Segment 6: Quasi Experiments

Section 03: Difference in Differences

Quasi-Experimental Methods

- Most of the methods we've discussed for analyzing observational studies rely in large part on:
  - Knowing (and observing) the "right" X to believe the conditional ignorability assumption
  - Using those X to "restructure" the data to recreate the conditions of a randomized experiment

- A different class of methods aims to directly leverage circumstances of the study to *avoid* conditional ignorability:
  - If the circumstances are right, we may not need to "restructure" with X
  - We may be lucky that we can otherwise leverage the conditions of an "as if randomized" study design
  - Even without conditional ignorability
  - "Automatically" adjust for **unobserved** confounders

The Power of Grouped Data

Setting: Repeated observations within groups, where only *some* units within a group are treated and where groups have different observed and unobserved characteristics

Key idea: Making comparisons on units *within* the same group implicitly holds constant all (observed and unobserved) group characteristics $\rightarrow$ these characteristics cannot confound treatment/control comparisons

“Fixed Effects” Model

AKA Varying Intercept Model

Regression model that *implicitly adjusts* for group-level characteristics by adjusting for group indicators in a regression model:

$$y_{ij} = \beta_0 + \tau Z_{ij} + \alpha_i + \epsilon_{ij}$$

adjusting for group $\leftrightarrow$ adjusting for all observed and unobserved group characteristics (that may differ across groups)

Differences version of the same model (with 2 observations per group):

$$y_{i2} - y_{i1} = \tau(Z_{i2} - Z_{i1}) + \epsilon_{i2} - \epsilon_{i1}$$

differencing outcomes within group “cancels out” any group characteristics in the comparison

Note: The term “fixed effects” is commonly used in econometrics, but can be a confusing name given the various other meanings of “fixed effects” in statistical modeling

Difference-in-Differences (D-in-D)

A popular extension of the fixed effects ideas where:

- Repeated observations within groups are repeated observations *across time* within units
  - "Panel data"
- Some units were treated and some not, where "treatment" does not vary over time

Key Idea:

(a) Use variation in outcomes over time to help adjust for (observed and unobserved) differences across groups

(b) Use comparisons across groups to help adjust for other changes across time

Example: School Busing

Estimate the effect of *initiating* a school busing program on housing prices in a school district where:

- Some neighborhoods are subject to the program, others not
- Housing prices are measured on every neighborhood before and after the program is initiated

Naive analyses:

- Compare post-program house prices *between* treated/untreated neighborhoods
  - Threat of confounding due to differences in neighborhoods
- Before/after comparisons *within* neighborhoods that had the program
  - Many other things may have changed during this time period to impact housing prices

D-in-D: Intuition

A D-in-D analysis is designed to use **both** the *between* and *within* neighborhood variation to estimate a causal effect

- A between unit comparison is threatened by neighborhood characteristics, *but would adjust for time trends common across all neighborhoods*
- A within unit before/after comparison is threatened by concurrent changes over time, *but would adjust for time-fixed neighborhood characteristics*

In the School Busing Example:

- Time-fixed neighborhood characteristics: socially disadvantaged neighborhoods likely to have lower housing prices
- Time trends: General economic boom/recession patterns that affect all house prices

D-in-D, Literally

Compare exposed/unexposed groups in terms of *differences* across time

1. First difference: Before/after difference within unit
   - "Change score" for each unit
   - Average change score in each treatment group
2. Second difference: Difference in average change between treatment groups

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 P_i + \tau Z_i P_i + \epsilon_i$$

$$D_i = \alpha + \tau Z_i + \epsilon_i$$

D-in-D Assumptions

Intuitively, using the change (over time) in control units represents what *would have happened* to the change (over time) in treated units had they not been treated

- $D^0 = Y^0 - Y^{obs}_{P=0}$
- $D^1 = Y^1 - Y^{obs}_{P=0}$
- Average Treatment Effect: $E[D^1 - D^0]$
- Ignorability assumption: $D^0, D^1 \perp\!\!\!\perp Z$
  - *Potentially* weaker than "standard" ignorability because we are only assuming that potential *changes* in outcomes are balanced across groups
  - Might be justified even without measuring all possible differences between neighborhoods

Quasi-Experiments, Closing Thoughts

We have discussed three examples of quasi-experimental methods, all based on different but specialized sets of "lucky" **circumstances**

- Instrumental variables
- Regression discontinuity
- Difference-in-Differences

Often touted as improvements over methods that explicitly adjust for confounding (e.g., propensity scores) on the basis that they don't need to measure all confounders

- But the attendant assumptions of quasi-experiments may not be any more viable than assumptions about conditional ignorability

A key takeaway is that quasi-experiments still need to be evaluated along similar lines as "standard" observational studies in terms of explicit assumptions about potential outcomes