Topics in Applied Econometrics

Matching

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How to tackle an empirical project

1. What causal effects are we interested in?
2. What ideal experiment would capture this effect?
3. What is our identification strategy?
4. What is our mode of statistical inference?

Applying the framework to observational data

- Imagine we have data on outcomes of two groups
- We did not ensure randomization
- Biggest fear: selection into treatment
- What if units select into treatment based on observable characteristics?
- *Example:* college wage premium
  - Treatment: getting a college degree
  - Control: no degree
  - Who chooses to go for a degree is not random
  - But imagine two identical persons (gender, age, ability, parents etc.), with / without a degree

Unconfoundedness

- Assignment to treatment is not random
- *But:* assignment to treatment is as good as random, for comparable units
- In other words, no observable characteristics confound the effect of the treatment

$$(Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i \,|\, X_i$$

- AKA selection on observables
- *Problem:* the unconfoundedness assumption cannot be tested
  - Why? Because of the fundamental problem of causal inference

Core idea behind matching

- Imagine we observe all possible confounding factors (X)
- Then, we can compare outcomes for people with the exact same characteristics

$$ATE(x) = \mathbb{E}(Y_i \,|\, D_i = 1, X_i = x) - \mathbb{E}(Y_i \,|\, D_i = 0, X_i = x)$$

- Assumptions:
  1. Overlap: we need enough units in both groups with the same characteristics
  2. Unconfoundedness: we need to observe all confounding X's
- Let's look at some matching procedures

Exact matching

- Match treatment units to control units by perfectly aligning X's
- Recall the college wage premium example
- But: are these matches really exact?
- College wage premium
  1. Overlap: we likely do not have enough identical grads/non-grads
  2. Unconfoundedness: we likely do not observe every single confounder
- Another example: twin studies
  1. Overlap: no problem
  2. Unconfoundedness: depends

Propensity score matching

- The overlap requirement is hard to fulfill in practice
- *Idea:* match units based on an overall score
- Propensity score: probability of being treated, given X

$$p(X_i) = \Pr(D_i = 1 \mid X_i)$$

- Reduces the dimension of X to one $\implies$ overlap is better
- Unconfoundedness assumption changes

$$(Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i \mid X_i \quad \implies \quad (Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i \mid p(X_i)$$

  - Intuitively: $p(X)$ fully captures the relationship between X and D
  - Technically: Rosenbaum and Rubin (1983, Biometrika)

Propensity score matching in practice

1. Estimate the propensity score model
   - Linear probability model: $D_i = X_i\beta + u_i$
   - Logit: $\Pr(D_i = 1) = \Lambda(X_i\beta)$
   - Probit: $\Pr(D_i = 1) = \Phi(X_i\beta)$
2. Forecast $\hat{p}(X_i)$
3. Check overlap of propensity scores
4. Form matches
   - Nearest neighbor: match closest units, with/without replacement
   - Block: match all units within a distance
   - Many fancy techniques; report various ones
5. Check overlap of confounders!
   - Similar propensity score does not automatically mean similar X's
6. Calculate treatment effects

What can we learn from matching?

The UK New Deal for Lone Parents (Dolton and Smith, 2011, IZA DP)

- Lone parents receive a personal advisor to find jobs or work longer
- Participation is voluntary $\Longrightarrow$ selection into treatment
- *Idea:* match participants to nonparticipants on benefit history
- Benefit takeup in six consequent periods generates “strings” $(101101, 000110 \ldots)$
- Match on 2^6 strings and other characteristics

  “[L]agged outcomes correlate strongly both with other observed determinants of participation and outcomes and with otherwise unobserved determinants such as tastes for leisure, particular family obligations such as seriously ill or disabled parents or children and so on. Thus, in our view, conditioning on these histories goes a long way toward solving the selection problem.”

Additional Slides

References I

Dolton, P. and J. A. Smith (2011). The Impact of the UK New Deal for Lone Parents on Benefit Receipt.

Rosenbaum, P. R. and D. B. Rubin (1983, 04). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika 70*(1), 41–55.