# Precept 12: Causality with Repeated Measurements

## Soc 400: Applied Social Statistics

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[1]Thanks to Ian Lundberg for providing examples.

# Today's Agenda

- A stratification walkthrough
- Repeated measurements
  - Diff-in-diff
  - Fixed effects
- Some coding advice
- General review

# Stratification

Two weighting strategies:

- ATE = sum of CATEs weighted by probability of being in each stratum
- ATT = sum of CATEs weighted by probability of being in each stratum *conditional on receiving treatment*

# ATE

$$\sum_x E[Y(1) - Y(0)|X = x]P(X = x)$$

# ATT

$$\sum_x E[Y(1) - Y(0)|X = x]P(X = x|D = 1)$$

# Stratification in `dplyr`

To RStudio!

# Repeated observations: Big ideas

- Difference in difference
- Fixed effects

# Difference in difference

The difference in difference (DID) estimator is:

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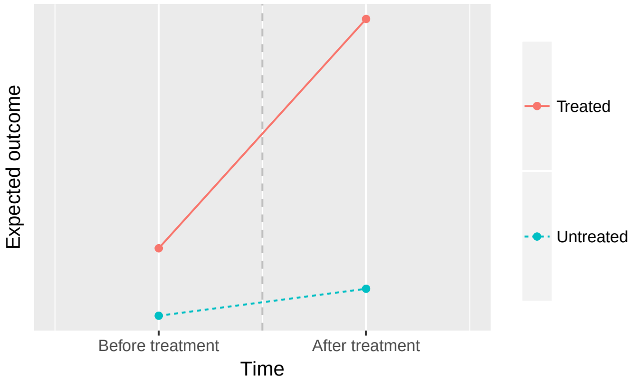

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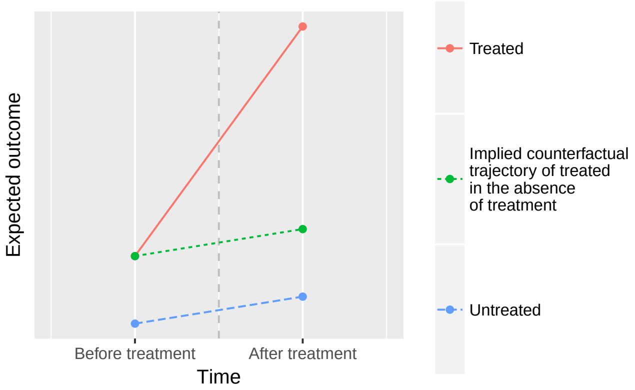

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  3. The difference in the differences: The causal estimate is (2) - (1)

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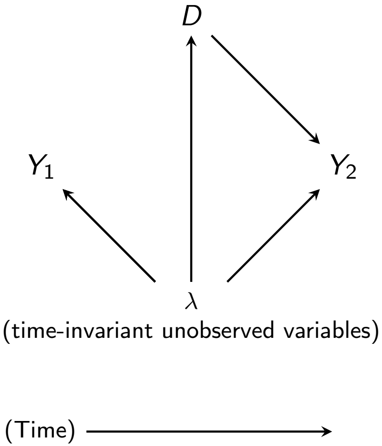
  - If the pre-treatment outcomes are different, it is hard to believe that the slopes would be the same in the absence of treatment.
- It is robust to unobserved time-invariant confounders
- It is sensitive to time-varying confounders

# DID is good if
(subscripts index time)



# Fixed effects

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The person fixed effects estimator with individuals indexed by $i$ and survey years indexed by $t$ estimates a unique intercept for each respondent in the data.

$$Y_{it} = \alpha_i + \beta D_{it} + \epsilon_{it}$$

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- It is often called a within-person estimator.
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- But it is sensitive to time-varying confounders

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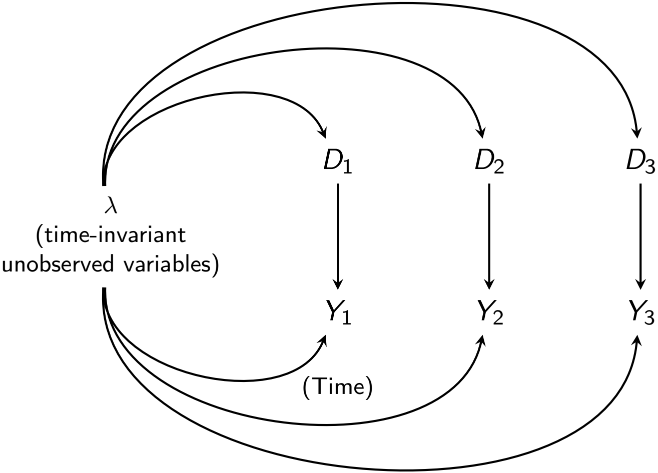

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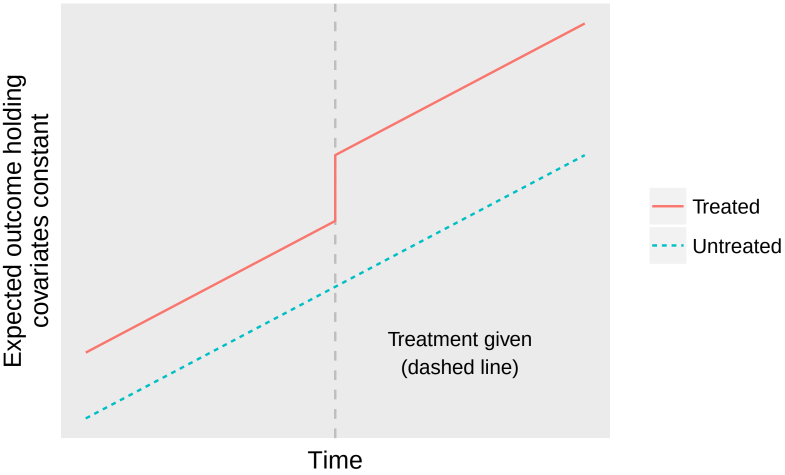

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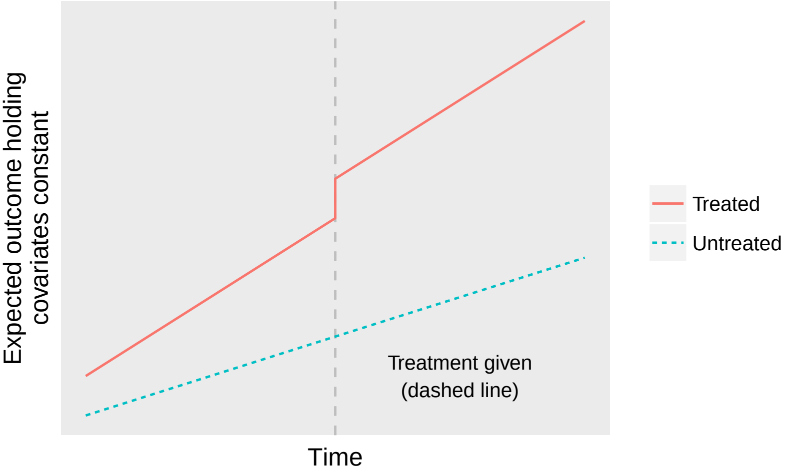

# Repeated observations example: Marriage and men's wages

- Suppose you want to estimate the causal effect of marriage on men's wages.
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- You have repeated wage observations on individuals before and after marriage.
- In the following scenarios, what estimation strategy would you use?

# Scenarios

1. Having married parents causes men to marry and causes higher wages.
2. People "mature" at different ages. Something changes, and you get your act together to become an adult. When you hit this "latent maturation," it causes you to marry and to earn more in the next year.

Scenario 1

$$\begin{tikzcd}
\text{Marriage (person } i \text{ in year } t\text{)} \arrow[rr] & & \text{Wages (person } i \text{ in year } t\text{)} \\
& \text{Married parents (person } i\text{, time-invariant, unmeasured)} \arrow[ul] \arrow[ur] &
\end{tikzcd}$$

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Scenario 2

$$\begin{tikzcd}
\text{Marriage (person } i \text{ in year } t\text{)} \arrow[rr] & & \text{Wages (person } i \text{ in year } t\text{)} \\
& \text{Latent maturation (person } i\text{, time } t-1\text{, unmeasured)} \arrow[ul] \arrow[ur] &
\end{tikzcd}$$

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- **Scenario 1:** Fixed effects adjusts for time-invariant confounders, so would be preferred here.
- **Scenario 2:** This is a case of time-varying unobserved confounding, so neither approach will yield a consistent causal estimate!

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- That said, learning to write good code will save you pain and heartache for years to come
- Here are some common issues I've seen and how to fix them

# Coding advice

1. Magic numbers
2. Abstraction: DRY code and WET code
3. Style
4. Commenting
5. Portability
6. Organization

# Any more questions?

# Come to the review session!

**January 14th** in the afternoon