

# COLLEGIO CARLO ALBERTO

## 2025



# Roadmap

## Introduction

Managing expectations

Diff-in-Diff Popularity

Origins of diff-in-diff in public health

## Diff-in-Diff Fundamentals

Average Treatment Effect on the Treated

Core Diff-in-Diff Assumptions

## Different Target Parameters

Clearly Defined Control Status

Imbalanced Panels

Population Weighting

## Four Means or One Regression?

# Introduction

- Welcome to a week of advanced panel methods at the Collegio Carlo Alberto!
- I'm Scott Cunningham, professor of economics at Baylor University (visiting this next year at Harvard University)
- Five days of difference-in-differences – some new, some review!
- This is my third time to teach here at the Collegio (I think?)

## Go to repository

- <https://github.com/scunning1975/collegio-carlo-alberto>
- Discuss schedule in our README

# What my pedagogy is like

- Workshop is intended to take someone from knowing nothing about difference-in-differences to a broad level of competency on advanced topics
- My stuff will mix basic things with subtle interpretation, my own subjective beliefs about "good science" (but not necessarily good papers), and developments
- It is a sequel to Juan Vargas' recent class, with the intention to build on that and deepen your familiarity, interpretation, application and problem solving
- Lecture, discussion, spreadsheets, application, several "coding together" exercises, as well as a homework assignment throughout the week

# Class goals

Pedagogical goal is to explain diff-in-diff and other panel estimators, but as a secondary objective to help foster in you:

1. **Confidence:** You will feel like you have a good enough understanding of diff-in-diff, both in its basics and some more contemporary issues, so that it seems like an intuitive and useful tool you could imagine using
2. **Comprehension:** You will have learned a lot both conceptually and in the specifics, particularly with regards to issues around identification and estimation in the diff-in-diff
3. **Competency:** You will have more knowledge of programming syntax in Stata and R so that later you can apply this in your own work

# What is difference-in-differences

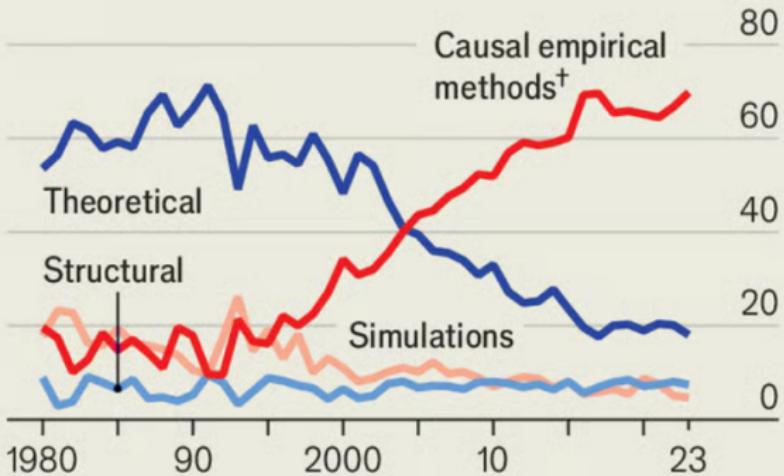
- DiD is when a group of units are assigned some treatment and then compared to a group of units that weren't before and after
- One of the most widely used quasi-experimental methods in economics and increasingly in industry
- Predates the randomized experiment by 80 years, but uses basic experimental ideas about treatment and control groups (just not randomized)
- Uses panel or repeated cross section datasets, binary treatments usually, and often covariates

# Causal Claims in Economics

## Data deluge

NBER and CEPR working papers\*, % of total

By method



\*44,800 papers published by National Bureau of Economic Research and Centre for Economic Policy Research

<sup>†</sup>Includes instrumental variables, randomised controlled trials, etc

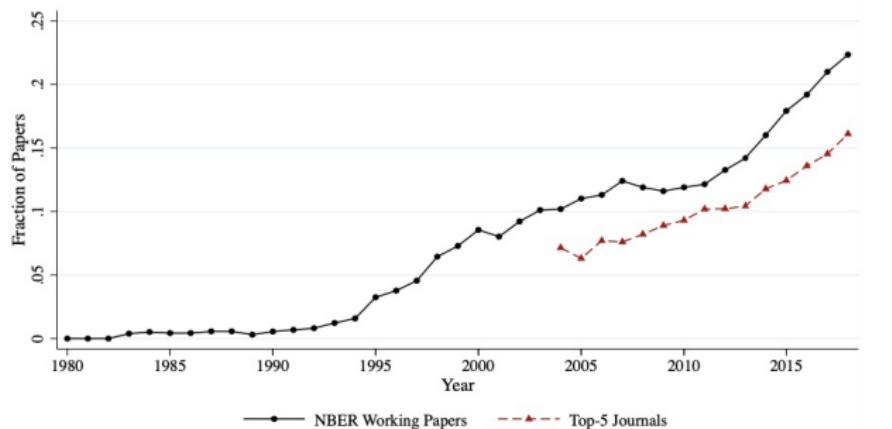
Source: "Causal claims in economics",

by P. Garg and T. Fetzer, 2025 (pre-print)

# Diff-in-Diff Over Time

Figure: Currie, et al. (2020)

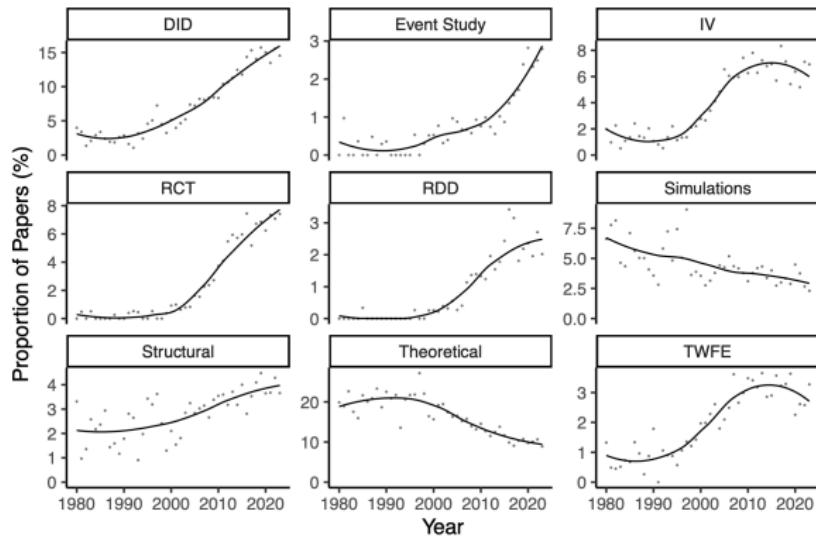
## A: Difference-in-Differences



# Diff-in-Diff Compared to Others Over Time

*Figure: Garg and Fetzer (2025)*

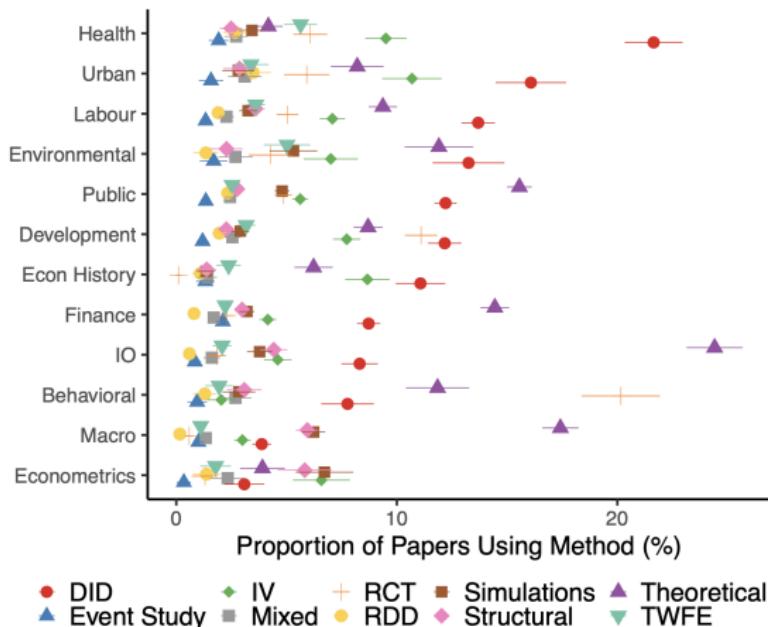
Figure 4: Proliferation of Empirical Methods Over Time in NBER and CEPR Working Papers



# Diff-in-Diff in the Cross-Section by Field

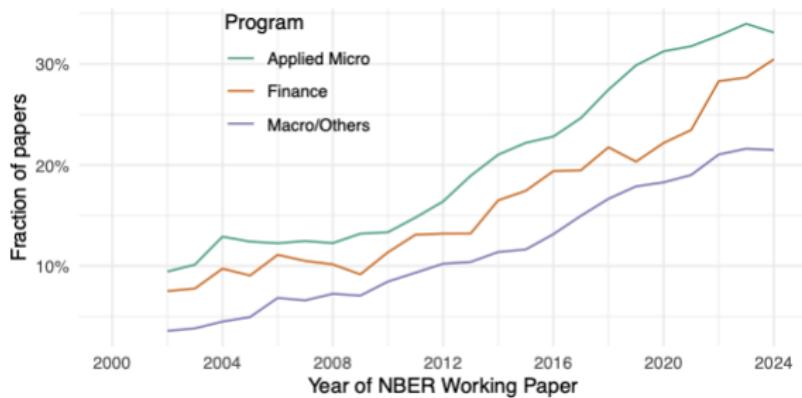
Figure: Garg and Fetzer (2025)

Figure 5: Cross-Sectional Breakdown of Empirical Methods by Field in NBER and CEPR Working Papers



# Diff-in-Diff Over Time by Field

*Figure: Goldsmith-Pinkham (2024)*



(a) Difference-in-differences

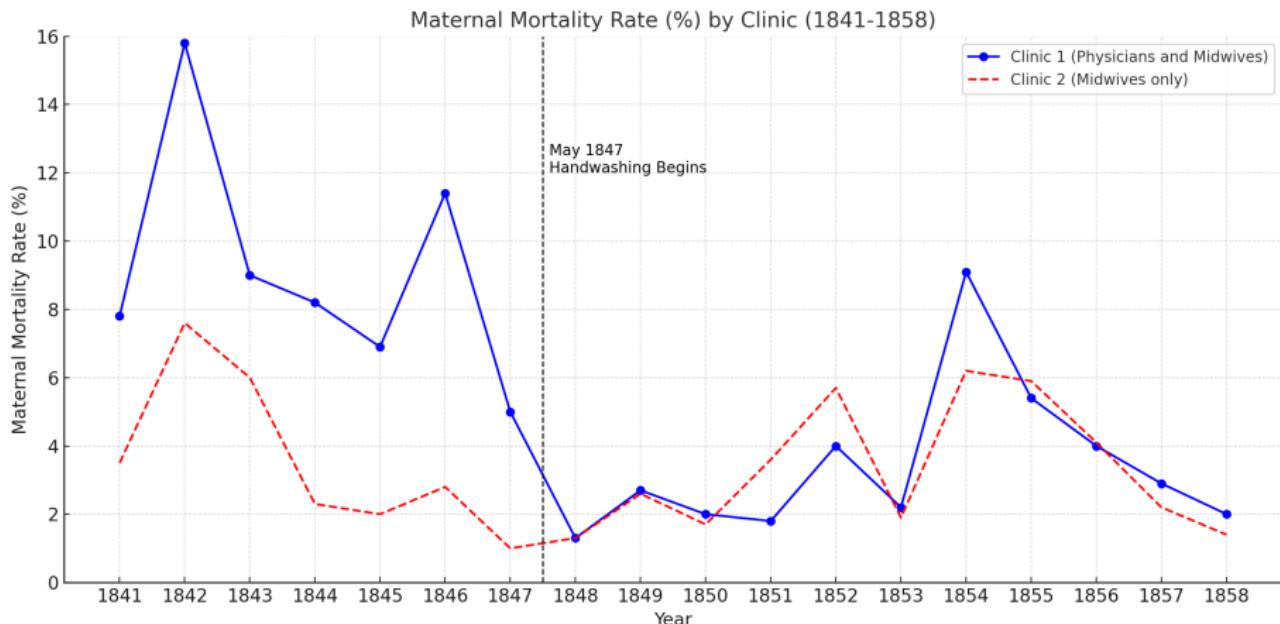
# Ignaz Semmelweis and washing hands

- Early 1820s, Vienna passed legislation requiring that if a pregnant women giving birth went to a public hospital (free care), then depending on the day of week and time of day, she would be routed to either the midwife wing or the physician wing (most likely resulting in random assignment)
- But by the 1840s, Ignaz Semmelweis noticed that pregnant women died after delivery in the (male) wing at a rate of 13-18%, but only 3% in the (female) midwife wing – cause was puerperal or “childbed” fever
- Somehow this was also well known – women would give birth in the street rather than go to the physician if they were unlucky enough to have their water break on the wrong day and time

# Ignaz Semmelweis and washing hands

- Ignaz Semmelweis conjectures after a lot of observation that the cause is the teaching faculty teaching anatomy using cadavers and then delivering babies *without washing hands*
- New training happens to one but not the other and Semmelweis thinks the mortality is caused by working with cadavers
- Convinced the hospital to have physicians wash their hands in chlorine but not the midwives, creating a type of difference-in-differences design

# Semmelweis diff-in-diff evidence



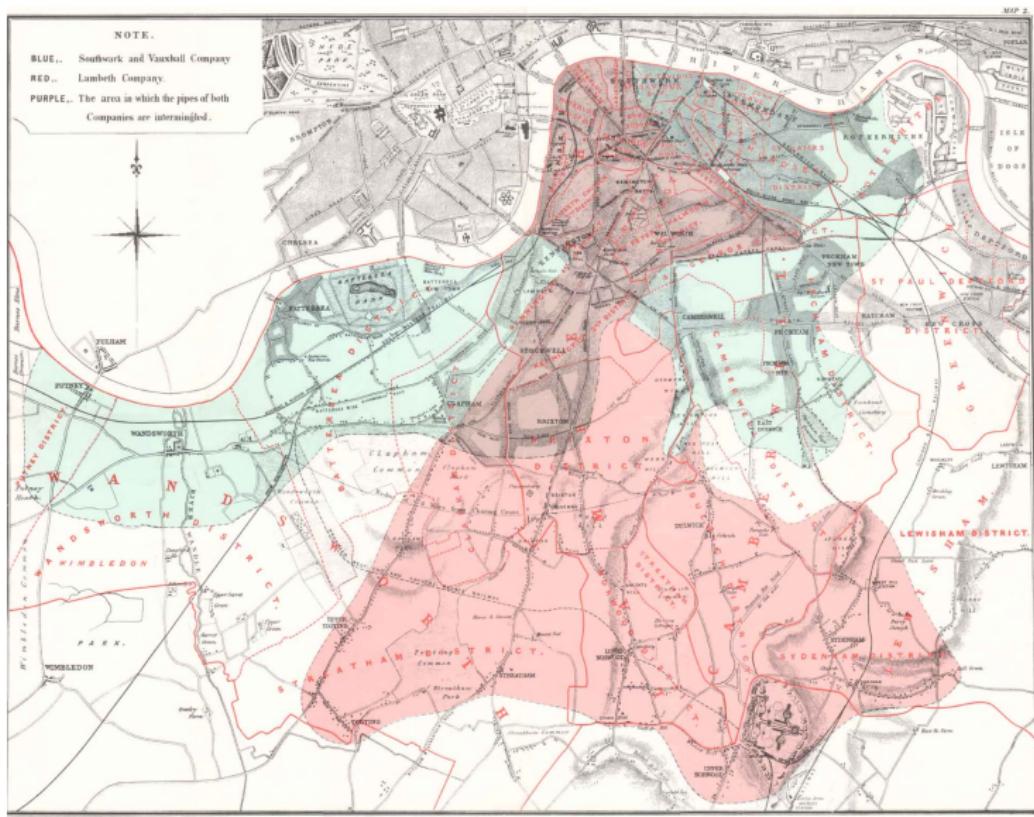
# Evidence Rejected

- Diff-in-diff evidence was rejected by Semmelweis' superiors claiming it was the hospital's new ventilation system
- Dominant theory of disease spread was caused by "odors" or miasma or "humors"
- Semmelweis began showing signs of irritability, perhaps onset of dementia, became publicly abusive, was committed to a mental hospital and within two weeks died from wounds he received while in residence
- Despite the strength of evidence, difference-in-differences was rejected – a theme we will see continue

# John Snow and cholera

- Three major waves of cholera in the early to mid 1800s in London, largely thought to be spread by miasma ("dirty air")
- John Snow believed cholera was spread through the Thames water supply through an invisible creature that entered the body through food and drink, caused the body to expel water, placing the creature back in the Thames and causing epidemic waves
- London passes ordinance requiring water utility companies to move inlet pipe further up the Thames, above the city center, but not everyone complies
- Natural experiment: Lambeth water company moves its pipe between 1849 and 1854; Southwark and Vauxhall water company delayed

*Figure: Two water utility companies in London 1854*



# Difference-in-differences

Table: Lambeth and Southwark and Vauxhall, 1849 and 1854

Companies	Time	Outcome	$D_1$	$D_2$
Lambeth	Before	$Y = L$		
	After	$Y = L + L_t + D$	$L_t + D$	
Southwark and Vauxhall	Before	$Y = SV$		$D + (L_t - SV_t)$
	After	$Y = SV + SV_t$	$SV_t$	

$$\hat{\delta}_{did} = D + (L_t - SV_t)$$

This method yields an unbiased estimate of  $D$  if  $L_t = SV_t$ , but note that  $L_t$  is a counterfactual trend and therefore not known

# Will You Be Able to Spot the Problem by Friday?

- Both of these have the correct *calculation*
- *But* one of them is robust to unrestricted heterogenous treatment effects but *one of them is not*
- **Which one is robust and which one is not!?**
- On Friday, let's see who has figured out which one and most importantly **why**

# Roadmap

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- Managing expectations

- Diff-in-Diff Popularity

- Origins of diff-in-diff in public health

## Diff-in-Diff Fundamentals

- Average Treatment Effect on the Treated

- Core Diff-in-Diff Assumptions

## Different Target Parameters

- Clearly Defined Control Status

- Imbalanced Panels

- Population Weighting

## Four Means or One Regression?

# Introducing Potential Outcomes to DiD

- Research question versus causal question – not the same thing
  - Research question would be you are wanting to know effect of job training programs on earnings
  - Causal question is expressed using potential outcomes
- Causal questions are usually averages of individual treatment effects for a specific population of units

## Identification vs Estimation

- We must start by making a distinction between the parameter we are attempting to identify and the manner in which we will estimate it
- Identification requires first stating explicitly our goal expressed using potential outcomes
- But often people skip this step and go directly to the  $2 \times 2$  calculation

## Potential outcomes notation

- Let the treatment be a binary variable:

$$D_{i,t} = \begin{cases} 1 & \text{if in job training program } t \\ 0 & \text{if not in job training program at time } t \end{cases}$$

where  $i$  indexes an individual observation, such as a person

## Potential outcomes notation

- Potential outcomes:

$$Y_{i,t}^j = \begin{cases} 1: & \text{wages at time } t \text{ if trained} \\ 0: & \text{wages at time } t \text{ if not trained} \end{cases}$$

where  $j$  indexes a state of the world where the treatment happened or did not happen

# Treatment effect definitions

## Individual treatment effect

The individual treatment effect,  $\delta_i$ , equals  $Y_i^1 - Y_i^0$

Missing data problem: No data on the counterfactual

# Average Treatment Effects for the Treated Subpopulation

## Average Treatment Effect on the Treated (ATT)

The average treatment effect on the treatment group is equal to the average treatment effect conditional on being a treatment group member:

$$\begin{aligned} E[\delta|D = 1] &= E[Y^1 - Y^0|D = 1] \\ &= E[Y^1|D = 1] - \textcolor{red}{E[Y^0|D = 1]} \end{aligned}$$

It's the average causal effect but only for the people exposed to some intervention; notice we can't calculate it, also, because we are missing the red term

## ATT vs ATE

- Potential outcomes is subtle and easily people are overconfident about its interpretation (probably because counterfactuals are seemingly easy to understand)
- Let's look at the "Potential Outcomes" tab at our Diff-in-Diff Worksheet; fill out all the instructions
- <https://docs.google.com/spreadsheets/d/1onabpc14JdrGo6NFv0zCWo-nuWDLLV2L1qNogDT9SBw/edit?usp=sharing>

# Deriving identification assumptions

- Diff-in-diff is two things
  1. It's **always** a calculation (i.e., four averages)
  2. It **sometimes** has a causal interpretation
- I'm going to walk us through two main assumptions using potential outcomes and algebra
- Then we will look at what happens when our control group has been treated (not an assumption, more like a promise)

## DiD equation is the 2x2

- The building block of diff-in-diff calculations is “four averages and three subtractions”
- Needs two groups, two time periods, which is four averages
- Often called the  $2 \times 2$  for that reason (Goodman-Bacon 2021)

$$\hat{\delta} = \left( E[Y_k|Post] - E[Y_k|Pre] \right) - \left( E[Y_U|Post] - E[Y_U|Pre] \right)$$

$k$  are the people in the job training program,  $U$  are the untreated people not in the program,  $Post$  is after the trainees took the class,  $Pre$  is the period just before they took the class, and  $E[y]$  is mean earnings.

- See <https://docs.google.com/spreadsheets/d/1onabpc14JdrGo6NFv0zCWo-nuWDLLV2L1qNogDT9SBw/edit?usp=sharing>

Replace with potential outcomes and add a zero

$$\hat{\delta} = \underbrace{\left( E[Y_k^1|Post] - E[Y_k^0|Pre] \right) - \left( E[Y_U^0|Post] - E[Y_U^0|Pre] \right)}_{\text{Switching equation}} + \underbrace{E[Y_k^0|Post] - E[Y_k^0|Post]}_{\text{Adding zero}}$$

## Parallel trends bias

$$\hat{\delta} = \underbrace{E[Y_k^1|Post] - E[Y_k^0|Post]}_{\text{ATT}} + \underbrace{\left[ E[Y_k^0|Post] - E[Y_k^0|Pre] \right] - \left[ E[Y_U^0|Post] - E[Y_U^0|Pre] \right]}_{\text{Non-parallel trends bias in 2x2 case}}$$

# Identification through parallel trends

## Parallel trends

Assume two groups, treated and comparison group, then we define parallel trends as:

$$E(\Delta Y_k^0) = E(\Delta Y_U^0)$$

**In words:** “The evolution of earnings for our trainees *had they not trained* is the same as the evolution of mean earnings for non-trainees”.

It's in red because parallel trends is untestable and critically important to estimation of the ATT using any method, OLS or “four averages and three subtractions”

## Don't Need More Than Two Periods

- Notice that diff-in-diff identifies the ATT *with only* two time periods
- Diff-in-diff does not "need" a long pre-treatment time series (unlike synthetic control which does) – two periods and two groups is enough
- But there is another assumption aside from parallel trends we want to learn

## No Anticipation

- First interpretation of No Anticipation (NA) is this:

$$Y_{i,t-1} = Y_{i,t-1}^0$$

- Future treatments do not spill over to the past – that is, a unit is not treated until the day it is treated
- A better word might be "no pre-treatment", rather than "no anticipation" because "anticipation" is a behavior and that confuses things
- What if a government announces a minimum wage increase that will take place in one year?

## No Anticipation

- Second interpretation of NA means this:

$$Y_{i,t-1}^1 - Y_{i,t-1}^0 = 0$$

which means "all pre-treatment treatment effects are zero.

- This means even if future minimum wage increases were known, their pre-treatment treatment effects were zero
- So no – knowing that something is going to happen does not automatically violate NA (but it absolutely could)
- Let's formalize what happens when NA is violated

## No Anticipation Violation

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^1 | Pre] \right) - \left( E[Y_U^0 | Post] - E[Y_U^0 | Pre] \right)$$

What if the  $k$  group had been treated at the baseline “pre” period in our 2x2?

Add in **two zeroes** instead of one, substitute and rearrange.

$$\begin{aligned} &+ E[Y_k^0 | Post] - E[Y_k^0 | Post] \\ &+ E[Y_k^0 | Pre] - E[Y_k^0 | Pre] \end{aligned}$$

## No Anticipation Violation

If the baseline period is treated, then the simple 2x2 identifies the following three terms:

$$\begin{aligned}\delta &= ATT_k(Post) \\ &\quad + \text{Non PT bias} \\ &\quad - ATT_k(Pre)\end{aligned}$$

First row is the ATT in the post period; middle row is parallel trends; third row subtracts the baseline ATT from the calculation. If treatment effects are constant, then the DiD coefficient will be zero despite positive treatment effects. Let's look in `na.do`.

## Do not use already treated controls

Using already treated units as controls is bad practice and here's why:

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^0 | Pre] \right) - \left( E[Y_U^1 | Post] - E[Y_U^1 | Pre] \right)$$

What if the  $U$  group had always been treated in both periods? Is parallel trends enough to identify the ATT?

Add in **three zeroes** instead of one, substitute and rearrange.

$$\begin{aligned} &+ E[Y_k^0 | Post] - E[Y_k^0 | Post] \\ &+ E[Y_U^0 | Post] - E[Y_U^0 | Post] \\ &+ E[Y_U^0 | Pre] - E[Y_U^0 | Pre] \end{aligned}$$

## Already Treated Control Group

If the baseline period is treated, then the simple 2x2 identifies the sum of the following three terms:

$$\begin{aligned}\delta &= ATT_k(Post) \\ &\quad + \text{Non PT bias} \\ &\quad - \Delta ATT_U\end{aligned}$$

Again, first row is the target parameter, plus parallel trends term, minus the changing ATT in our control group

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# SUTVA

- SUTVA: Stable Unit Treatment Value Assumption
  1. **Most common understanding:** No interference between units
  2. **Less well known:** No hidden variation in treatment
- We usually focus on the "clearly defined treatment" but the counterfactual is also a treatment
- Both the treatment is the same for all units, *and also the control state* ("clearly defined control status")
- Because of diff-in-diff structure, it places a limit on what is possible with diff-in-diff

## Clearly Defined Control Status

Look again at the result when you have NA and no treated control group:

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^0 | Pre] \right) - \left( E[Y_U^0 | Post] - E[Y_U^0 | Pre] \right)$$

- Be explicit about the **0** just like you would be with the **1**
- For the diff-in-diff, note that assuming NA,  $k$  at baseline was  $Y^0$  – what explicit alternative treatment status was this?
- Whatever it was, that's what  $U$  must be in both periods as we use  $U$ 's change in mean  $Y^0$  to impute the missing  $Y^0$  for our treatment group

# Clearly Defined Control Status

Make our substitutions

$$\hat{\delta} = \underbrace{E[Y_k^1|Post] - E[Y_k^0|Post]}_{\text{ATT}} + \underbrace{\left[ E[Y_k^0|Post] - E[Y_k^0|Pre] \right] - \left[ E[Y_U^0|Post] - E[Y_U^0|Pre] \right]}_{\text{Non-parallel trends bias in 2x2 case}}$$

1. Notice that embedded in parallel trends is NA, untreated controls, and clearly defined control status.
2. Notice that your target parameter is based on the same  $Y^0$  as the  $Y^0$  at baseline and a clearly defined control state

## Clearly Defined Control Status

$$\hat{\delta} = \underbrace{E[Y_k^1|Post] - E[Y_k^0|Post]}_{\text{ATT}} + \underbrace{\left[ E[Y_k^0|Post] - E[Y_k^0|Pre] \right] - \left[ E[Y_U^0|Post] - E[Y_U^0|Pre] \right]}_{\text{Non-parallel trends bias in 2x2 case}}$$

- Your control group is untreated  $Y^0$  in both periods and so under parallel trends will be a valid *imputation*
- But notice the role of  $Y_U^0$  – parallel trends, clearly defined control state, NA – is complex

## Example: Clearly Defined Control Status

- United States has prohibited cannabis use (e.g., Texas), medical marijuana (e.g., Oklahoma) and recreational cannabis (e.g., California)
- Researcher wants to know the effect of *recreational marijuana* on opiate addiction, but relative to what?

$$\delta_i = Y_i^1 - Y_i^0$$

- Note: All states with legalized recreational cannabis started with medical marijuana. Does that matter?

# Different Target Parameters

$E[Y_k^1|Post]$  in both of the following cases is treated with recreational cannabis, but  $Y^0$  is:

1.  $ATT_1 = E[Y_k^{1=recreational}|Post] - E[Y_k^{0=medical}|Post]$
2.  $ATT_2 = E[Y_k^{1=recreational}|Post] - E[Y_k^{0=prohibition}|Post]$

Do you think these *must* be the same thing? Why/why not?

What data do you need for  $ATT_1$  vs  $ATT_2$  when using diff-in-diff?

## Clearly Defined Control Status

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^0 | Pre] \right) - \left( E[Y_U^0 | Post] - E[Y_U^0 | Pre] \right)$$

- Diff-in-diff can only identify  $ATT_1$  if states transitioned from prohibition to recreational

## Clearly Defined Control Status

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^0 | Pre] \right) - \left( E[Y_U^0 | Post] - E[Y_U^0 | Pre] \right)$$

- Diff-in-diff can only identify  $ATT_1$  if states transitioned from prohibition to recreational
- In the US, that has never happened, which means we cannot in the US identify the average effect of recreational marijuana relative to prohibition

## Clearly Defined Control Status

$$\hat{\delta} = \left( E[Y_k^1 | Post] - E[Y_k^0 | Pre] \right) - \left( E[Y_U^0 | Post] - E[Y_U^0 | Pre] \right)$$

- Diff-in-diff can only identify  $ATT_1$  if states transitioned from prohibition to recreational
- In the US, that has never happened, which means we cannot in the US identify the average effect of recreational marijuana relative to prohibition
- We can only identify the effect of recreational marijuana relative to medical marijuana using diff-in-diff because the baseline in every case in the US is medical marijuana – which means only  $ATT_2$  is possible in US using diff-in-diff without strong assumptions

## Target Parameter

- But diff-in-diff has a limitation that not all the other designs suffer from – the control group *must* have the same control status as the treatment group at baseline
- So you must decide ahead of time:
  1. What is your target parameter and why?
  2. Can you estimate it with diff-in-diff in your data? How do you know?
- Interestingly, matching and regression adjustment can estimate either  $ATT_1$  or  $ATT_2$  (but only under also strong assumptions called unconfoundedness)

## Summarizing the basics

- With two time periods (before and after treatment), and two groups (one treated and one not), then the  $2 \times 2$  identifies the ATT if parallel trends and no anticipation holds so long as you do not have an already treated group as a control
- Let's now look at some basic data requirements and what happens when you don't meet those basic things

# Longitudinal Data

- Diff-in-diff requires four means – pre and post for two groups
- Traditionally, the "pre" is a baseline mean at year just prior to treatment,  $t - 1$  or  $b$  depending on author
  - Though sometimes you will see people present any interaction as diff-in-diff, we will focus only on time in our workshop
  - Just remember the interaction regression we presented is calculating four means and three subtractions
  - Interpreting parallel trends is a bit stranger otherwise

# Longitudinal Data

- Two types of longitudinal data:
  - Panel Data: same units tracked over time (e.g., National Longitudinal Survey of Youth 1997)
  - Repeated Cross-Sections: different units sampled at each time (e.g., Census, Current Population Survey)
- Violations of parallel trends can arise differently across data types.

## How does it change the parameter?

- In the potential outcomes framework, a treatment effect is defined at the individual level,  $\delta_{it}$
- So if you are missing a person,  $i$ , in a period,  $t$ , then it does not contribute
- The more heterogeneity in the treatment effects, the more the broken panel will shift away from what you think you're after

## Imbalanced ATE

Let's work together on an example of the effect of imbalanced panels versus balancing imbalanced panels at <https://docs.google.com/spreadsheets/d/1sgFjJgKaD5ARhkQy2cg3-r-6LV8kheEJGc4rpEtcoMk/edit?usp=sharing> ("Imbalanced")

<https://docs.google.com/spreadsheets/d/1sgFjJgKaD5ARhkQy2cg3-r-6LV8kheEJGc4rpEtcoMk/edit?usp=sharing> ("Imbalanced")

## Missing at Random (MAR)

- Wooldridge (2010) notes that missing at random (MAR) does not bias estimates under large samples
- This is because missingness is independent of  $E[\Delta Y^0]$ , therefore parallel trends will still hold in the large sample.
- This is somewhat testable, too, because if MAR holds, then baseline covariates for the  $M = 1$  and  $M = 0$  groups should on average be the same
- But maybe this is not plausible always so is there anything else we can do?

## Conditional Missing at Random

- What if the missing is conditionally random

$$Y^0 \perp M \mid X$$

- This implies:

$$E[Y^0 | M = 1, X] = E[Y^0 | M = 0, X]$$

- So you can impute  $\widehat{Y}^0$  for missing units using  $Y^0 \sim X$  with your non-missing data with a regression estimator
- Stronger assumptions needed for  $Y^1$  imputation

# Conditional Missing at Random

- This is a "missing based on observables" type of unconfoundedness assumption
  - You will need an overlap assumption or a functional form assumption for regression-based imputation
- Should you impute missing potential outcomes?
  - It is technically weaker than assuming MAR,
  - We impute potential outcomes under conditional parallel trends as we'll see
  - Nonetheless, to economists this is likely controversial since it requires knowing the observable  $X$  that determine missingness (and MAR is probably not plausible)
- Tradeoffs: Leave imbalanced or impose balance, change parameter vs impute missingness under strong assumptions

# Should You Weight Your Data by Population?

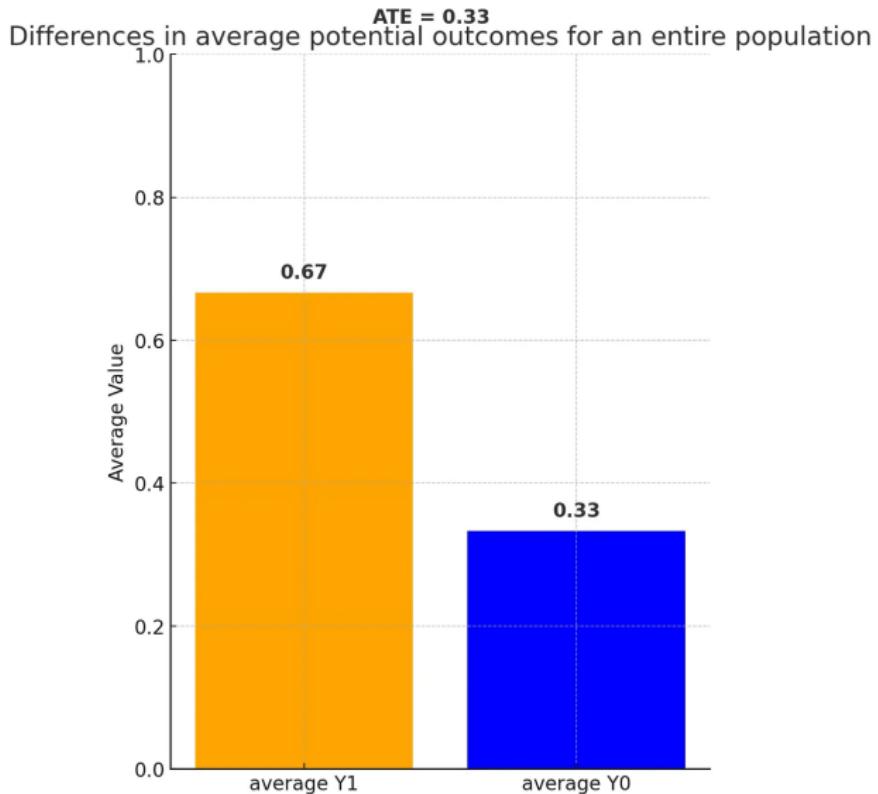
- Causal parameters are averaged *treatment effects* and that has three ingredients
  - Treatment effects expressed as potential outcomes
  - Averaging treatment effects for a sub-population of units
  - Weights
- You only weight your data by population in order to identify a previously stated target parameter
- I'll use as an example a gun law in the United States called "concealed carry" or "right to carry" that lets people carry weapons "concealed" on their bodies or in their vehicles

# Average Treatment Effects

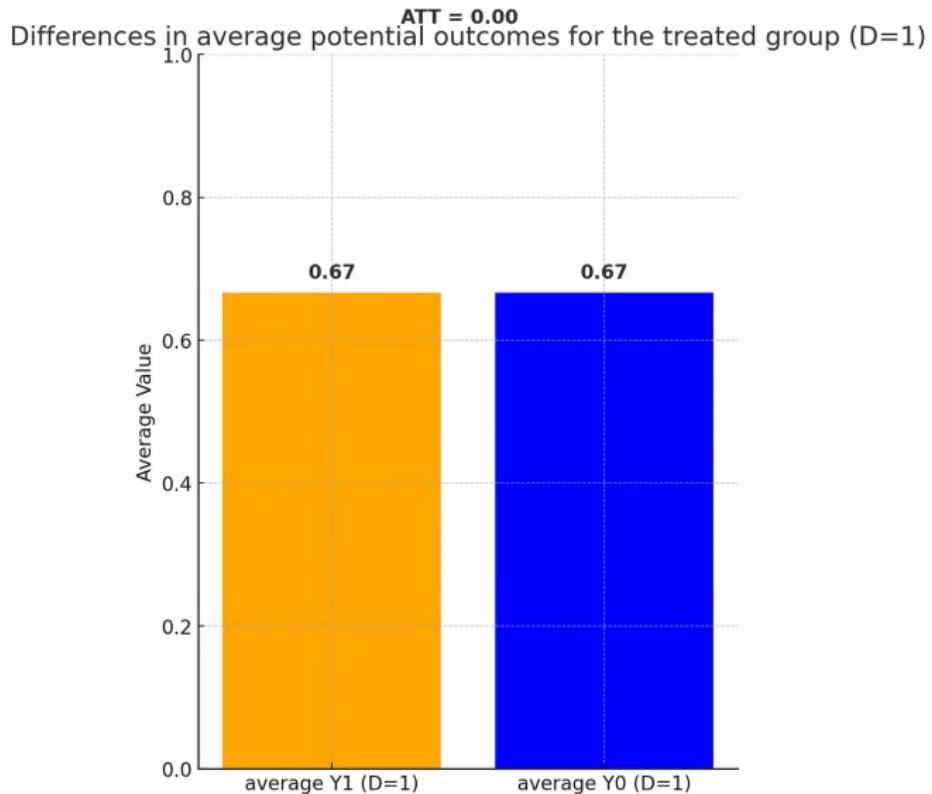
*Table:* Illustration of Potential Outcomes and Treatment Effects

Name	$Y^1$	$Y^0$	$\delta$	D
Alan	1	0	1	1
Betty	0	1	-1	1
Chad	1	1	0	1
Daniel	0	0	0	0
Edith	1	0	1	0
Frank	1	0	1	0
$ATE =$		0.33		
$ATT =$		0		

# Average Treatment Effects



# Average Treatment Effect on the Treated



# Which causal effect do you want?

- We know diff-in-diff identifies the ATT not the ATE but there are still more than one ATT!
- Solon, Haider and Wooldridge (2015), "What are we weighting for?"
- Why you weight in surveys and why you weight in causal inference are different
  - Survey weights are to make estimates nationally representative
  - Population weighting in causal inference is because you want a different parameter
- How do we interpret adjustments made with population weights versus not?

# Different Levels of Aggregation, Different Weights

Individuals	$Y_1$	$Y_0$	$\delta$	County
Alan	1	0	1	1
Betty	1	1	0	1
Chad	1	1	0	1
Daniel	0	0	0	1
Edith	1	0	1	1
Frank	1	0	1	1
George	0	0	0	1
Hank	1	0	1	1
Ida	0	1	-1	2
Janet	0	1	-1	2

County	ATE <sub>c</sub>
1	0.5
2	-1

ATE for average county	-0.25
ATE for average person	0.2

## Weighting formula

- What if you have city or county level data but you want the ATE for the average person?
- Then that is when you weight by population – because you want to know the effect for the *average person*

$$ATE_{\text{people}} = \frac{\sum_c ATE_c \cdot N_c}{\sum_c N_c} \quad (1)$$

$$\begin{aligned} ATE_p &= \frac{(0.5 \times 8) + (-1 \times 2)}{8 + 2} \\ &= \frac{4 - 2}{10} \\ &= 0.2 \end{aligned}$$

# Different Levels of Aggregation, Different Weights

- Heterogenous treatment effects is causing this, but so is weighting
- Consider Texas
  - Texas has 31 million residents
  - Texas 254 counties
- Where do they live?
  - 13 million live in Harris, Dallas, Fort Worth, San Antonio and Austin, or rather 41%
- What if concealed carry increases firearm deaths in cities, but reduces them in counties, because of sorting by treatment effects?

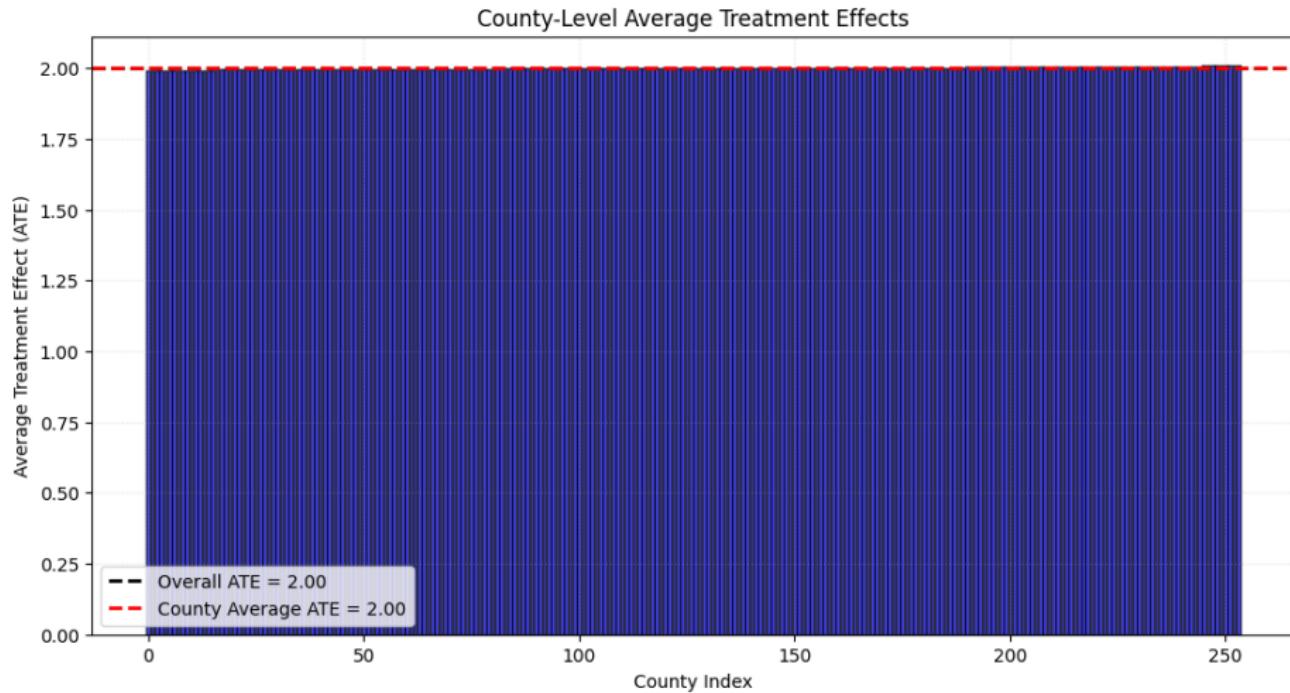
# Simulation

- Assume a state with 30 million people and 254 counties
  - 15 million live in 5 counties
  - 15 million live equally spread in the other 249 counties (around 60,000 each)
- Assume that  $\delta_i$  varies, sometimes positive and sometimes negative and  $E[Y^1 - Y^0] = 2$

## Selection into Counties is Random

- People choose where to live in Texas, but the mechanism by which they do so will have implications for our datasets
- What if they sort into counties (i.e., where they live) by lottery
- Every county will therefore have the same distribution of  $Y^1$  and  $Y^0$
- Every county will have an ATE of 2

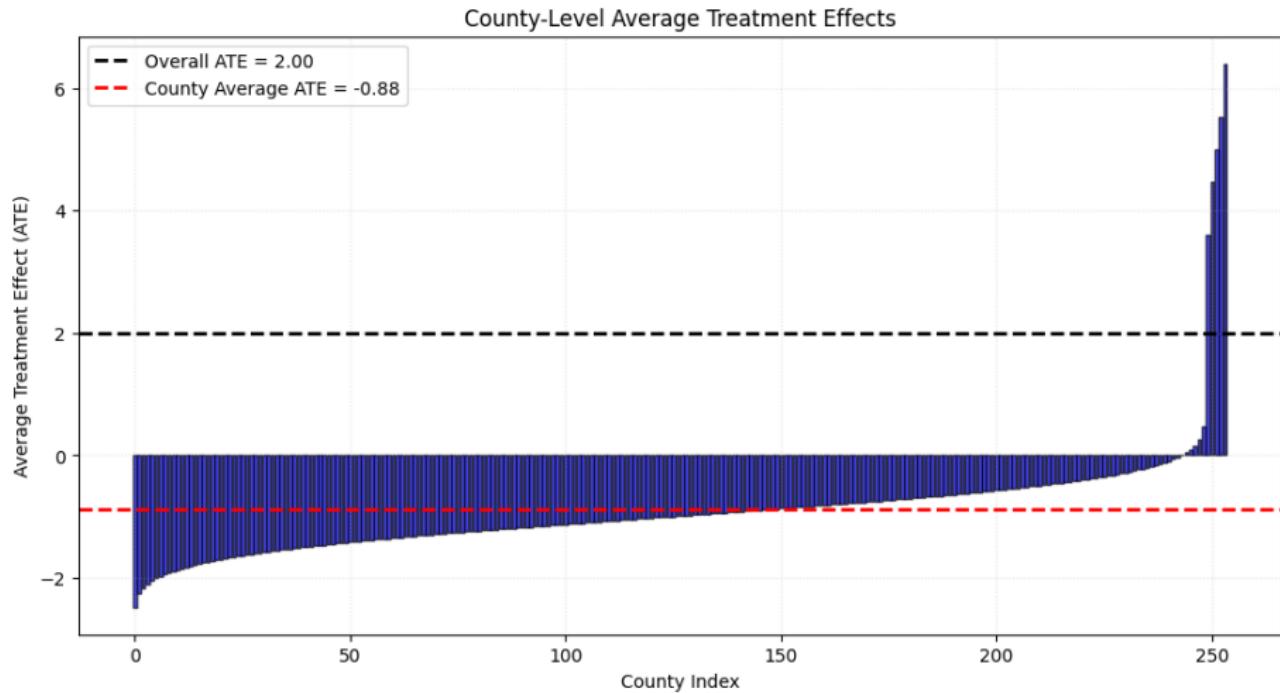
# Average County ATE and Overall ATE Are the Same



## Selection into Counties is Based on Potential Outcomes

- Now assume that people sort into five largest counties have the highest treatment effects ( $\delta_i$ )
- Thus the five largest counties are those people for whom concealed carry guns law cause homicides
- Remaining 249 small counties, in decreasing order, get residents with lower treatment effects (i.e., for whom concealed carry reduces murders)

# Average County ATE and Overall ATE Differ



## Both Are Valid, But Not Necessarily Your Research Question

- Do you want to know the ATT for the *average person* or the *average county*?
  - It depends on what your study is about, and it will absolutely matter for policy relevance, estimation and interpretability
  - If it's about the average person, then you want the overall ATT (i.e., the first case)
  - If it is about the average county, then you want the county average ATT (i.e., the second case)
- Since you're averaging over *units* in *data*, it's imperative you make a decision early on as it changes what you decide
- You can always use population weights but in causal inference, you ask what your target parameter is, and then decide your weights

## Choosing your ATT parameter

- As a rule, imagine who your audience is, and what you both agree the policy levers are
- In the US, local municipalities have a lot of discretion to pass their own laws – even in areas where you might think it was impossible to imagine like the decriminalization of drugs
- It may be *local* policy makers want to know the causal effect on *local communities* in which case you **don't weight**
- If you are ever unsure, *do both to avoid cherry picking but be clear.*

# Roadmap

## Introduction

- Managing expectations

- Diff-in-Diff Popularity

- Origins of diff-in-diff in public health

## Diff-in-Diff Fundamentals

- Average Treatment Effect on the Treated

- Core Diff-in-Diff Assumptions

## Different Target Parameters

- Clearly Defined Control Status

- Imbalanced Panels

- Population Weighting

## Four Means or One Regression?

# Why do Diff-in-Diff

- Appeal of diff-in-diff has *always* been its simplicity, its transparency, and its ease of conveying analysis to an audience
  - Giovanni Mastrobuoni graduated from Princeton University in 2006 and studied with a famous labor economist named Orley Ashenfelter
  - Orley invented the term "difference-in-differences" used it in the 1970s to explain regressions with fixed effects to US Bureaucrats
- Diff-in-diff is four averages and three subtractions and everyone knows what those are

$$\hat{\delta} = \left( \bar{y}_k^{post(k)} - \bar{y}_k^{pre(k)} \right) - \left( \bar{y}_U^{post(k)} - \bar{y}_U^{pre(k)} \right)$$

- But  $\hat{\delta}$  is just the OLS coefficient in this regression:

$$Y_{ist} = \alpha_0 + \alpha_1 Treat_{is} + \alpha_2 Post_t + \hat{\delta}(Treat_{is} \times Post_t) + \varepsilon_{ist}$$

## Data example

- Medicaid is a US policy for the poor – provides access to healthcare to the poor – and it's been a research question whether it has any effect on mortality
  - Finkelstein, et al. (2012) found no effect on mortality from RCT, but it was probably underpowered to find small effects
  - Borgschulte and Vogler (2020) used county level publicly available mortality data and found evidence that it did
  - Miller, Johnson and Wherry (2022) used linked administrative data and also found it did
- Let's review the Borgschulte and Vogler (2020) approach

# Simple 2x2 DD

Table 2: Simple  $2 \times 2$  DiD

	Unweighted Averages			Weighted Averages		
	Expansion	No Expansion	<i>Gap/DiD</i>	Expansion	No Expansion	<i>Gap/DiD</i>
2013	419.2	474.0	-54.8	322.7	376.4	-53.7
2014	428.5	483.1	-54.7	326.5	382.7	-56.2
<i>Trend/DiD</i>	<b>9.3</b>	<b>9.1</b>	<b>0.1</b>	<b>3.7</b>	<b>6.3</b>	<b>-2.6</b>

Notes: This table reports average county-level mortality rates (deaths among adults aged 20-64 per 100,000 adults) in 2013 (row 1) and 2014 (row 2) in states that expanded adult Medicaid eligibility in 2014 (columns 1 and 4) and states that have not expanded by 2019 (columns 2 and 5). The first three columns present unweighted averages and the second three columns present population-weighted averages. Columns 1, 2, 4, and 5 in the third row show time trends in mortality between 2013 and 2014 for each group of states. The first two rows of columns 3 and 6 show the cross-sectional gap in mortality between expansion and non-expansion states in 2013 and 2014. The entries in bold red text in row 3 show the simple  $2 \times 2$  difference-in-differences estimates without weights (column 3) and with them (column 6)

# Three Regressions

- Three regression specifications give you those exact same numbers
  1. Regress mortality onto treatment dummy, post dummy and interaction (no fixed effects)
  2. Regress mortality onto interaction with county and year fixed effects (but no constant)
  3. Regress long difference (i.e., post value minus pre) onto a treatment dummy
- Those are all numerically identical to "four averages and three subtractions"

Table 3: Regression  $2 \times 2$  DiD

	Unweighted			Weighted		
	Crude Mortality Rate		$\Delta$	Crude Mortality Rate		$\Delta$
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	474.0*** (4.3)		9.1*** (2.6)	376.4*** (7.6)		6.3*** (1.1)
Medicaid Expansion	-54.8*** (6.3)			-53.7*** (11.5)		
Post	9.1** (2.6)			6.3*** (1.1)		
Medicaid Expansion $\times$ Post	0.1 (3.7)	0.1 (3.7)	0.1 (3.7)	-2.6* (1.5)	-2.6* (1.5)	-2.6* (1.5)
County fixed effects	No	Yes	No	No	Yes	No
Year fixed effects	No	Yes	No	No	Yes	No

Notes: This table reports the regression  $2 \times 2$  DiD estimate comparing counties that expand Medicaid in 2014 to counties that do not expand Medicaid by 2019, using only data for the years 2013 and 2014. Columns 1-3 report unweighted regression results, while columns 4-6 weight by county population aged 20-64 in 2013. Columns 1 and 4 report results from regressing the crude mortality rate for adults ages 20-64 on indicators for expansion states (Treat) and post-expansion year (Post), with the DiD estimate being the coefficient on the interaction term. Columns 2 and 5 report the corresponding results for the interaction term using county and year fixed effects. Finally, Columns 3 and 6 report the results of the long difference in county mortality rates on a treatment indicator. Standard errors (in parentheses) are clustered at the county level.

# Equivalence

- Please open `equivalence.do` and `equivalence.R` in  
`./Example-Code`
- We will review these three "unweighted" regressions
- Can you figure out how to do the "weighted" regressions?

# Equivalence

- Equivalence between calculating these 2x2s by hand or with a regression has appealing features
- Regressions are simple to run, and they do the averaging behind the scenes
- They also allow us to use statistical inference tools from OLS like clustering decisions
- Bertrand, Duflo and Mullainathan (2004) show that conventional standard errors will often severely underestimate the standard deviation of the estimators and propose clustering standard errors at the aggregate unit level of treatment