Recitation 7: fixed effects and difference-in-differences

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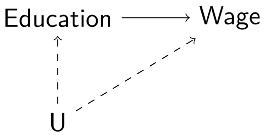
- There are many unobserved confounders in observational studies. This generates omitted variables bias!
- Imagine you are studying the effect of years of education on adult Wage test scores, from 18 y/o until 28 y/o.
- Likely unobserved confounders are:
  - Innate skill for studying and obtaining good marks.
  - The household environment growing up.
  - Resources for studying when growing up.
  - Can you think of other?

The crux of observational studies



The crux of observational studies

$$\begin{tikzcd} \text{Education} \arrow[r] & \text{Wage} \\ \text{U} \arrow[u, dashed] \arrow[ur, dashed] & \end{tikzcd}$$

In regression form:

$$Wage_i = \alpha + \beta Education_i + \underbrace{\gamma U_i + \epsilon_i}_{\varepsilon_i}.$$

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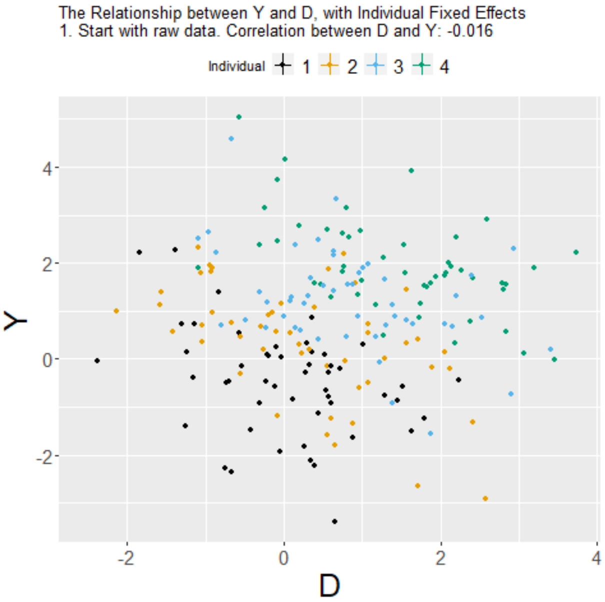
What do fixed effects do?



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If you control for fixed effects this occurs:

$$Wage_{it} - \overline{Wage}_i = (\alpha - \alpha) + \beta(Edu_{it} - \overline{Edu}_i) + (\mu_i - \mu_i) + (\varepsilon_{it} - \overline{\varepsilon}_i).$$

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Therefore

$$\widetilde{Wage}_{it} = \beta(\widetilde{Education}_{it}) + \tilde{\varepsilon}_{it}.$$

Limitations of fixed effects

- You still have to worry about time-varying observable confounders (X).
- You still have to worry about time-varying unobservable confounders (U).
- But if your most worrisome source of confounding is fixed at the time of the study, you can present compelling results.

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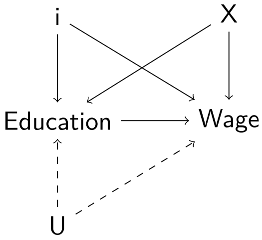

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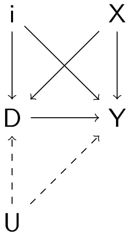
- Selection bias concerns:
    - Economic activity $\rightarrow$ mining $\rightarrow$ canon.
    - Districts with more political power secure more Canon transfers.
- But...
    - We control for mining production.
    - Canon transfer rule is fixed for the period of analysis.
    - The impact of politics is fixed at the district level.

$$
\begin{tikzcd}
i \arrow[d] \arrow[dr] & X \arrow[d] \arrow[dl] \\
D \arrow[r] & Y \\
U \arrow[u, dashed] \arrow[ur, dashed] &
\end{tikzcd}
$$



$$Scores_{idt} = \alpha + \beta Canon_{idt} + \gamma_d + \rho_t + \delta X_{idt} + \varepsilon_{idt}.$$

Using time to identify the causal effect

- The time dimension is useful, we can control for time-invariant confounding. But can do more with it?
- In our example, some individuals get a masters' degree while some others don't.
- The treatment interacts with time!

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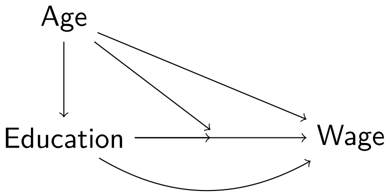

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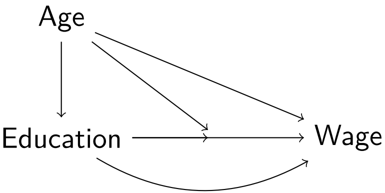
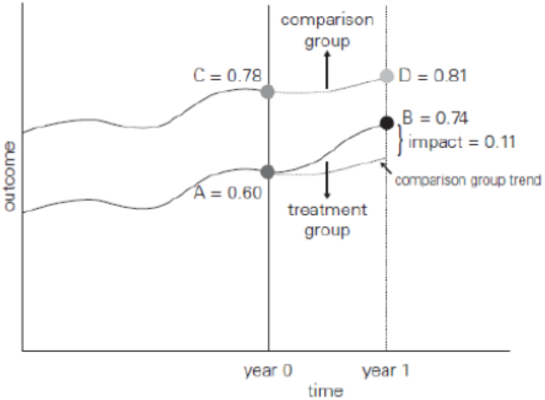


Can we use this to identify causal effects?

$$Wage_{it} = c + \beta_1 Age_t + \beta_2 Education_{it} + \beta_3 (Age_t \times Education_{it}) + \varepsilon_{it}$$

Introducing differences-in-differences (DID)



- 1st difference: Effect of treatment on treated.
- 2nd difference: Pre-treatment gap between groups.
- Difference-in-differences:

$$(\text{2nd difference}) - (\text{1st difference})$$

A simple example

$$y_{it} = c + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 (Treated_i \times Post_t) + \varepsilon_{it}$$

y_{it}	$Treated = 1$	$Treated = 0$	Difference
$Post_t = 1$	y_{22}	y_{12}	$y_{22} - y_{12}$
$Post_t = 0$	y_{21}	y_{11}	$y_{21} - y_{11}$
Change	$y_{21} - y_{22}$	$y_{11} - y_{12}$	$(y_{11} - y_{21}) - (y_{12} - y_{22})$

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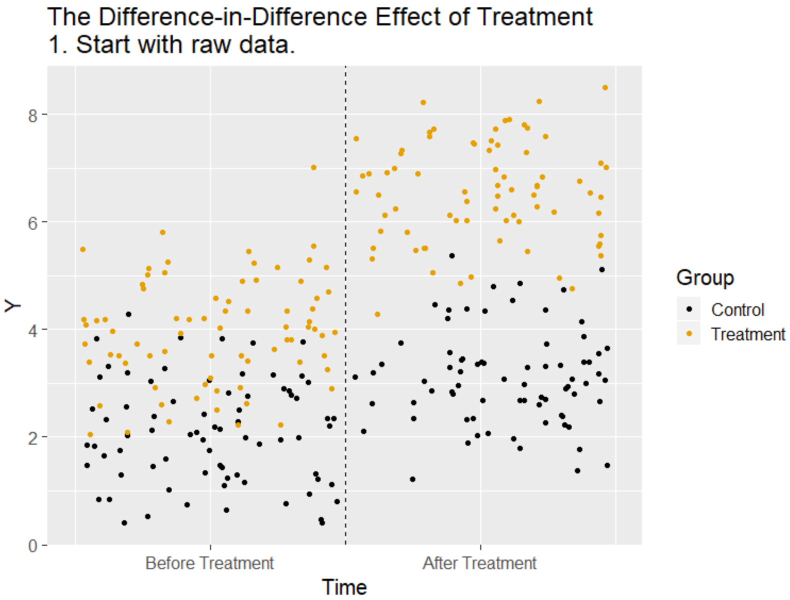
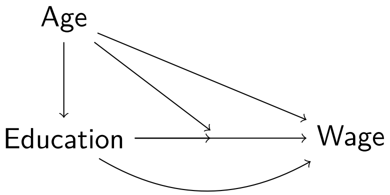
Change	$y_{21} - y_{22}$	$y_{11} - y_{12}$	$(y_{11} - y_{21}) - (y_{12} - y_{22})$

This only works if the parallel trends assiumption holds!

What does DID do?



- It rests heavily on the parallel trends assumption.
- Controlling for fixed-effects helps!
- Controlling for time-varying confounders helps.



Limitations of DID

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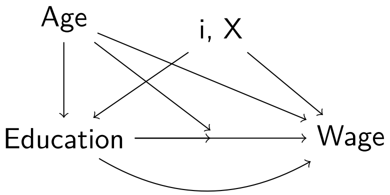

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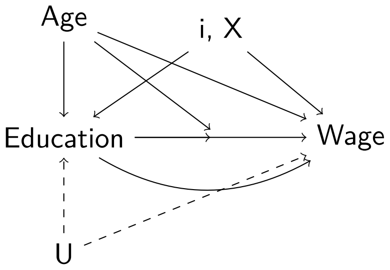
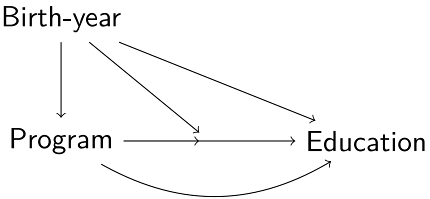


- The problem is whether to meet the parallel trends assumption we would need to control for time-varying unobservable confounders.

Does the construction of schools increase education and wages? (Duflo, 2001)

- Investments in school infrastructure should increase educational attainment.
- Educational attainment should in turn increase wages.
- From 1973-74 and 1978-79, the Indonesian government launched a major school construction program.
- Program should only affect 12-year old, or younger, in 1974.

DAG and regression



$$Edu._{it} = c + \beta_1 BY + \beta_2 Program_{it} + \beta_3 (BY \times Program) + \delta_{it} X + \varepsilon_{it}$$

Visually testing the parallel trends assumption

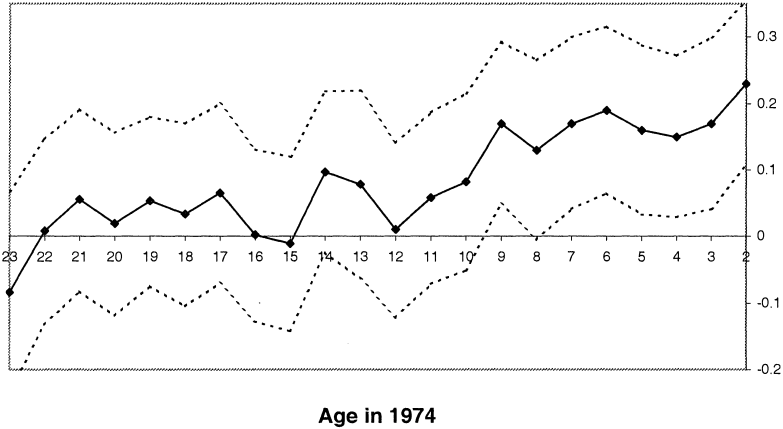


FIGURE 1. COEFFICIENTS OF THE INTERACTIONS AGE IN 1974* PROGRAM INTENSITY IN THE REGION OF BIRTH IN THE EDUCATION EQUATION