

# Lecture 4: Difference in Difference, 2 of 2

February 4, 2026

## Course Administration

- 1 Returned comments on proposals
- 2 Will send update with summary grading
- 3 Lab after class this week
- 4 PS 2 due in two weeks
- 5 Any problem set 2 issues?
- 6 If you haven't identified a replication paper, I'm nervous
- 7 Any other issues?

## Relaxing diff-in-diff: event study

- 1 Simplest possible event study
- 2 Diff-in-diff event study
- 3 Estimating trends
- 4 Testing for trends
- 5 Estimation concerns with diff-in-diff

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## Janssen and Zhang

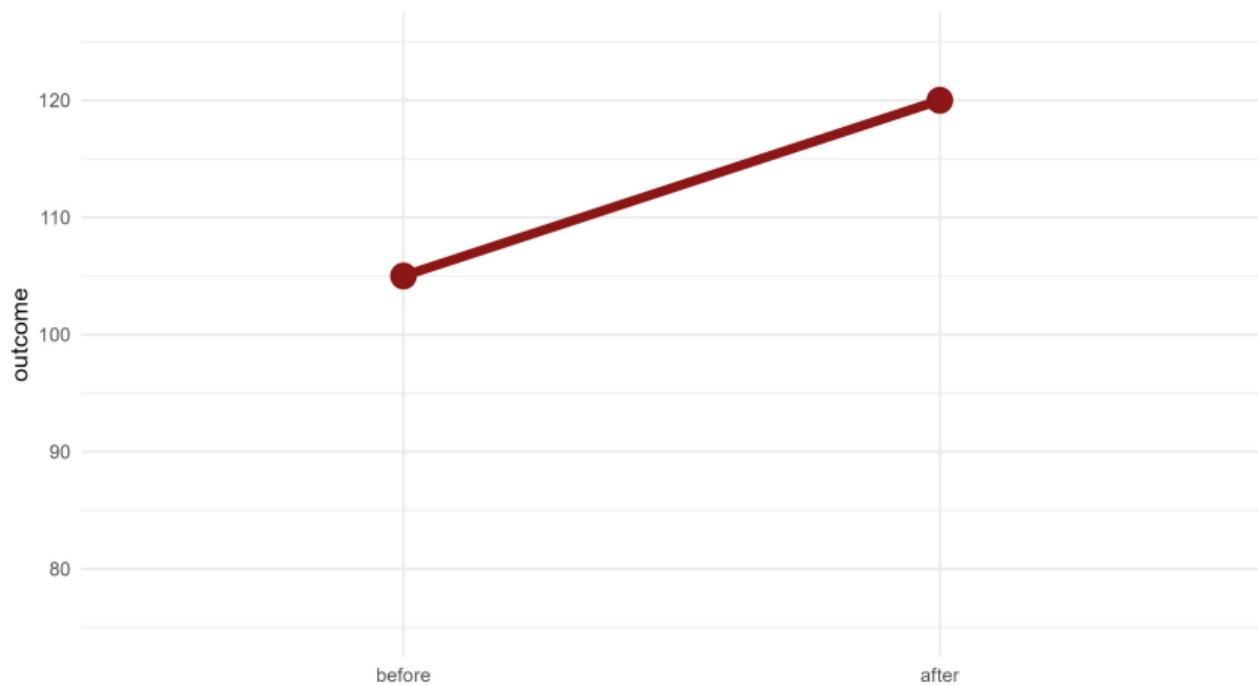
- 1 Diff-in-diff specification
- 2 Event study specification

# 1. Simplest Event Study

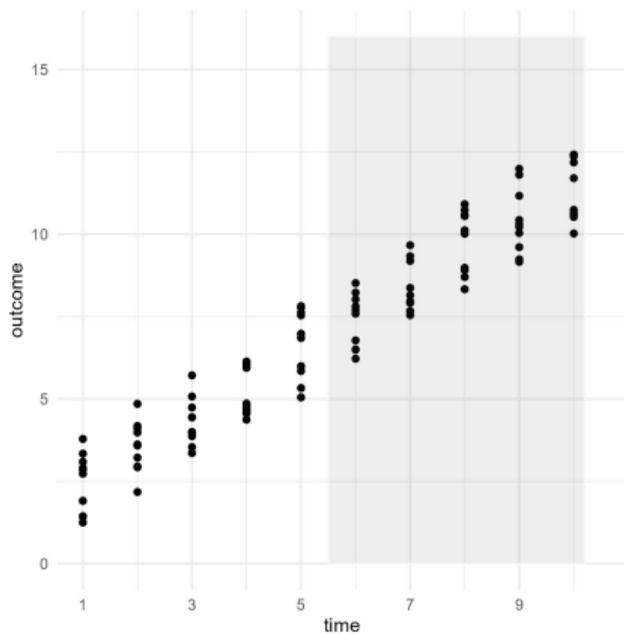
## Basic Set-Up

- We want to know the impact of  $X$  on  $Y$
- Over time, the impact of treatment  $X$  changes – increases, decreases, appears, disappears
- Compare outcomes  $Y$  before and after change in  $X$
- Examples, please!

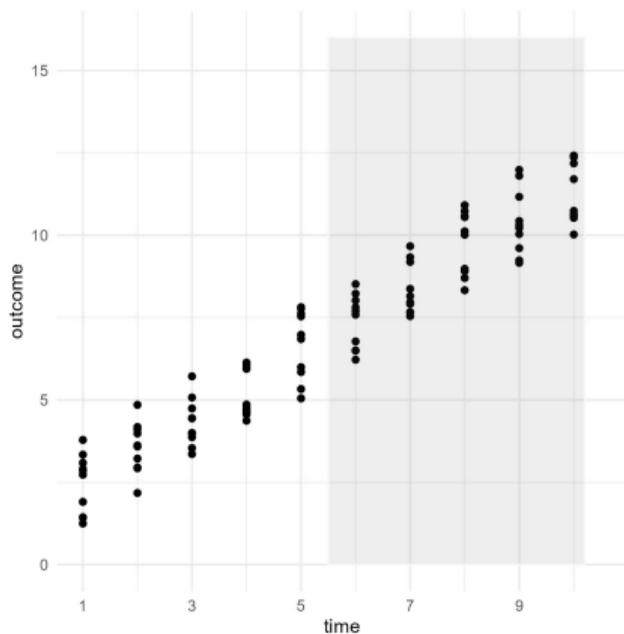
## Last Week: Only Before and After



## More Dots: Observe Each $i$ in each time $t$



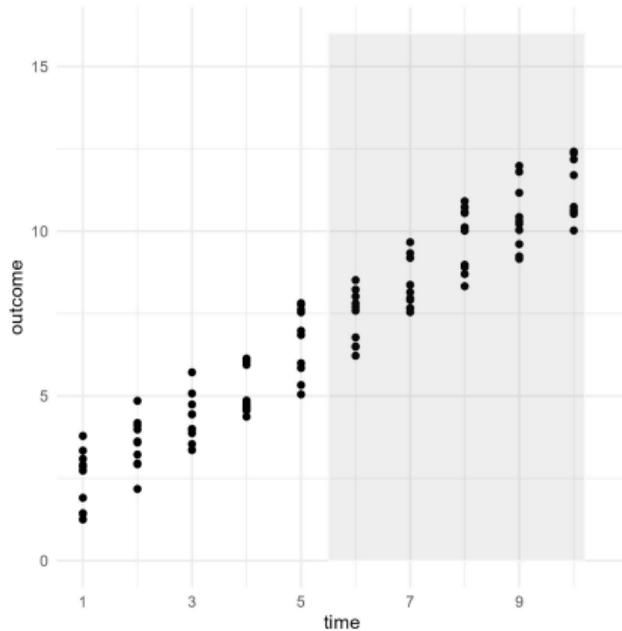
## More Dots: Observe Each $i$ in each time $t$



- All  $i$  are treated
- At all times  $t > T_0$

Equation to estimate average  $Y$  after?

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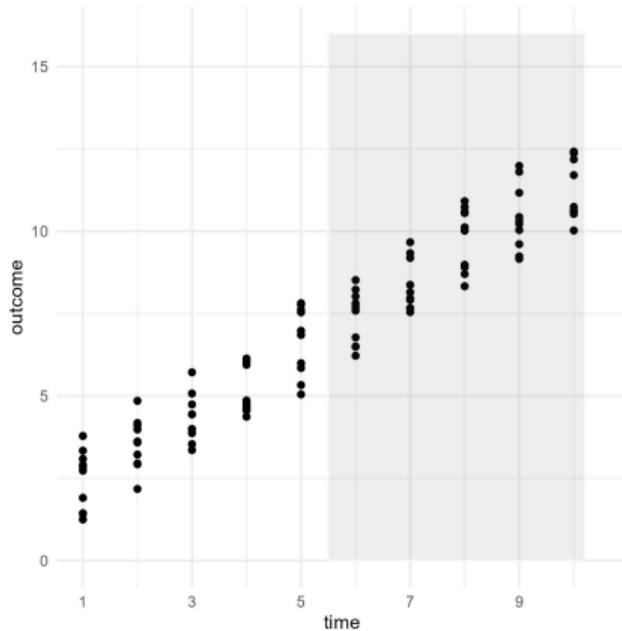
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$$Y_{i,t} = \beta_0 + \beta_1 \text{after}_t + \epsilon_{i,t}$$

where  $\text{after}_t$  is 1 for years  $t > T_0$ .

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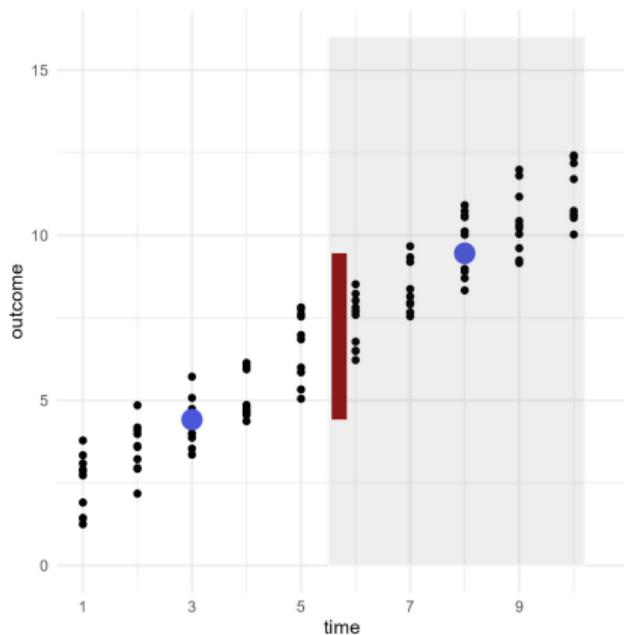
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What does  $\beta_1$  report?

## What $\beta_1$ Reports

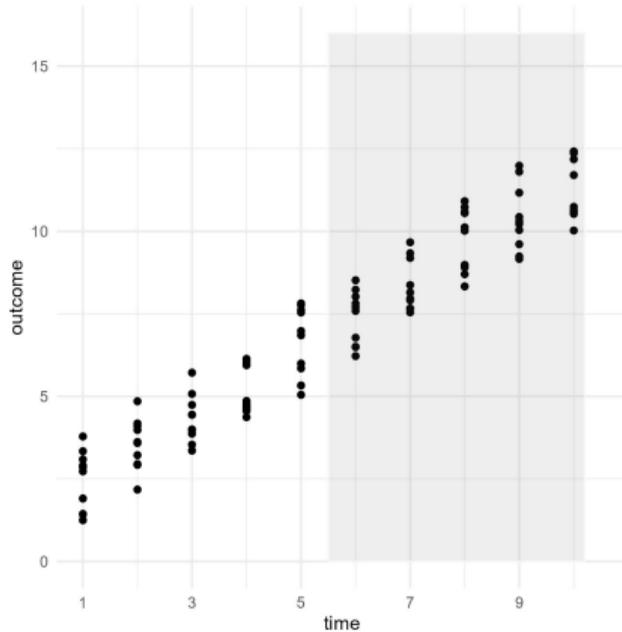


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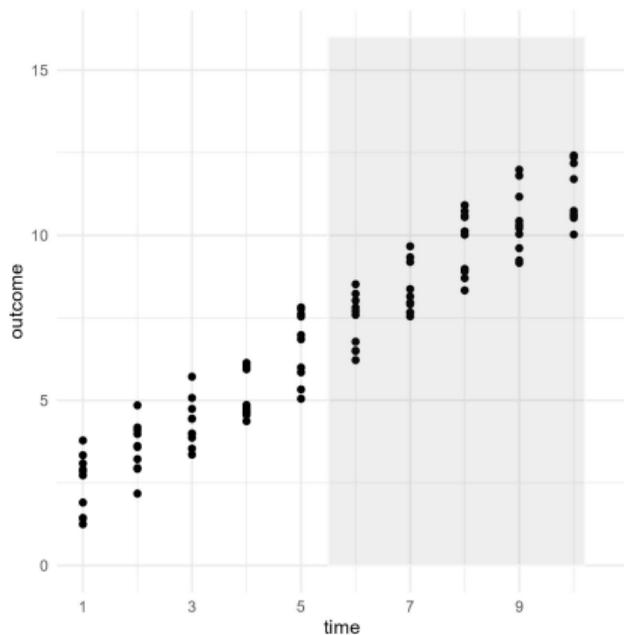
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# Estimating the Impact of Time Granularly



How do we estimate the impact of treatment in each period individually?

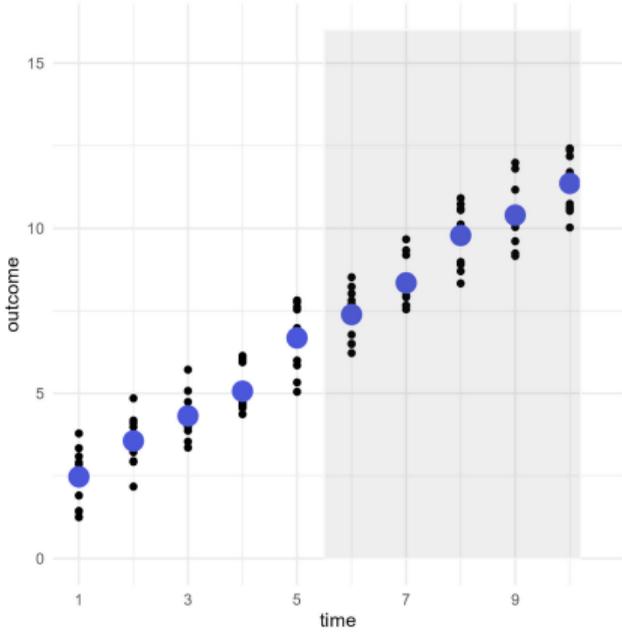
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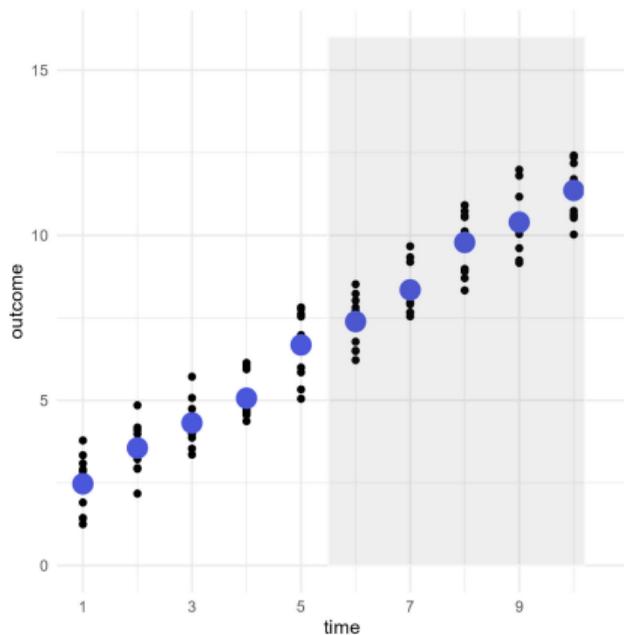
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# Raw Data: Event Study Diagram



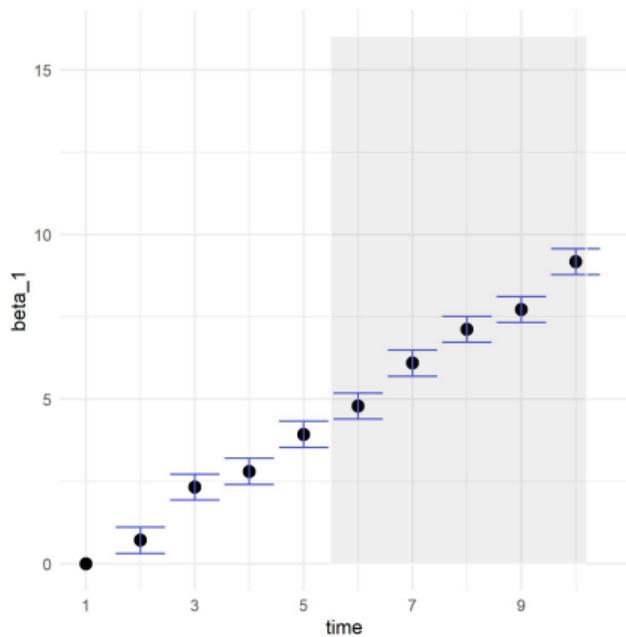
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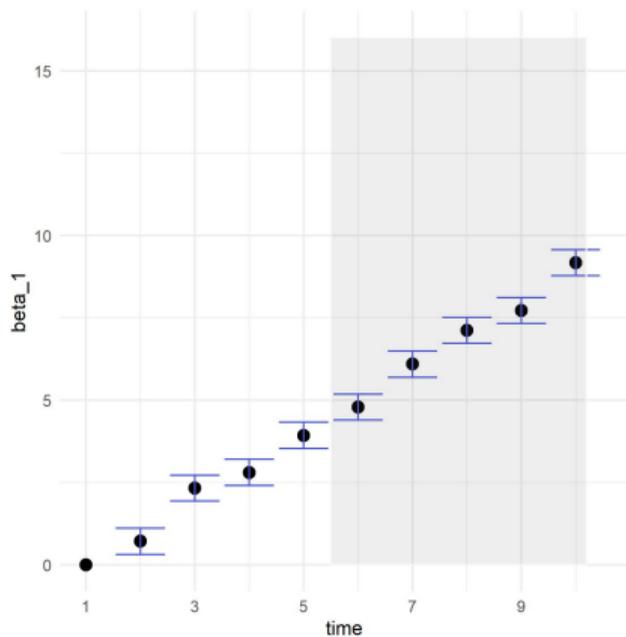
$$Y_{i,t} = \beta_0 + \beta_{1,t}1\{\text{time} = t\}_t + \epsilon_{i,t}$$

- Regression coefficients should measure these means in the raw data
- What do you think a plot of  $\beta_{1,t}$  should look like?

# Regression Coefficients: Event Study Diagram

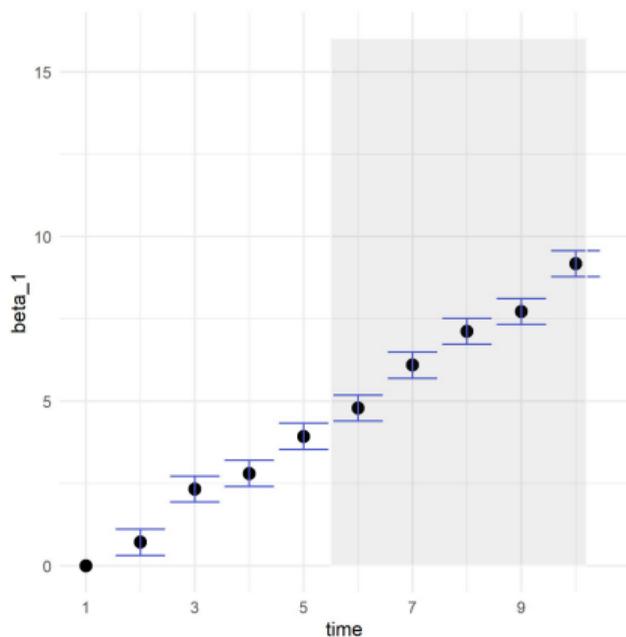


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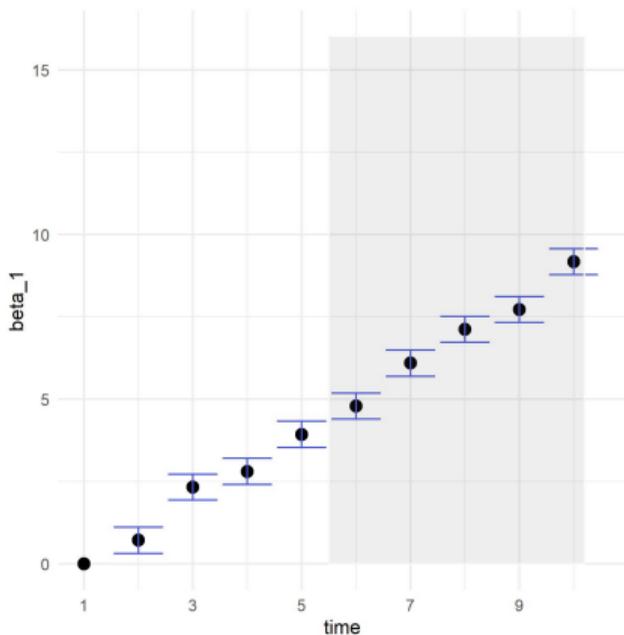
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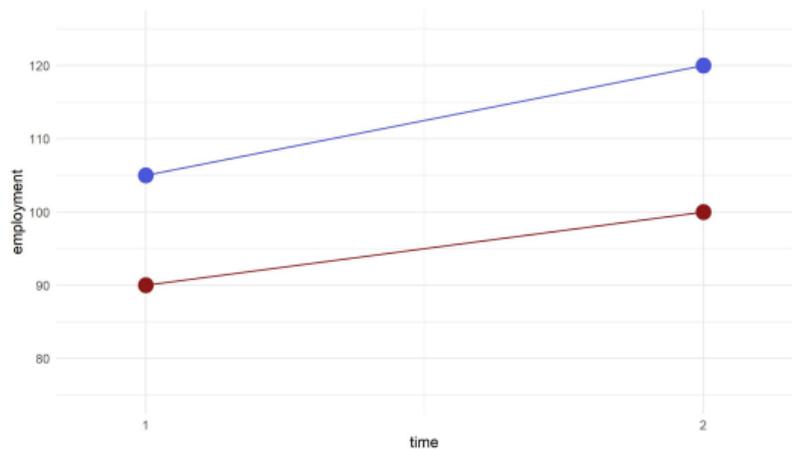
- Everything is relative to mean in year 1
- Why might comparing pre- and post blue dots not give the causal impact of  $X$  on  $Y$ ?
- How do we fix with the strategy from last lecture?

## 2. Diff-in-diff Event Study

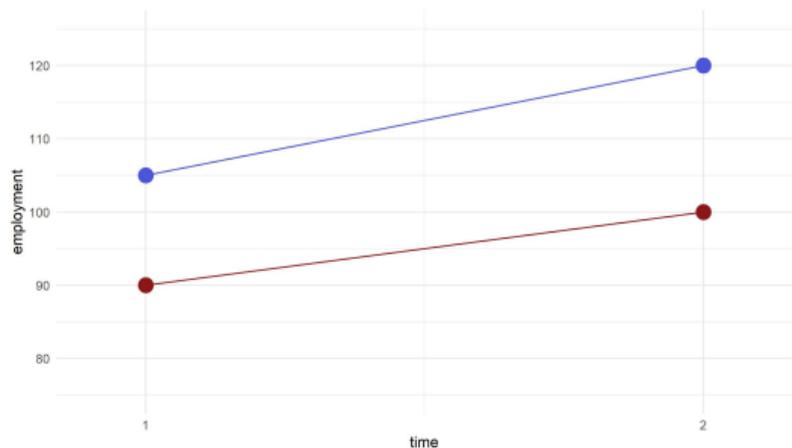
## Basic Set-Up

- We want to know the impact of  $X$  on  $Y$
- Over time, the impact of treatment  $X$  changes – increases, decreases, appears, disappears
- **Some units experience a change in  $X$  – are treated – and others are not**
- Compare outcomes  $Y$  before and after change in  $X$
- Examples, please!

## Review: How We Do This with Just Before and After



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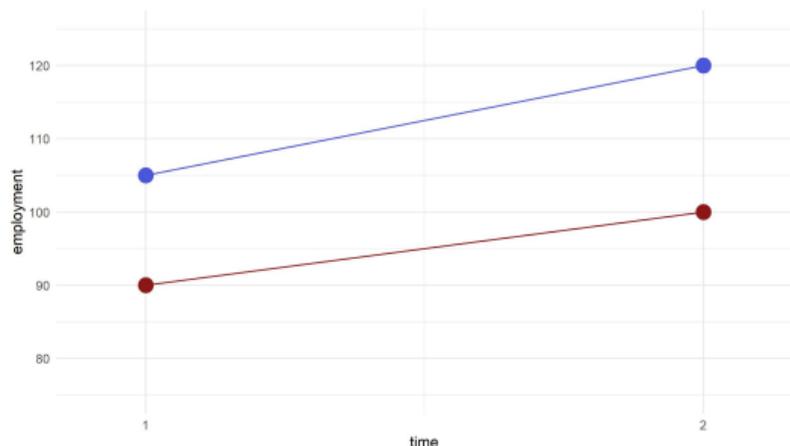


Equation to estimate impact of treatment?

- For treated  $i$  assign  $\text{treated}_i = 1$
- Treatment at all times  $t > T_0$

Equation to estimate diff-in-diff?

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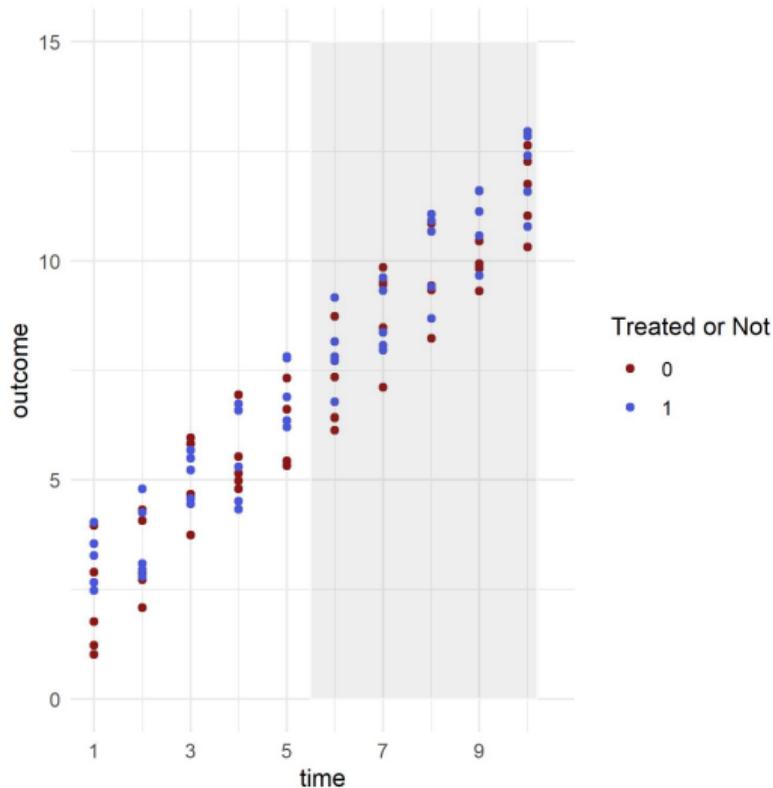
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$$Y_{i,t} = \beta_0 + \beta_1 \text{treated}_i * \text{after}_t \\ + \beta_2 \text{treated}_i + \beta_3 \text{after}_t + \epsilon_{i,t}$$

# Treated and Untreated in an Event Study Framework



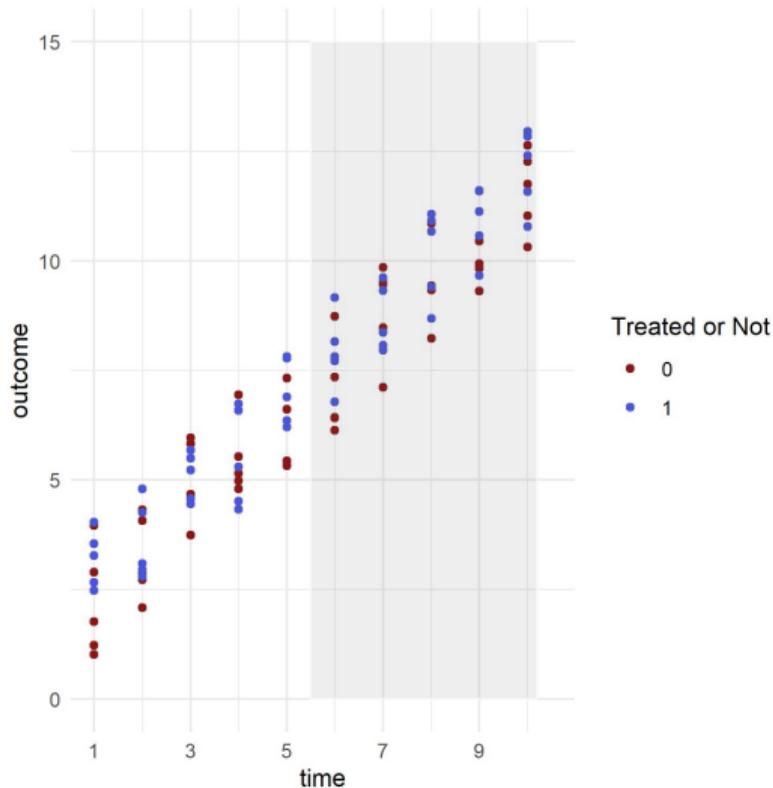
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what does it compare?

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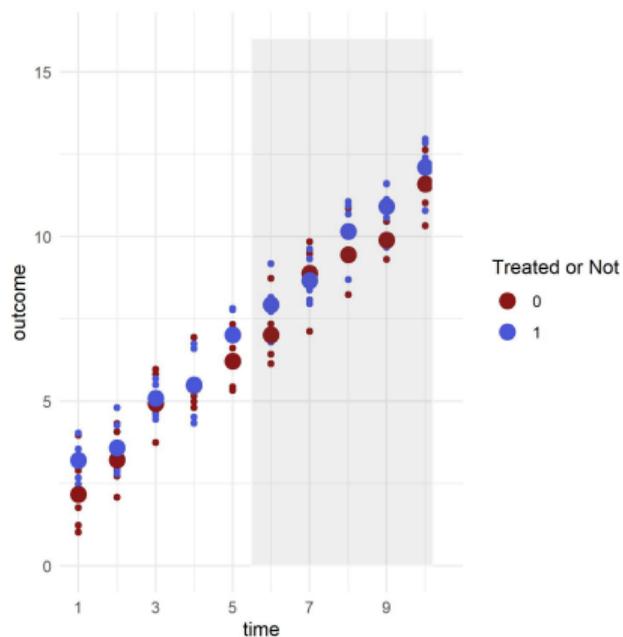
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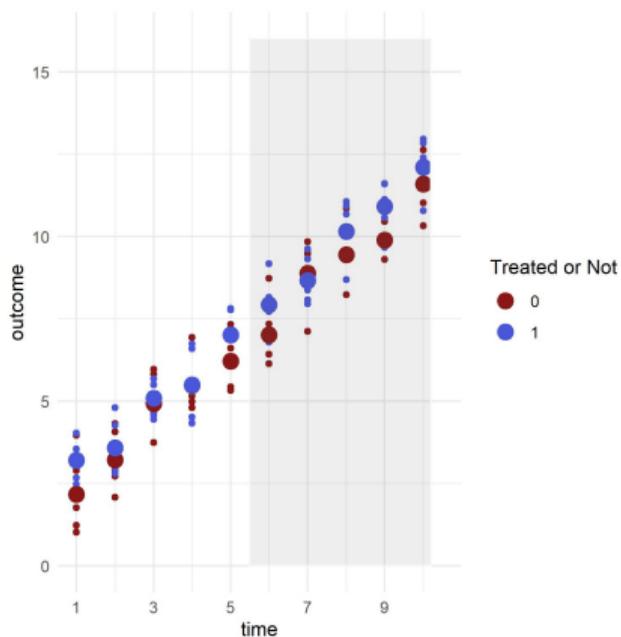
what does it compare? Comparison is **still** all before vs all after, but relative to untreated

# Estimating the Impact of Time Granularly: Event Study



Can we estimate the impact of each period individually?

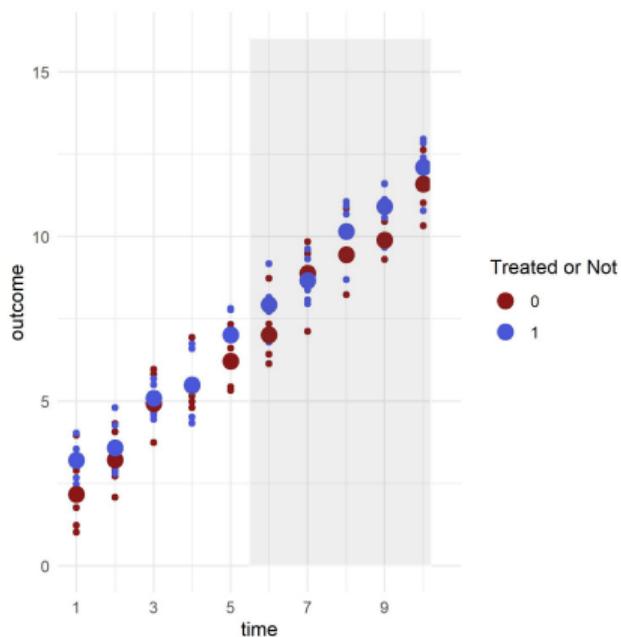
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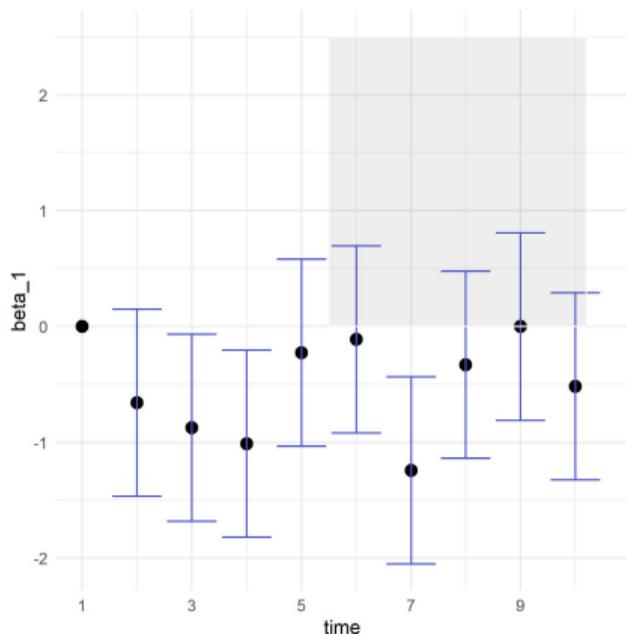


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What do you expect  $\beta_{1,t}$  to be given this figure?

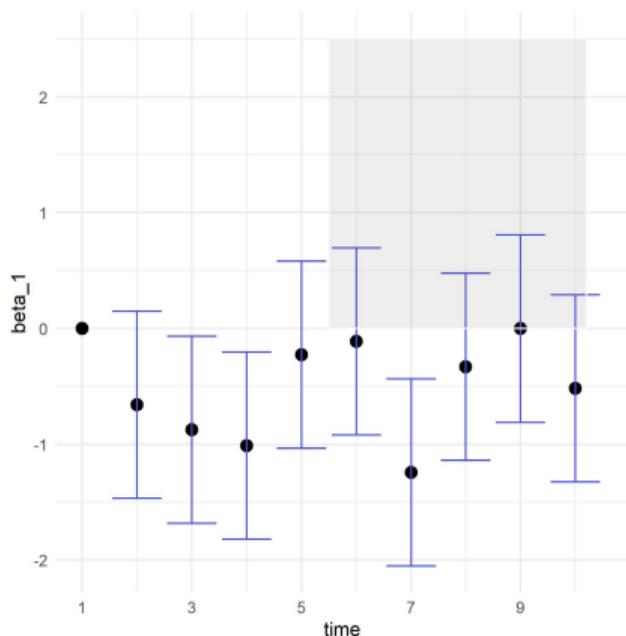
# Estimating the Impact of Time Granularly: Regression Coefficients



Plot  $\beta_{1,t}$  :

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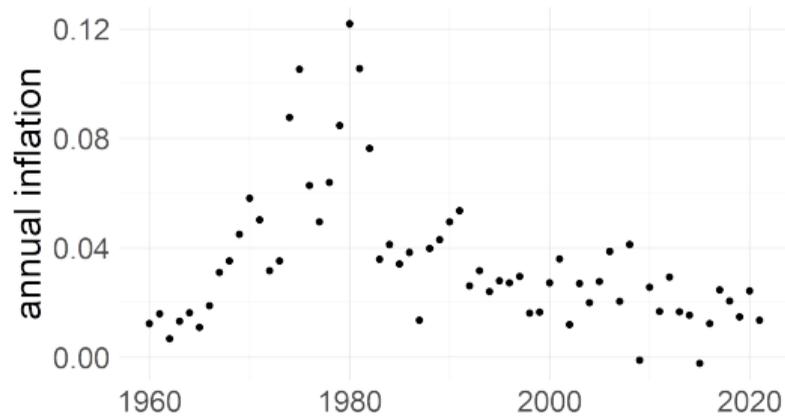
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But ...

- you may care about the change in trends
- you may want to estimate the effect net of trends

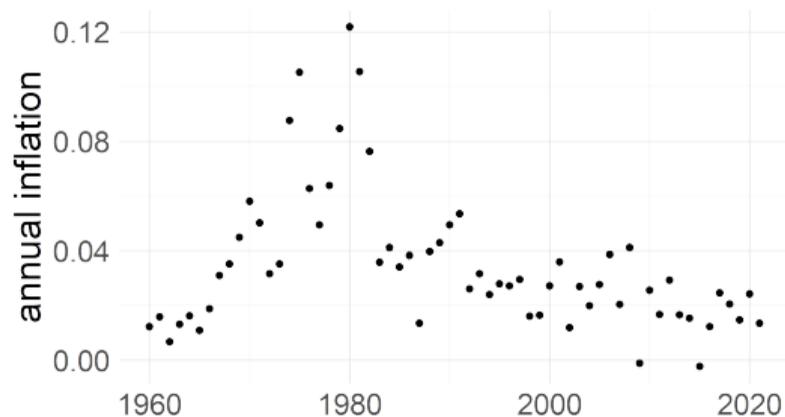
### 3. Estimating Trends

# On Trends



How do we calculate a linear trend for these data?

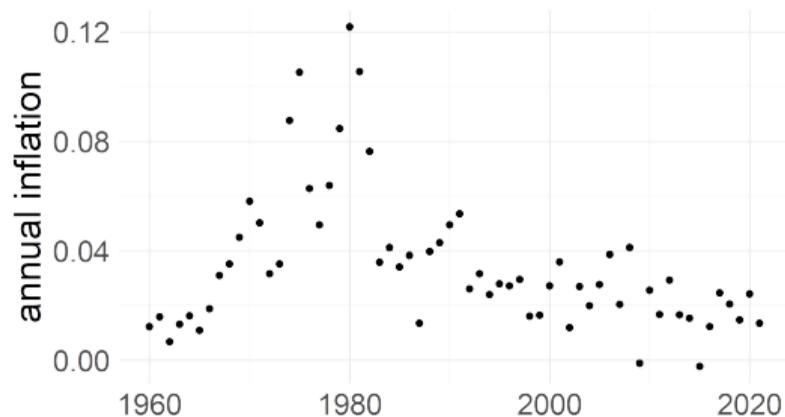
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## On Trends



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$$\text{inflation}_t = \alpha_0 + \alpha_1 \text{year}_t + \epsilon_t$$

Graph  $\alpha_0 + \alpha_1 * \text{year}_t$  where  $\text{year}_t$  is  $\{1, 2, 3, \dots\}$

## Just To Be Clear on Data

year	inflation	year2
1980	0.12	1
1981	0.10	2
1982	0.07	3
1983	0.03	4

$$\text{inflation}_t = \alpha_0 + \alpha_1 \text{year}_t + \epsilon_t$$

and

$$\text{inflation}_t = \gamma_0 + \gamma_1 \text{year2}_t + \epsilon_t$$

yield  $\alpha_1 = \gamma_1$

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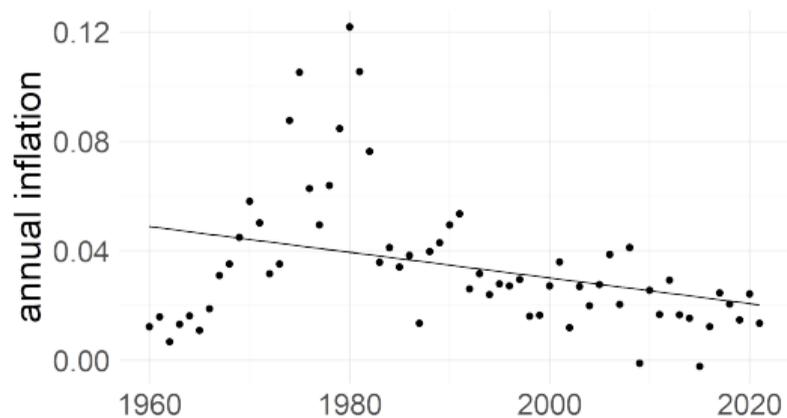
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$$\text{inflation}_t = \gamma_0 + \gamma_1 \text{year2}_t + \epsilon_t$$

yield  $\alpha_1 = \gamma_1$  , but not  $\alpha_0 = \gamma_0$

## Adding Trends

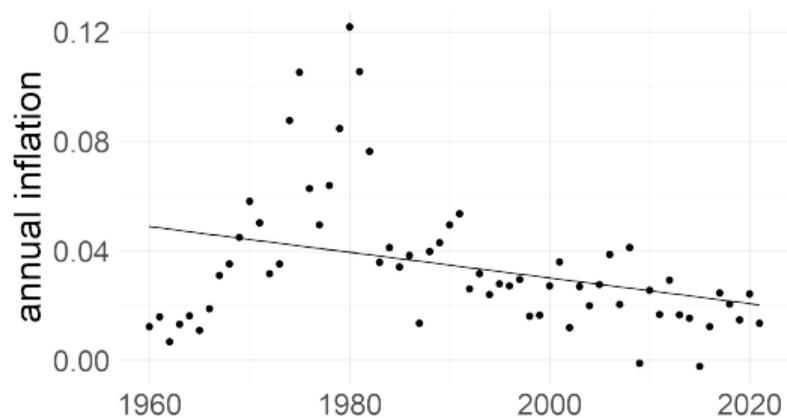
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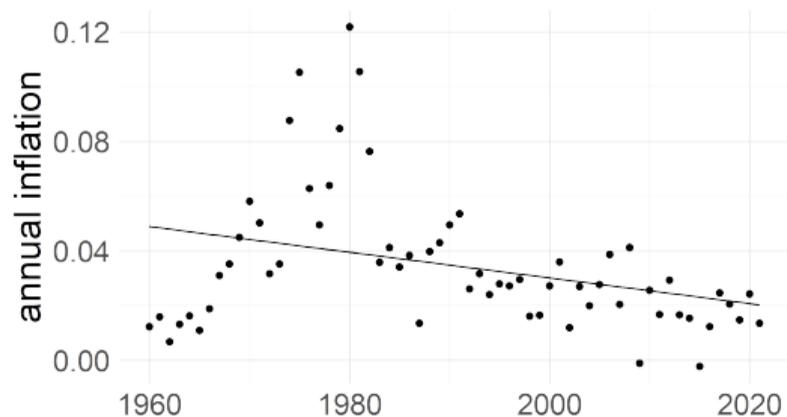
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Make two lines



## Adding Trends



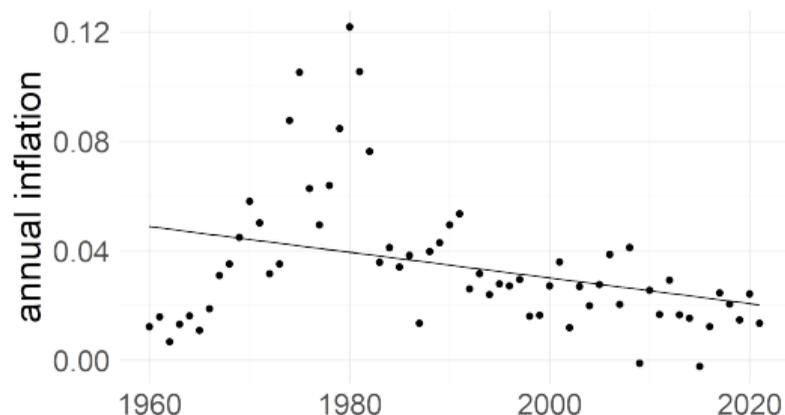
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where  $A_t$  is 1 if  $\text{year}_t > T_0$  and 0 otherwise.

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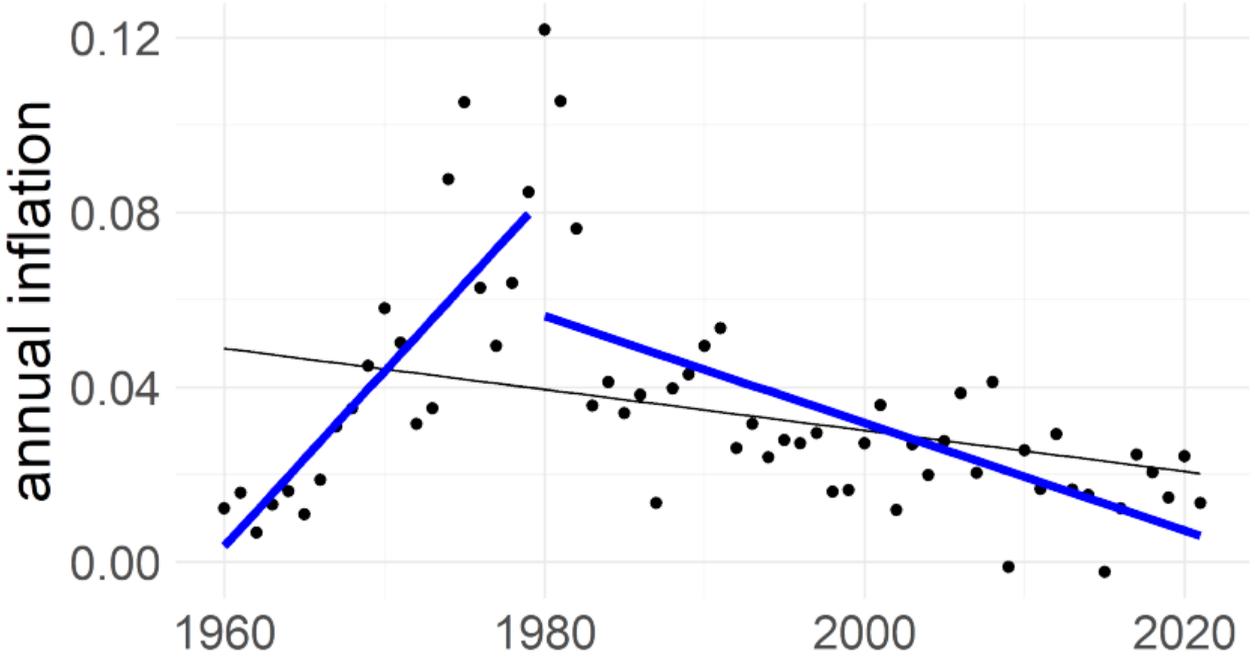
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where  $A_t$  is 1 if  $\text{year}_t > T_0$  and 0 otherwise.

What might you want  $T_0$  to be?

# Separate Trends



## Adding Linear Trends

What is a linear trend?

- a variable that increases linearly for each unit of time – here a year
- the calendar year is a trend variable
- this is different than a fixed effect

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ID	year	t1	t2
A	1990	1	5
A	1991	2	10
A	1992	3	15
B	2000	11	55
B	2001	12	60
B	2002	13	65

## 4. Validity Tests

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- Parallel trends in the absence of treatment is unobservable
- But you can assess parallel trends pre-treatment
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- But you can assess parallel trends pre-treatment
- This is precisely estimable
- Pre-treatment parallel trends neither necessary nor sufficient
- See Angrist for discussion about concerns

## Adding a Pre-Treatment Trend

Suppose you start with

$$Y_{i,t} = \beta_0 + \beta_1 \text{treated}_i * \text{after}_t + \beta_2 \text{treated}_i + \beta_3 \text{after}_t + \epsilon_{i,t}$$

and you want to test for pre-treatment trends. What do you do?

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- Use only data from before treatment
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- What do we expect if there is no pre-treatment trend?  $\alpha_3 = 0$

## Additional Validity Tests

- Add unit-specific time trends. If these kill the effect, what does this tell us?
  - for example, you have state by year data
  - looking for the impact of a policy that hits some states and not others

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  - looking for the impact of a policy that hits some states and not others
- Triple difference – not always possible

## 5. Recent Diff-in-diff Concerns

# Time Is Limited, So We Skip Important Things

A non-exhaustive list includes

① Standard errors too small

- Serial correlation in treatment can inflate estimated standard errors. See [Bertrand, et al., 2004](#)
- Largely solved with clustered standard errors

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## ② Bias in estimate

- Staggered treatment timing
- Heterogeneous treatment effects

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Give a real world example!

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Toy example

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	1	2	3	1	2	3
treatment	0	1	1	0	0	1
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- What is the diff-in-diff estimate for period 3 vs 2?  
 $(S_{2,t=3} - S_{2,t=2}) - (S_{1,t=3} - S_{1,t=1})$

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  - not how we generally estimate event study
  - but useful for pointing out role of changing treatment
- What is the diff-in-diff estimate for period 2 vs 1?  
 $(S_{1,t=2} - S_{1,t=1}) - (S_{2,t=2} - S_{2,t=1})$   
 $(1 - 0) - (0 - 0) = 1$
- What is the diff-in-diff estimate for period 3 vs 2?  
 $(S_{2,t=3} - S_{2,t=2}) - (S_{1,t=3} - S_{1,t=1})$   
 $(1 - 0) - (4 - 1) = 1 - 3 = -2$
- Average across two periods?

## Suppose the Impact of Treatment Varies Over Time

Give a real world example!

Toy example

Period	State 1			State 2		
	1	2	3	1	2	3
treatment	0	1	1	0	0	1
$Y_{st}(0)$	0	0	0	0	0	0
$Y_{st}(1)$	-	1	4	-	-	1

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- Average across two periods? -0.5
- Plain TWFE fails

## Suppose the Impact of Treatment Varies Across Units

Give a real world example!

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- Problem occurs when we implicitly compare later treated units with earlier treated units

## Solutions?

- Does the problem apply to you?
  - Varying treatment time?
  - Potentially heterogeneous impacts?

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  - Callaway and Sant'Anna (2019) \*
  - Sun and Abraham (2020) \*
  - Borusyak, Jaravel and Spiess (2024)
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\* have Stata and R packages

# Opioids and Event Studies

# Order of Events

- 1 Paper background
- 2 Diff-in-diff strategies
  - 1 independent vs chain, geographic fixed effects
  - 2 exploit independents that change to chain
  - 3 independent vs chain, before and after reformulation

# Paper Basics

- What are the two key pharmacy types?

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## Data

- morphine equivalent doses (MEDs)
- by pharmacy
- by month

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- What are the two key pharmacy types?
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## Data

- morphine equivalent doses (MEDs)
- by pharmacy
- by month
- What is the unit of observation?
- And the unit of analysis?

## E1: Independents vs Everyone Else

$$Y_{it} = \beta \text{Indep}_i + \mu_t + \gamma_{FE} + \epsilon_{it}$$

- $Y_{i,t}$  MED at pharmacy  $i$  at time  $t$
- $\text{Indep}_i$ : 1 if independent
- $\mu_t$ : year-month FE
- $\gamma_{FE}$ : place FE

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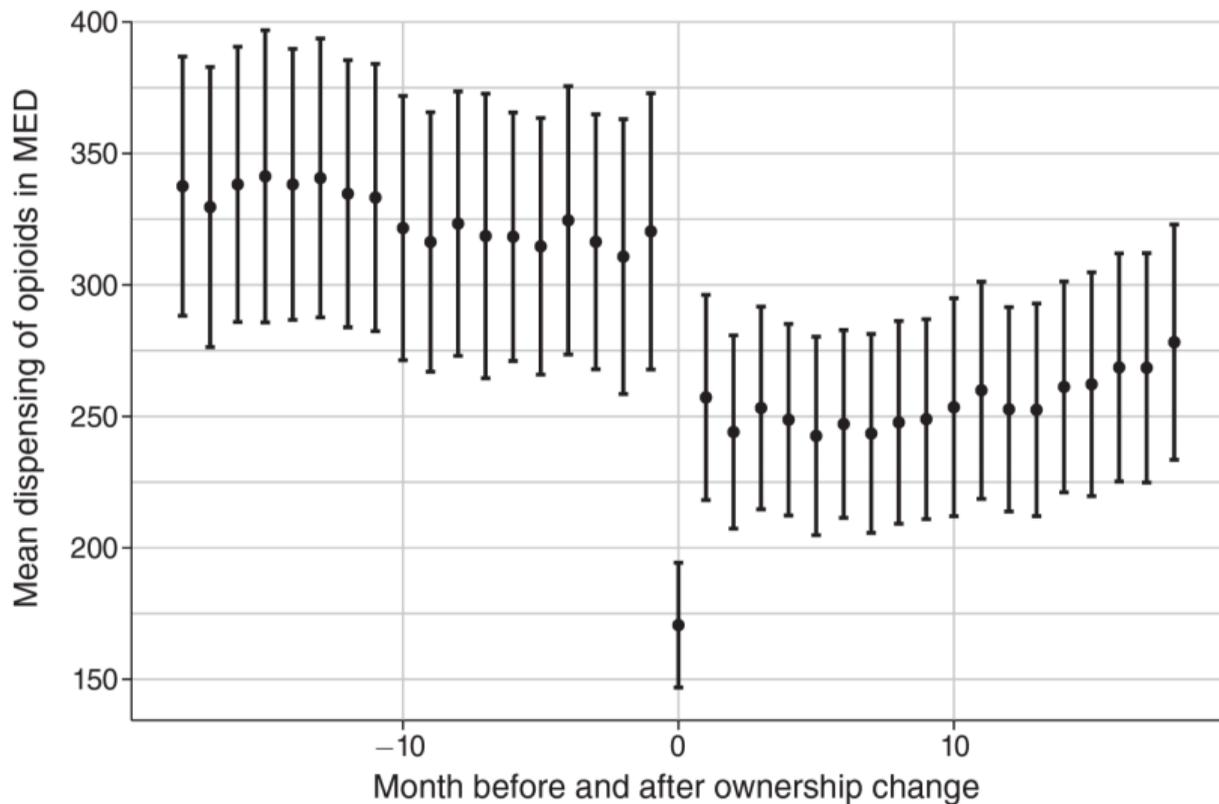
What sign do we expect for  $\beta$ ?

	(1)	(2)	(3)	(4)
<i>Independent</i>	50.131 (4.908)	51.362 (4.912)	107.826 (5.551)	128.016 (5.875)
Constant	306.488 (2.109)			
Year-month fixed effects	No	Yes	Yes	Yes
County fixed effects	No	No	Yes	No
Zip code fixed effects	No	No	No	Yes
Mean outcome	327.19	327.19	327.19	327.19
Mean effect in percent	15.32	15.7	32.96	39.13
Observations	5,055,761	5,055,761	5,055,761	5,055,761
$R^2$	0.002	0.010	0.089	0.225

## Putting Independent Finding in Context

	All	Chain	Independent
<i>Panel D. Opioid dispensing</i>			
Monthly MED dispensing, all opioids	327.19 (541.11)	306.49 (342.89)	356.62 (735.15)

## E2: Change in Ownership, Raw Data



## E2: Change in Ownership, Regression Form

Estimate either

$$Y_{i,t} = \beta_0 D_{it}^{\text{PRE}} + \beta_1 D_{it}^{\text{POST}} + \beta_C \text{CHAIN}_i + \mu_t + \epsilon_{i,t}$$

or

$$Y_{i,t} = \beta_1 D_{it}^{\text{POST}} + \alpha_i + \mu_t + \epsilon_{i,t}$$

- $D_{it}^{\text{PRE}}$ : 1 for indep's that change to chain, before change
- $D_{it}^{\text{POST}}$ : 1 for indep's that change to chain, after change
- $\text{CHAIN}_i$ : 1 for always chains
- $\alpha_i$ : pharmacy FE

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- $\alpha_i$ : pharmacy FE
- how do we interpret  $\beta_0$ ?

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- and  $\beta_1$ ?

## E2: Change in Ownership, Regression Form

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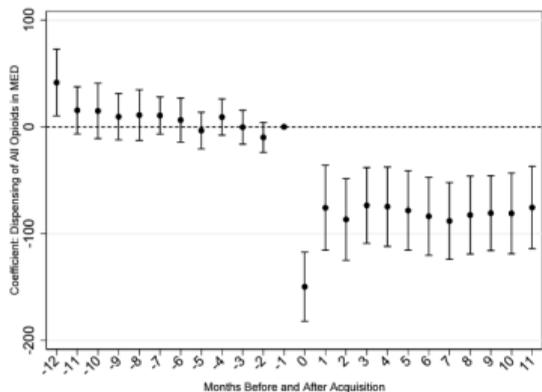
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- $\alpha_i$ : pharmacy FE
- how do we interpret  $\beta_0$ ?
- and  $\beta_1$ ?
- why no  $D_{it}^{\text{PRE}}$  in second equation?

## E2: Change in Ownership, Results

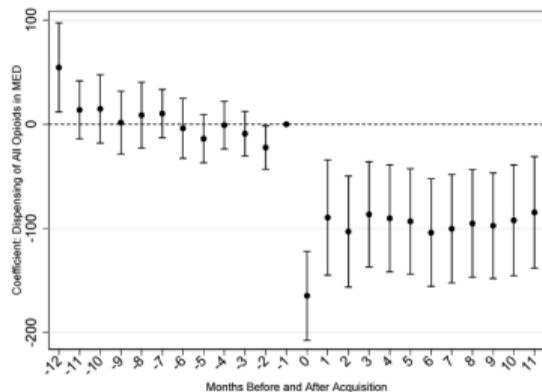
	All			
	OLS (1)	OLS (2)	OLS (3)	OLS (4)
$D^{PRE}$	1.516 (33.915)	32.777 (33.655)	-1.226 (32.747)	
$D^{POST}$	-102.89 (19.755)	-130.867 (19.61)	-153.215 (20.439)	-110.507 (16.65)
$CHAIN$	-49.933 (4.931)	-50.89 (4.934)	-127.879 (5.912)	
Constant	356.624 (4.883)			
Year-month fixed effects	No	Yes	Yes	Yes
Zip code fixed effects	No	No	Yes	No
Facility fixed effects	No	No	No	Yes
Mean outcome	327.19	327.19	327.19	327.19
Mean effect in percent	-31.45	-40	-46.83	-33.77
Observations	5,055,761	5,055,761	5,055,761	5,055,761
$R^2$	0.002	0.01	0.225	0.809

## E2: Change in Ownership, Event Study Estimates

From Online Appendix, Figure E.1



(a) Dispensing of all opioids in MED, facility and year-month fixed effects



(b) Dispensing of all opioids in MED, facility and ZIP code  $\times$  year-month fixed effects

## E3: Reformulation

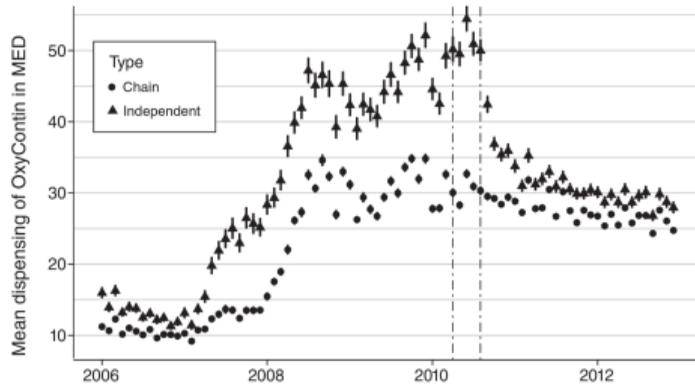


Figure 2

## E3: Reformulation

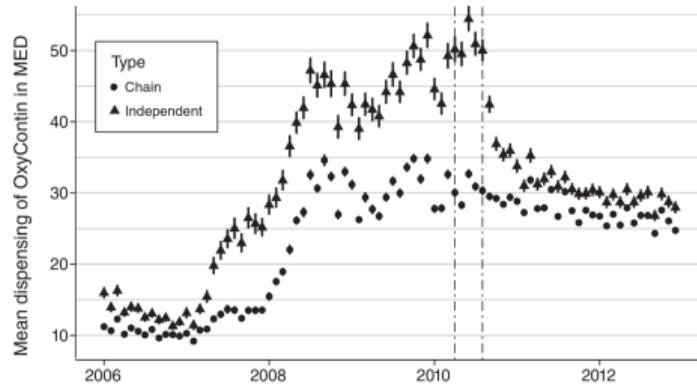


Figure 2

- why should reformulation matter?
- what should we be comparing in this figure to see the double diff?
- what should we be comparing to look for validity?

## E3: Specification

What regression should we use to test impact of reformulation at independent pharmacies vs chains?

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## E3: Specification

What regression should we use to test impact of reformulation at independent pharmacies vs chains?

$$Y_{it} = \beta \text{Indep}_i * \text{Post}_t + \alpha_i + \mu_t + \epsilon_{it}$$

- Why no chain indicator?
- How do we interpret  $\beta$ ?

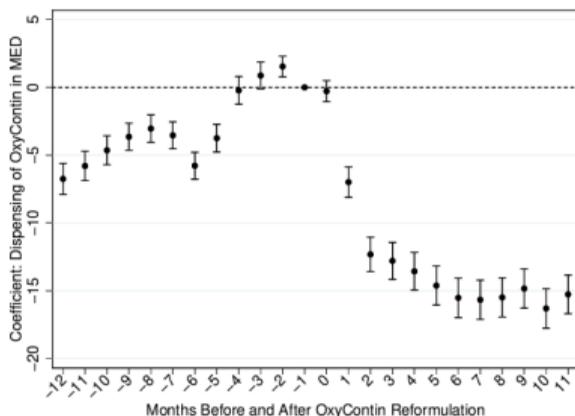
## E3: Reformulation, Results

Full sample: 2006–2012

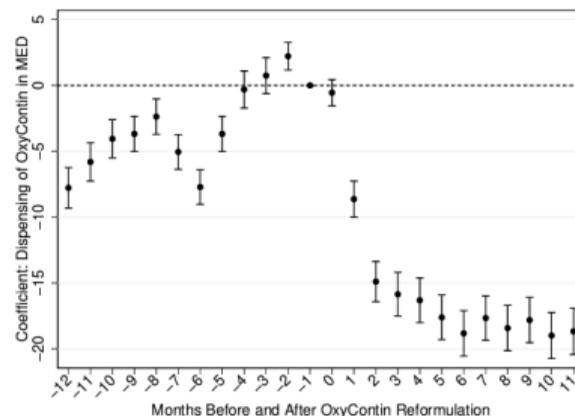
	(1)	(2)	(3)	(4)
<i>Independent</i> × <i>Post</i>	−6.097 (0.529)	−6.436 (0.529)	−6.996 (0.565)	−5.339 (0.484)
<i>Independent</i>	10.569 (0.681)	10.912 (0.683)	18.886 (0.832)	
<i>Post</i>	6.095 (0.154)			
Constant	21.495 (0.281)			
Year-month fixed effects	No	Yes	Yes	Yes
Zip code fixed effects	No	No	Yes	No
Pharmacy fixed effects	No	No	No	Yes
Mean outcome	27.14	27.14	27.14	27.14
Mean effect in percent	−22.47	−23.72	−25.78	−19.67
Observations	5,055,761	5,055,761	5,055,761	5,054,885
$R^2$	0.004	0.019	0.159	0.650

# E3: Reformulation Event Study Results

Online Appendix Figure E.5



(a) Dispensing of OxyContin in MED, pharmacy and year-month fixed effects



(b) Dispensing of OxyContin in MED, pharmacy and ZIP code  $\times$  year-month fixed effects

## Next Lecture

- Read
  - *Mastering Metrics* Chapter 3
  - an oldie but goodie: Angrist and Krueger, 1991
  - Skim 2c
- Turn in PS 2 in two weeks
- Summary due next week if you're on the list