22. Treatments that turn on once

Difference in difference
Interrupted time series
Regression discontinuity
Synthetic control

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Cornell Info 6751: Causal Inference in Observational Settings
Fall 2022

8 Nov 2022

Learning goals for today

At the end of class, you will be able to:

1. Recognize the promises and pitfalls of four methods to study the effects of treatments that turn on once
   1.1 Difference in difference (DID)
   1.2 Interrupted time series (ITS)
   1.3 Regression discontinuity (RD)
   1.4 Synthetic control (SC)

Economic theory: A higher minimum wage reduces employment

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Data

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- Apr 1 1992: New Jersey minimum wage rises to $5.05

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Economic theory: A higher minimum wage reduces employment

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- Apr 1 1991: Federal minimum wage rises to \$4.25
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Theoretical Estimand: Effect of the law on employment in NJ

$$\underbrace{Y^1_{\text{NJ,After}}}_{\text{Observed}} - \underbrace{Y^0_{\text{NJ,After}}}_{\text{Counterfactual}}$$

where Y is employment,
superscript $A = 1$ is \$5.05 minimum wage, and
pause superscript $A = 0$ is \$4.25 minimum wage

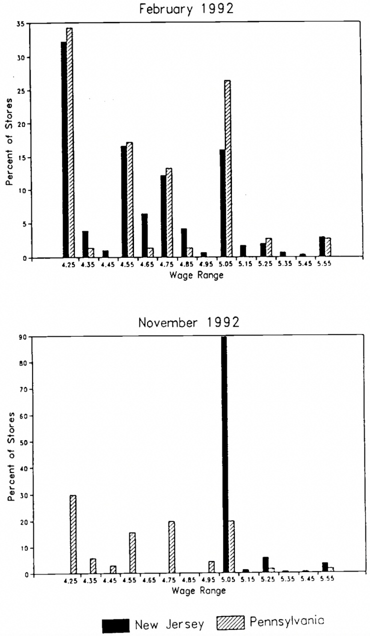

New Jersey
Minimum Wage
Rose

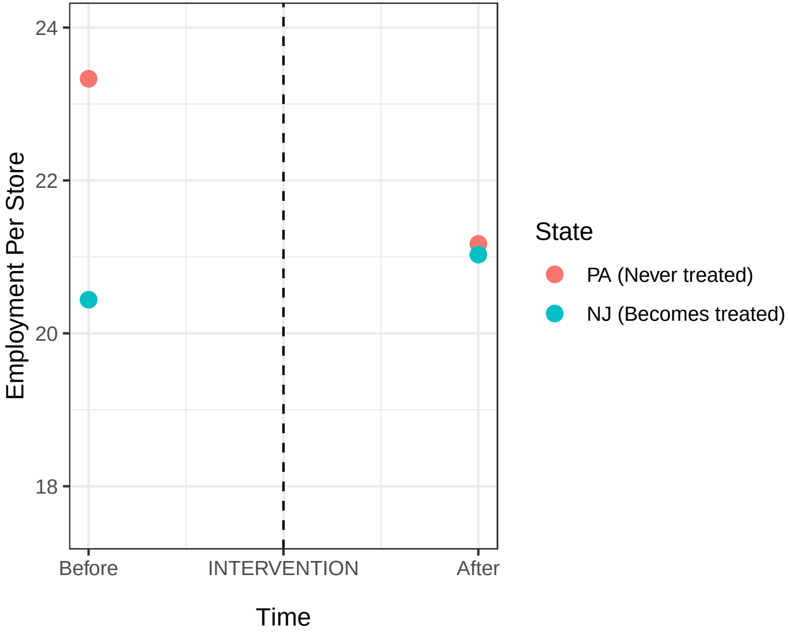

New Jersey
Minimum Wage
Rose
Pennsylvania
No change

Card & Krueger 1994: Fast food stores near the NJ / PA border

- 171 Burger King stores
- 80 KFC stores
- 99 Roy Rogers stores
- 60 Wendy's stores

Figure 1
Distribution of Starting Wage Rates




24
22
20
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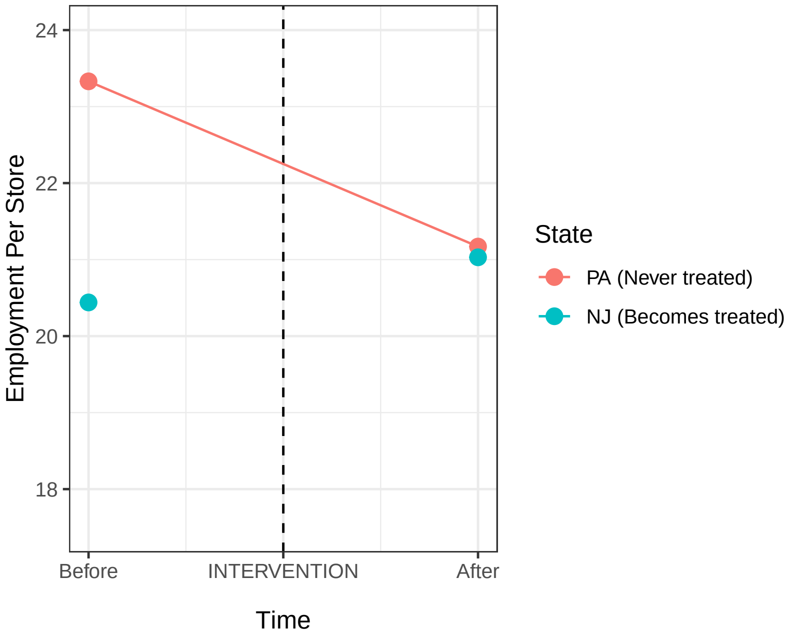
Employment Per Store
Before
INTERVENTION
After
Time
State
PA (Never treated)
NJ (Becomes treated)



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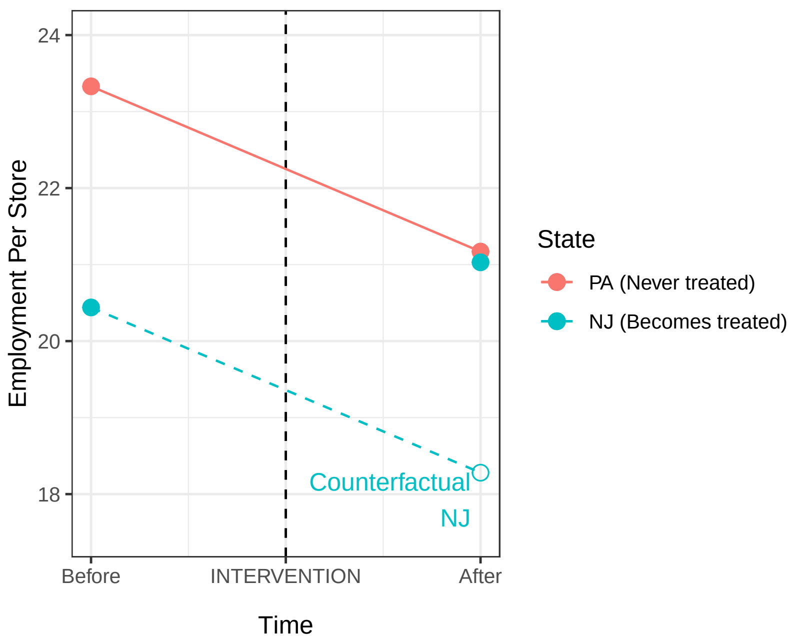

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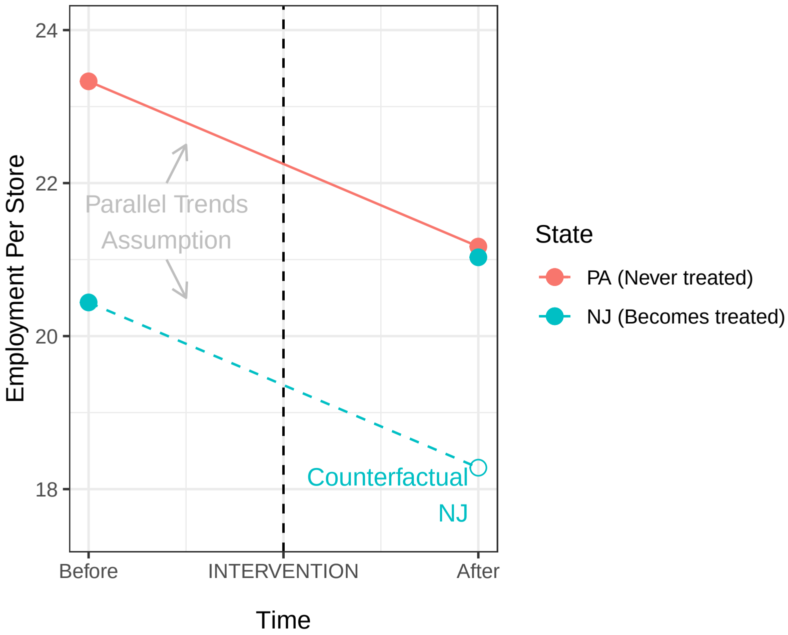

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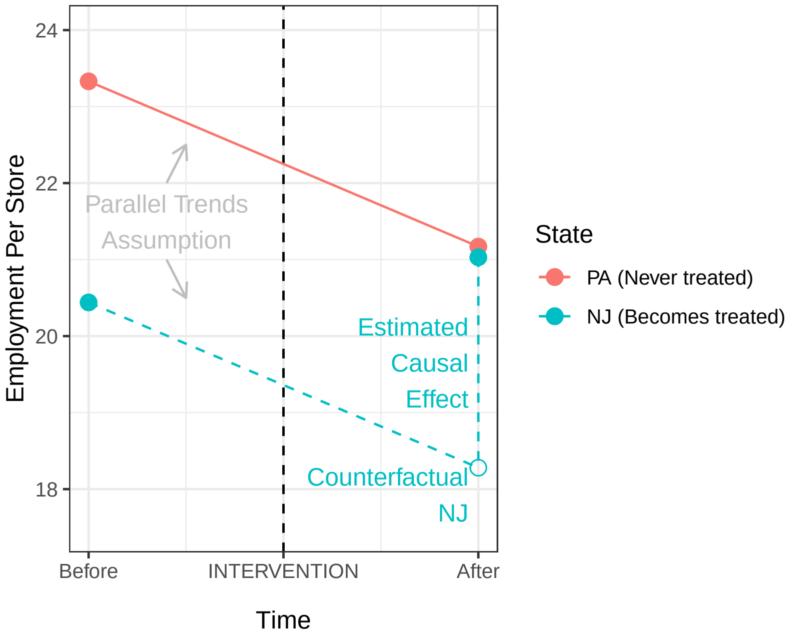

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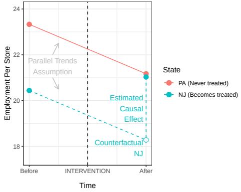

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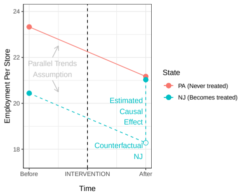
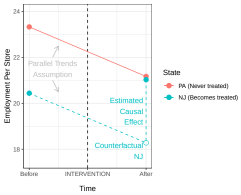


Parallel trends assumption:



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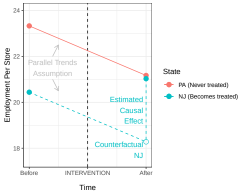

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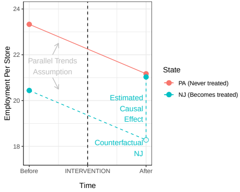
$$\overbrace{Y^0_{\text{NJ,After}} - Y^0_{\text{NJ,Before}}}^{\text{the trend in NJ}} \overbrace{=}^{\text{would equal}} \overbrace{Y^0_{\text{PA,After}} - Y^0_{\text{PA,Before}}}^{\text{the trend in PA}}$$



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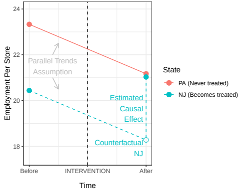
Rearranging yields a formula for the counterfactual outcome



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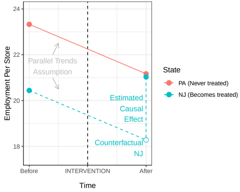

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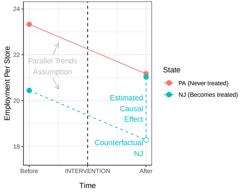
$$\underbrace{Y^0_{\text{NJ,After}}}_{\text{Counterfactual}} \overbrace{=}^{\text{By Assumption}} \underbrace{Y^0_{\text{NJ,Before}} + Y^0_{\text{PA,After}} - Y^0_{\text{PA,Before}}}_{\text{Factual}}$$



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$$\text{Effect in NJ} = \underbrace{Y^1_{\text{NJ,After}}}_{\text{Observed}} - \underbrace{Y^0_{\text{NJ,After}}}_{\text{Estimated by Above}}$$

Can we test the parallel trends assumption?

$$\overbrace{Y^0_{\text{NJ,After}} - Y^0_{\text{NJ,Before}}}^{\text{Assumption: The trend in NJ}} \overbrace{=}^{\text{would equal}} \overbrace{Y^0_{\text{PA,After}} - Y^0_{\text{PA,Before}}}^{\text{the trend in PA}}$$

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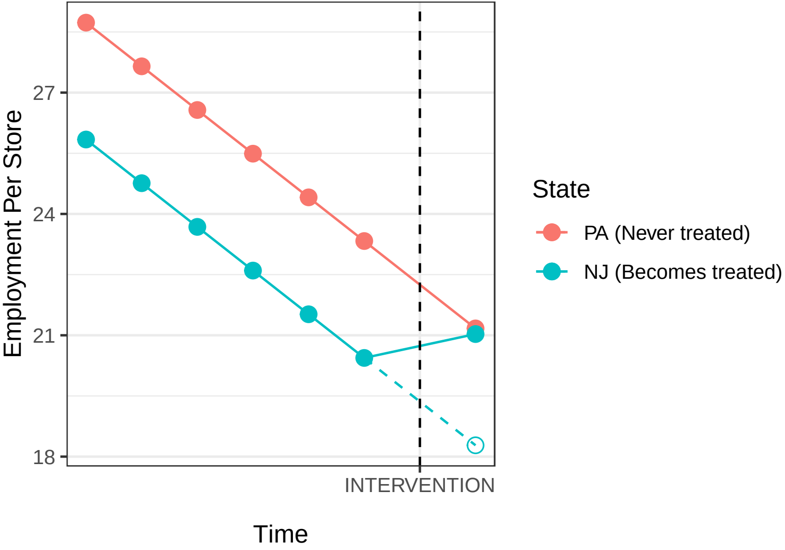
You can make it credible by looking at many pre-treatment periods

DID would be very credible



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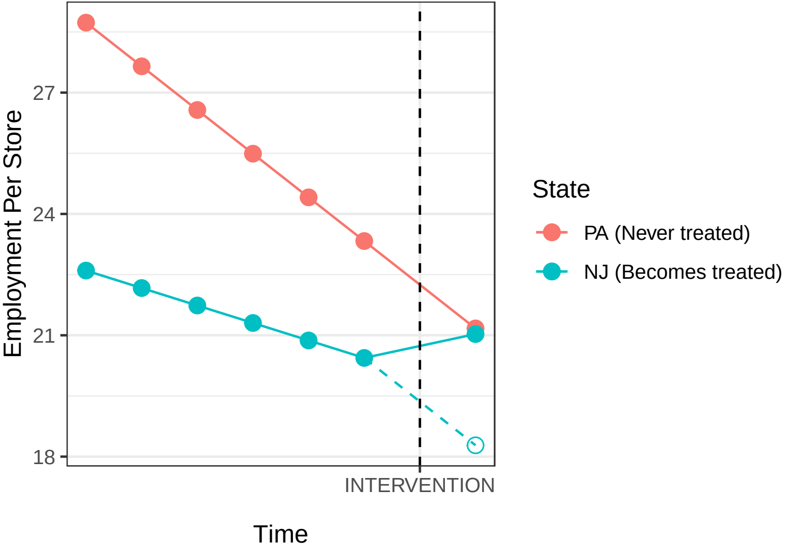

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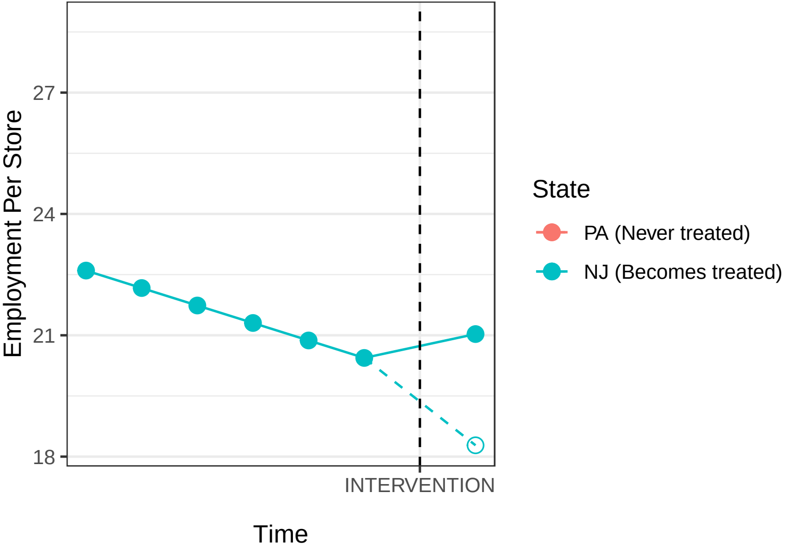

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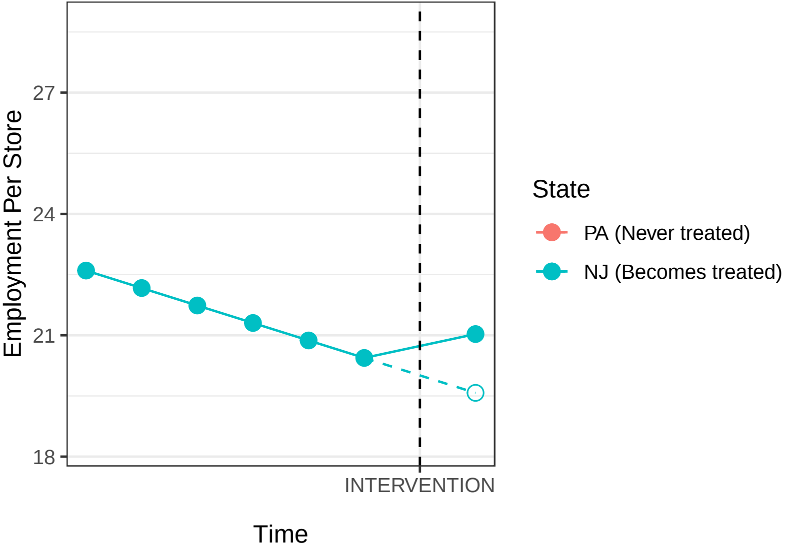

Interrupted time series[1]

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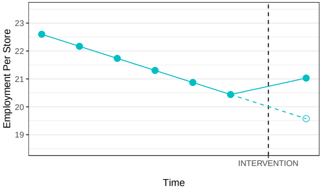
Interrupted time series[1]

You study one unit. It is untreated. Then it is treated.



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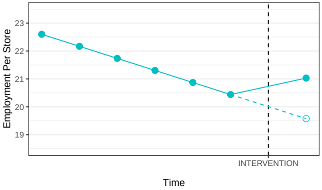

In what settings does this work well?

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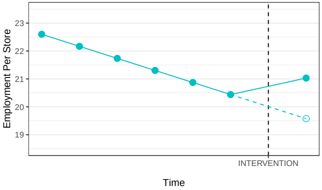

In what settings does this work well?

- When you have a strong pre-treatment trend to forecast Y_t^0

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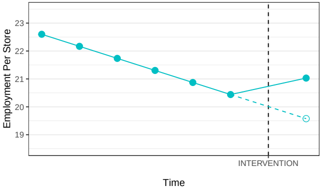

In what settings does this work well?

- When you have a strong pre-treatment trend to forecast Y_t^0
- When you don't have a comparable unit that is never treated

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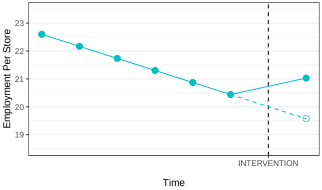

Theoretical Estimand

$$E(Y^1 - Y^0 \mid T > t_{\text{Intervention}})$$

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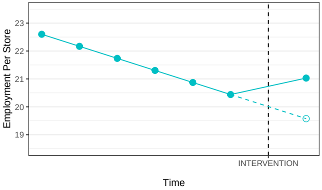

Identifying Assumption

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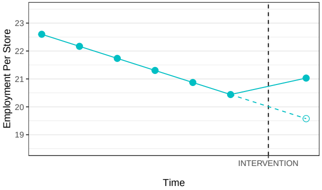

Identifying Assumption

- In the absence of the intervention, the pre-intervention trend in Y^0 would have continued

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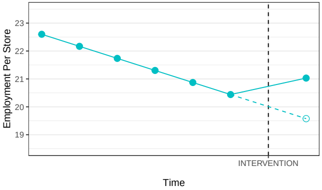

Concrete steps:

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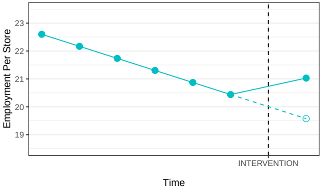

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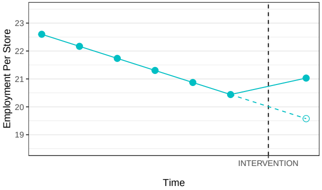

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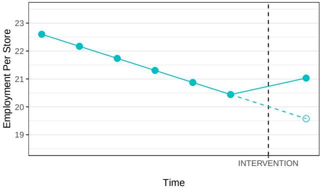

Concrete steps:

1. Learn a model on the pre-treatment period
   - Evaluation metric: Forecast within the pre-treatment period
2. Forecast Y^0 for the post-treatment period

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Interrupted time series: When it becomes doubtful

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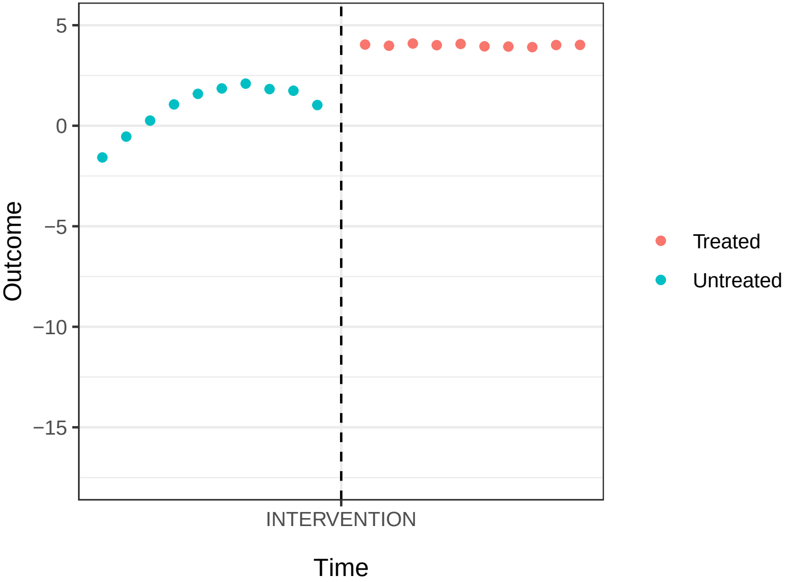

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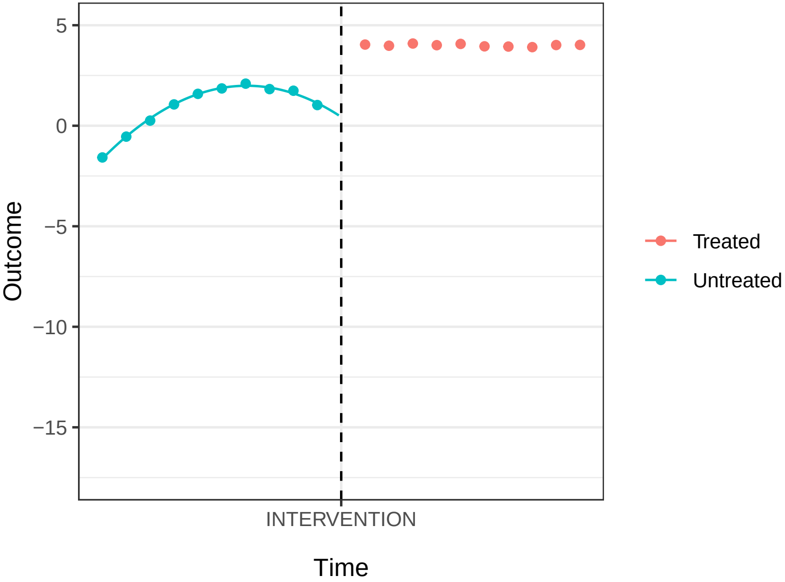

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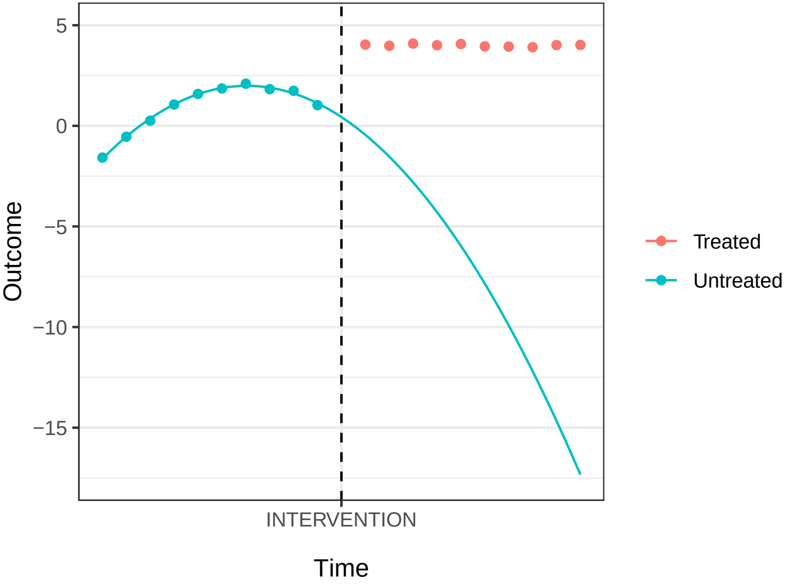

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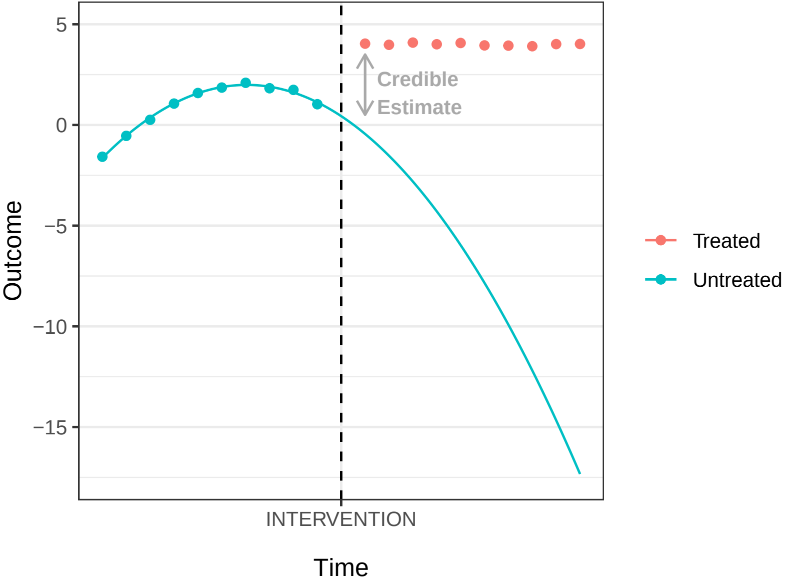

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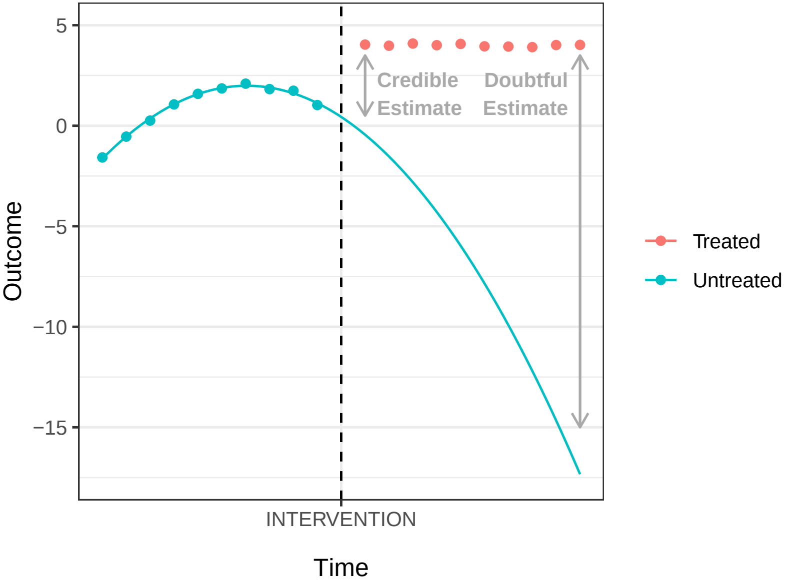


Interrupted time series: Recap

- ITS applies when treatment turns on at one time for all units
- ITS requires a parametric model to extrapolate
- ITS is most credible near the time when treatment turns on

When to use each method

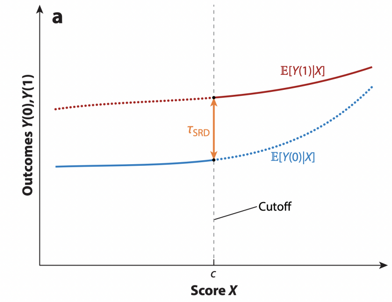
- Difference in difference
  - One unit becomes treated — New Jersey
  - One unit never becomes treated — Pennsylvania
  - The trends in Y^0 are parallel
- Interrupted time series
  - Everyone becomes treated at $X = c$ — New drug
  - You believe you can forecast Y^0 from $X < c$ to $X > c$ — Deaths would have been stable

Regression discontinuity[2]

[2] Cattaneo, M. D., & Titiunik, R. (2022). Regression discontinuity designs. Annual Review of Economics, 14, 821-851.

Regression discontinuity[2]

Cattaneo & Titiunik 2022 Fig 1a



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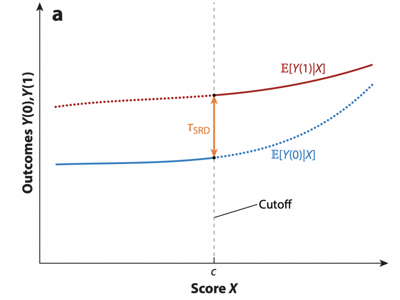

Examples

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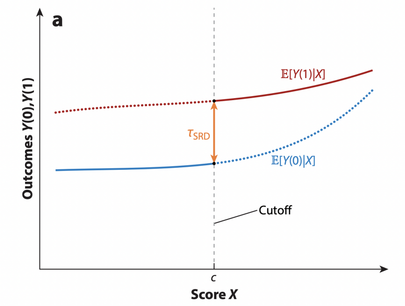

Examples

X is PSAT test score
c is a score cutoff
A is National Merit Scholarship

(Thistlewaite & Campbell 1960)

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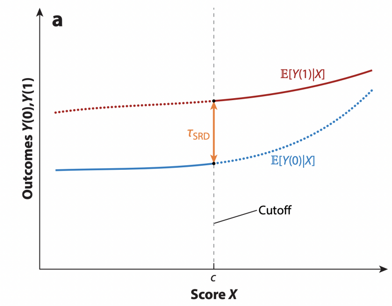

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(Thistlewaite & Campbell 1960)

X is vote share
c is 50%
A is winning the election

(De la Cuesta & Imai 2016)

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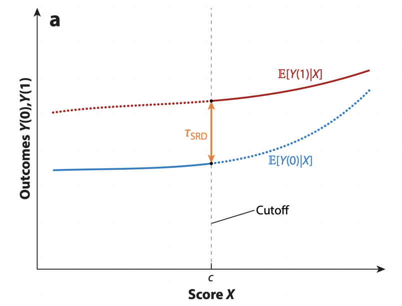

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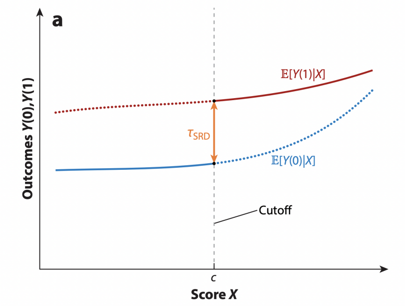
A is winning the election
(De la Cuesta & Imai 2016)

X is date
c is 2am Nov 6 2022
A is hours of PM darkness

[2] Cattaneo, M. D., & Titiunik, R. (2022). Regression discontinuity designs. Annual Review of Economics, 14, 821-851.

Regression discontinuity[2]

Cattaneo & Titiunik 2022 Fig 1a



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Regression discontinuity[2]

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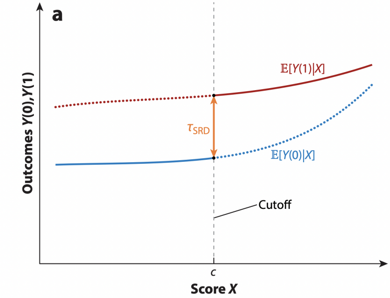

Theoretical Estimand

$E(Y(1) - Y(0) \mid X = c)$

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Regression discontinuity[2]

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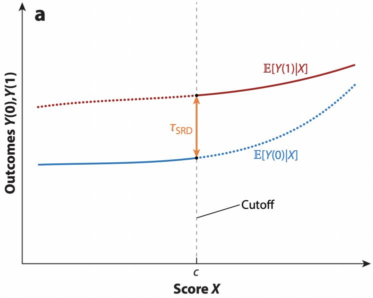

Theoretical Estimand

$$E(Y(1) - Y(0) \mid X = c)$$

Empirical Estimand

$$\lim_{x \downarrow c} E(Y \mid X = x) - \lim_{x \uparrow c} E(Y \mid X = x)$$

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Regression discontinuity[2]

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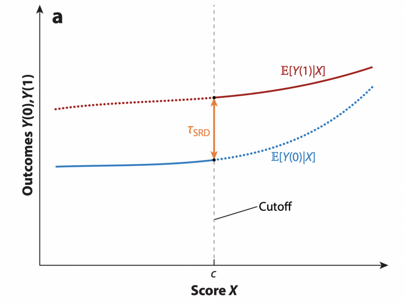

Theoretical Estimand

$E(Y(1) - Y(0) \mid X = c)$

Empirical Estimand

$\lim_{x \downarrow c} E(Y \mid X = x)$

$-$

$\lim_{x \uparrow c} E(Y \mid X = x)$

Identifying Assumptions

$E(Y(1) \mid X = x)$ and $E(Y(0) \mid X = x)$ are continuous at $x = c$

and $f_X(x) > 0$ for x near c

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Regression discontinuity[2]

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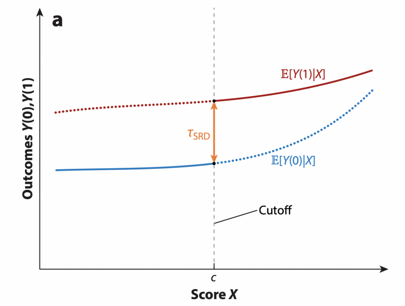

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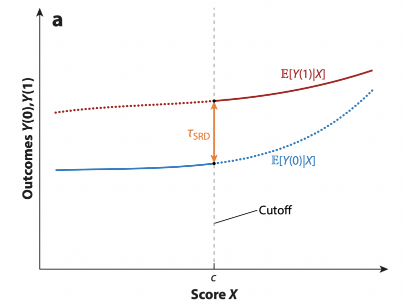

Promises of RD

Drawbacks of RD

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Regression discontinuity[2]

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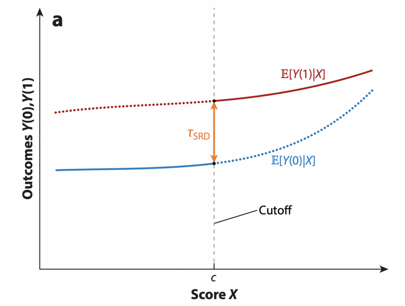

Promises of RD

— Highly credible

Drawbacks of RD

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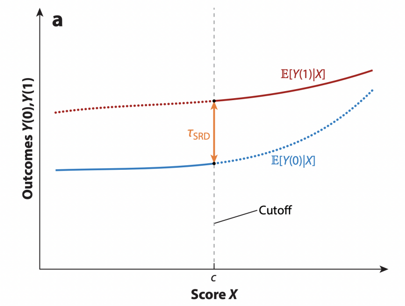
Regression discontinuity[2]

Cattaneo & Titiunik 2022 Fig 1a



Promises of RD

— Highly credible

— Easy to visualize

Drawbacks of RD

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Regression discontinuity[2]

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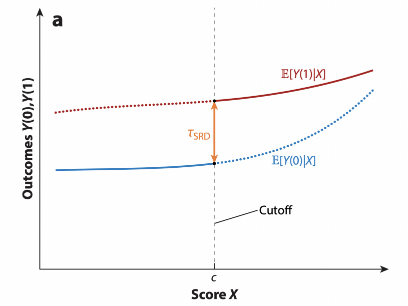

Promises of RD

— Highly credible

— Easy to visualize

Drawbacks of RD

— Local to $X = c$

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Regression discontinuity[2]

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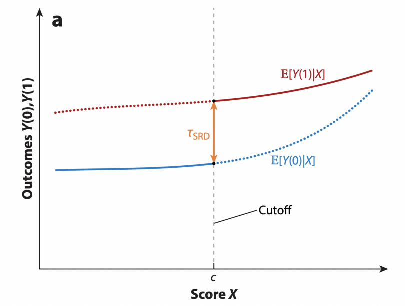

Promises of RD

— Highly credible

— Easy to visualize

Drawbacks of RD

— Local to $X = c$

— Sensitive to sorting

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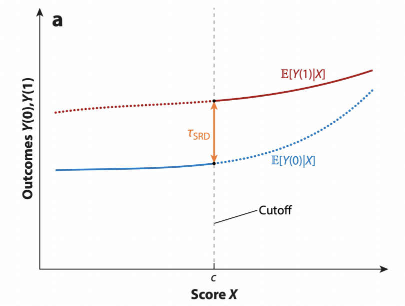

Promises of RD

— Highly credible

— Easy to visualize

Drawbacks of RD

— Local to $X = c$

— Sensitive to sorting

(people moving strategically over the cutoff)

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When to use each method

- Difference in difference
  - One unit becomes treated — New Jersey
  - One unit never becomes treated — Pennsylvania
  - The trends in Y^0 are parallel
- Interrupted time series
  - Everyone becomes treated at $X = c$ — New drug
  - You believe you can forecast Y^0 from $X < c$ to $X > c$ — Deaths would have been stable
- Regression discontinuity
  - Everyone becomes treated at $X = c$ — Win the election
  - You want a local estimate $\text{E}(Y^1 - Y^0 \mid X = c)$ at the cutoff — Close elections
  - Y^0 and Y^1 are continuous at $X = c$

Synthetic control[3]

[3] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association, 105(490), 493-505.

Synthetic control[3]

In 1988, California implemented a tobacco control program

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Synthetic control[3]

In 1988, California implemented a tobacco control program

- New tax: 25 cents per pack

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In 1988, California implemented a tobacco control program

- New tax: 25 cents per pack
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Synthetic control[3]

In 1988, California implemented a tobacco control program

- New tax: 25 cents per pack
- Money earmarked for smoking-reduction programs

How much did it reduce CA cigarette sales in 1990? 1995? 2000?

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Synthetic control[4]

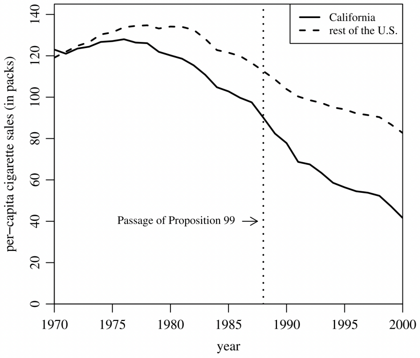

Figure 1. Trends in per-capita cigarette sales: California vs. the rest of the United States.

Can't use RD

— Effect at 1988 not of interest

Can't use ITS

— Hard to extrapolate Y^0 trend

Can't use DID

— No other state like CA

Idea: Create a **synthetic CA** to estimate $Y^0_{\text{CA},t}$ for $t \geq 1988$

[4] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association, 105(490), 493-505.

Synthetic control[5]

Synthetic CA as a weighted average of other states

Table 1. Cigarette sales predictor means

Variables	California Real	California Synthetic	Average of 38 control states
Ln(GDP per capita)	10.08	9.86	9.86
Percent aged 15–24	17.40	17.40	17.29
Retail price	89.42	89.41	87.27
Beer consumption per capita	24.28	24.20	23.75
Cigarette sales per capita 1988	90.10	91.62	114.20
Cigarette sales per capita 1980	120.20	120.43	136.58
Cigarette sales per capita 1975	127.10	126.99	132.81

NOTE: All variables except lagged cigarette sales are averaged for the 1980–1988 period (beer consumption is averaged 1984–1988). GDP per capita is measured in 1997 dollars, retail prices are measured in cents, beer consumption is measured in gallons, and cigarette sales are measured in packs.

[5] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association, 105(490), 493-505.

Synthetic control[6]

Synthetic CA as a weighted average of other states

$$\text{Theoretical Estimand:} \quad \tau(t) = Y^1_{\text{CA},t} - Y^0_{\text{CA},t} \qquad t \geq 1988$$

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Synthetic control[6]

Synthetic CA as a weighted average of other states

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$$\text{Empirical Estimand:} \quad \theta(t) = Y^1_{\text{CA},t} - Y^0_{\text{SyntheticCA},t} \qquad t \geq 1988$$

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$$\text{Identifying Assumption:} \quad \underbrace{Y^0_{\text{CA},t}}_{\text{Counterfactual}} = \underbrace{Y^0_{\text{SyntheticCA},t}}_{\text{Factual}} \qquad t \geq 1988$$

[6] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association, 105(490), 493-505.

Synthetic control[7]

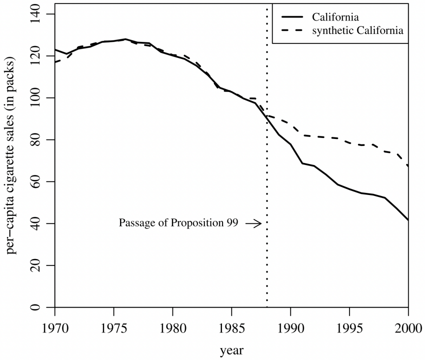

Figure 2. Trends in per-capita cigarette sales: California vs. synthetic California.

[7] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of the American Statistical Association, 105(490), 493-505.

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  - Y^0 and Y^1 are continuous at $X = c$
- Synthetic control
  - One unit becomes treated — California
  - Many units are never treated — Other states
  - You want to extrapolate far from the cutoff — 1988→2000

Learning goals for today

At the end of class, you will be able to:

1. Recognize the promises and pitfalls of four methods to study the effects of treatments that turn on once
   1.1 Difference in difference (DID)
   1.2 Interrupted time series (ITS)
   1.3 Regression discontinuity (RD)
   1.4 Synthetic control (SC)

Let me know what you are thinking

tinyurl.com/CausalQuestions

Office hours TTh 11am-12pm and at
calendly.com/ianlundberg/office-hours
Come say hi!