Handling Correlation in Stacked Difference-in-Differences Estimates with Application to Medical Cannabis Policy

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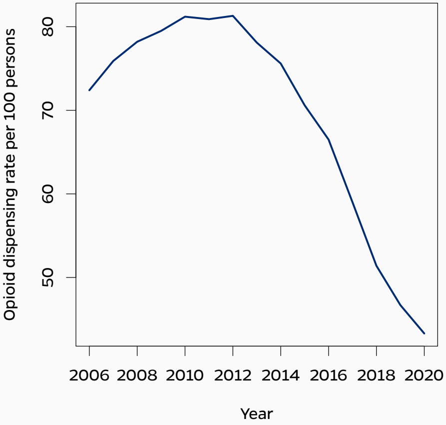
Slides are online!

slides.nickseewald.com/acic2023.pdf

Motivating Example: Medical Cannabis Laws and Opioid Prescribing

- **4x** increase in opioid prescribing in U.S. from 1999-2012
  - Opioid prescribing for chronic non-cancer pain has played a meaningful role
- Getting better: prescribing down since 2012, but still ~3x higher than 1999



Dart et al., (2015), *New England Journal of Medicine*.

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

Do Medical Cannabis Laws Change Opioid Prescribing?

- Cannabis industry & advocates argue medical cannabis for chronic pain could be a partial solution to opioid crisis via substitution
- Patients with chronic non-cancer pain are eligible to use cannabis under all existing state medical cannabis laws
- Some evidence of substitution among adults with chronic non-cancer pain

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

Bicket, Stone, and McGinty, (2023), *JAMA Network Open*.

Motivating Example: Medical Cannabis Laws and Opioid Prescribing

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

1. No individual-level data
2. General population samples lead to policy endogeneity

Motivating Example: Medical Cannabis Laws and Opioid Prescribing

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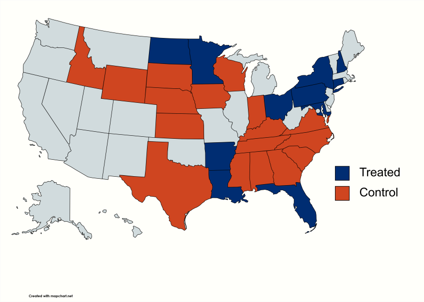
1. No individual-level data
2. General population samples lead to policy endogeneity

Individual-level data lets us identify the population, but adds methodological complexity.

Motivating Example: Medical Cannabis Laws and Opioid Prescribing

Our sample:

- 12 *treated* states that implemented a medical cannabis law between 2012 and 2019 and *do not also have recreational cannabis laws*
- 17 *comparison* states without medical or recreational cannabis laws



Motivating Example: Medical Cannabis Laws and Opioid Prescribing

Our sample:

- 12 *treated* states that implemented a medical cannabis law between 2012 and 2019 and *do not also have recreational cannabis laws*
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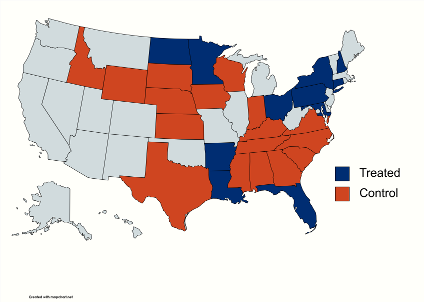
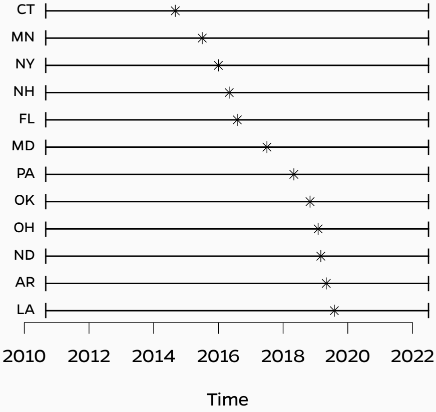
Goal: Estimate the effect of implementing a medical cannabis law on opioid prescribing outcomes, relative to what would have happened in the absence of treatment, among states that implemented such a law (an ATT).



Medical Cannabis Study: Study Periods



States implemented medical cannabis laws at different times

Difference-in-Differences with Multiple Time Periods

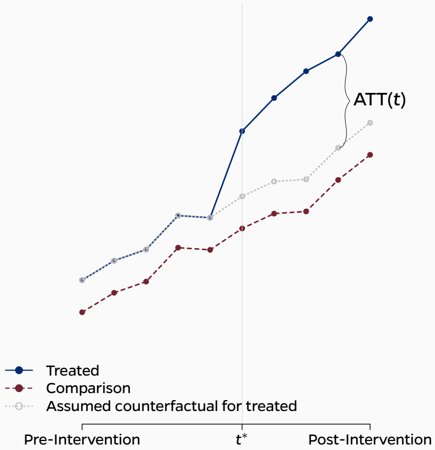
Now, times $t = \{1, \ldots, t^*, \ldots, T\}$; t^* first measurement after treatment.

Alternative estimands:

$$\text{ATT}(t) = \text{E}\left[Y_t(1) - Y_t(0) \mid A = 1\right], \quad t \geq t^*$$

$$\text{ATT}_{\text{avg}} = \text{E}\left[\bar{Y}_{\{t \geq t^*\}}(1) - \bar{Y}_{\{t \geq t^*\}}(0) \mid A = 1\right]$$

Strength of counterfactual parallel trends assumption varies with choice of estimand.



Two-Way Fixed Effects Estimation

A common "modeling" approach to estimate ATT:

$$Y_{sit} = \beta_{0,s} + \beta_{1,t} + \boldsymbol{\beta_2} A_{st} + \varepsilon_{sit},$$

where

- $A_{st} = \mathbb{1}\left\{\text{state } s \text{ treated at time } t\right\}$
- β_0's are *state fixed effects*
- β_1's are *time fixed effects*

With 1 treated state or "simultaneous adoption",

$$\hat{\beta}_2 \equiv \left(\bar{Y}^{\text{tx}}_{\{t \geq t^*\}} - \bar{Y}^{\text{tx}}_{\{t < t^*\}}\right) - \left(\bar{Y}^{\text{ctrl}}_{\{t \geq t^*\}} - \bar{Y}^{\text{ctrl}}_{\{t < t^*\}}\right)$$

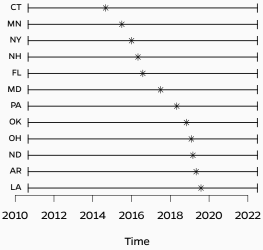
Two-Way Fixed Effects under Staggered Adoption

$$Y_{sit} = \beta_{0,s} + \beta_{1,t} + \boldsymbol{\beta_2} A_{st} + \varepsilon_{sit}$$

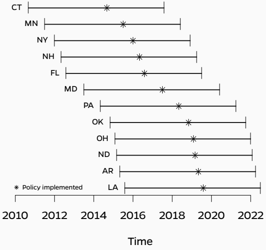
- Not all states implemented medical cannabis policy at the same time.
- Two-way fixed effects can yield a (very) biased overall effect estimate in this setting.
    - Problematic under time-varying treatment effects
    - Estimator inadvertently adjusts for post-treatment information

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

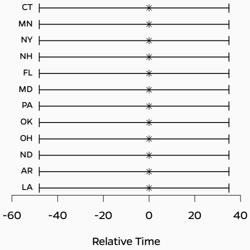
Stacked Difference-in-Differences / Serial Trial Emulation



Start with full data



Anchor time



Estimate and aggregate

Hernán and Robins, (2016), *American Journal of Epidemiology*; Ben-Michael, Feller, and Stuart, (2021), *Epidemiology*.

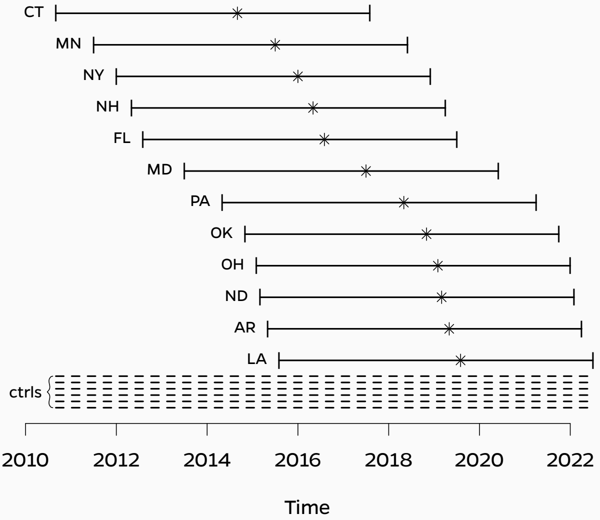
Medical Cannabis Study: State Cohorts

Data are individual-level commercial health insurance claims from $N = 583,820$ unique individuals in 29 states.

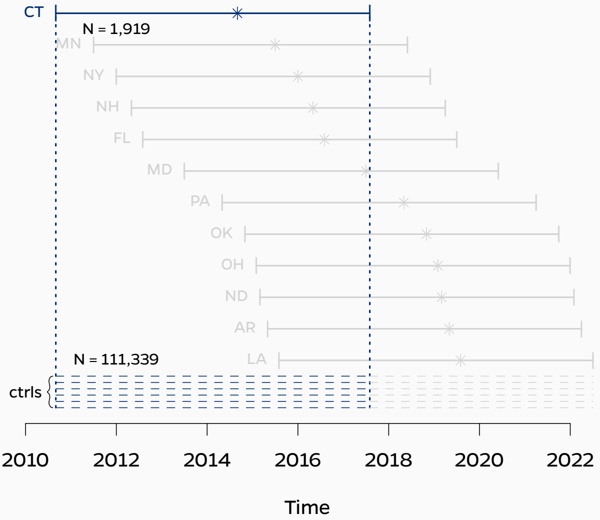
For each treatment state, we build a *cohort* of individuals in that state and the control states over the study period.

- Individuals 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: State Cohorts



Medical Cannabis Study: State Cohorts



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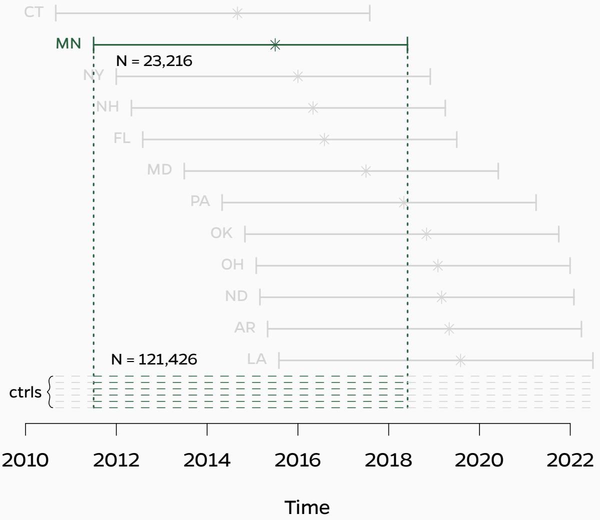

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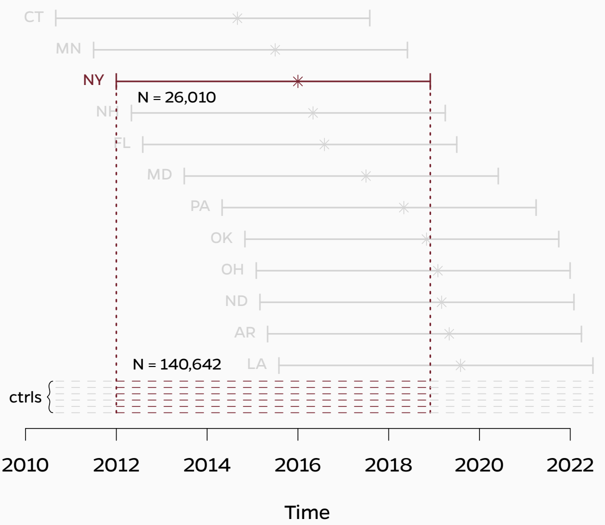
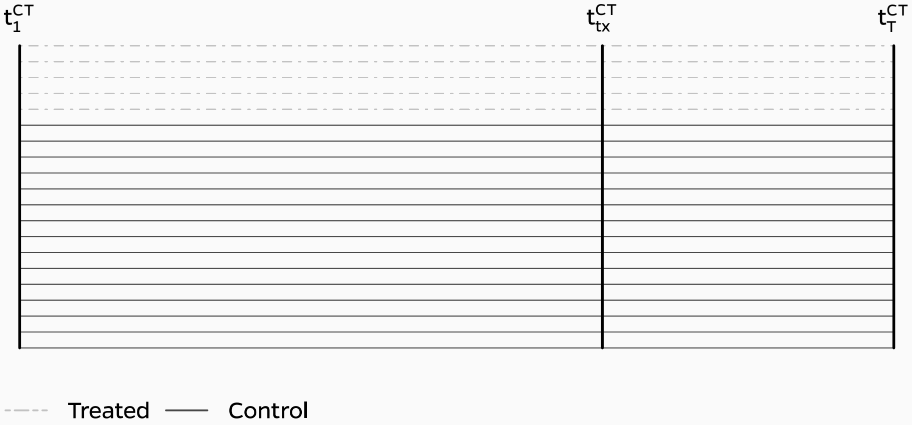
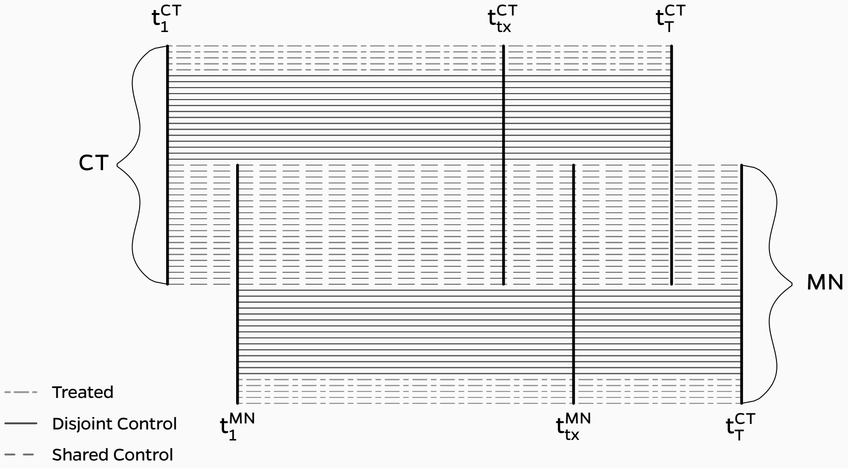


Cohort Schematic



Shared Control Individuals



Handling Correlation Induced by Shared Control Indviduals

Goal: Improved inference on overall ATT averaged across treated units.

- ATT estimates remain unbiased under usual assumptions
- Failure to account for shared control individuals can lead to *incorrect inference*

Big Idea: Incorporate pairwise correlation between estimates into inverse-variance weighted average

Covariance between Diff-in-Diff Effect Estimates

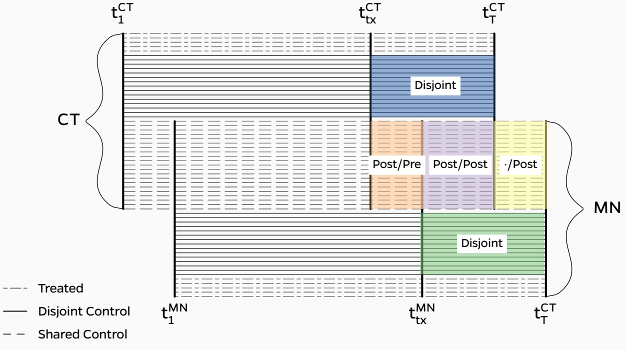
With only one treated unit, we could estimate ATT for cohort C as

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

Assuming states are independent,

$$\begin{aligned}\text{Cov}\left(\widehat{\text{ATT}}_{C_1}, \widehat{\text{ATT}}_{C_2}\right) = \text{Cov}\left(\bar{Y}^{\text{ctrl}}_{C_1,\text{post}}, \bar{Y}^{\text{ctrl}}_{C_2,\text{post}}\right) + \text{Cov}\left(\bar{Y}^{\text{ctrl}}_{C_1,\text{pre}}, \bar{Y}^{\text{ctrl}}_{C_2,\text{pre}}\right) \\ - \text{Cov}\left(\bar{Y}^{\text{ctrl}}_{C_1,\text{post}}, \bar{Y}^{\text{ctrl}}_{C_2,\text{pre}}\right) - \text{Cov}\left(\bar{Y}^{\text{ctrl}}_{C_1,\text{pre}}, \bar{Y}^{\text{ctrl}}_{C_2,\text{post}}\right)\end{aligned}$$

Covariances with Shared Control Individuals



$$\mathrm{Cov}\left(\bar{Y}^{\text{ctrl}}_{\text{CT,post}}, \bar{Y}^{\text{ctrl}}_{\text{MN,post}}\right) \text{ “ = ” } \mathrm{Cov}\Big(\bar{Y}_{\text{CT Disjoint}} + \bar{Y}_{\text{Post/Pre}} + \bar{Y}_{\text{Post/Post}},$$
$$\bar{Y}_{\text{MN Disjoint}} + \bar{Y}_{\text{Post/Post}} + \bar{Y}_{\cdot/\text{Post}}\Big)$$

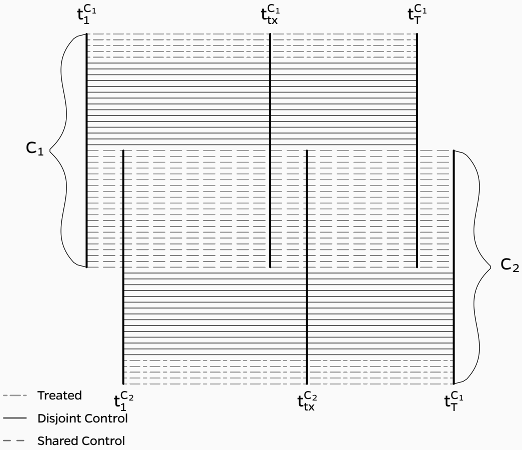
When Does This Matter?

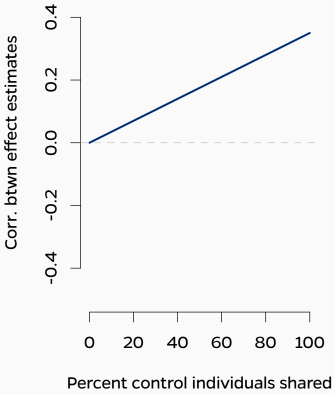
- Setting / simplifying assumptions:
  - Exchangeable within-person correlation ρ
  - Within-period correlation ϕ, between-period correlation ψ
  - Interest is in ATT_{avg}
  - Individuals are independent of people who live in other states

Depends on:

  - Number of measurement occasions in pre- and post-treatment periods
  - Number of measurement occasions *between* law implementations
  - Numbers of shared and unshared individuals in each control state

Correlation Due to Shared Controls





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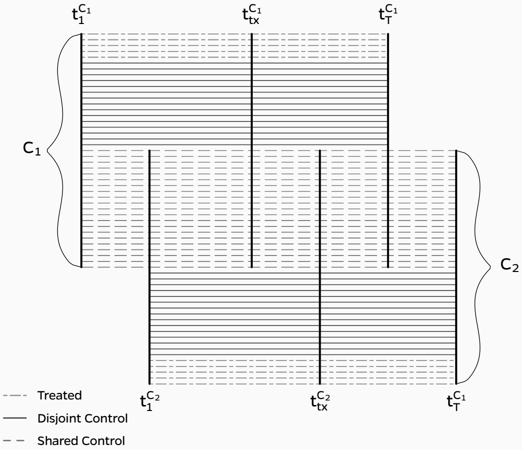

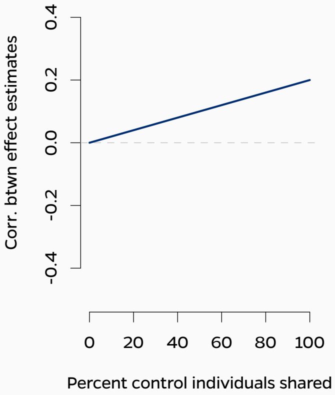

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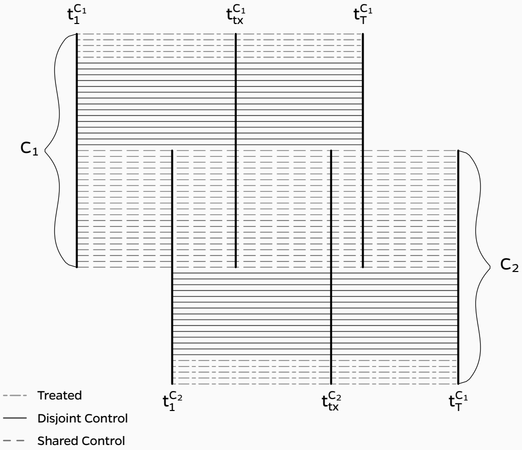

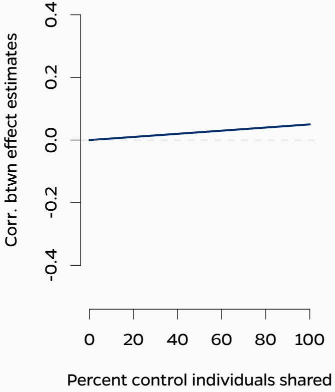

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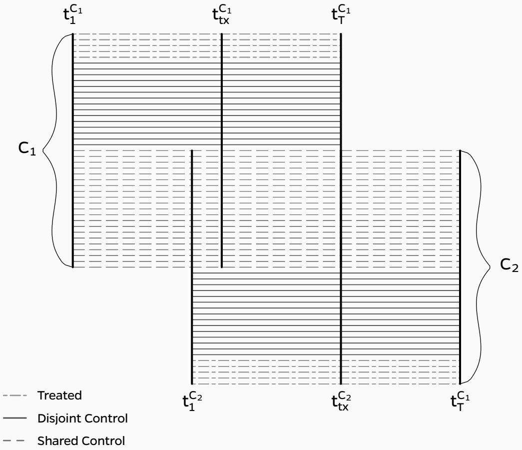

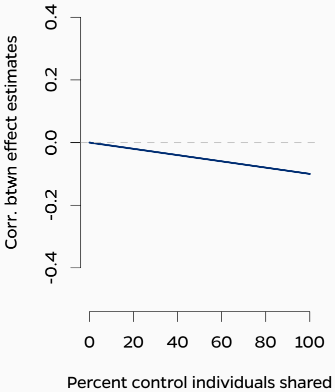

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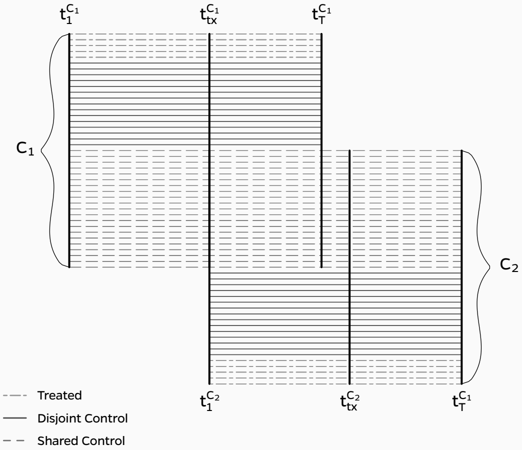

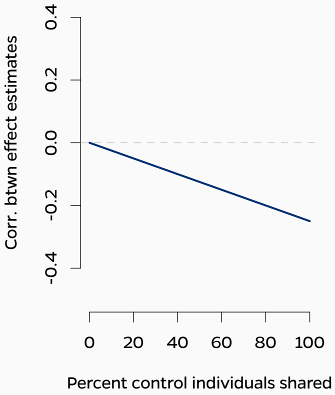

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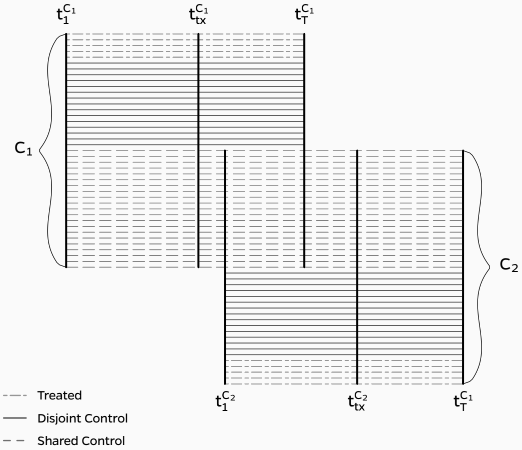

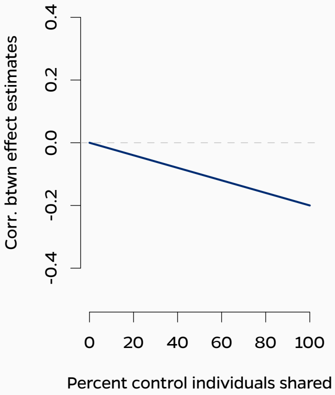

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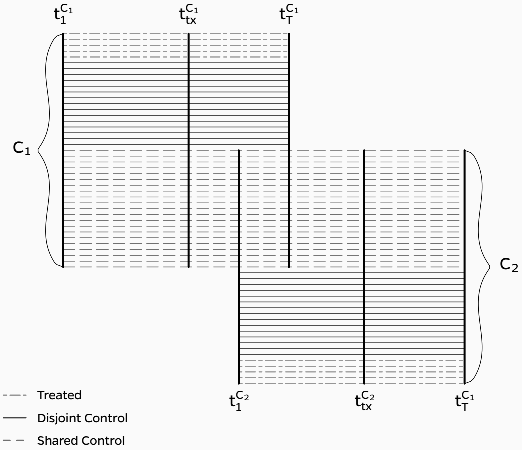

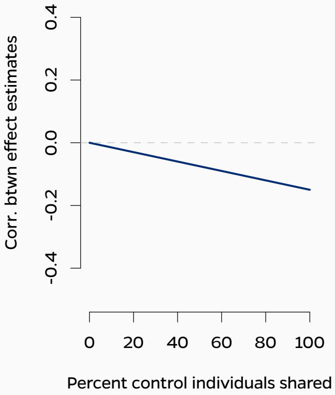

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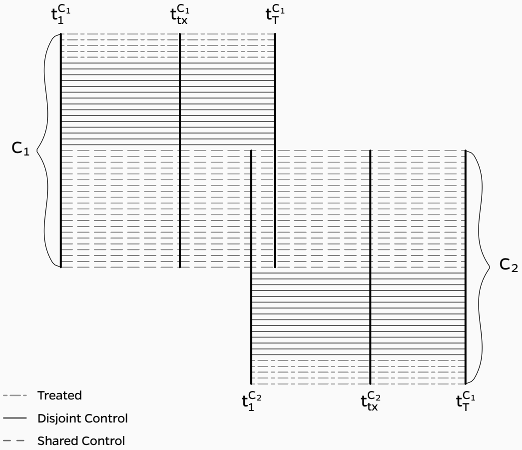

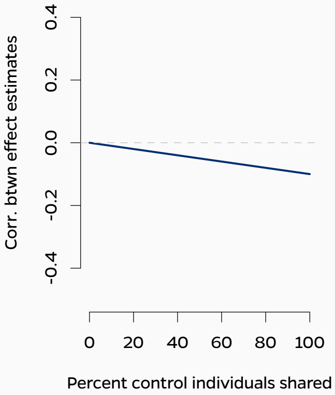

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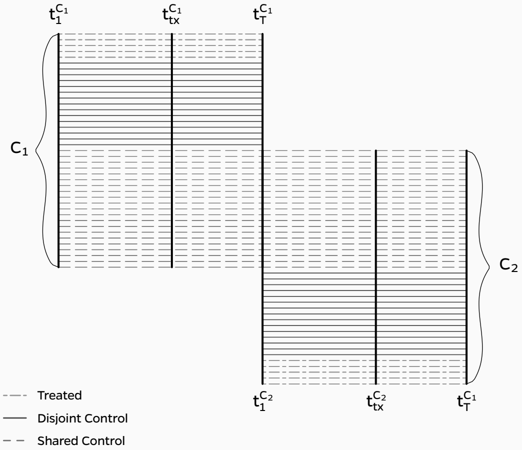

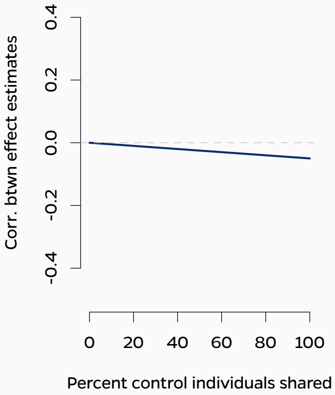

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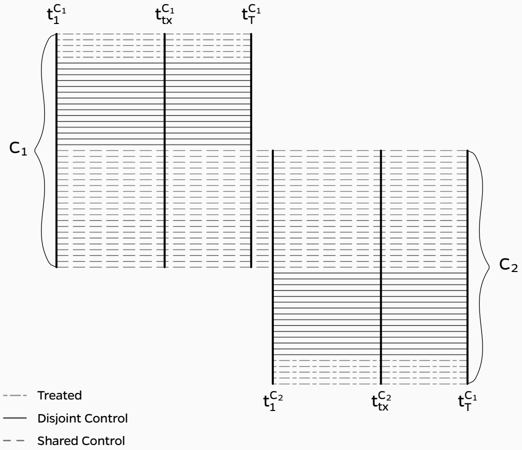
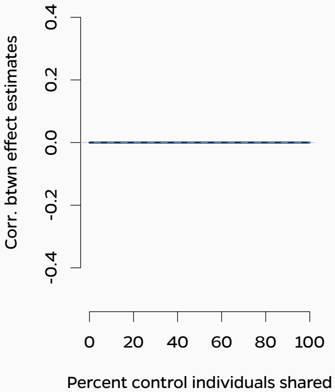




Inverse Variance Weighted Averaging

Estimating correlations (covariances) lets us construct a covariance matrix Σ for all state-specific ATTs.

Then,

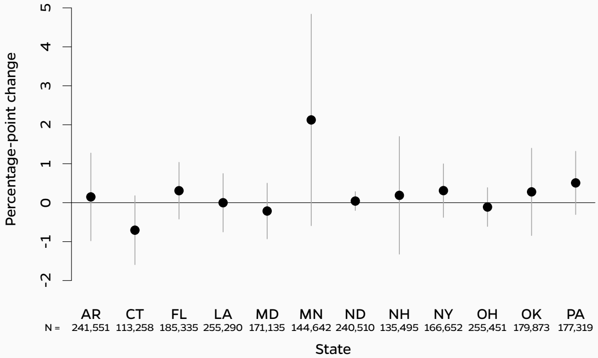
$$\widehat{\text{ATT}}_{\text{overall}} = \frac{1}{\sum_s (1/\sigma_s^2)} \sum_s \widehat{\text{ATT}}_s / \sigma_s^2$$

and

$$\text{Var}\left(\widehat{\text{ATT}}_{\text{overall}}\right) = \frac{1}{\left(\boldsymbol{v}^\top \boldsymbol{v}\right)^2} \boldsymbol{v}^\top \boldsymbol{\Sigma} \boldsymbol{v},$$

where $\boldsymbol{v}^\top = \left(1/\sigma_1, \ldots, 1/\sigma_S\right)$

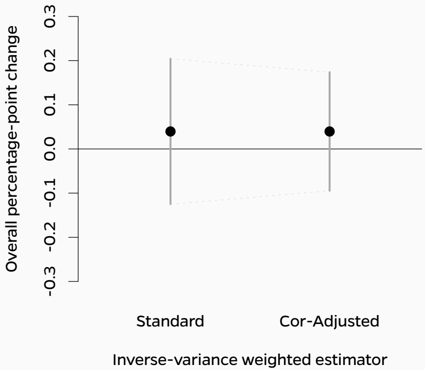
Medical Cannabis Study: Results



State-specific effects of medical cannabis laws on proportion of chronic noncancer pain patients receiving *any opioid prescription*, on average in a given month in first 3 years of law implementation

Medical Cannabis Study: Results

- In this case, accounting for between-estimate correlation gives *smaller* SE (here, by 18.5%)
- State-level policy evaluations are (often) notoriously underpowered – this could be a step in the right direction!



Schell, Griffin, and Morral, (2018).

Conclusions

- Individual-level data is useful for identifying populations of interest in policy evaluation, but introduces methodological complexity.
- When using individual-level data that might be shared across cohorts in stacked diff-in-diff, it may be important to account for correlation between estimates
- A closed-form formula for induced correlation is available for select analyses

Acknowledgements

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