Chapter 1: Introduction to ECON 1630

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Mathematical Econometrics I
Brown University

Outline

1. Course Preliminaries
2. What is Econometrics?
3. Why is Econometrics Challenging?
4. Course Roadmap

Introducing Ourselves

Welcome to ECON 1630! I'm looking forward to teaching you all

I'm Professor Jonathan Roth

- Group OH on Zoom (link): Mon 220-250
- Individual OH: Typically Tue 3-4; sign up on my website: here, 8 Fones Alley 014 (or Zoom by request)

Our Grad TAs are Moritz Poll and Max Grozovsky
Our undergrad TAs are Matt Kutam and Preetish Juneja (star students from previous semesters!)

- All TAs will hold OHs
- Grad TAs will hold weekly sessions
  - Review material and teach coding
- Times/locations for TA OHs and sections will be announced shortly on Canvas

Canvas and EdDiscussion

Course materials and communications will be posted on Canvas:
`https://canvas.brown.edu/courses/1100468`

The Canvas page has an EdDiscussion board, which is a great place to ask (and answer) questions. The TAs will monitor the Qs.

Meeting times:

- Lectures: Mon/Wed 830-950 (S01) or 3-420pm (S02). **Recordings will be posted online after class.**
- TA Sessions: Time/location TBD
- **Attendance** is not required but is **highly encouraged**

Prerequisites:

- Multivariate calculus, probability/statistics, and linear algebra
- Some familiarity with reading/writing proofs and code

Software:

- Default is Stata for statistical analyses (to be covered in TA sessions)
  - You're welcome to use R instead; TAs are familiar with R
- LaTeX for typing up problem sets (optional, for extra credit)
- Ask us for help if you're having any problems accessing software

Assessments:

- 6 problem sets due approximately every 2 weeks, submitted via Gradescope
- 1 midterm exam (November 3, in class)
- 1 final exam

Grading:

- 30% problem sets, 35% on each exam.
- I'll drop your lowest PSet grade. Use your drop wisely!
- Psets are due at 4PM on Fridays; late submissions won't be graded. Collaboration is OK (please list collaborators)
- The exams will be in-class, closed-book, "cheat-sheet" allowed
- 5 points extra credit if you use LaTeX for assignments. Please attach your code + output as a single PDF regardless

AI Policy

My view is that AI is a useful tool and we shouldn't ignore it. But need to use it in a way that enhances rather than impedes learning.

- **Exams (70%):** closed-book; *no AI allowed*.
- **Problem sets:** AI OK if it *helps you learn*, not if it replaces learning/effort.
  - **Good:** debugging R/Stata errors.
  - **Bad:** writing free-form answers.
- I can't police what you do on the psets, but if you don't put in effort you probably won't do well on the exams
- Include brief **AI use disclosure** on each pset.

Course materials:

- Main material: Lectures and lecture slides, which will be posted on Canvas
- Optional text: Stock & Watson – Intro to Econometrics (4th ed)

Any questions on logistics?

Outline

1. Course Preliminaries ✓
2. What is Econometrics?
3. Parameters, Estimands, and Estimators
4. Course Roadmap

What is Econometrics?

$\rightarrow$ The statistical toolkit that economists use to answer economic questions with data

What types of questions might we be interested in:

- Has economic inequality increased since 1960?
  - **Descriptive Q:** asks about how things are (or were) in reality
- How do increases in the minimum wage affect employment?
  - **Causal Q:** What would have happened in a counterfactual world?
- What will the unemployment rate be next quarter?
  - **Forecasting Q:** What will happen in the future?

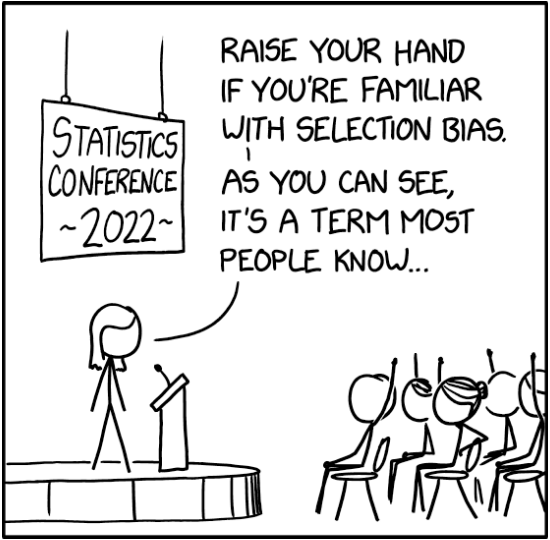
In this course, we will focus mainly on descriptive and causal questions, with an emphasis on causal questions

Why is answering these questions hard?

- For descriptive Qs: we only observe data for a **sample** of individuals, not for the full **population**
  - Example: we want to know how the distribution of income in the US has changed. But we only observe income for a survey of workers
- Best case scenario:
  Our sample is **randomly** selected from the population
  - E.g., the workers in our survey were drawn out of hat with names of all possible workers
  - If so, need to account for the fact that by chance the sample might have different characteristics from the population
- Worst case scenario: our sample is *not representative* of the population that we care about
  - E.g., workers with certain characteristics were more likely to respond to the survey

- In 1948, Chicago Tribune writes that Thomas Dewey defeats Harry Truman in the 1948 presidential election, based on survey of voters.
- But their survey was conducted by phone. In 1948, only rich people had phones: sample $\neq$ population $\rightarrow$ misleading results!

Selection bias referes to settings like Dewey-Truman where the sample is not drawn randomly from the population of interest



Why is answering these questions hard? (Part II)

- Answering causal questions is often *even harder* than descriptive ones. Why?

- Causal Qs involve both a descriptive component (what are outcomes in reality?) and a *counterfactual* component (how would things have been under a different treatment?)

- Example: what is the causal effect on your earnings of going to Brown instead of URI?
  - Descriptive Q: how much do Brown students earn after graduation?
  - Counterfactual Q: how much would Brown students have earned if they went to URI?

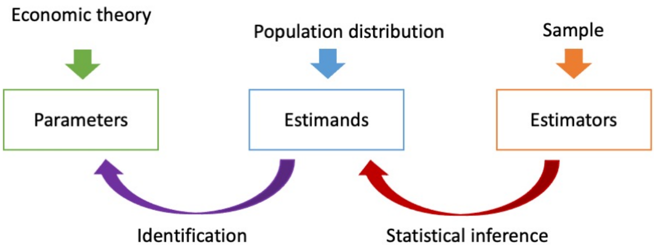
- Counterfactual Qs can't ever be answered with data alone. Need additional assumptions to learn about them!

Splitting up the problem

- 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

Framework for thinking about these steps

- **Sample:** the data that you actually observe
  - A survey of students from Brown and URI graduates about their earnings
- **Estimator:** a function of the data in the sample
  - Difference in earnings between Brown and URI students in survey
- **Estimand:** a function of the observable data for the *population*
  - Difference in earnings between all Brown and URI students
- **Target (aka structural) parameter:** what we actually care about
  - Causal effect on earnings of going to Brown relative to URI
- 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...

- Introduce **potential outcomes** notation
  - Super useful framework for thinking about causality!
    See the 2021 Nobel Prize writeup on Canvas!

- $D_i =$ indicator if get treatment (1 if Brown, 0 if URI)

- $Y_i(1) =$ outcome under treatment $=$ earnings at Brown

- $Y_i(0) =$ outcome under control $=$ earnings at URI

- Observed outcome Y_i is $Y_i(1)$ if $D_i = 1$ and $Y_i(0)$ if $D_i = 0$. (Y_i is your actual earnings)

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

- Example sample: (Y_i, D_i) for $i = 1, ...N$. Data with earnings and where you went to school
- Example estimator:
  - Difference in sample mean of earnings for people who went to Brown and people who went to URI:

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

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

$$\underbrace{E[Y_i|D_i = 1]}_{\text{Avg earnings at Brown in population}} \quad - \quad \underbrace{E[Y_i|D_i = 0]}_{\text{Avg earnings at URI in population}}$$

- 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:

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

- The causal effect of Brown for Brown students is

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

- 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:

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

- 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?"

- 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
  2. *Identification:* how do observable features of the population relate to (causal) parameters we care about

- **Part II ($\sim$ 9 lectures): Linear regression:** We'll discuss ordinarly least squares (OLS), the workhorse model for estimation in econometrics. When does it work, and when will it fail?

- **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)