WHAT TO DO WITH CROSS-SECTIONAL TIME-SERIES DATA?

2023 CIS PhD winter retreat

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OUTLINE

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Introduction

About me

St. Gallen, ETH, UC Berkeley, ...?

3rd year @ ICR

Nationalism, ethnic politics and sometimes partisanship

I love panel data < 3

Goals for today

Give you an overview of DiD literature

Discuss useful developments

Help you choose the right model for your data

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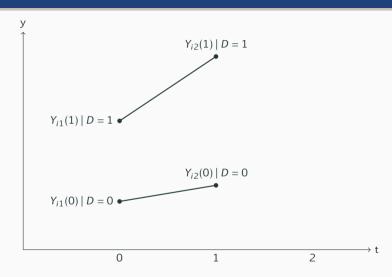
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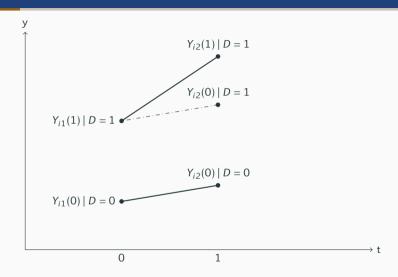
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Basic DiD Dust-Off

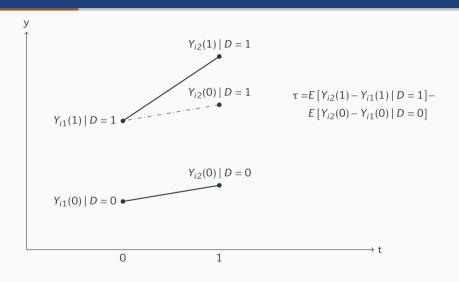
DID SETUP



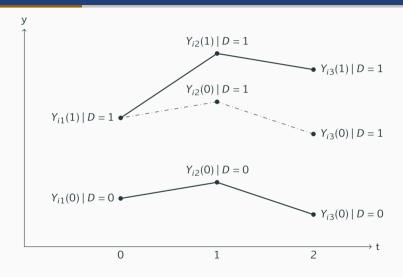
COUNTERFACTUAL OUTCOME



Inference with DiD



THREE-PERIOD DID



THE BRILLIANCE OF DIDS

Inferential problem

Counterfactual outcomes as missing data

How to produce valid counterfactual outcome $\hat{Y}(0)|D=1$?

- \rightarrow Find unbiased function g(Y), s.t. $E[\hat{Y}(0)|D=1-Y(0)|D=1]=0$
- ightarrow Exploit parallel trends assumption and SUTVA

Solutions in basic DiD

Traditionally, use linear g() on all within-individual variation.

All ITEs need to have same weight

Easily estimated with TWFE, DiM, first-difference

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LIMITATIONS OF BASIC DID SETTING

THE BREAKTHROUGH

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Mid 2010s

Econometricians question the validity of TWFE

Main culprit: DiD with staggered adoption.

(e.g., Goodman-Bacon 2021, Sun and Abrams 2021, Callaway and Sant'Anna 2021

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Problems identified

Researchers refer to theory of 2-period DiD, do completely different things.

TWFE makes problematic comparisons.

Overall TWFE ATT is weighted average of cohort-specific ATTs

→ Cohort-ATTs can get weird weights.

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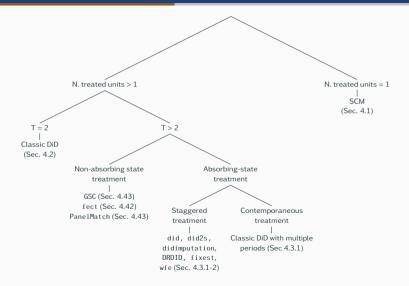
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New Approaches to DiD

Example: Non-absorbing state treatment



Go-to packages in (early) 2023

```
did package

Non-absorbing state DiDs
felm package

PanelMatch package
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Staggered DiD settings

```
# Load packages
library(tidyverse)
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Non-absorbing state DiDs

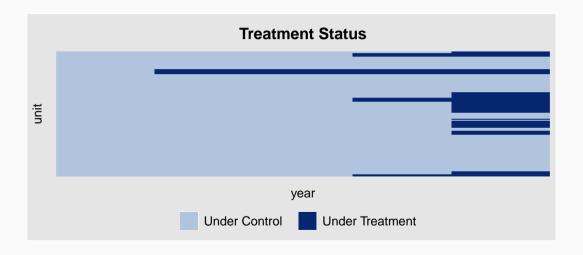
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Example: Staggered treatment



EXAMPLE: STAGGERED TREATMENT

Example: Staggered treatment cont'd

Insights

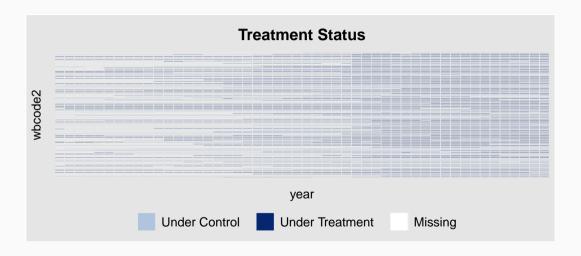
TWFE's bias is generally conservative

Example: Staggered treatment cont'd

Insights

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Example: Non-absorbing state



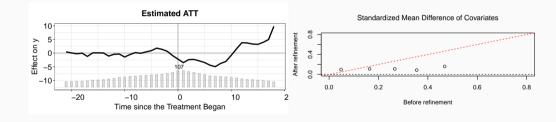
Example: Non-absorbing state treatment

```
# Fit baseline model
mod twfe <- feols(v ~ dem | wbcode2 + year, dat dem)
# Fit other models
mod ife <- fect(v ~ dem , dat dem, index = c("wbcode2", "year"), se = F,</pre>
                 method = "ife", na.rm = T)
mod mc <- fect(y ~ dem , dat dem, index = c("wbcode2", "vear"), se = F,</pre>
                 method = "mc", na.rm = T)
matched <- PanelMatch(lag = 5, lead = 0:5, unit.id = "wbcode2", time.id = "vear",
                       covs.formula = ^{\sim}I(lag(y, 1:4)),
                       treatment = "dem", outcome.var = "y", goi = "att",
                       data = dat dem, refinement.method = "mahalanobis")
mod pm <- PanelEstimate(matched, dat dem, pooled = T)</pre>
```

Example: Non-absorbing state treatment cont'd

```
# Compare estimates
data.frame(twfe = as.numeric(mod twfe$coefficients[1]),
           "fect ife" = as.numeric(mod ife$att.avg),
           "fect mc" = as.numeric(mod mc$att.avg),
           "panelmatch" = as.numeric(summary(mod pm)$summary[, 1]))
## Weighted Difference-in-Differences with Mahalanobis Distance
## Matches created with 5 lags
##
## Standard errors computed with 1000 Weighted bootstrap samples
##
## Estimate of Average Treatment Effect on the Treated (ATT) by Period:
##
          twfe fect.ife fect.mc panelmatch
## 1 -10.11222 1.214884 2.08486
                                 1.84098
```

Example: Non-absorbing state treatment cont'd



Your Turn!

Tell us your data struggles

Do you work with TSCS data?

Have you encountered limitations in TWFE models?

Has the absence of methods held you from researching sth?
...

WRAP-UP

DID AS PREDICTION EXERCISE

Problems with estimation led to rethink DiD

Counterfactual outcomes as non-linear prediction task

 \rightarrow Generalized synthetic control

Counterfactual outcomes as missing data

→ Matrix completion method

Counterfactual outcomes as matching problem

→ PanelMatch method

Outcome of the literature

Different perspectives led to different solutions to problems.

Broad set of concrete tools to apply DiD logic in broad set of cases.

Great set of R packages!

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DEBATE: LET'S TALK CAUSALITY!

How causality is often discussed

Your *X* is not exogenous to *Y*: I don't believe you.

There might be confounders: I don't believe you.

 \rightarrow If a statistic is not **unbiased**, it might be anything.

A better way of discussing causality (?)

Your estimate is confounded: What is the chance that your results have another sign?

Your X is not exogenous: Are you sure the variation means what you argue? What kind of bias do you have, and what does it tell on the "true" τ ?

→ Focus on substantive meaning of estimates and biases

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