

Introductions and Overview

Dr. Adam Soliman

Introduction to Econometrics (ECON 4050)
Clemson University
Fall 2024

Outline

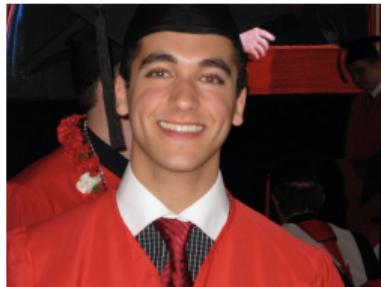
1 Course Preliminaries

2 Why is Econometrics Challenging?

3 Course Roadmap

A little bit about your econometrics professor

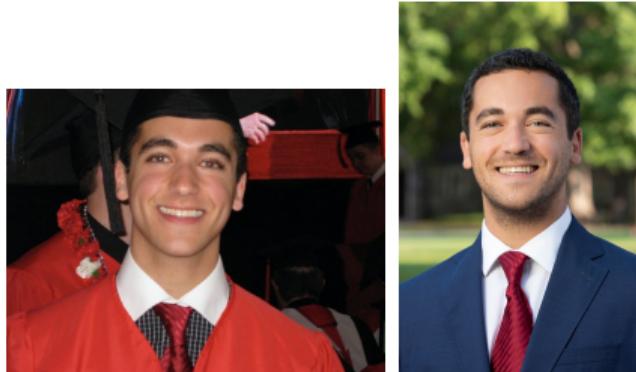
- I have been in school for a while...from Boston University (undergrad) to Michigan State (masters) to Duke (PhD) to London School of Economics (post-doc)



- My first job was teaching math and economics in Dubai

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- My first job was teaching math and economics in Dubai
- I study topics in the economics of crime & some research questions of interest include
 - What are the impacts of cracking down on rogue doctors during the opioid epidemic on street drug prices, overdose mortality, and other doctors behavior?
 - Do police respond to changes in punishment severity?
 - What happens to neighborhood crime when investors buy many properties?

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- What will the unemployment rate be next quarter?
 - ▶ **Forecasting Question:** What will happen in the future?

Causal questions will be our focus in this course

More causal questions:

- ① Does immigration *lead to* lower wages and/or higher unemployment for locals?
- ② Does getting a college degree *afford* higher wages?
- ③ Do higher public debt levels *lead to* lower economic growth?
- ④ Does the neighborhood you grew up in have an *impact* on your life outcomes?

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- Note that many other factors could have caused each of these outcomes
- Often, we'll want to focus on the causal impact of just one of these factors (immigration, minimum wage, education, etc.)
- Econometrics is about spelling out *conditions* under which we can *claim to measure causal relationships*
- We will encounter most basic of those conditions, and talk about some potential pitfalls

A little bit about your classmates

Insert some info from survey

Expectations

- Ask questions: to me, your TAs, each other
- Make mistakes, but always try
- You will be learning a powerful set of skills that apply well outside of this course, so enjoy where you can and try to think of where else they may be useful

Logistics

1) Schedule and Location:

- ▶ Lectures: 4050-001 TR from 11:00AM to 12:15PM in Powers Hall 207
- ▶ Lab: 4051-001 T 5:30PM-8:30PM, -002 W 5:30PM-8:30PM, or -003 R 5:30PM-8:30PM
- ▶ My office hours are Wednesdays from 3PM to 5PM on Zoom
- ▶ Our Teaching Assistants (TAs) are TBD
 - ★ All TAs will hold OHs. Times/locations for TA OHs will be announced shortly

2) Content and communication:

- ▶ We will **exclusively** use Slack for our interactions. Please do not contact me by email unless there's a legitimate reason to
 - ★ I will be checking Slack sparingly so please help one another in the meantime
- ▶ The main course materials are currently posted on [the Github course website](#). Other communication will be via Slack and Canvas.

Logistics

3) Software:

- ▶ R for statistical analyses (to be covered in Lab sessions and throughout the course)

4) Assessments:

- ▶ In-class quizzes/attendance: 10%
- ▶ Lab work: 25%
- ▶ 1 midterm exam: 25%
- ▶ Final project and associated presentation: 30% and 10%, respectively

5) Prerequisites:

- ▶ ECON2110 and 2120 Principle of Microeconomics and Macroeconomics
- ▶ MATH1080 Calculus One
- ▶ STAT3090/MATH3090 Introduction to Statistics

Resources

- **Econometrics**

- ▶ SciencesPo Online Book
- ▶ Causal Inference: The Mixtape by Cunningham
- ▶ Ben Lambert's youtube channel

- **Metrics and 'R'**

- ▶ ModernDive
- ▶ Introduction to Econometrics with R
- ▶ Awesome R Learning Resources
- ▶ R for Data Science

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3 Course Roadmap

Why is answering these questions hard?

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 - ▶ 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

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- Best case scenario: Our sample is **randomly** selected from the population
 - ▶ For example, workers in the survey were drawn out of hat with names of all possible workers
- Worst case scenario: Our sample is *not representative* of the population that we care about
 - ▶ For example, workers with certain characteristics were more likely to respond to the survey

An example from before we were born



- In 1948, Chicago Tribune writes that Thomas Dewey defeats Harry Truman in the 1948 presidential election, based on survey of voters.

An example from before we were born \Rightarrow error known as selection bias



- 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!

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- Answering causal questions is often *even harder* than descriptive ones because they involve both a descriptive component (what are outcomes in reality?) and a *counterfactual* component (how would things have been under a different treatment?)

Why is answering these questions hard? (Part II)

- Answering causal questions is often *even harder* than descriptive ones because they 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 Clemson instead of USC?
 - ▶ Descriptive Question: how much do Clemson students earn after graduation?
 - ▶ Counterfactual Question: how much would Clemson students have earned if they went to USC?
- Counterfactual questions can't ever be answered with data alone. Need additional assumptions to learn about them!

Splitting up the problem

- When thinking about causal questions, 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 Clemson and USC graduates about their earnings
- **Estimator:** a function of the data in the sample
 - ▶ Difference in earnings between Clemson and USC students in survey
- **Estimand:** a function of the observable data for the *population*
 - ▶ Difference in earnings between all Clemson and USC students
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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**

Let's add some math...by introducing potential outcomes notation

- D_i = indicator if get treatment (1 if Clemson, 0 if USC)
- $Y_i(1)$ = outcome under treatment = earnings at Clemson
- $Y_i(0)$ = outcome under control = earnings at USC
- 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 $Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0)$

What is the causal effect on earnings of going to Clemson instead of USC?

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

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- **Target parameter:** Causal effect of Clemson for Clemson students:

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

Why is causal identification hard?

- Thought experiment: suppose we had data on earnings for every Clemson and USC graduate
- We can learn from the data:

$$\underbrace{E[Y_i(1)|D_i = 1]}$$

Earnings at Clemson for Clemson Students

and

$$\underbrace{E[Y_i(0)|D_i = 0]}$$

Earnings at USC for USC students

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- The data doesn't tell us $\underbrace{E[Y_i(0)|D_i = 1]}_{\text{Earnings at USC for Clemson Students}}$. Why not?

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

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

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- Why might this give us the wrong answer?
- Because Clemson students may be different from USC 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 Clemson and USC 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 Clemson and USC students is the college they went to
- Hence,

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

since we've eliminated any confounding factors

But running experiments is often hard/impossible

- Unfortunately, Clemson/USC 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

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Course Roadmap – Where we're going

- Topics

- ① Simple Linear Regression
- ② Introduction to Causality
- ③ Multiple Linear Regression
- ④ Linear Regression Extensions
- ⑤ Sampling
- ⑥ Confidence Intervals & Hypothesis Testing
- ⑦ Regression Inference
- ⑧ Regression Discontinuity
- ⑨ Instrumental Variables
- ⑩ Difference-in-Differences
- ⑪ Panel Data

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- Important Dates

- ▶ October 3rd: No Class
- ▶ October 15th: No Class (Fall Break)
- ▶ October 17th: Midterm Exam
- ▶ November 5th: No Class (Election Day)
- ▶ November 28th: No Class (Thanksgiving Break)
- ▶ Final Project Presentations (Tentatively): November 21st, November 26th, December 3rd, and December 5th

And now...

A brief introduction to R