Difference-in-Difference: An Introduction

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  - Unlike individual-level exposures (e.g., vaccines), these exposures are often difficult to randomize.
- Fortunately, econometricians have developed a set of tools to understand the effects of these macro- and meso-level changes:
  1. Instrumental variables
  2. Synthetic controls
  3. Regression discontinuity designs
  4. Interrupted time series
  5. **Difference-in-differences**

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  - Time-invariant confounding threatens our identification of the causal effect of our exposure because the observed correlation between exposure and outcome may simply be a consequence of the effect of shared causation.
- FE are most commonly employed by taking the average value of each variable per your group and subtracting it from the corresponding variable at each of your groups' observation.

Fixed Effects Equation

$$Y_{it} = \beta_1 INCOME_{it} + \epsilon_{it} \tag{1}$$

$$Y_{it} = \beta_1 INCOME_{it} + \alpha_i + \mu_{it} \tag{2}$$

$$Y_{it} = \beta_1 (INCOME_{it} - \bar{(}INCOME_i) + (\alpha_i - \bar{(}\alpha_i)) + (\mu_{it} - \bar{(}\mu_i) \tag{3}$$

$$Y_{it} = \beta_1 (C_I NCOME_{it}) + \mu_{it} \tag{4}$$

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  - Time-invariant confounding threatens our identification of the causal effect of our exposure because the observed correlation between exposure and outcome may simply be a consequence of the effect of shared causation.
- FE are most commonly employed by taking the average value of each variable per your group and subtracting it from the corresponding variable at each of your groups' observation.
- However, DiD studies typically employ an alternative approach to group-mean centering: the least-squares-dummy-variable (LSDV) approach.
  - In other words, include a dummy variable per group minus the reference group (n-1 dummy variables).

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- The standard DiD equations looks something like this:

$$Y_{it} = \gamma_1 TREAT_i + \gamma_2 Post_t + \gamma_3 (TREAT_i * POST_t) + \phi_{it} + \epsilon_{it} \quad (5)$$

  - TREAT $= 0$ for untreated group; 1 for treated group
  - POST $= 0$ for period when both groups are untreated; 1 for when treated group is actually treated
  - $\gamma_3 =$ Averaged treatment on the treated (ATT) (i.e., our estimated causal effect)
  - $\phi_{it} =$ vector of time-varying confounders.
  - $\epsilon_{it} =$ error term

Example: Organ Donations

- In the US, organ donor status is typically determined through driver's license applications:
  - Opt-out - the default status in most US states
  - Opt-in - fewer states have this as the default.
- In 2011, California implemented switched from opt-in to "active choice."
- Judd Kessler and Alvin Roth (2014) investigated whether this change had an effect on donor registration rates.
  - They found that this switch resulted in a decrease in donor status registration. (See R Code)

Parallel Trends Assumption

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    - This is known as the parallel trends assumption (PTA).
- In other words, the PTA states that the difference between treated and control groups would have remained the same over time had the intervention not occurred.
    - Since this is a counterfactual, we will never actually know if this is true, but we can do some checks to increase our confidence in it.

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- With the Kessler and Roth data, we'll drop all the waves in the post-treatment period and create a fake treatment period by selecting 1 or 2 the waves in the pre-treatment period. (See R Code).

Future Presentations

- Future presentations may want to consider recent advancements in DiD methodology, particularly those pertaining to issues of staggered treatment designs.
  - Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of Econometrics, 225(2), 254-277.
  - Baker, A. C., Larcker, D. F., Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates?. Journal of Financial Economics, 144(2), 370-395.
  - Callaway, B., Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. Journal of Econometrics, 225(2), 200-230.

Acknowledgments

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