Conceptual Causality: IV

Section 2

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Spring 2025

Gov 51: Data Analysis and Politics

Overview

1. Instrumental variables (IV)
2. R crash course
3. Back to IV

Roadmap

Last week: the **fundamental problem of causal inference**, and introduction to one estimation strategy (DiD)

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In this section, we continue to examine ways to estimate causal quantities via instrumental variables (IV)

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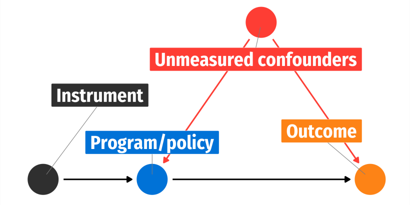

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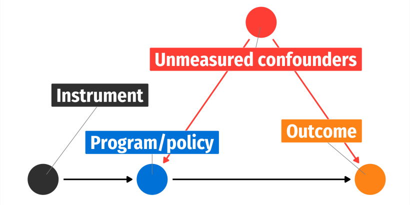

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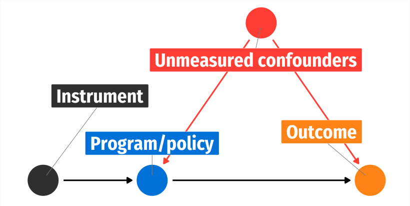

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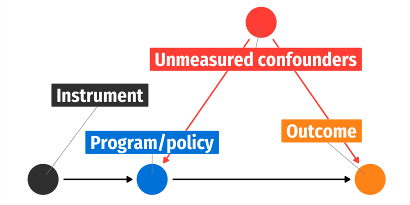
    - *Check-in*: why?



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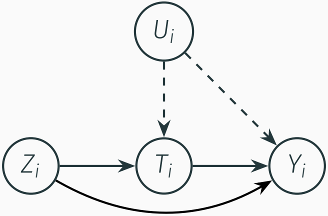
- IF we meet these assumptions $\rightarrow$ consistent estimate of the local Average Treatment Effect (LATE)
  - Check-in: the LATE is an estimate of the causal quantity for the compliers, why?

IV assumptions: a DAG

Does this DAG fit our necessary assumptions for a IV strategy?



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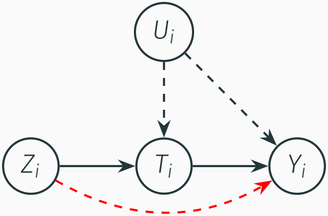

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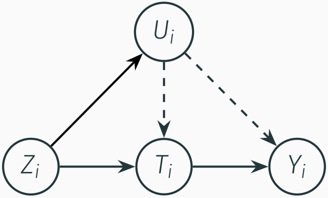

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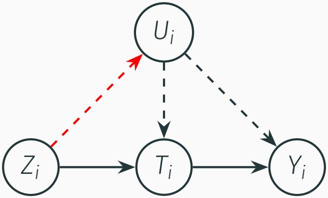

No, because this also violates the exclusion restriction!

The assumptions strike back

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- Is this a useful estimate? Why or why not?

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How do we achieve identification?

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$\Rightarrow$ Candidate strength in any given election is independent (does not affect the variation) in turnout caused by rain

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- Scripts allow us to save our code, AND run the functions in our console

Working directories

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- `getwd()` and `setwd()` respectively ”get” your working directory and ”set” your working directory.
- If you get an error along the lines of ”Cannot establish connection....,” it is because you are loading in data that is not in your working directory.

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setwd("/Users/simabiondi/GitHub/teaching/gov51")
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- *Note*: R Projects set your working directory to the folder that it is in.

Loading data from a URL

- You can also load in data easily from the course website if you have an internet connection:

```
url <- "https://naijialiu.github.io/Gov_51/
    Causal/simulated_iv.csv"
df <- read.csv(url)
```

Why do we use base R?

Advantages of tidyverse: Efficient recall of variable names, consistent within the Tidyverse universe, some unique data wrangling functions

↪ BUT: Clunky in function creation, reliance on package functions

Pedagogical reason: **Reliance on package functions** - think a calculator before learning basic arithmetic

Grammar of base R

Some basic functions and their tidyverse equivalents:

```
# Creating new variable
df$newvar <- 1:10

df <- df |>
  mutate(newvar = 1:10)
```

For more information, check out the tidyverse guide to base R:
`https://dplyr.tidyverse.org/articles/base.html`

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```
# Creating a conditional new variable
df$newvar2 <- ifelse(df$newvar %% 2 == 0,
                     1,
                     0)

df <- df |>
  mutate(newvar2 = ifelse(df$newvar %% 2 == 0,
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What if I have a coding question? $\rightarrow$ *Come to office hours*!

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- IMPORTANT: we are estimating the LATE, not the ATE, *why?*
    - $\rightarrow$ Can't estimate ATE because we don't know the proportions of compliers, always, and never takers

IV example: estimation using Wald estimator

The Wald Estimator estimates the LATE among compliers

$$\frac{\widehat{ITT}}{\widehat{Encouragement}} = \frac{\widehat{ITT_Y}}{\widehat{ITT_T}}$$

$$= \frac{E[Y_i(Z_i = 1] - E[Y_i(Z_i = 0)]}{E[T_i(Z_i = 1] - E[T_i(Z_i = 0)]}$$

What does this mean in English?

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What does this mean in English?

Let's go to R!

IV example: using Wald estimator

```
set.seed(02138)
mydf <- data.frame(draft = rbinom(20, 1, 0.5),
                   military = rbinom(20, 1, 0.3),
                   earning = rnorm(20, 10000, sd =
                       5000))
summary(mydf)
dim(mydf)
ITT <- mean(mydf$earning[mydf$draft == 1]) -
  mean(mydf$earning[mydf$draft == 0])
Encouragement <- mean(mydf$military[mydf$draft ==
    1]) -
  mean(mydf$military[mydf$draft == 0])
tauhat <- ITT/Encouragement
```

Estimate of the effect of military service on lifetime earnings (for compliers) is `r round(tauhat,2)`

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    - -6261.08 vs. 583.49 is huge!!
- Instrumental variables are a useful strategy to achieve identification of an estimand
- Finding a good instrument is difficult, as the assumptions are stringent

Next week

- Matching
- In the background: start brainstorming and talking to classmates