DIFFERENCE-IN-DIFFERENCES

Twice as good as a single difference

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Difference-in-differences compares the change in an outcome in treated units before and after receiving the treatment to the change in the outcome in untreated units over the same time period.

WHEN TO USE

Requirement 1

Some units are treated and some are not

- E.g., some states enact a policy and others do not, some workers receive a training and others do not, etc.
- You observe data before and after treatment for types of units.
- "Spillovers" or "externalities" are negligible (i.e. untreated units not affected by treatment).

Requirement 2

Treated units may vary in terms of levels but are on the same trends prior to the policy

- It is reasonable to expect that after accounting for level differences, the untreated units capture how the treated units' outcome would have evolved in the absence of treatment.

WHAT TO DO: THE BASICS

Step 1

Plot data of treated and untreated units against time

- Ideally all treated units are treated at the same time.
- Do you observe a trend break in the raw data?
- Do treated and untreated units appear to be on a similar trend before the treatment, but diverge after the treatment?

Step 2

"Event Study" Version

- If treatment time is t^*, estimate a model of the form $y_{it} = \beta_i + \beta_t + Treated_i \times \sum_t \beta_z I(t - t^* = z) + \epsilon_{it}$.
- Ideally, you will see that coefficients on indicators prior to the treatment (β_z for $z < 0$) are small and not statistically significant.
- If coefficients on post-treatment indicators (β_z for $z \geq 0$) are statistically significant, that indicates the treatment had an effect.

Step 3

"Diff in Diff" Version

- Regress a model of the form $y_{it} = \beta_i + \beta_t + \beta_{DD} Treated_i \times After_t + \epsilon_{it}$.
- $Treated_i = 1$ if unit is treated; $After_t = 1$ if time is after treatment.
- The difference-in-differences effect is β_{DD}.

INFERENCE

- Cluster at the level of treatment to account for within-unit correlation of the error term over time (Bertrand, Duflo, and Mullainathan 2004).
- Do you have a small # of clusters? Use a clustered wild bootstrap or permutation test (Cameron, Gelbach, and Miller 2008, Hagemann 2019).

PITFALLS

- Do treated and untreated units appear to be on different pre-treatment trends? You have options!
  - Re-weight untreated units using synthetic control (Abadie, Diamond, and Hainmueller 2010) or inverse propensity score weighting (Hirano, Imbens, and Ridder 2003).
  - Use your knowledge of the setting to select only untreated units you think will be on a similar trend (e.g. states in the same region, rather than all states).
- Are units treated at different times? This can cause problems. See Abraham and Sun 2018 and Goodman-Bacon 2018.
- Do you have adequate power to detect "pre-trends" if they are present? Check with method in Roth 2019, Section 5.2.

RATING

Difficulty
Fun
Validity

MAKE IT SIZZLE

- Can you identify a subgroup within the treated units that was not affected by treatment? This could serve as a placebo test, and may even allow you to estimate the elusive "triple difference" model!

SOURCES

References

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