

Differences-in-Differences

ECON 8830

Anant Nyshadham

What if we had data from before the program?

What if we estimated this equation using data from before the program?

$$(1) Y_i = a + bT_i + cX_i + e_i$$

Specifically, what would our estimate of b be?

What if we had data from before the program?

What if we estimated this equation using data from before the program?

$$(1) Y_i = a + bT_i + cX_i + e_i$$

$$(2) E(Y_{i0} | T_{i1}=1) - E(Y_{i0} | T_{i1}=0)$$

$$= [a + \mathbf{0} + cE(X_{i0} | T_{i1}=1) + E(e_{i0} | T_{i1}=1)] \\ - [a + 0 + cE(X_{i0} | T_{i1}=0) + E(e_{i0} | T_{i1}=0)]$$

$$= c [E(X_i | T_i=1) - E(X_i | T_i=0)]$$

“Omitted variable/selection bias” term

**ALL THAT'S LEFT IS THE PROBLEMATIC TERM – HOW
COULD THIS BE HELPFUL TO US?**

Differences-in-Differences (just what it sounds like)

- Use two periods of data
 - add second subscript to denote time

$$= \{E(Y_{i1} | T_{i1}=1) - E(Y_{i1} | T_{i1}=0)\} \quad (\text{difference btwn T\&C, post})$$
$$- \{E(Y_{i0} | T_{i1}=1) - E(Y_{i0} | T_{i1}=0)\} \quad - (\text{difference btwn T\&C, pre})$$

$$= b + c [E(X_{i1} | T_{i1}=1) - E(X_{i1} | T_{i1}=0)]$$
$$- c [E(X_{i0} | T_{i1}=1) - E(X_{i0} | T_{i1}=0)]$$

Differences-in-Differences (just what it sounds like)

- Use two periods of data
 - add second subscript to denote time

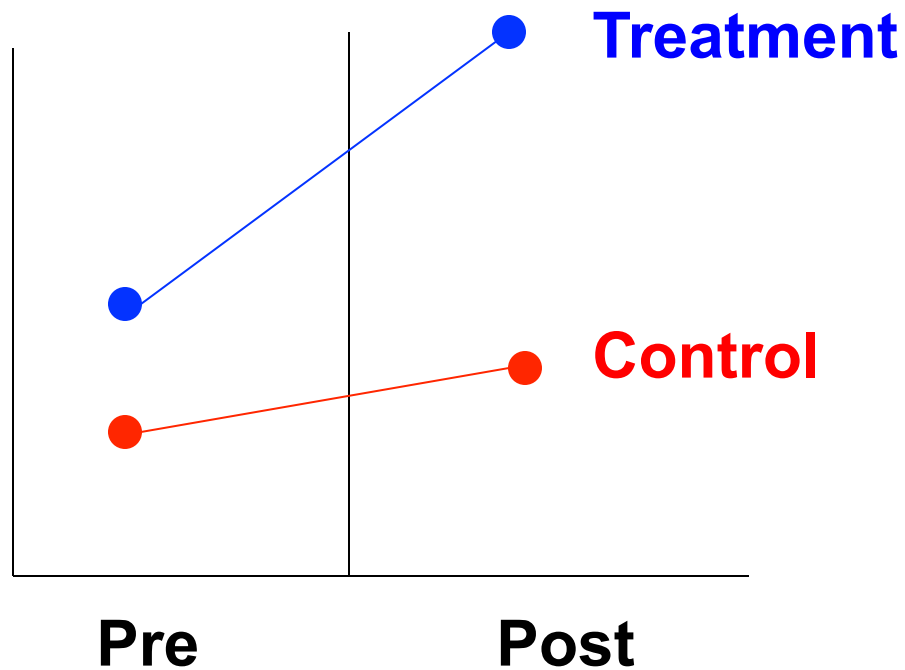
$$= \{E(Y_{i1} | T_{i1}=1) - E(Y_{i1} | T_{i1}=0)\} \quad (\text{difference btwn T\&C, post})$$
$$- \{E(Y_{i0} | T_{i1}=1) - E(Y_{i0} | T_{i1}=0)\} \quad - (\text{difference btwn T\&C, pre})$$

$$= b + c [E(X_{i1} | T_{i1}=1) - E(X_{i1} | T_{i1}=0)]$$
$$- c [E(X_{i0} | T_{i1}=1) - E(X_{i0} | T_{i1}=0)]$$

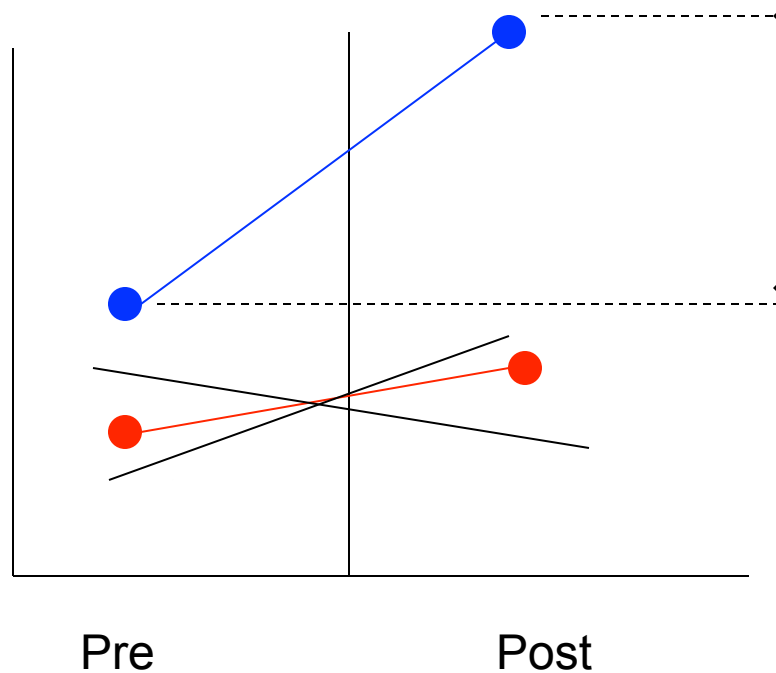
$$= b \quad \text{YAY!}$$

- Assume differences between X don't change over time.

Differences-in-Differences, Graphically

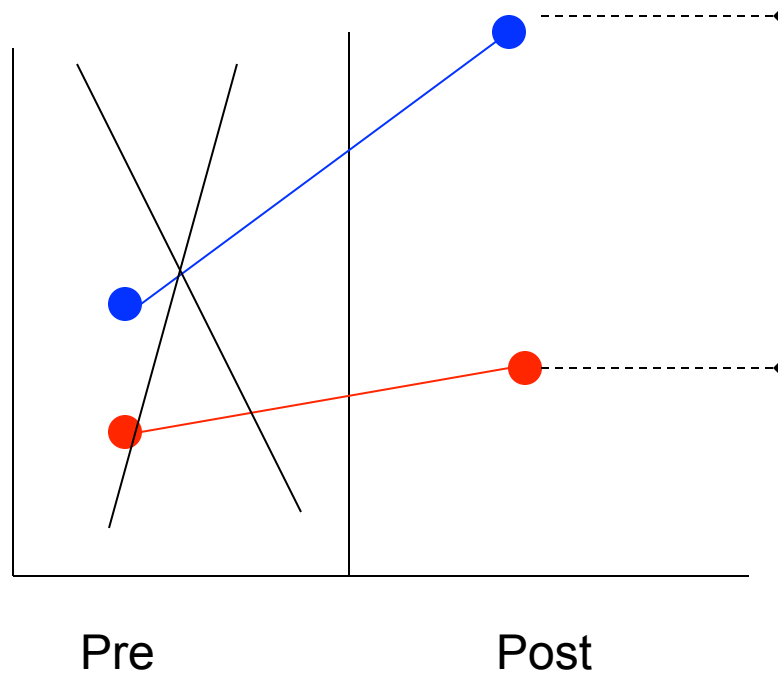


Differences-in-Differences, Graphically



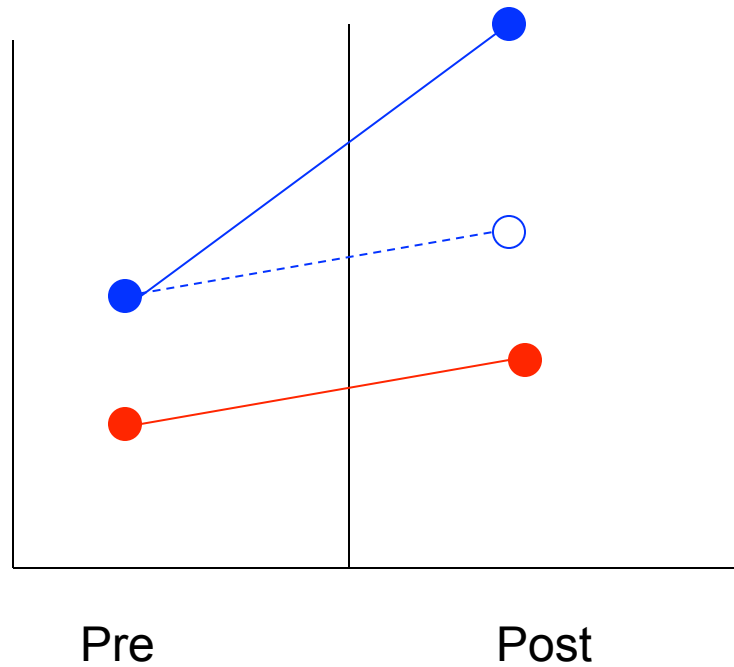
Effect of program using only pre- & post- data from T group (ignoring general time trend).

Differences-in-Differences, Graphically

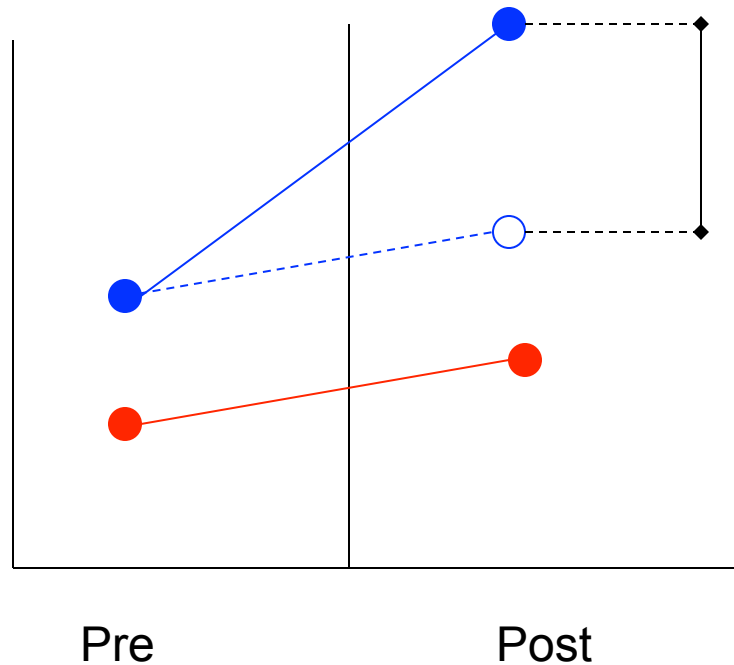


Effect of program using only T & C comparison from post-intervention (ignoring pre-existing differences between T & C groups).

Differences-in-Differences, Graphically



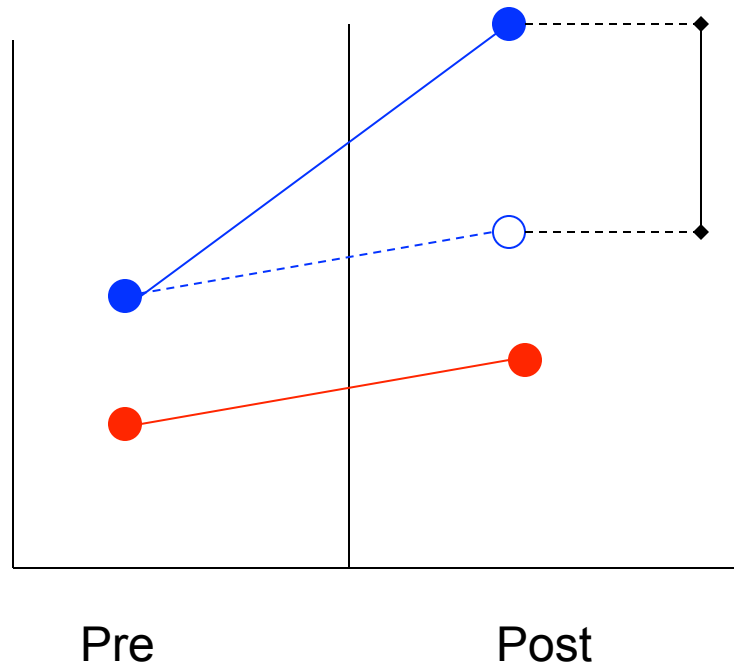
Differences-in-Differences, Graphically



Effect of program
difference-in-difference
(taking into account pre-
existing differences
between T & C and
general time trend).

Identifying Assumption

- Whatever happened to the control group over time is what would have happened to the treatment group in the absence of the program.



Effect of program
difference-in-difference
(taking into account pre-
existing differences
between T & C and
general time trend).

Uses of Diff-in-Diff

- Simple two-period, two-group comparison
 - very useful in combination with other methods
 - Randomization
 - Regression Discontinuity
 - Matching (propensity score)
- Can also do much more complicated “cohort” analysis, comparing many groups over many time periods

The (Simple) Regression

$$Y_{i,t} = a + bTreat_{i,t} + cPost_{i,t} + d(Treat_{i,t}Post_{i,t}) + e_{i,t}$$

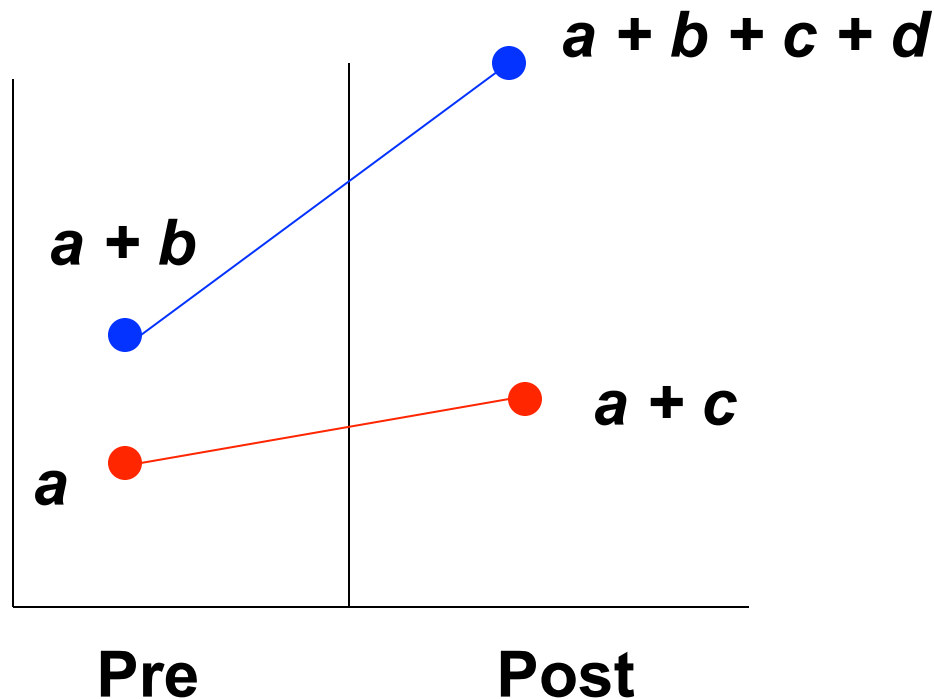
- $Treat_{i,t}$ is a binary indicator (“turns on” from 0 to 1) for being in the treatment group
- $Post_{i,t}$ is a binary indicator for the period after treatment
- and $Treat_{i,t}Post_{i,t}$ is the interaction (product)

Interpretation of a , b , c , d is “holding all else constant”

Putting Graph & Regression Together

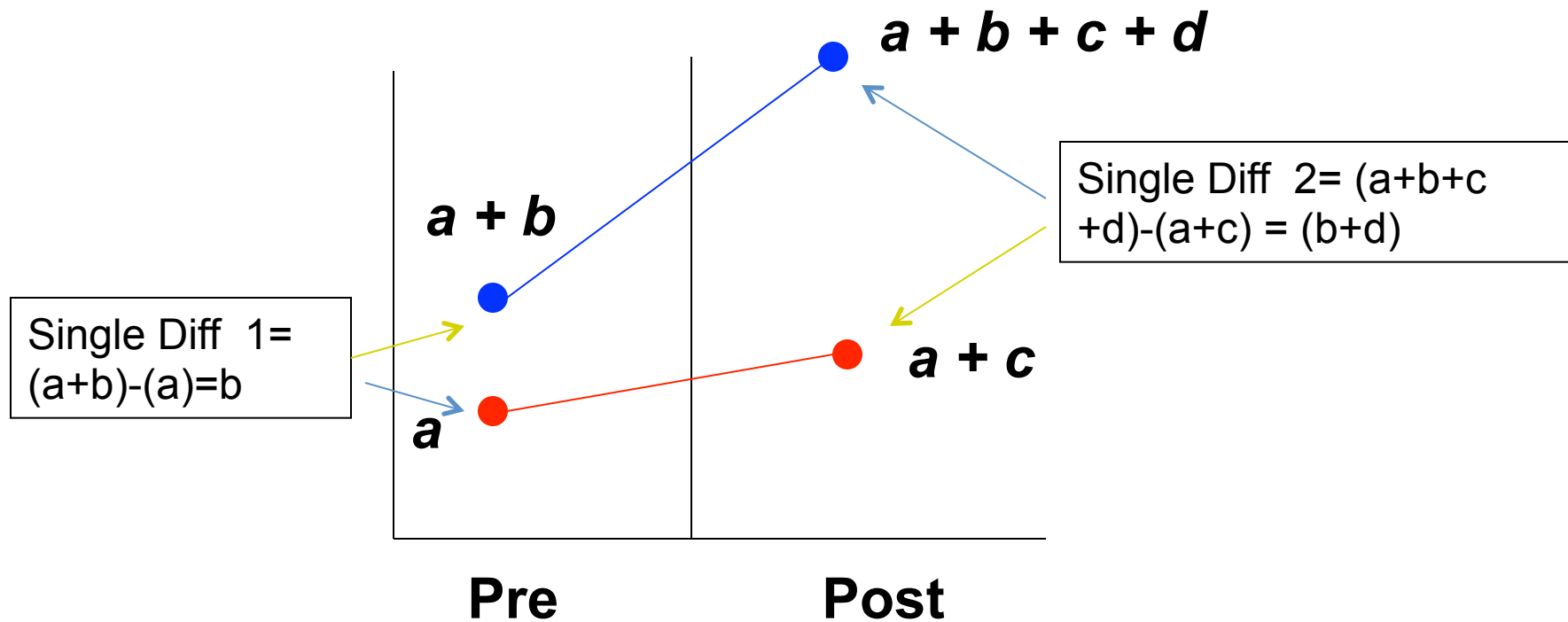
$$Y_{i,t} = a + bTreat_{i,t} + cPost_{i,t} + d(Treat_{i,t}Post_{i,t}) + e_{i,t}$$

d is the causal effect of treatment



Putting Graph & Regression Together

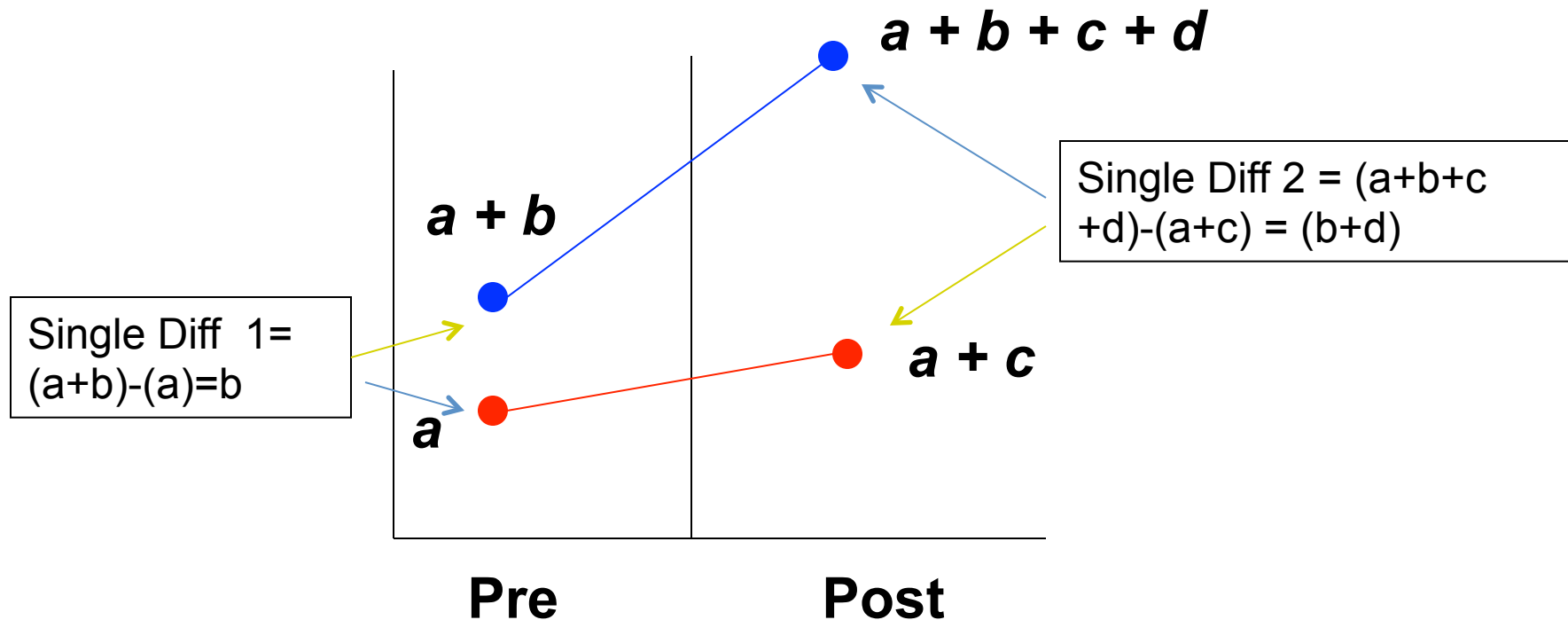
$$Y_{i,t} = a + bTreat_{i,t} + cPost_{i,t} + d(Treat_{i,t}Post_{i,t}) + e_{i,t}$$



Putting Graph & Regression Together

$$Y_{i,t} = a + bTreat_{i,t} + cPost_{i,t} + d(Treat_{i,t}Post_{i,t}) + e_{i,t}$$

$$\text{Diff-in-Diff} = (\text{Single Diff 2} - \text{Single Diff 1}) = (b+d) - b = d$$



Cohort Analysis

- When you've got richer data, it's not as easy to draw the picture or write the equations
 - cross-section (lots of individuals at one point in time)
 - time-series (one individual over lots of time)
 - repeated cross-section (lots of individuals over several times)
 - ★ panel (lots of individuals, multiple times for each) ★
- Basically, control for each time period and each “group” (fixed effects) – the coefficient on the treatment dummy is the effect you're trying to estimate

DiD Data Requirements

- Either repeated cross-section or panel
- Treatment can't happen for everyone at the same time
- If you believe the identifying assumption, then you can analyze policies ex post
 - Let's us tackle really big questions that we're unlikely to be able to randomize

Malaria Eradication in the Americas (Bleakley 2007)

Question: What is the effect of malaria on economic development?

Data: Malaria Eradication in United States South (1920' s) Brazil, Colombia, Mexico (1950' s)

Diff-in-Diff: Use birth cohorts (old people vs. young people) & (regions with lots of malaria vs. little malaria)

Idea: Young Cohort X Region w/malaria

Result: This group higher income & literacy

What's the intuition

- Areas with high pre-treatment malaria will most benefit from malaria eradication
- Young people living in these areas will benefit most (older people might have partial immunity)
- Comparison Group: young people living in low pre-treatment malaria areas (malaria eradication will have little effect here)

Robustness Checks

- If possible, use data on multiple pre-program periods to show that difference between treated & control is stable
 - Not necessary for trends to be parallel, just to know function for each
- If possible, use data on multiple post-program periods to show that unusual difference between treated & control occurs only concurrent with program
- Alternatively, use data on multiple indicators to show that response to program is only manifest for those we expect it to be (e.g. the diff-in-diff estimate of the impact of ITN distribution on diarrhea should be zero)

Effect of 2ndary School Construction in Tanzania

- Villages
- “Treatment Villages” got 2ndary schools
- “Control Villages” didn’ t
- Who benefits from 2ndary schools?
Young People benefit
Older people out of school shouldn’ t benefit
- Effect: (Young People X Treatment Villages)