Lecture 2: Causality, potential outcomes and experiments

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- When thinking about causal Qs, it's often easier to split the problem in two
- **Identification:** what could we learn about the parameters we care about (causal effects) if we had the observable data for the entire population
    - Need to make assumptions about how observed outcomes relate to outcomes that would have been realized under different treatments
- **Statistics**: what can we learn about the full population that we care about from the finite sample that we have?
    - Need to understand the process by which our data is generated from the full population

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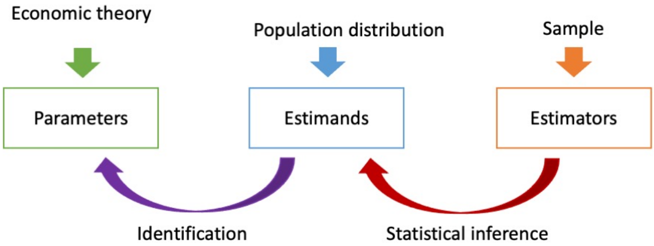
- The process of learning about the *estimand* from the estimator constructed with your *sample* is called **statistical estimation/inference**.
- The process of learning about the *parameter* from the *estimand* is called **identification**.


Economic theory
Population distribution
Sample
Parameters
Estimands
Estimators
Identification
Statistical inference

Let's add some math...

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- We can write the observed outcome as $Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$

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- Example estimator:
  - Difference in sample mean of earnings for people who went to Brown and people who went to URI:

$$\underbrace{\frac{1}{N_1} \sum_{i:D_i=1} Y_i}_{\text{Avg earnings at Brown in sample}} \quad - \quad \underbrace{\frac{1}{N_0} \sum_{i:D_i=0} Y_i}_{\text{Avg earnings at URI in sample}}$$

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- Example estimand:
  - Difference in population mean of earnings for people went to Brown and people who went to URI:

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- Example target parameter:
  - Causal effect of Brown for Brown students:

$$\underbrace{E[Y_i(1)|D_i = 1]}_{\text{Earnings at Brown for Brown students in pop}} \quad - \quad \underbrace{E[Y_i(0)|D_i = 1]}_{\text{Earnings at URI for Brown students in pop}} \quad .$$

Why is causal identification hard?

- Thought experiment: suppose we had data on earnings for *every* Brown and URI graduate
- We can learn from the data:

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- The data doesn't tell us $\underbrace{E[Y_i(0)|D_i = 1]}_{\text{Earnings at URI for Brown Students}}$. Why not?
  - Because we never see Brown students going to URI!

- One idea to solve this problem would be to assume that:

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- Why might this give us the wrong answer?
- Because Brown students may be different from URI students in other ways that would affect their earnings (regardless of where they went to college)
  - Academic ability, family background, career goals, etc.
- These differences are referred to as *omitted variables* or *confounding factors*

What about experiments?

- The gold standard for learning about causal effects is a randomized controlled trial (RCT), aka experiment
- Suppose that the Brown and URI administration randomized who got into which college (assume these are the only 2 colleges for simplicity)
- Since college is randomly assigned, the only thing that differs between Brown and URI students is the college they went to
- Hence,

$$\underbrace{E[Y_i(0)|D_i = 1]}_{\text{Earnings at URI for Brown Students}} = \underbrace{E[Y_i(0)|D_i = 0]}_{\text{Earnings at URI for URI Students}}$$

since we've eliminated any confounding factors

But running experiments is often hard/impossible

- Unfortunately, Brown/URI have not let us randomize who gets into which college
  - At least not yet! If you could convince them to do this, it'd make for a cool senior thesis!
- Likewise, it is difficult to convince states to randomize their minimum wages, or other policies
- In some cases, randomization is not just difficult but would be immoral
  - "What is the causal effect of spousal death on labor supply?"

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- In some cases, randomization is not just difficult but would be immoral
  - "What is the causal effect of spousal death on labor supply?"
- In this course, we'll discuss tools economists try to use when running experiments is not possible.

Course Roadmap – Where we're going

- **Part I ($\sim$ 7 lectures): Review of probability/statistics**. This will give us a mathematical language to talk about:
  1. *Statistical estimation/inference:* how does the sample we observe relate to the population of interest
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- **Part III ($\sim$ 7 lectures:) Other "quasi-experimental" strategies**: We'll discuss other strategies for "mimicking" an experiment when it's not available, including instrumental variables (IV) and regression discontinuity (RD)