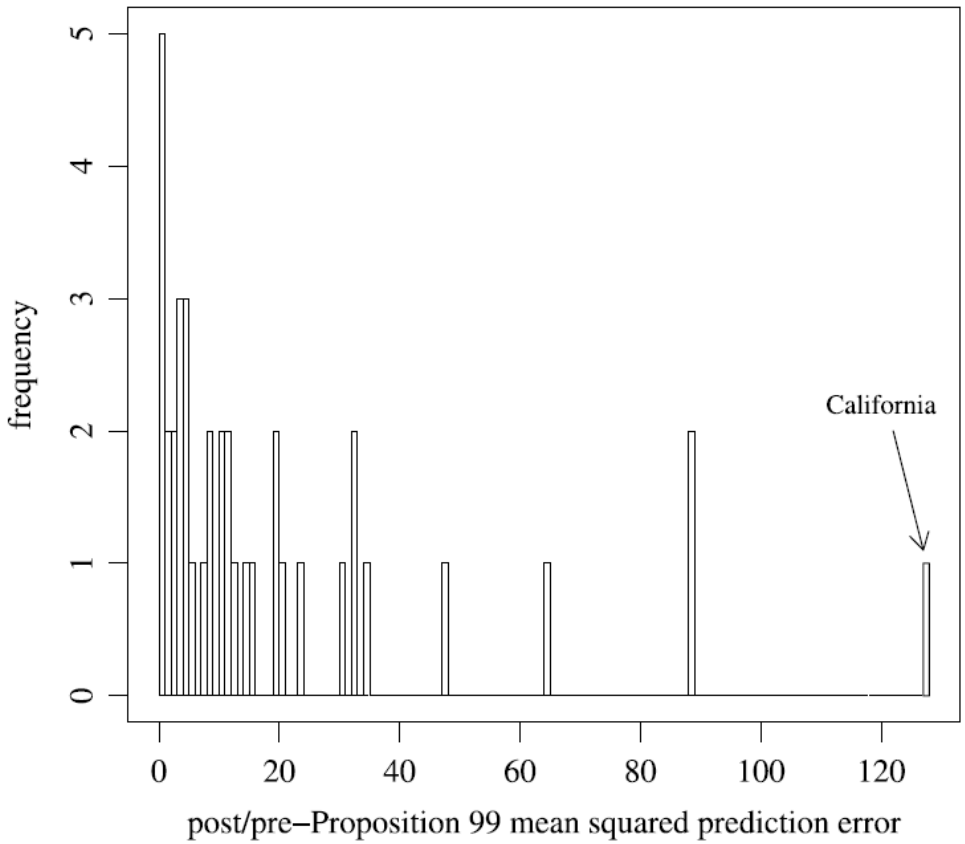
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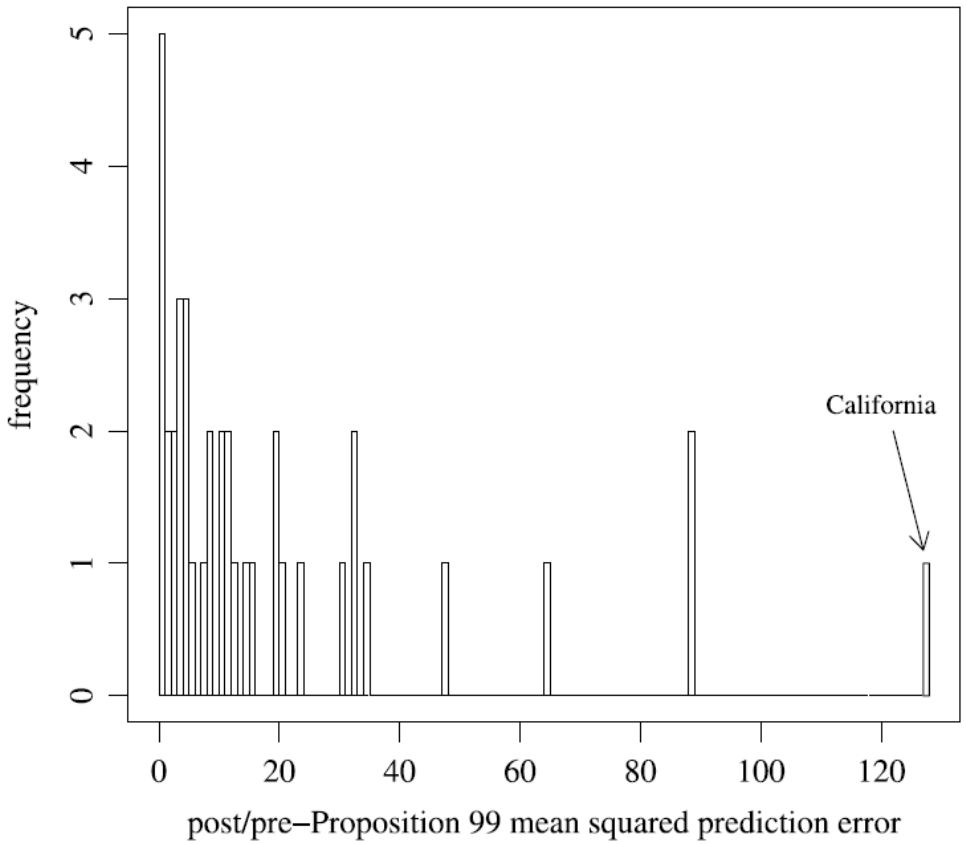
Histogram of Placebo MSPE's

Q: How interpret this histogram?



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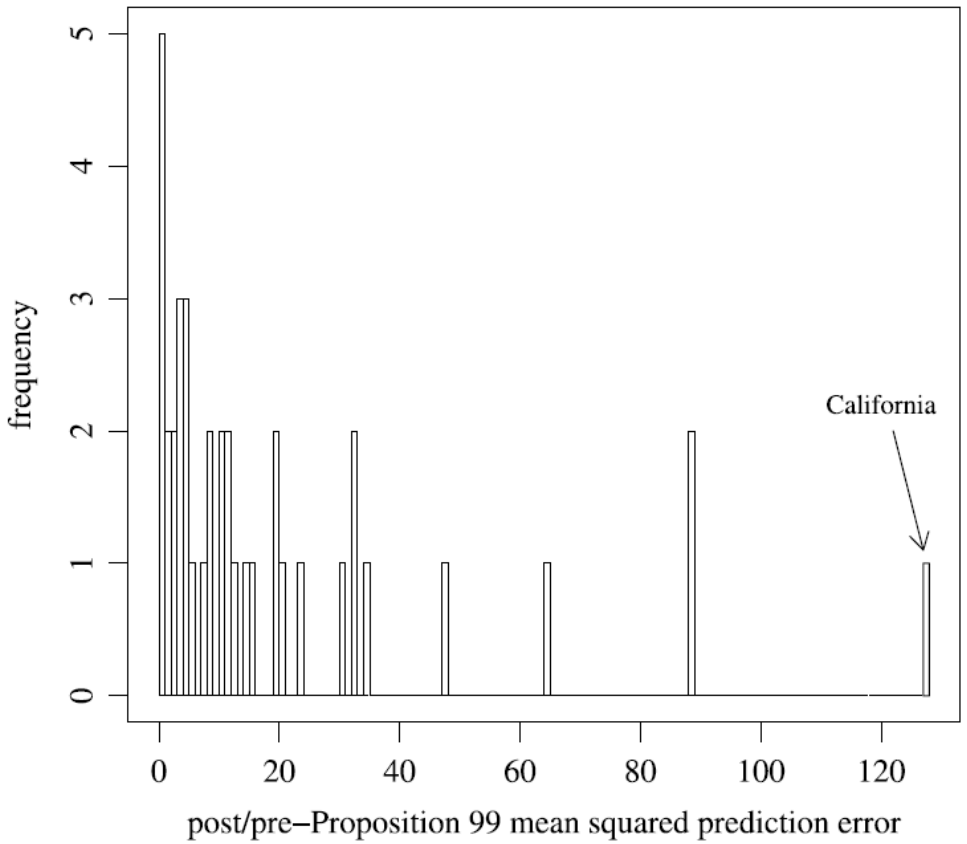
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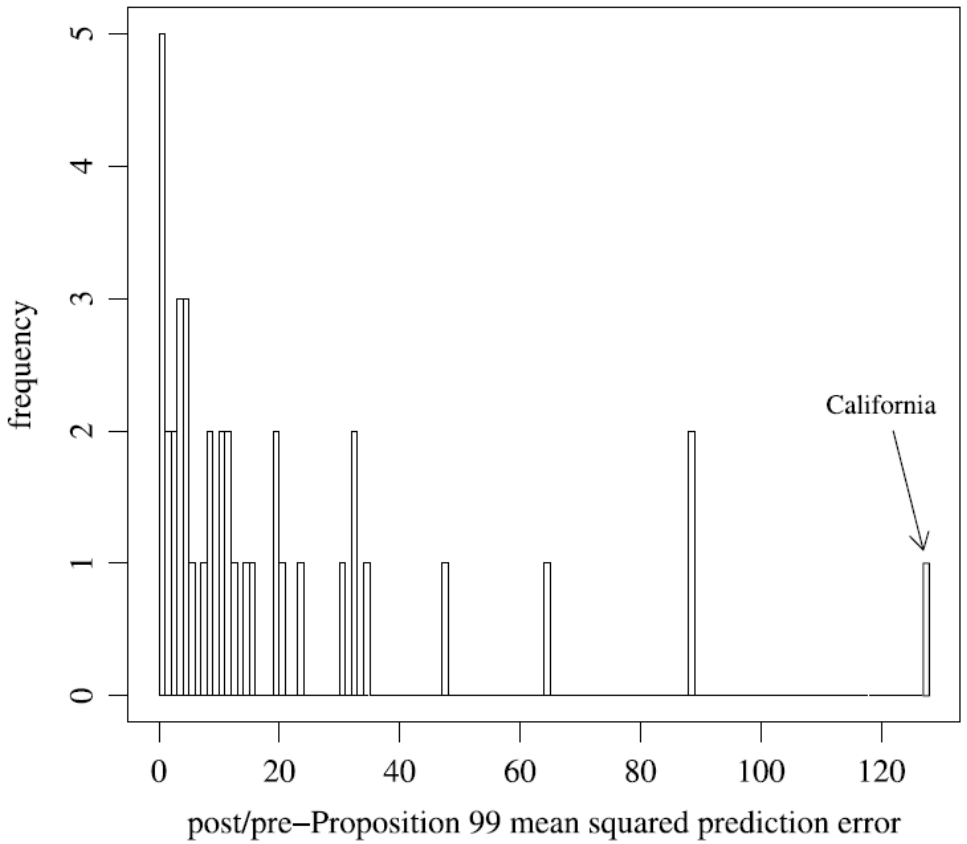
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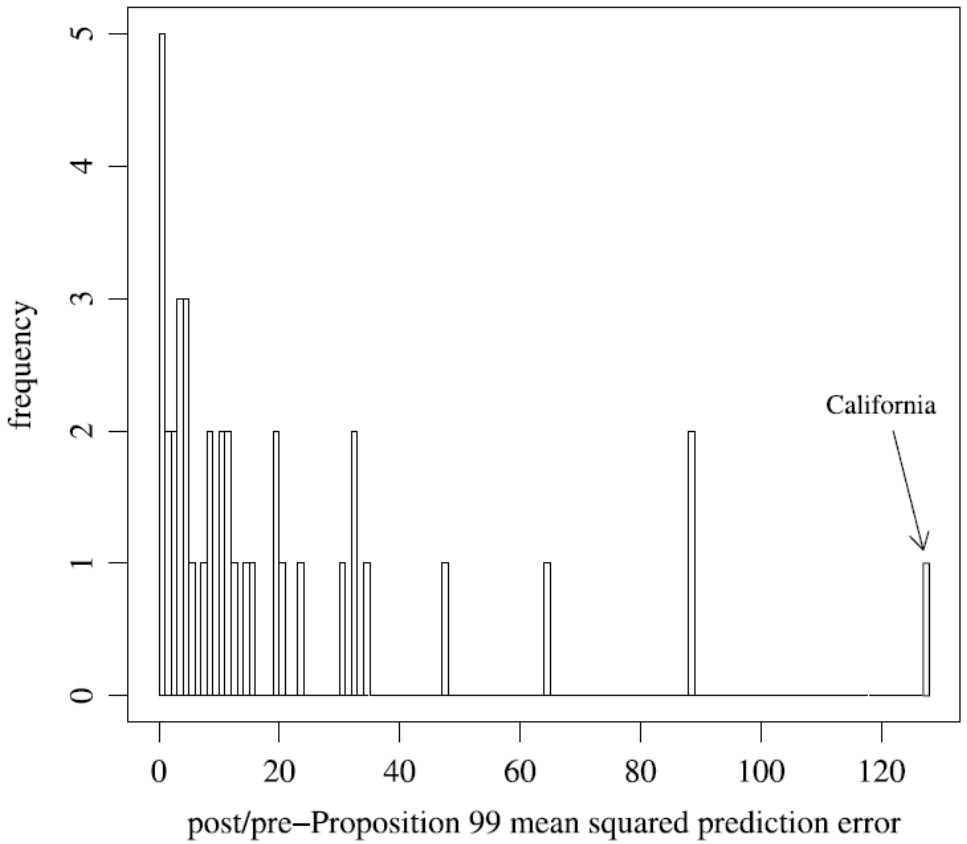
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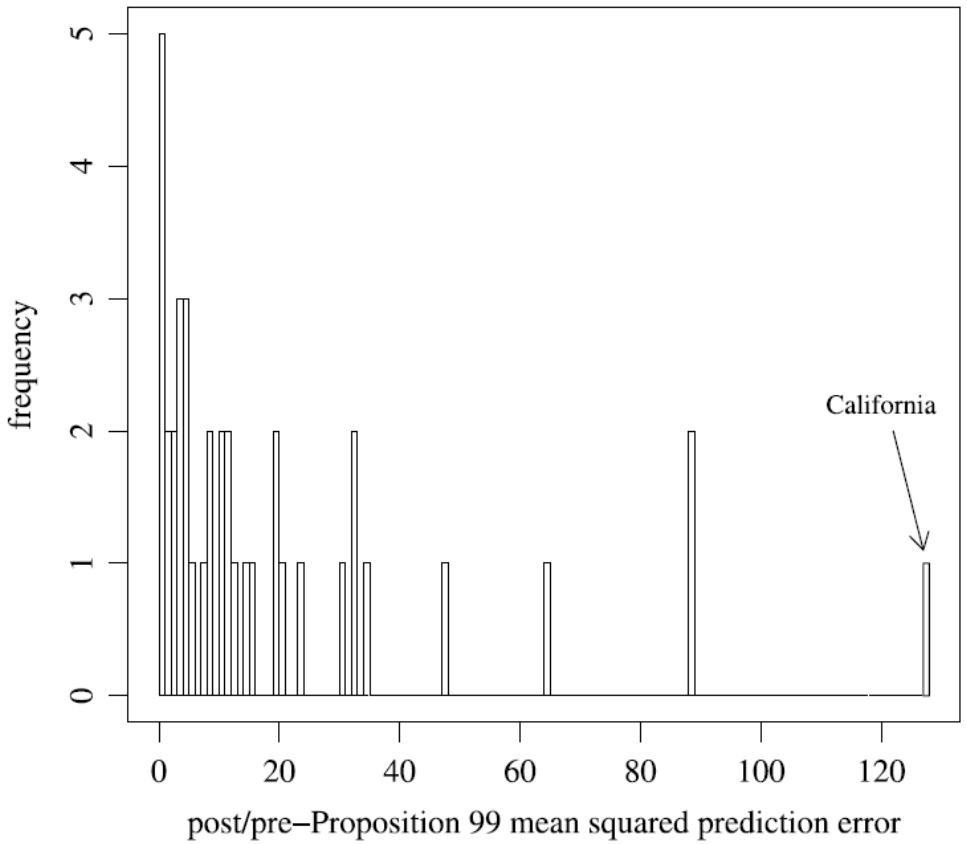
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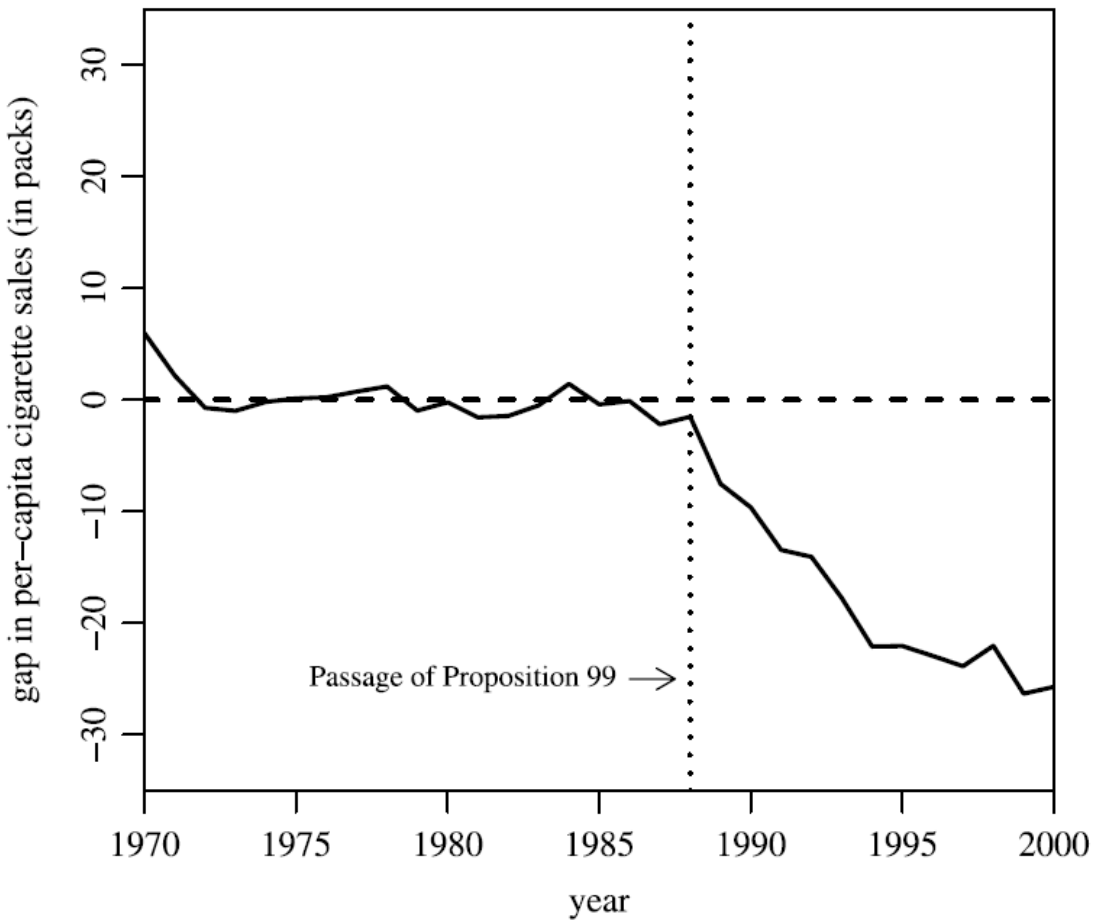
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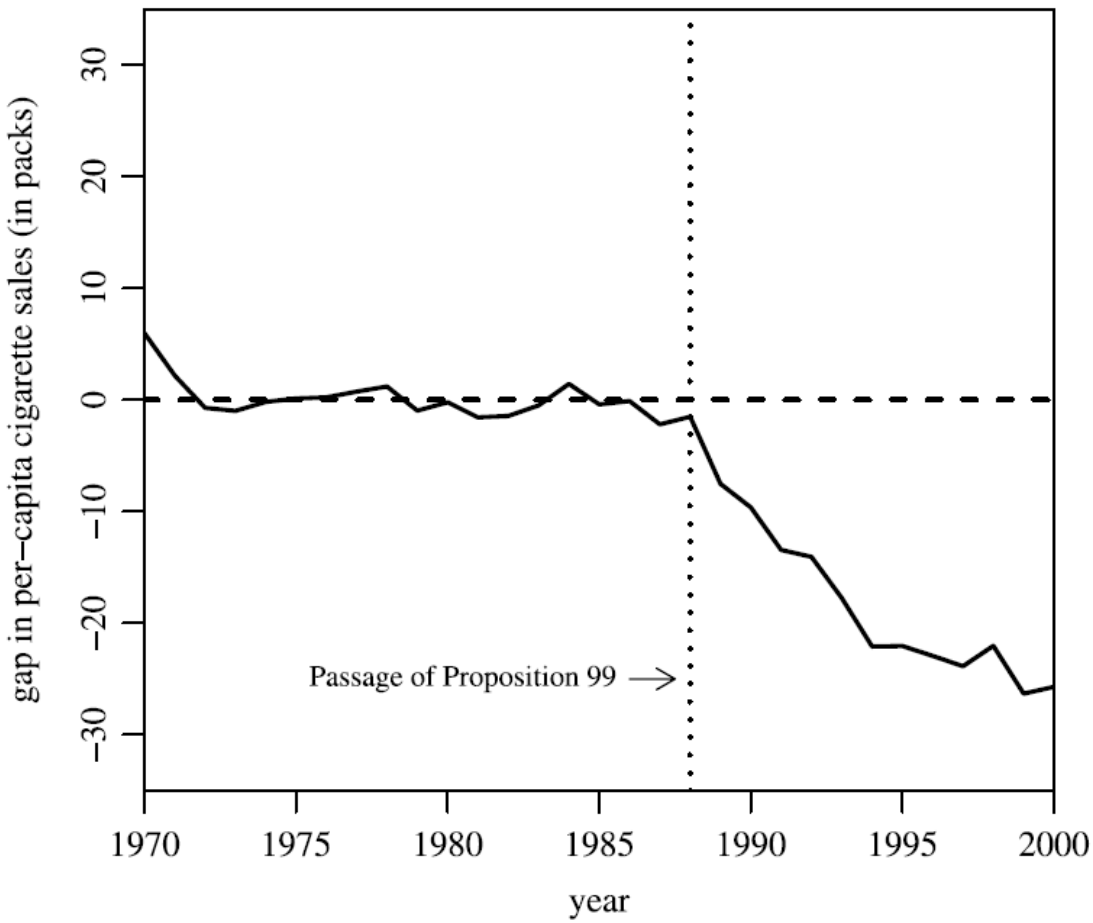
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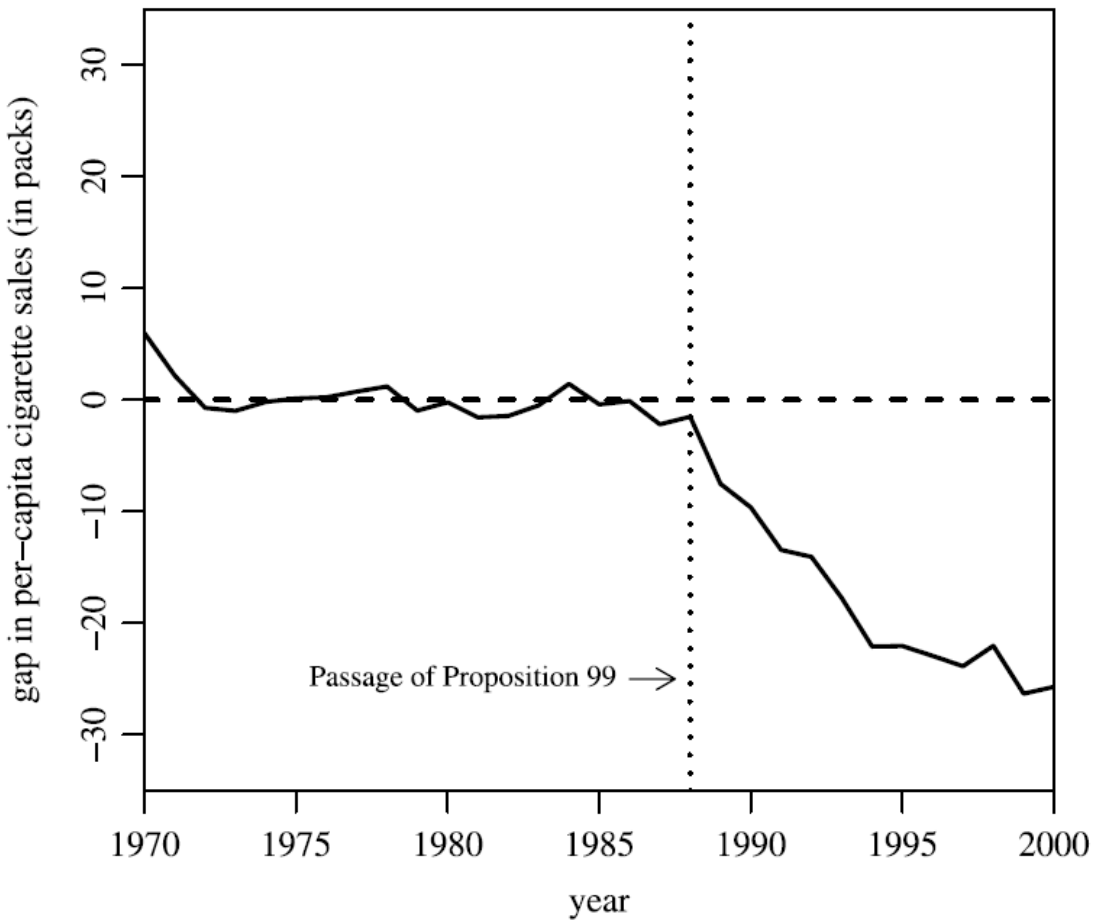
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Plotting Placebo Gaps

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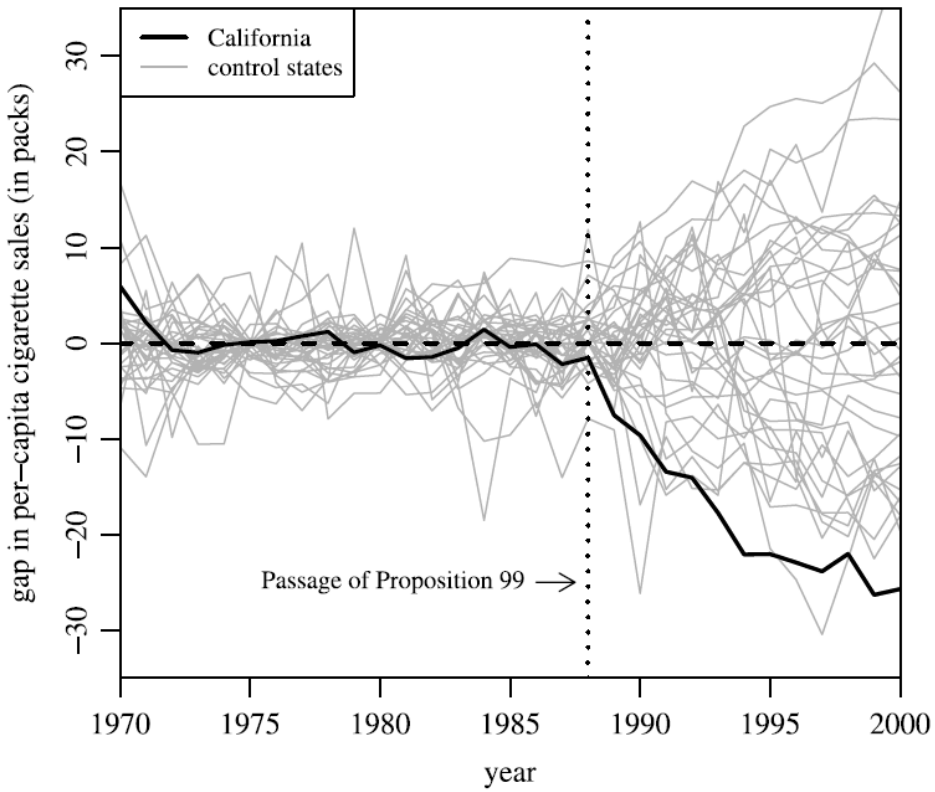


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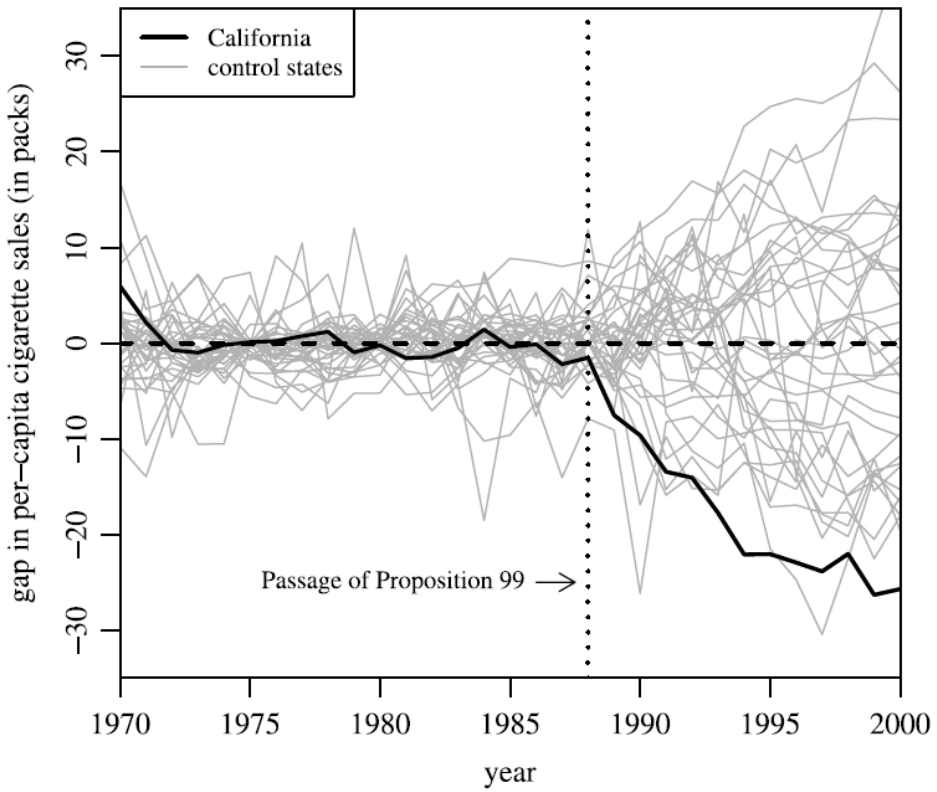


Figure 5. Per-capita cigarette sales gaps in California and placebo gaps in 34 control states (discards states with pre-Proposition 99 MSPE twenty times higher than California's).

A: CA (dark black) appears near the extremes of the placebo confidence interval, implying that the treatment effect might be statistically significant.

Outline

1. Motivation - Case Study
   - The Case Study DAG
   - Problem with our usual methods
   - The Synthetic Control Solution
2. Synthetic Control Details
   - Framing with Potential Outcomes
   - Synthetic California
   - Inference
   - Summary

Advantages & Disadvantages of Synthetic Control

Not an exhaustive list

Advantages

- Intuitive
- No extrapolation beyond support of data, which is a possible shortcoming of regression adjustment methods
- Possibly less likely to let post-intervention results influence model specification
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