

Chapter 1: Introduction to ECON 1630

Jonathan Roth

Mathematical Econometrics I
Brown University
Fall 2023

Outline

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

Course Preliminaries I - Introducing Ourselves

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

I'm Professor Jonathan Roth

- Individual OH: Typically Mon 415-445 and Tue 330-4; Sign up on my website: [here](#), 8 Fones Alley 014 (or Zoom by request)
- Group OH on Zoom ([link](#)): Thu 330-4

Our Grad TAs are Tommaso Coen and Eddie Wu

Our undergrad TAs are Henry Powers and Preetish Juneja (star students from last semester!)

- All TAs will hold OHs
- Grad TAs will hold weekly sessions: TBA shortly
- Times/locations for TA OHs will be announced shortly on Canvas

Course preliminaries II

Course materials and communications will be posted on Canvas:
<https://canvas.brown.edu/courses/1093393>

Course Preliminaries III

Meeting times:

- Lectures: Tues/Thurs 9-1020 (S02) or 1-220pm (S01).
Recordings will be posted online after class.
- TA Sessions: Time/location TBD
 - Sessions will review concepts from class and help with Stata
- 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:

- Stata for statistical analyses (to be covered in TA sessions)
 - You're welcome to use R/Python instead, but we can't promise any help with coding issues
- LaTeX for typing up problem sets (optional, for extra credit)
- Ask us for help if you're having any problems accessing software

Course Preliminaries III

Assessments:

- 6 problem sets due approximately every 2 weeks
- 1 midterm exam (October 19, in class)
- 1 final exam

Grading:

- 40% problem sets, 30% 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, 1-page "cheat-sheet" allowed
- 5 points extra credit if you use LaTeX for assignments. Please attach your Stata code + output as a single PDF regardless

Course materials:

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

Course Preliminaries IV

- Lecture recordings will be posted on Canvas (but you cannot join live)
- Office hours will be in person, unless Zoom is requested
- Please submit all problem sets using Gradescope
- You are encouraged to use EdDiscussion for questions

Any questions on logistics?

Outline

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

What is Econometrics?

→ 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

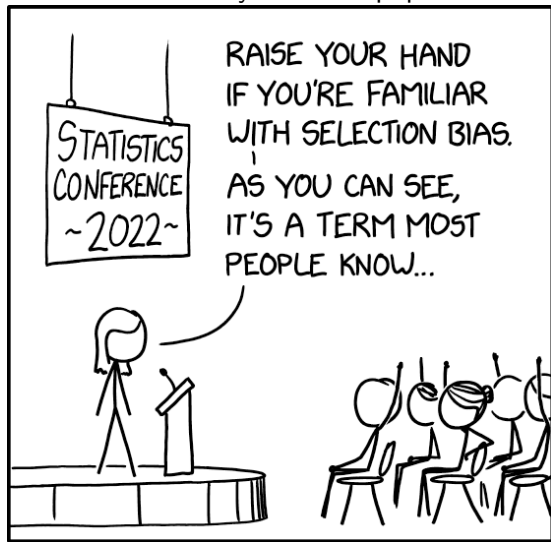
Why is answering these questions hard?

- 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 refers 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)

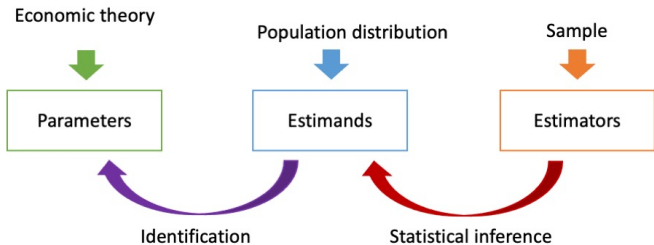
- Answering causal questions is often *even harder* than descriptive ones. Why?
- Causal Qs involve both a descriptive component (what are outcomes in reality?) and a *counterfactual* component (how would things have been under a different treatment?)
- Example: what is the causal effect on your earnings 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**.



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 $i = 1, \dots, N$. 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:

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

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

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

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

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

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