EKT-816 Lecture 3

Counterfactuals, Causality, and Potential Outcomes

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Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

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The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E[Y^1|D=1] - E[Y^1|D=0] \\ &\quad + E[Y^1|D=0] - E[Y^0|D=0] \\ &= E[Y^1 - Y^0|D=1] \\ &\quad + E[Y^1|D=0] - E[Y^0|D=0] \end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
  - similar definitions for the effect of treatment on the *untreated* (TUT)
  - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^1|D=0] - E[Y^0|D=0]$ is called "selection bias"
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Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
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Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
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  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
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What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
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- also known as: "what is the source of the identifying variation?"
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
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