Using Individual-Level Data in Difference-in-Differences for Health Policy and Service Evaluation

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ALACRITY Center RIP Meeting
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Follow along!

https://slides.nickseewald.com/alacrityRIP.pdf

Who am I?

- Postdoc in Health Policy and Management with Liz Stuart and Beth McGinty
- ALACRITY trainee
- Statistician by training

- I develop and apply statistical methodology to answer key questions in public health through thoughtful study design and analysis combined with deep collaboration with applied scientists.

Motivation: Medical Cannabis Laws and Opioid Prescribing

- **4x** increase in opioid prescribing in U.S. from 1999-2012
  - Meaningfully driven by opioid prescribing for chronic non-cancer pain
- Getting better: prescribing down since 2012 peak
  - 2020 had lowest opioid dispensing rate in previous 15 years (nationally, est. by IQVIA)

- Cannabis is a potentially effective treatment for chronic non-cancer pain, but evidence is limited

https://www.cdc.gov/drugoverdose/rxrate-maps/index.html

Motivation: Medical Cannabis Laws and Opioid Prescribing

- Patients with chronic non-cancer pain are eligible to use cannabis under all existing state medical cannabis laws

- **Question**: What are the effects of state medical cannabis laws on receipt of opioid *and* non-opioid treatment among patients with chronic non-cancer pain?

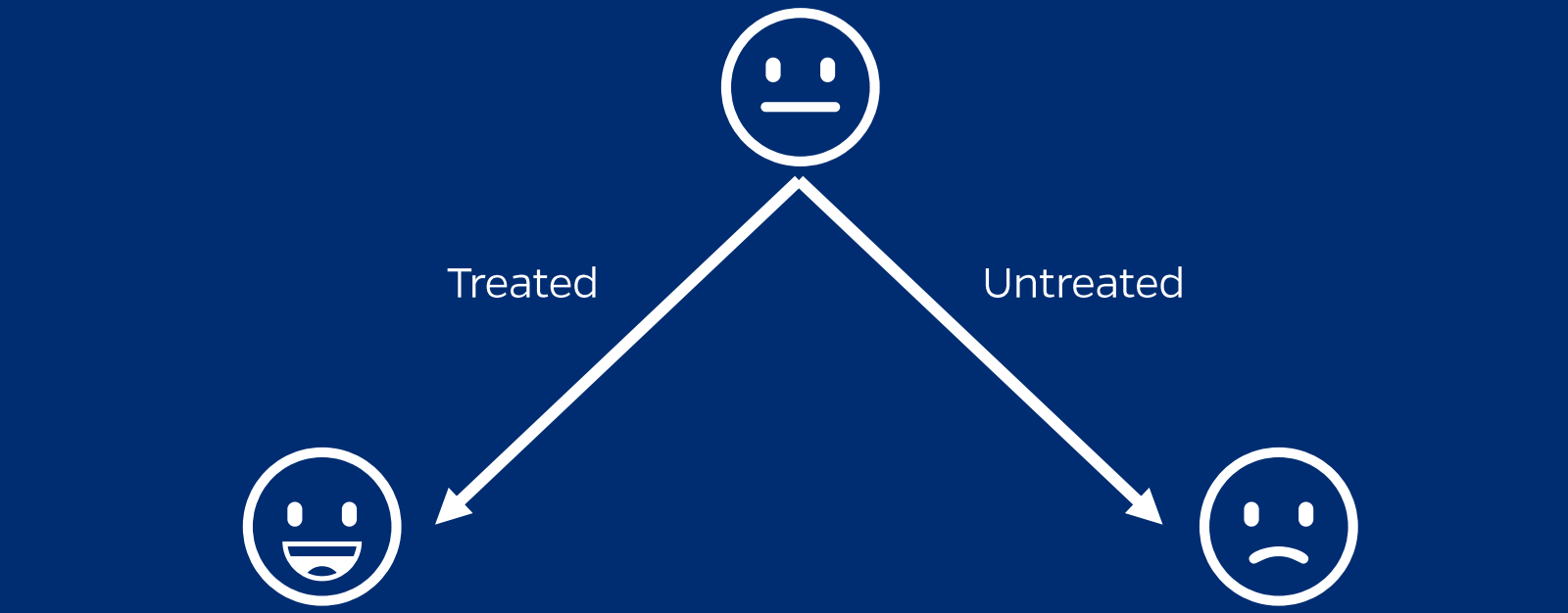
Motivation: Medical Cannabis Laws and Opioid Prescribing

- Previous studies have found mixed results, but have key methodological limitations:

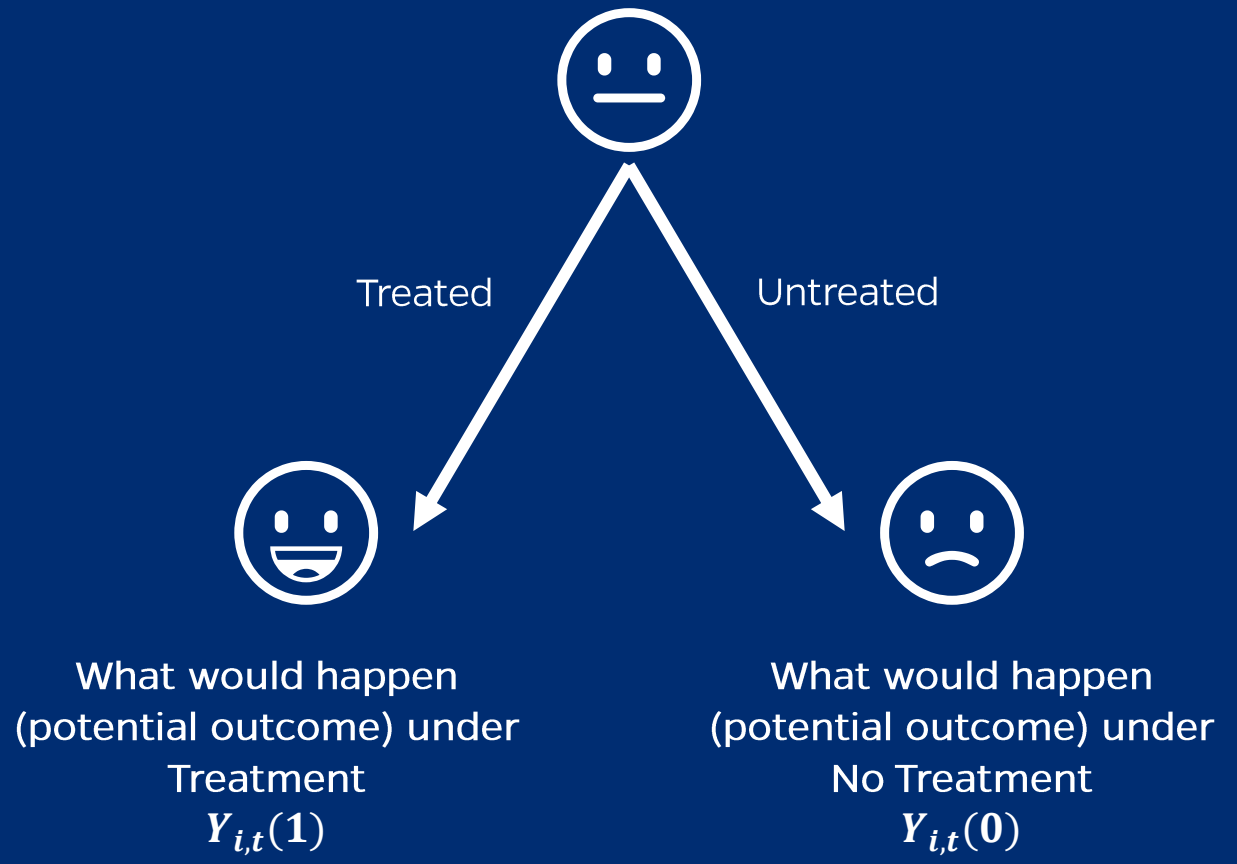
1. General population samples with no individual-level data to identify sample with chronic non-cancer pain
2. Policy endogeneity not addressed

Individual-level data lets us identify the population of interest but adds methodological complexity. My work addresses that complexity.

Potential Outcomes and Causal Inference



Potential Outcomes and Causal Inference



- $Y_{i,t}(1)$ is the outcome we would observe for unit i at time t had they received treatment
- $Y_{i,t}(0)$ is the outcome we would observe for unit i at time t had they *not* received treatment
- An *individual causal effect* is
$$Y_{i,t}(1) - Y_{i,t}(0) = 😀 - ☹$$
- For each person, we can only observe $Y_{i,t}(1)$ OR $Y_{i,t}(0)$, not both!
- We can estimate *average* causal effects (over a population of interest)

Average treatment effect among the treated (ATT)

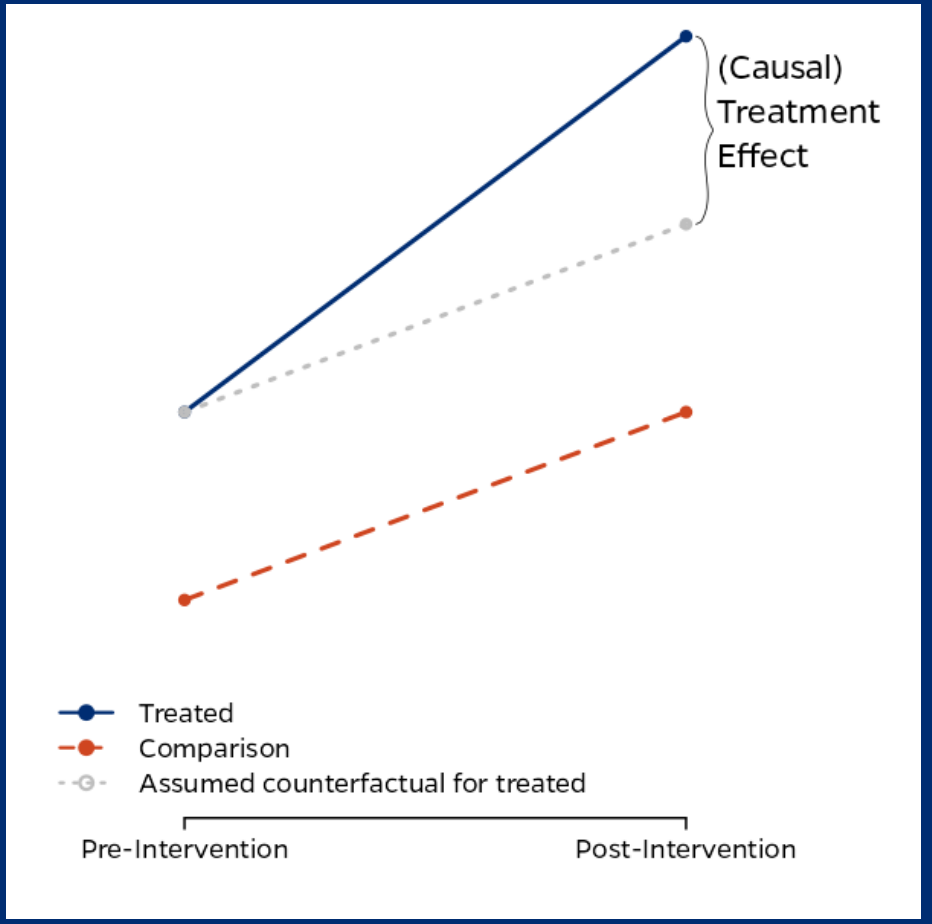
$$ATT = E[\,Y(1) - Y(0) \mid A = 1\,]$$
$$= E[\,Y(1) \mid A = 1\,] - E[\,Y(0) \mid A = 1\,]$$

where A is treatment status.

The problem is that we can't directly estimate this from data: we don't observe $Y(0)$ in the $A = 1$ group.

Difference-in-Differences

- A commonly-used method for estimating the ATT in policy evaluation
- **Idea:** compare change in outcome over time between treated and comparison groups
- **Key assumption:** in the absence of treatment, the outcome evolution in the treated group would have looked like the outcome evolution in the comparison group
  - This is called the *counterfactual parallel trends assumption*.

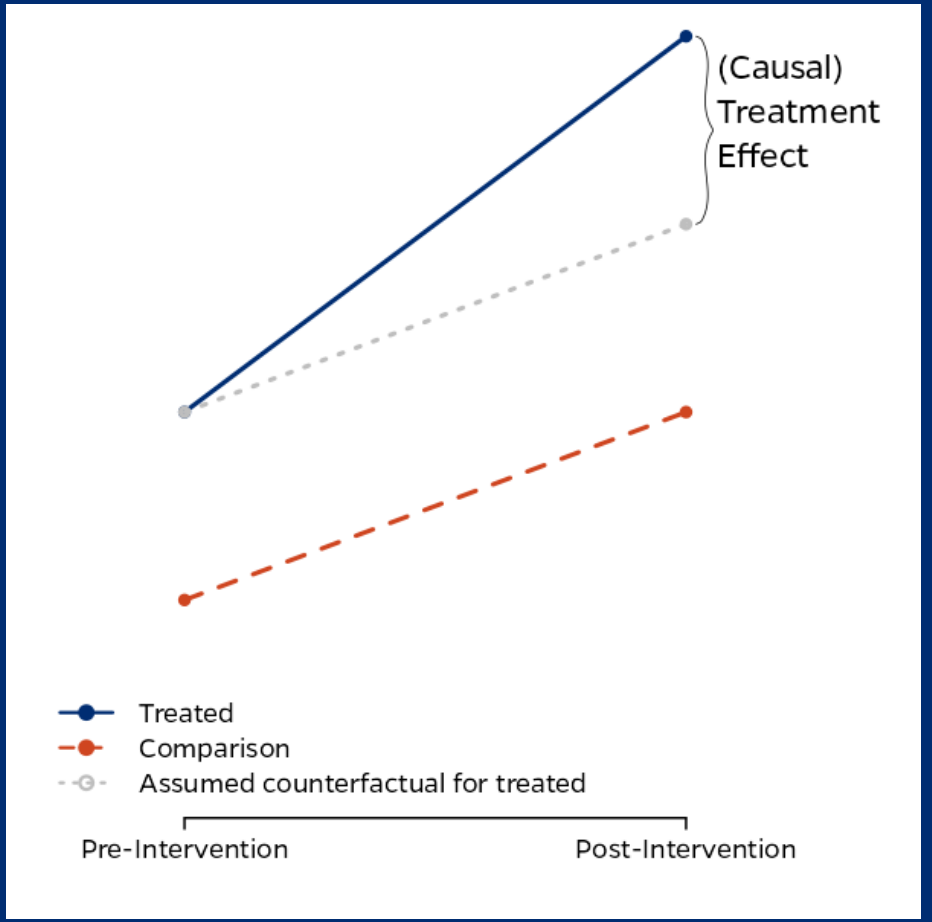


How does DiD estimate the ATT?

Under the counterfactual parallel trends assumption, we can write the ATT as

$$
\begin{aligned}
&ATT \\
&= \left(E\left[Y_{\text{post}} \mid A = 1\right] - E[Y_{\text{pre}} \mid A = 1]\right) \\
&- \left(E\left[Y_{\text{post}} \mid A = 0\right] - E[Y_{\text{pre}} \mid A = 0]\right)
\end{aligned}
$$

- The ATT is literally a *difference in differences!*
- We can estimate all these components from our data just using sample means or via regression.



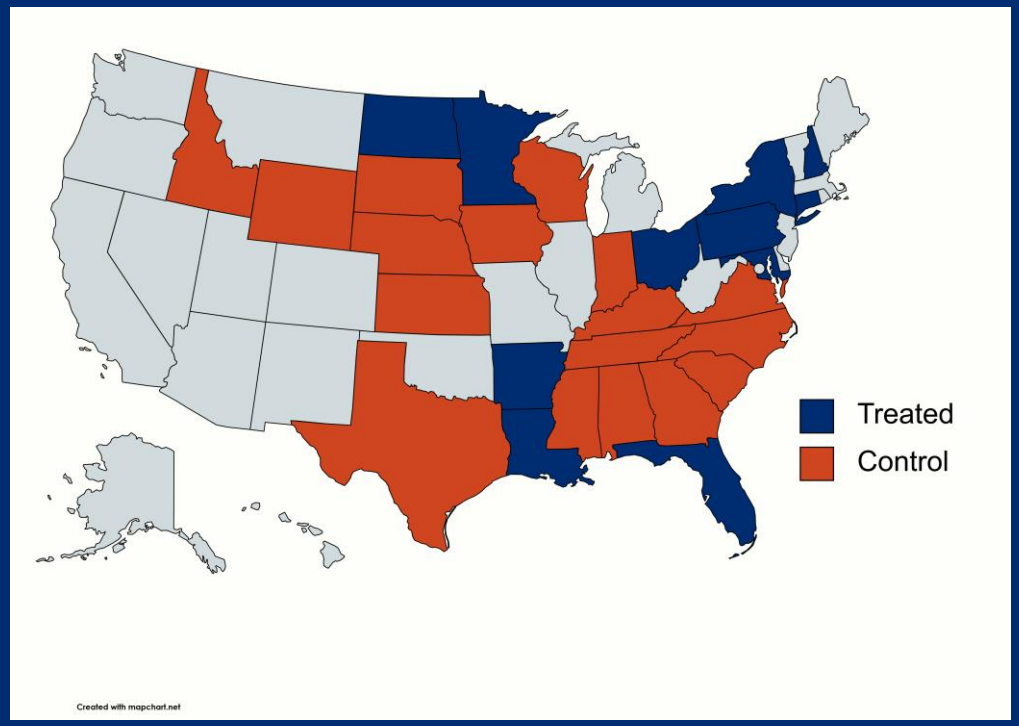
Want more on Difference-in-Differences?

- Check out Elizabeth Stone's lecture on the ALACRITY Center's YouTube channel!

https://youtu.be/EYVYTlYGdq4

Medical Cannabis Study

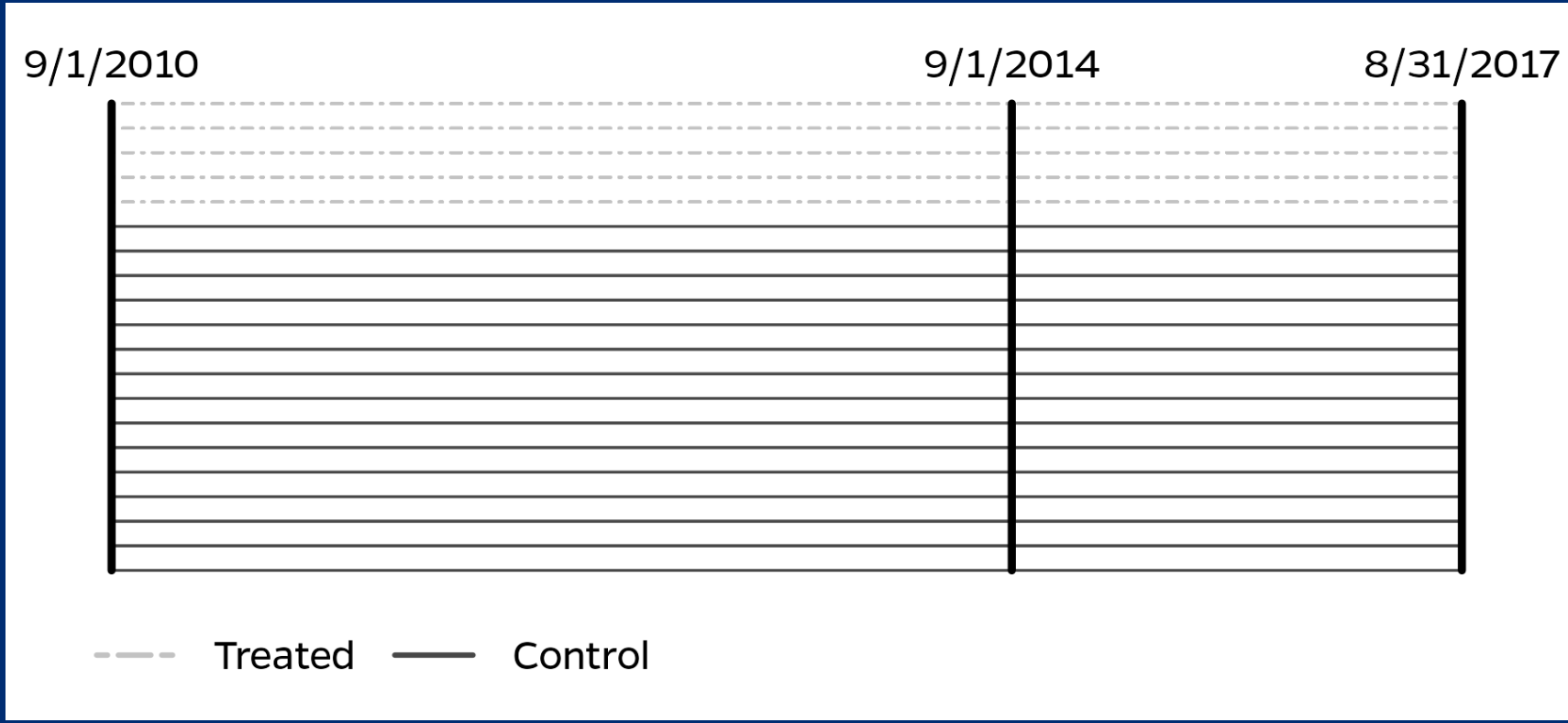
- Our study:
  - 12 *treated* states that implemented medical cannabis law between 2012 and 2019, and *do not also have recreational cannabis laws*.
  - 17 *comparison* states without medical or recreational cannabis laws, 2012-2019
- **Goal:** Estimate the effect of implementing a medical cannabis law on opioid prescribing outcomes *in each treated state*, relative to what would have happened in the absence of treatment.



Medical Cannabis Study

- Data are individual-level longitudinal commercial health insurance claims from OptumLabs Data Warehouse, collected monthly.
- Each treated state has its own 7-year study period anchored at its law's implementation date
  - 4 years pre-law, 3 years post-law
- For each treated state, we build a *cohort* of individuals in that state and the control states over that state's study period.
  - Individuals are included if they have a chronic non-cancer pain diagnosis in the pre-law period *and* are continuously enrolled in commercial health insurance for the full study period.

Medical Cannabis Study: CT Cohort



Difference-in-Differences with Multiple Time Periods

- Previous difference-in-differences setup was for two units (one treated, one control) over two time periods (pre- / post-treatment).
- When there are more than two time periods, we need to adapt our setup!

$$ATT(t) = E[Y_t(1) - Y_t(0) \mid A = 1]$$

- Extend counterfactual parallel trends assumption to apply to all pairs of pre/post observations (can be relaxed)

Two-Way Fixed Effects Estimation

- Traditional way of estimating the ATT in multi-period difference-in-differences

$$\mathrm{Y}_{uit} = \beta_{0u} + \beta_{1t} + \boldsymbol{\beta} A_{ut} + \epsilon_{uit}$$

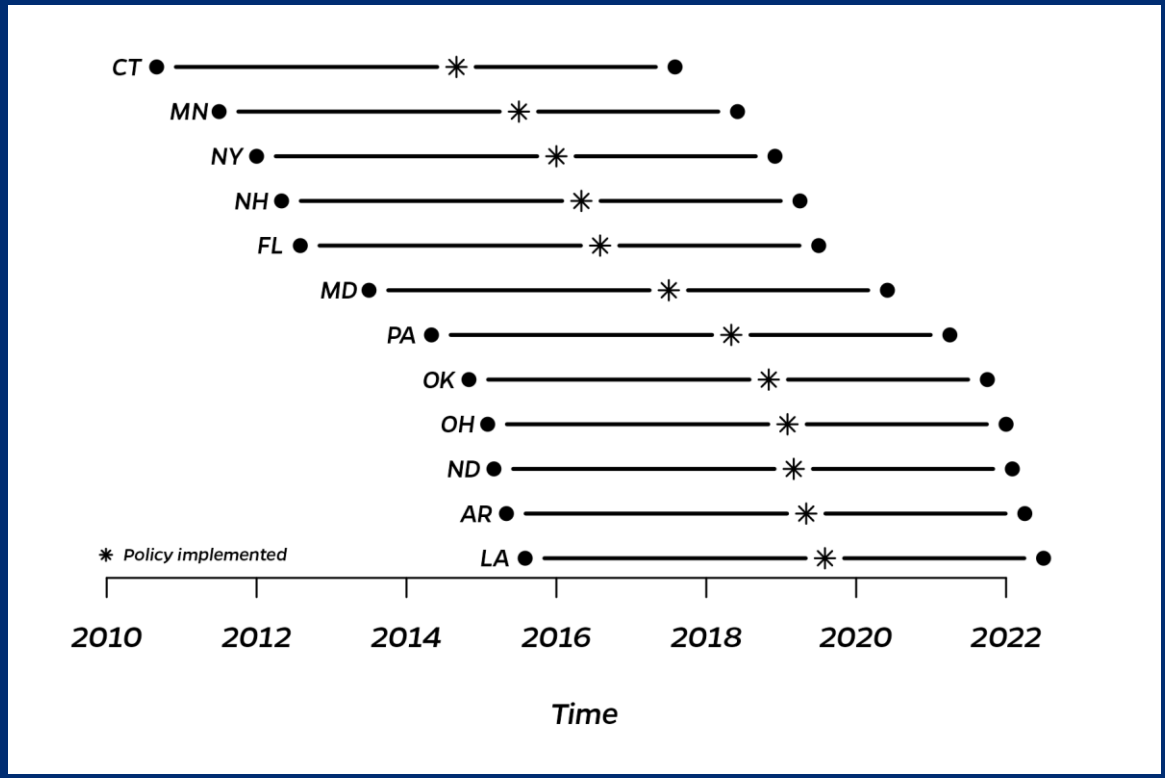
where u is unit, i is individual, t is time.

- $\hat{\beta}$ is the estimate of the ATT (averaged over time):

$$\hat{\beta} \equiv \left(\bar{Y}_{\mathrm{post,tx}} - \bar{Y}_{\mathrm{pre,tx}}\right) - \left(\bar{Y}_{\mathrm{post,ctrl}} - \bar{Y}_{\mathrm{pre,ctrl}}\right)$$

Two-Way Fixed Effects Estimation

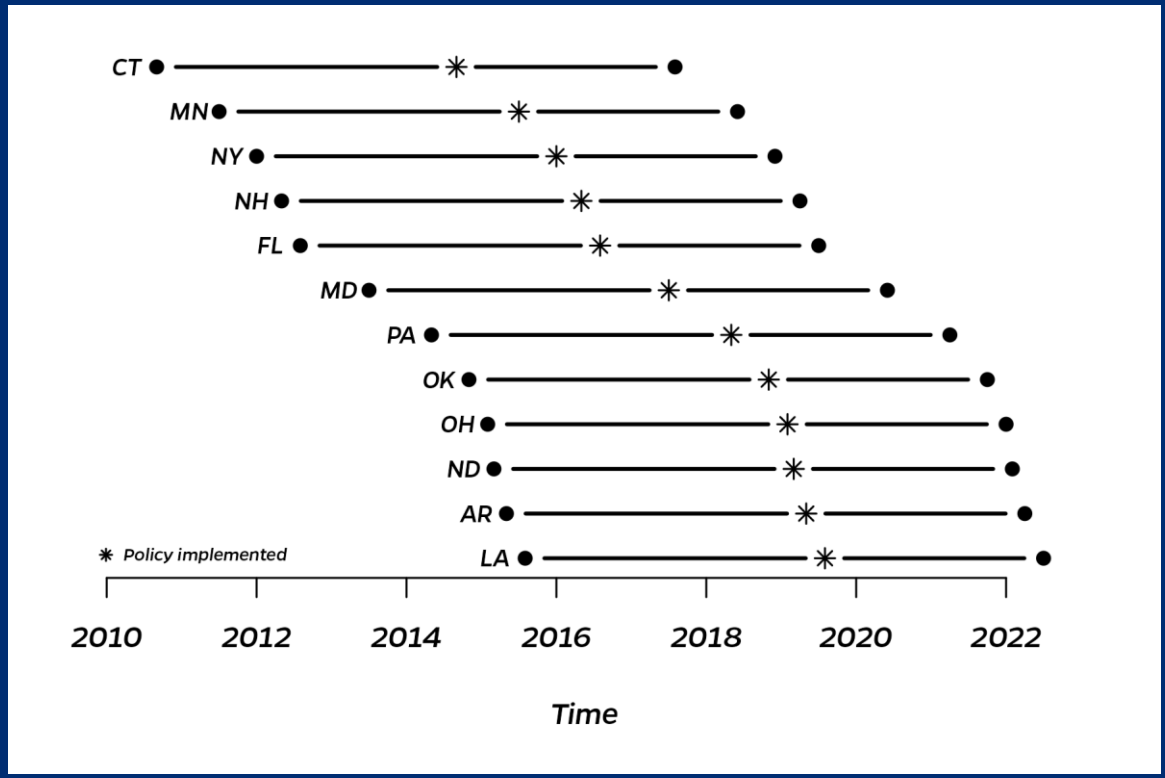
- Two-way fixed effects model can yield extremely biased effect estimates
  - when used with multiple treated units under “staggered adoption” **and**
  - when trying to estimate an overall effect across treated units
- Estimator implicitly (and inappropriately) adjusts for post-treatment information from some units



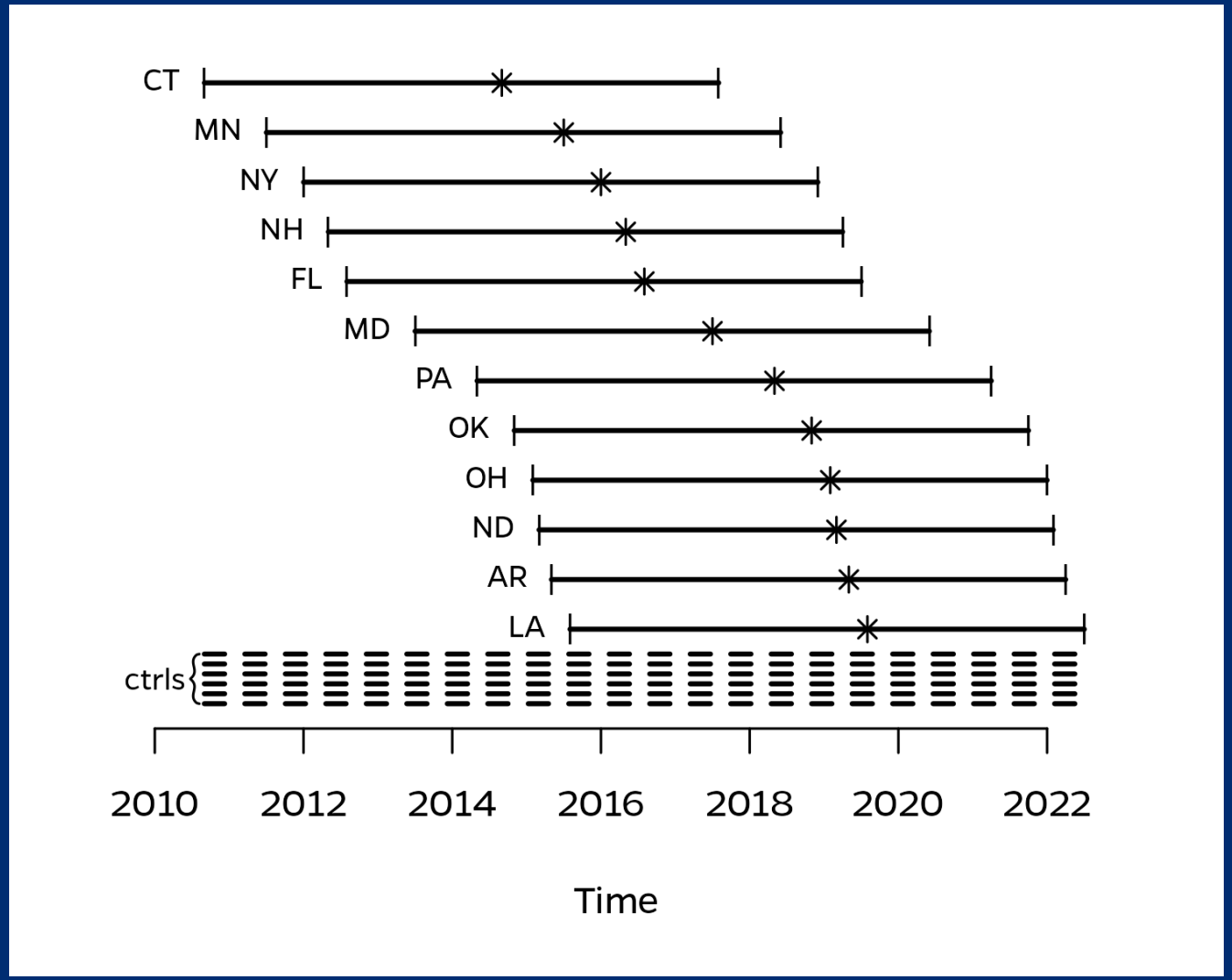
Goodman-Bacon, A. (2021). Journal of Econometrics.

Stacked Difference-in-Differences

- A solution is to use **stacked** difference-in-differences
  - Also called “trial emulation”
- We’ll estimate an ATT for each treated state, then pool the estimates to get an overall ATT



Medical Cannabis Study: State Cohorts



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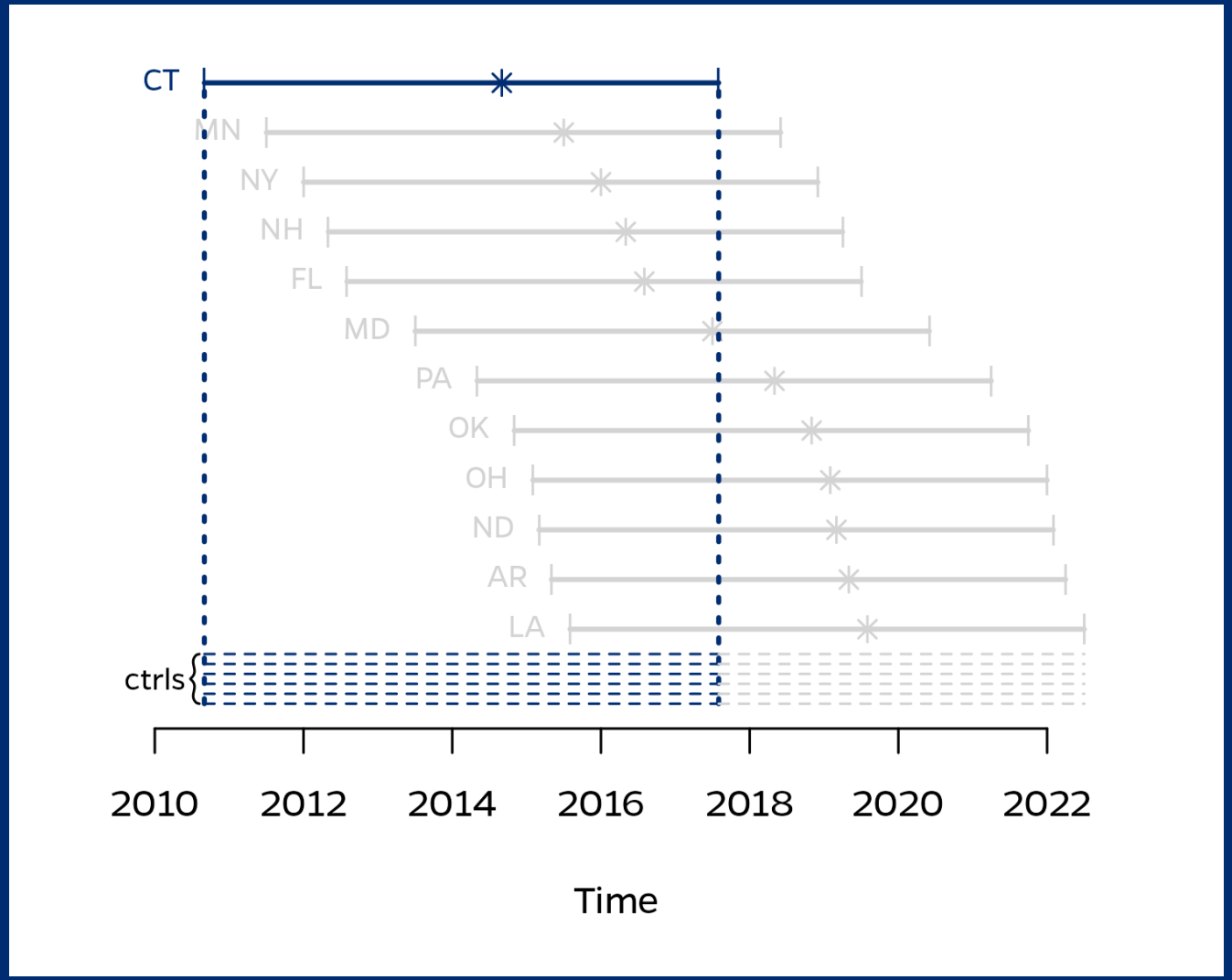

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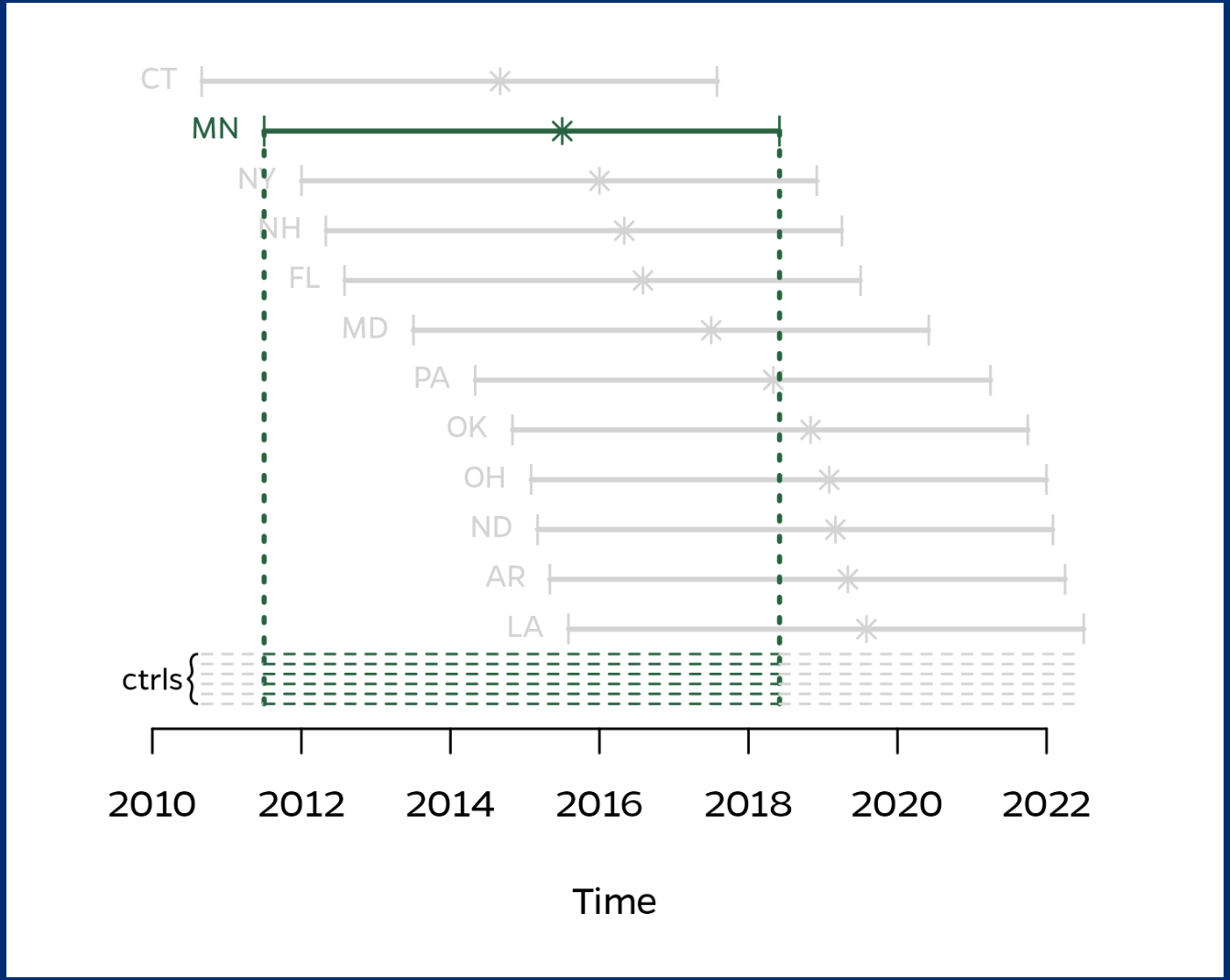

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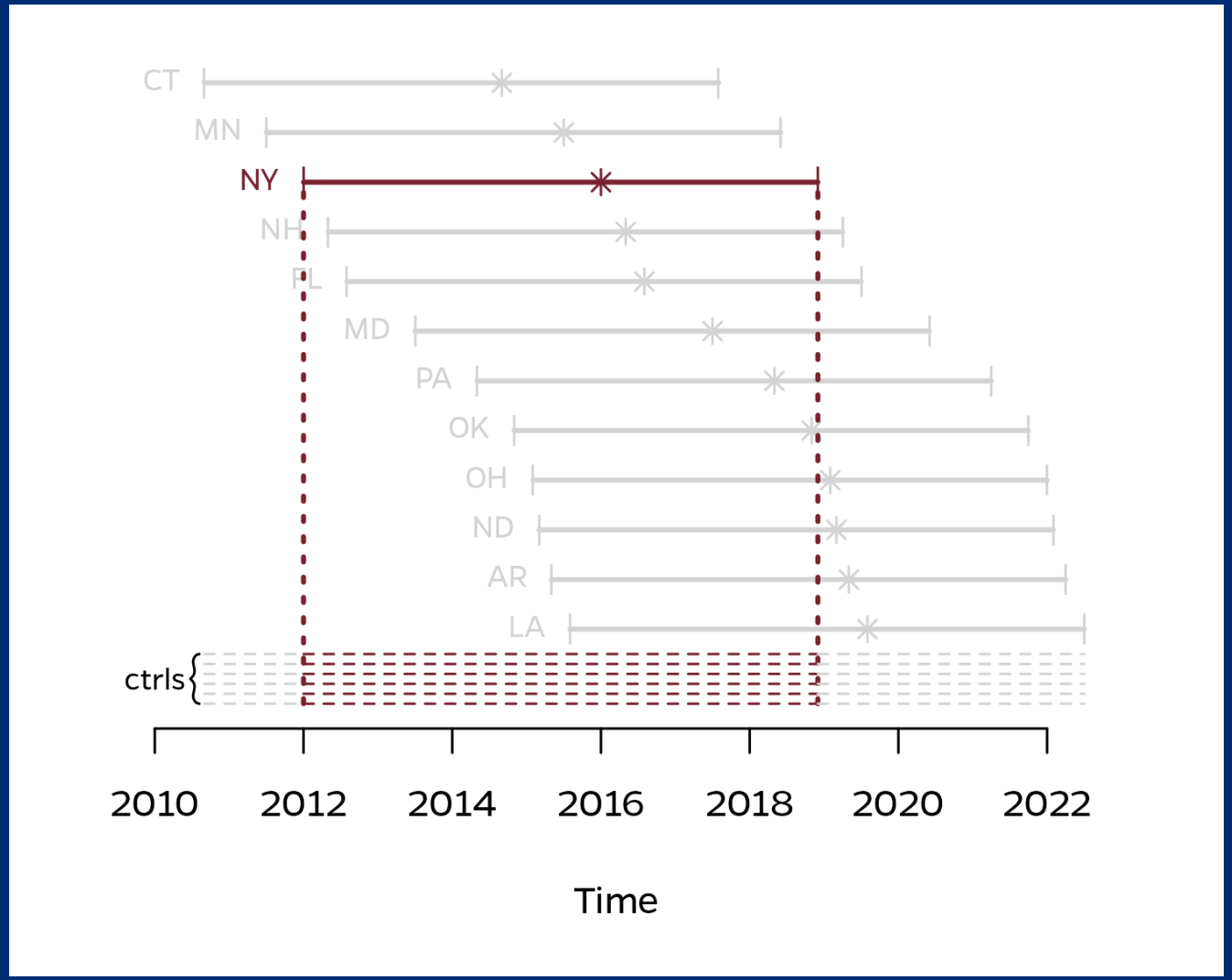
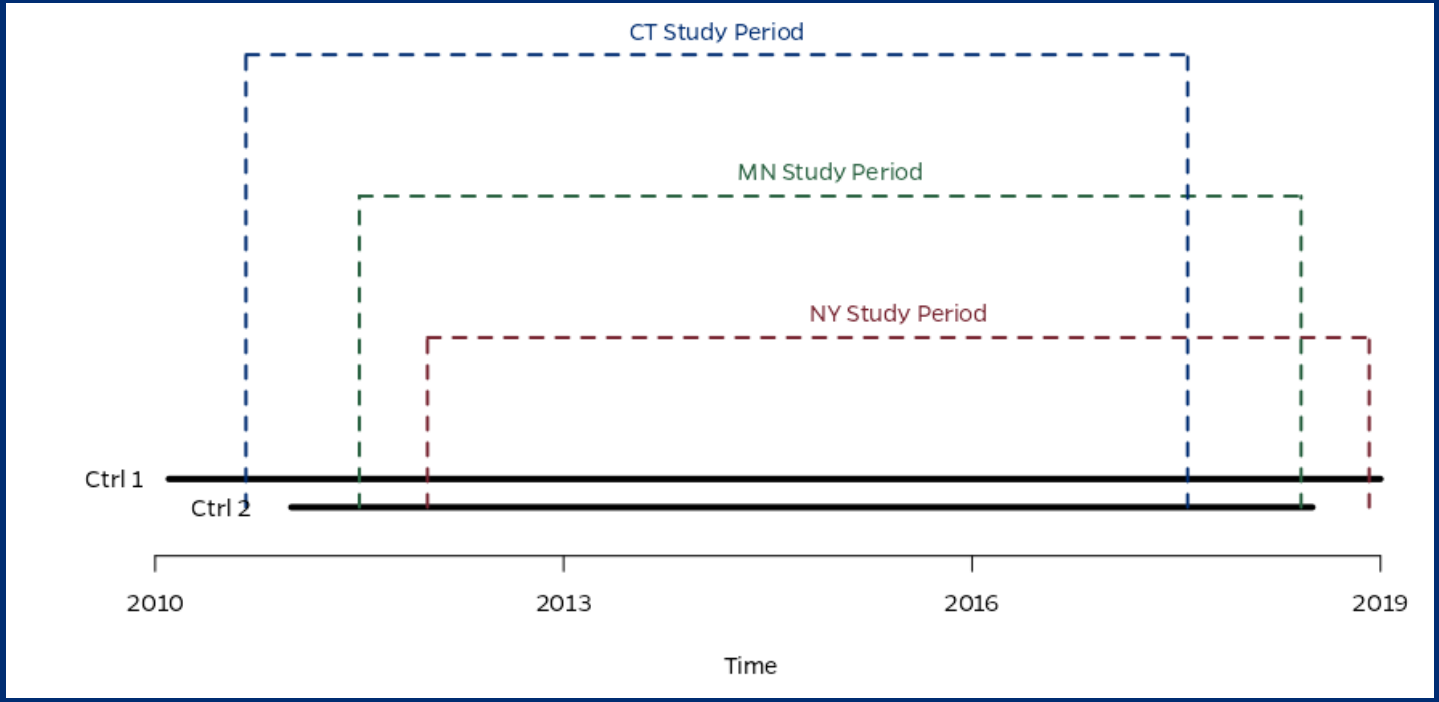
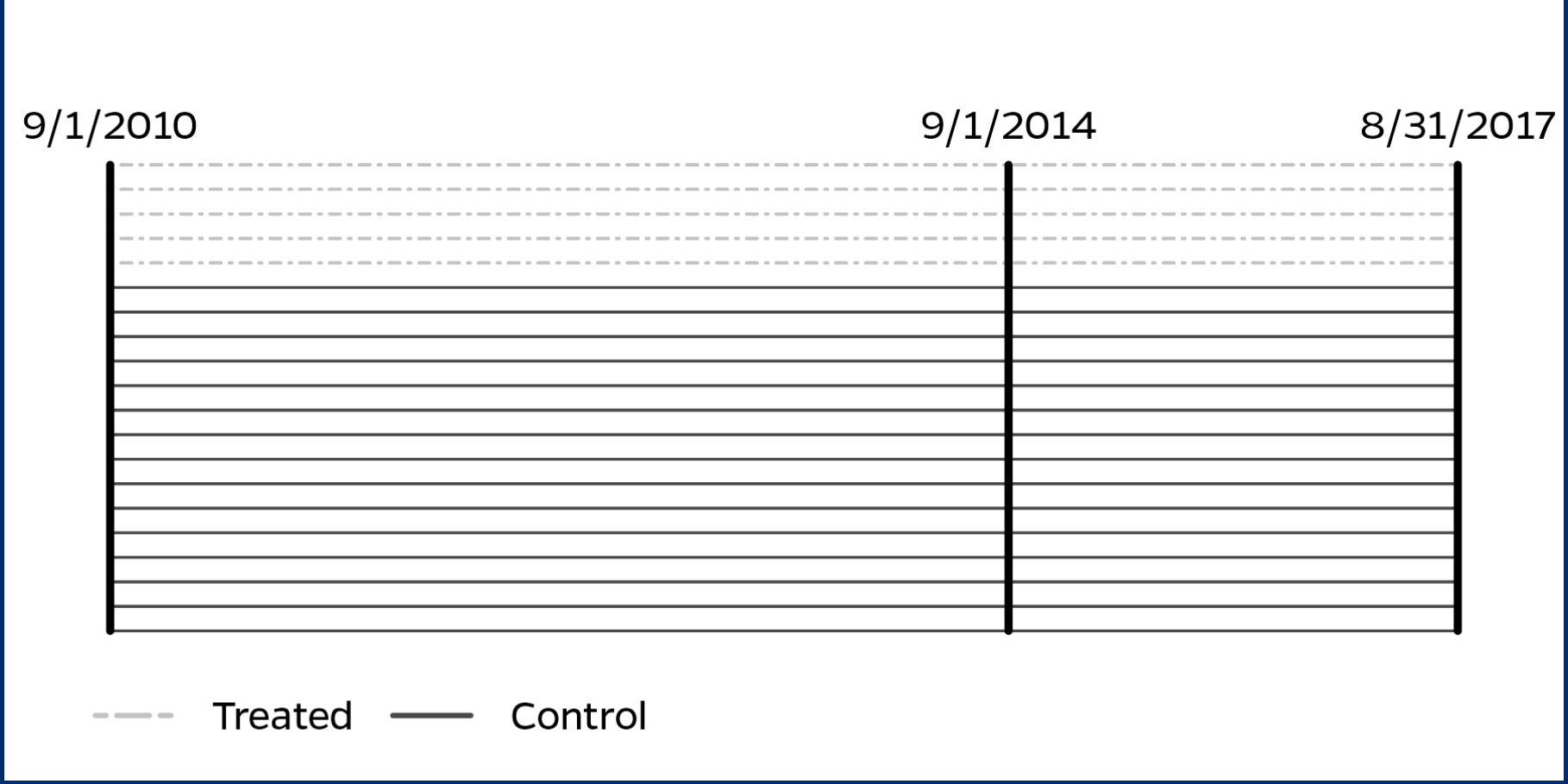


Shared Control Individuals

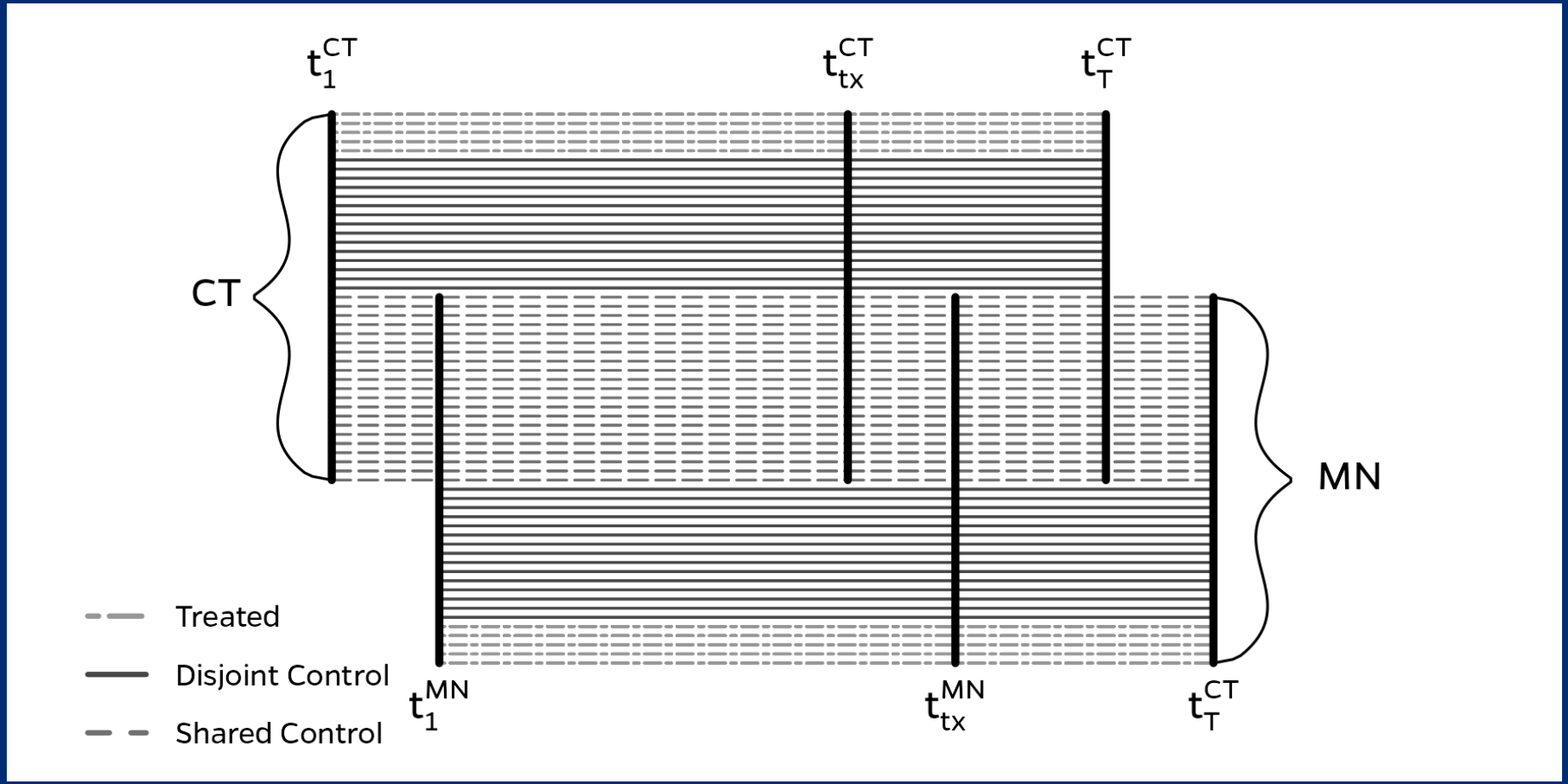
- Individuals in control states might appear in multiple cohorts.
  - "Ctrl 1" is in CT, MN, NY cohorts, but "Ctrl 2" is in MN cohort only.
- This induces correlation between treatment effect estimates for different cohorts!



Medical Cannabis Study: CT Cohort



Shared Control Individuals



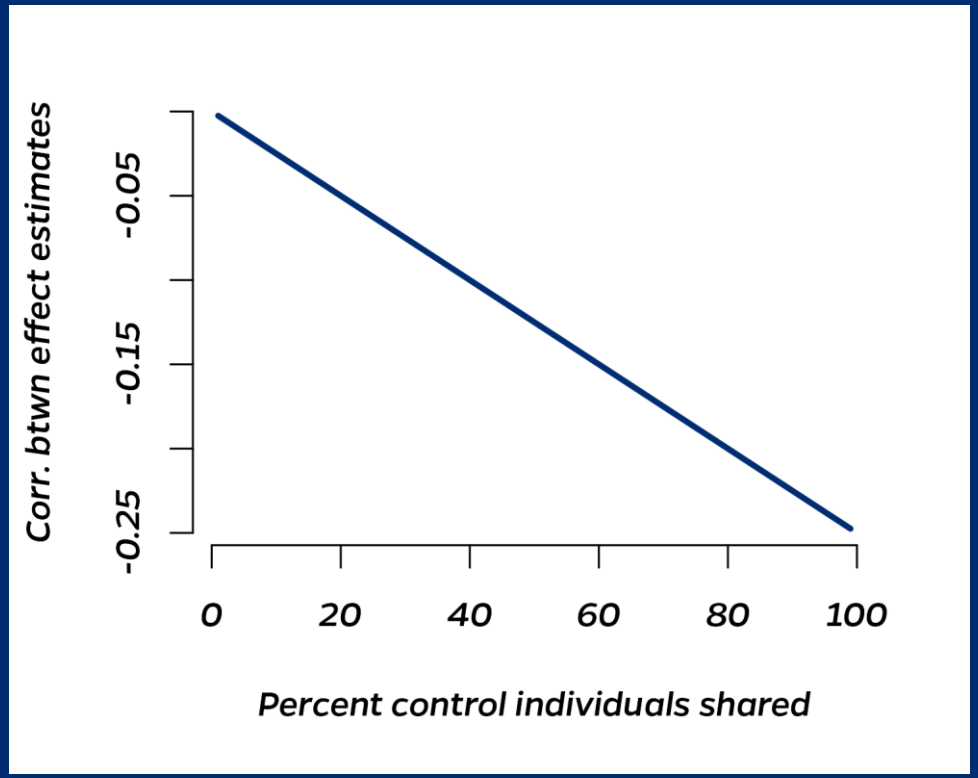
Correlation induced by shared control individuals

- **Overall goal:** Estimate an overall ATT across treated states
- Only an issue when *pooling* effect estimates (not for single-state ATTs)
- This approach is for when individual-level data is available

- Things that affect correlation:
  1. Proportion of control individuals who are shared
  2. Duration of pre- and post-treatment periods
  3. Length of time between state implementation dates
  4. Within-person correlation in the outcome
  5. Between-person correlation in the outcome

Two timepoints, 1-unit gap

- Very simple case:
  - One observation in each of pre- and post-treatment periods
  - One time unit between cohorts
- Key is percent of controls shared
- Correlation is negative!

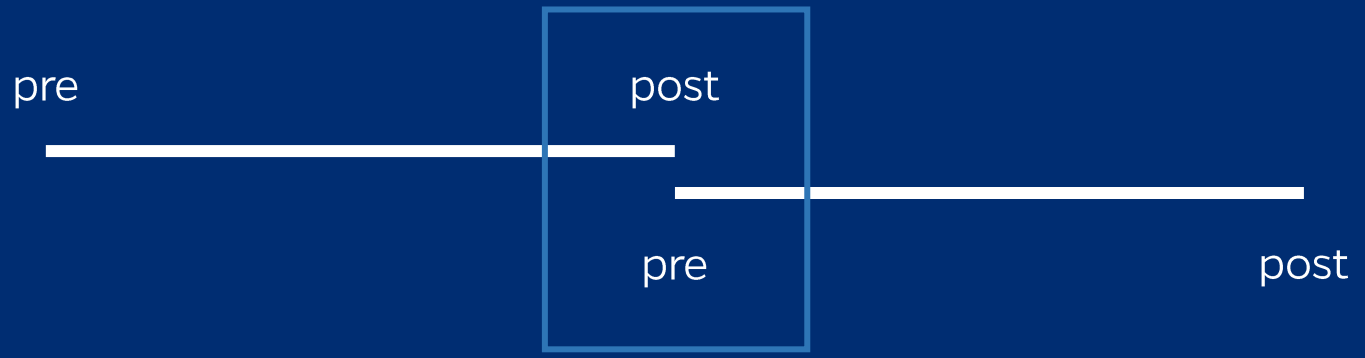


Why is the correlation negative?

- Remember the diff-in-diff ATT estimate for two timepoints:

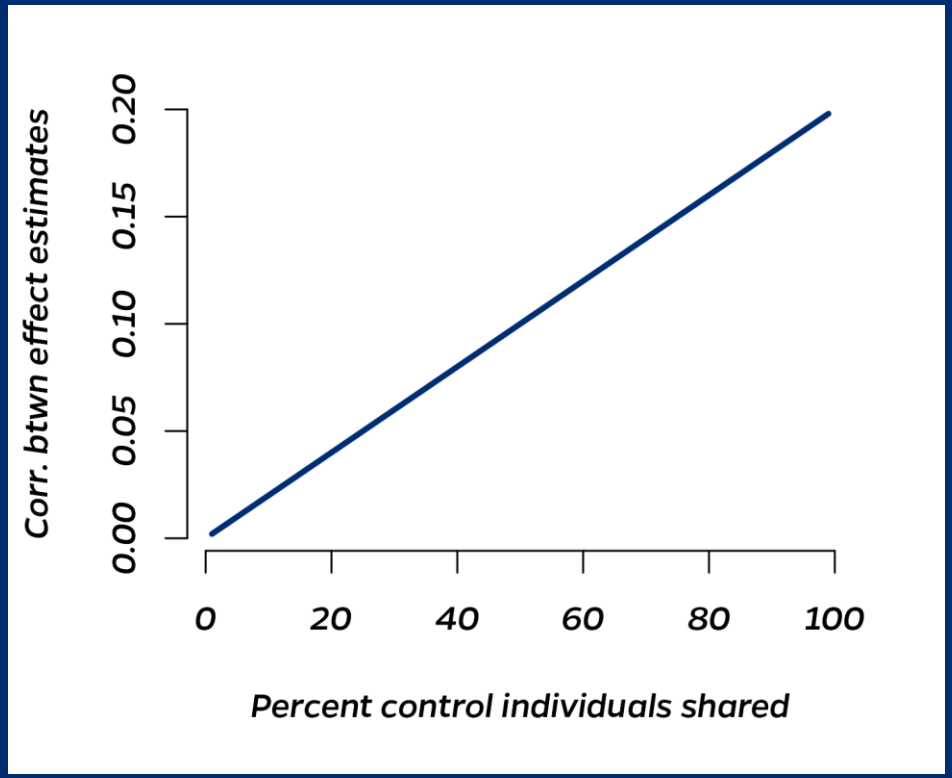
$$\widehat{ATT} = \left(\bar{Y}_{\text{post,tx}} - \bar{Y}_{\text{pre,tx}}\right) - \left(\bar{Y}_{\text{post,ctrl}} - \bar{Y}_{\text{pre,ctrl}}\right)$$

- When there's a 1-unit gap in a 2-timepoint setting, one cohort's post period is the other's pre.



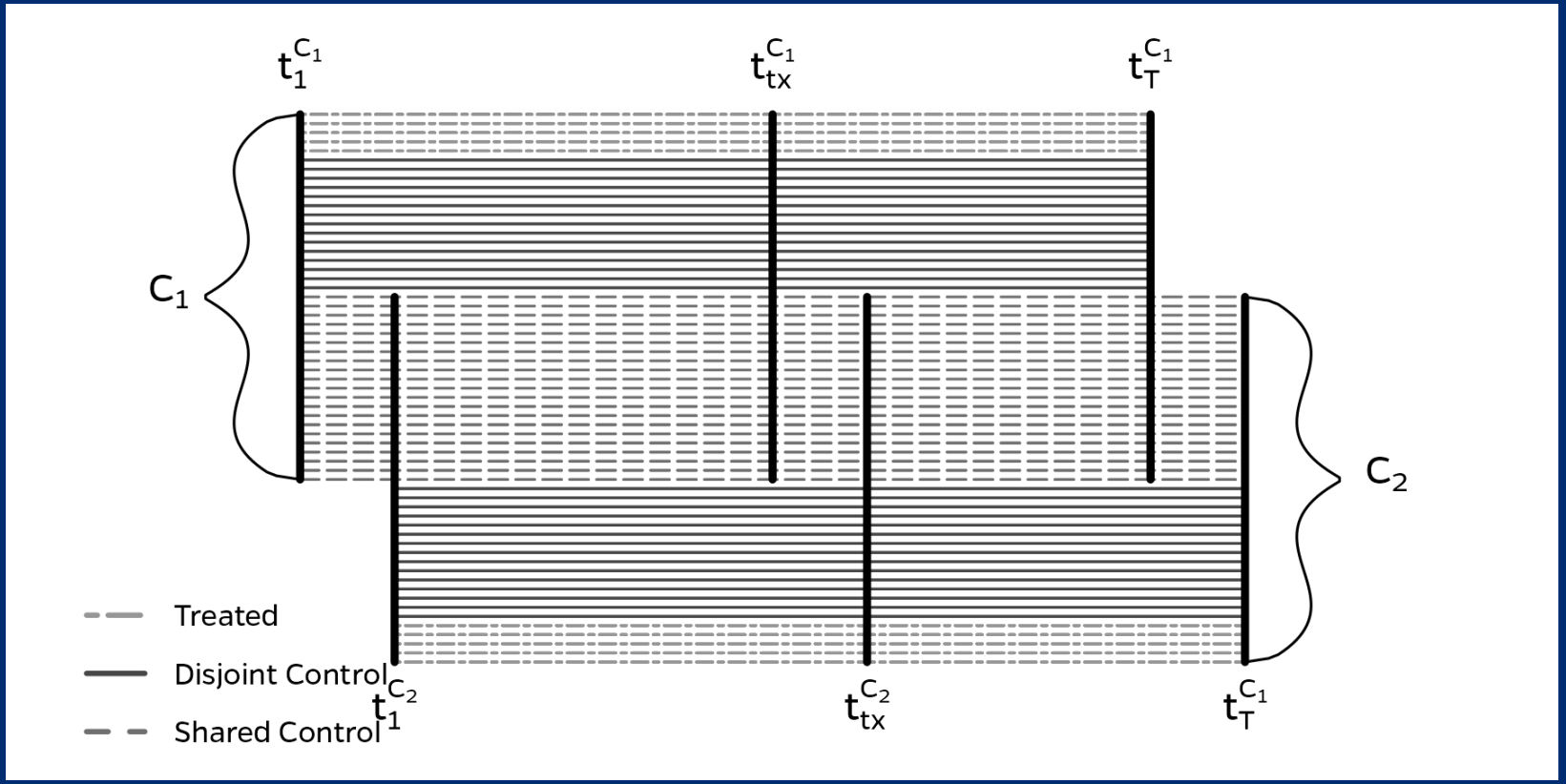
10 timepoints, 1-unit gap

- 5 observations pre, 5 post
- Now correlation *increases* with the percent of shared controls and is positive.

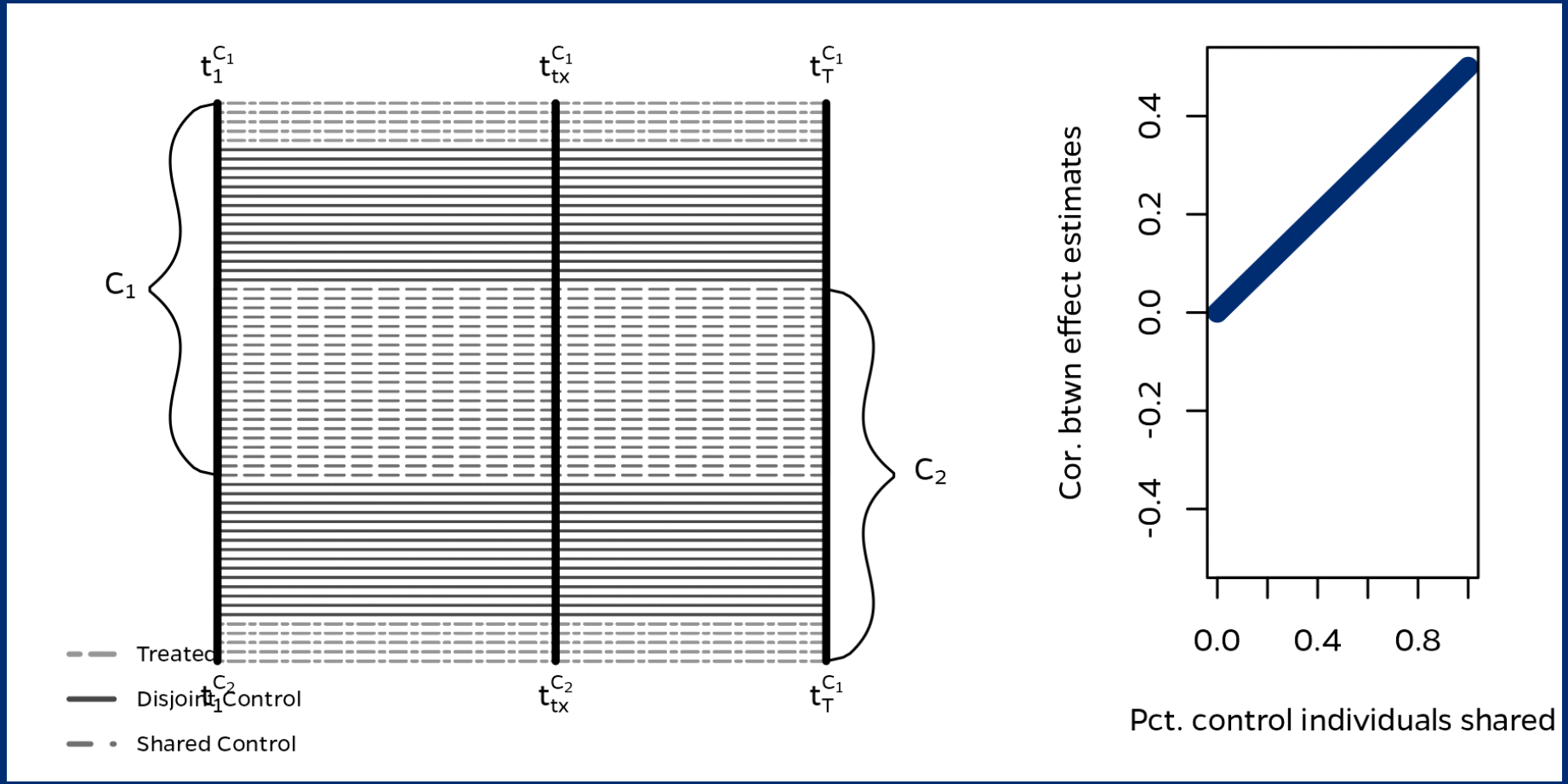


Why is the correlation positive?

More opportunities for observations to be in *both* pre periods and *both* post periods!



Correlation depends on time gap



What do we do with this?

- Inverse-variance weighting to average estimates
  - Modifiable to incorporate correlation between estimates
- Overall average is **not** affected by correlation: only standard errors
  - Variance of a 2-state average changes by a factor of $(1 + \rho)$
- Example in simplified setting:
  - Correlation of -0.25 → 25% *deflation* in SE
  - Correlation of +0.25 → 25% *inflation* in SE

When do individual data matter for policy evaluation?

- Individual data let us better identify the population of interest
  - E.g., restrict to only people with chronic non-cancer pain
  - Can ensure constant sample composition over time (longitudinal data)
- Policies are implemented at “higher” levels (e.g., states)
  - Unclear that individual-level data is helpful in these analyses

Individual vs. Aggregate Analyses

- Individual level data is **very big** in these contexts (millions of people)
  - Rich data on individual trajectories seems useful!
  - Probably requires big data techniques (challenging)
- Aggregate level data is **much smaller** (e.g., 84 observations per state)
  - Significantly easier to work with!
  - *Feels* like there could be loss of statistical efficiency

Simulation Study

- Generate “fake” data from a model that we specify – we know the truth

$$Y_{uit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3(t) X_{uit} + b_{0si} + b_{0s} + \epsilon_{uit}$$

  - Key here is that the relationship between Y_{uit} and covariate X_{uit} can vary with time.
- Analyze simulated data using a variety of methods
- Repeat 2000 times

Simulation Study

$$Y_{uit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3(t) X_{uit} + b_{0si} + b_{0s} + \epsilon_{uit}$$

Initial scenarios:

1. No effect of X_{uit} (i.e., $\beta_3(t) = 0$)
2. Constant covariate X_{uit} with constant effect (i.e., $\beta_3(t) = \beta_3$)
3. Constant covariate X_{uit} with time-varying effect
4. Time-varying X_{uit} with constant effect

Do individual-level data improve statistical efficiency?

- So far, doesn't look like it.
- Models using individual-level data have slightly smaller SE's but at the cost of poor ergonomics
- Bigger takeaway might be about when to "cluster adjust" standard errors.
- Scenario at right is **time-varying covariate** with **constant effect**

Model	SE	RMSE	95% CI Covg.
Indiv. w/ OLS SE	0.017	0.016	96.8%
Indiv. w/ Indiv. SE	0.016	0.016	95.1%
Indiv. w/ State SE	0.015	0.019	91.4%
Agg. w/ OLS SE	0.018	0.018	95.0%
Agg. w/ State SE	0.018	0.13	91.7%

Do individual-level data improve statistical efficiency?

- Because policies are implemented at state level, individual-level data does not appear to improve statistical efficiency vs. aggregate-level data in evaluating state policy effects
  - Based on limited simulations!
- This is ongoing work – still feels sort of counterintuitive.
  - We're actively trying to "break it" and find a situation where individual-level data does very well, but it's hard

Conclusions

- Individual-level data is useful for policy evaluation!
  - Helps identify population of interest
- When individual-level data is available, estimates from stacked difference-in-differences should be adjusted for correlation due to shared control individuals.
  - Sometimes sharing helps efficiency, sometimes it hurts
- Aggregate-level analyses (so far) don't seem to hurt anything
  - These are much easier to do – fewer data

Acknowledgements

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Collaborators

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