# **n-person** Session 9

#### March 13, 2025

PMAP 8521: Program evaluation Andrew Young School of Policy Studies

## **Plan for today**

### Diff-in-diff II



Quarto websites (and other fun)

# Diff-in-diff II







#### Cholera deaths per 100,000

Southwark & Vauxhall: 1,349

Lambeth: **847** 

Cholera deaths per 100,000

Southwark & Vauxhall: 1,466

Lambeth: **193** 



#### Reading a story about math reduces math anxiety

Experiment in four 4th grade classes



When doing your subtracting to get your differences in the matrix, is it better to do the vertical or horizontal subtractions?

> Are there situations where one is preferable to the other?

Why are we learning two ways to do diff-in-diff? (2x2 matrix vs. lm())

## What happened to confounding??

Now we're only looking at just two "confounders"?

Should we still control for things?



The effect of mandatory maternity benefits on wages

New Jersey implements policy; Pennsylvania doesn't

Only applies to married women who have kids

### Married women 20–40 single men/unmarried women/older women in NJ and PA

TABLE 3—DDD ESTIMATES OF T ON HOURI	he Impact of y Wages	STATE MAN	NDATES
Location/year	Before law change	After law change	Time difference for location
A. Treatment Individuals: Married Women, 2	20 – 40 Years C	Old:	
Experimental states	1.547 (0.012) [1,400]	1.513 (0.012) [1,496]	-0.034 (0.017)
Nonexperimental states	1.369 (0.010) [1,480]	1.397 (0.010) [1,640]	0.028 (0.014)
Location difference at a point in time:	0.178 (0.016)	0.116 (0.015)	
Difference-in-difference:	-0.0 (0.0	)62 )22)	
B. Control Group: Over 40 and Single Males	20 - 40:		
Experimental states	1.759 (0.007) [5,624]	1.748 (0.007) [5,407]	-0.011 (0.010)
Nonexperimental states	1.630 (0.007) [4,959]	1.627 (0.007) [4,928]	-0.003 (0.010)
Location difference at a point in time:	0.129 (0.010)	0.121 (0.010)	
Difference-in-difference:	-0.008: (0.014)		
DDD:	-0.054 (0.026)		

# Can you walk through an example of diff-in-diff in class?

# Two-way fixed effects (TWFE)

#### Two states: Alabama vs. Arkansas

# $egin{aligned} ext{Mortality} &= eta_0 + eta_1 ext{ Alabama} + eta_2 ext{ After 1975} + \ eta_3 ext{ (Alabama imes ext{ After 1975)} \end{aligned}$

#### All states: Treatment == 1 if legal for 18-20-year-olds to drink

#### Mortality = $\beta_0 + \beta_1$ Treatment + $\beta_2$ State + $\beta_3$ Year

# $\begin{array}{l} \text{Mortality} = \beta_0 + \beta_1 \text{ Alabama} + \beta_2 \text{ After 1975} + \\ \beta_3 \text{ (Alabama \times After 1975)} \end{array}$

#### VS.

Mortality =  $\beta_0 + \beta_1$  Treatment +  $\beta_2$  State +  $\beta_3$  Year

# $\begin{array}{l} \text{Mortality} = \beta_0 + \beta_1 \text{ Alabama} + \beta_2 \text{ After 1975} + \\ \beta_3 \text{ (Alabama \times After 1975)} \end{array}$

VS.

Mortality =  $\beta_0 + \beta_1$  Treatment +  $\beta_2$  State +  $\beta_3$  Year vs.

 $egin{aligned} ext{Mortality} &= & eta_0 + eta_1 ext{ Treatment} + eta_2 ext{ State} + eta_3 ext{ Year} + \ & eta_4 ext{ (State} imes ext{Year)} \end{aligned}$ 

Dependent variable	(1)	(2)	(3)	(4)
All deaths	10.80	8.47	12.41	9.65
	(4.59)	(5.10)	(4.60)	(4.64)
Motor vehicle accidents	7.59	6.64	7.50	6.46
	(2.50)	(2.66)	(2.27)	(2.24)
Suicide	.59	.47	1.49	1.26
	(.59)	(.79)	(.88)	(.89)
All internal causes	1.33	.08	1.89	1.28
	(1.59)	(1.93)	(1.78)	(1.45)
State trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes

 TABLE 5.2

 Regression DD estimates of MLDA effects on death rates

*Notes:* This table reports regression DD estimates of minimum legal drinking age (MLDA) effects on the death rates (per 100,000) of 18–20-year-olds. The table shows coefficients on the proportion of legal drinkers by state and year from models controlling for state and year effects. The models used to construct the estimates in columns (2) and (4) include state-specific linear time trends. Columns (3) and (4) show weighted least squares estimates, weighting by state population. The sample size is 714. Standard errors are reported in parentheses.

# $egin{aligned} ext{Donation rate} &= eta_0 + eta_1 ext{ California} + eta_2 ext{ After Q22011} + \ eta_3 \ ( ext{California} imes ext{After Q22011}) \end{aligned}$

VS.

# What about this staggered treatment stuff?

See this

LLMS

#### How have you used LLMs like ChatGPT?

### What worries have you had?

#### Can we use LLMs like ChatGPT?

How do we use them?

Is it okay to use them?

### LLMs are not magical. They're stats.

# Basic Markov chain example with R



# LLMs are essentially super fancy Markov chains

"Stochastic parrots" and "fancy autocorrect"



# Reasoning models

## So many ethical issues!

#### **Environmental concerns**

"Environmental Impact of Large Language Models" and "The mounting human and environmental costs of generative AI" and "AI water footprint suggests that large language models are thirsty"



"OpenAl Used Kenyan Workers on Less Than \$2 Per Hour to Make ChatGPT Less Toxic"

#### Racial and gender bias

"Al chatbots use racist stereotypes even after anti-racism training"

#### Stolen training data

"ChatGPT Stole Your Work. So What Are You Going to Do?" and "Congress Wants Tech Companies to Pay Up for AI Training Data" and "ChatGPT can leak training data, violate privacy"

#### **Ouroboros effect**

"Meet the Serbian DJ Running an AI Clickbait Business" and "The Perfect Webpage"



"AI models make stuff up. How can hallucinations be controlled?"

## Just this week!

#### ars **TECHNICA**

🔍 "FREEDOM TO LEARN"

#### OpenAI declares AI race "over" if training on copyrighted works isn't fair use

National security hinges on unfettered access to AI training data, OpenAI says.

ASHLEY BELANGER – MAR 13, 2025 12:20 PM | 🗩 173

## Just this week!

The New York Times

#### Yale Suspends Scholar After A.I.-Powered News Site Accuses Her of Terrorist Link

The deputy director of a liberal project at Yale Law School was put on leave over allegations that she is linked to Samidoun, a group the U.S. government has said funds terrorists.

## Just this week!

#### **AXIOS**

Mar 6, 2025 - Politics & Policy

#### Scoop: State Dept. to use Al to revoke visas of foreign students who appear "pro-Hamas"



36 / 42

# You need to figure out your own ethics.

# LLMs and programming

### GitHub Copilot tuned specifically for code

Uses ChatGPT, Claude, or Gemini behind the scenes

You can also use Claude, DeepSeek, etc. directly instead of from GitHub

These work *surprisingly* well

But they're dangerous if you don't know what you're doing!

# **Getting coding help from LLMs**

Talking to LLMs for code requires special skills and practice!

Think about coverage

**Rep**roducible **ex**amples!

**Reprex slides** 

**GitHub Gists** 

# Things code-focused LLMs are good at

Explaining and annotating code

Translating between languages

Generating boilerplate/starter code

Cleaning and rewriting code

BUT (and I cannot emphasize this enough) THEY ARE STILL CONFIDENTLY WRONG



# Quarto websites (and other fun)