Lecture 3 Notes: Intro to Causal Inference

Econ 4523: Economics of Education
Prof. Tyler Ransom
University of Oklahoma

Fall 2019

Today's Big Questions

- Brief stats review
- What is the principle of causality?
- What methods to researchers use to distinguish between correlation and causation?

1 Statistics review

Below is a table summarizing the basic statistics we will use in the course. Suppose that the population consists of M units, and our sample consists of N units, each indexed by i. Let's lable our first random variable t and our second random variable u.

	Population (parameter)	Sample (statistic)
Mean	$\mu_t = \frac{\sum_{i=1}^{M} t_i}{M}$	$\bar{t} = \frac{\sum_{i=1}^{N} t_i}{N}$
Variance (Var)	$\sigma_t^2 = \frac{\sum_{i=1}^{M} (t_i - \mu_t)^2}{M}$	$s_t^2 = \frac{\sum_{i=1}^{N} \left(t_i - \bar{t}\right)^2}{N-1}$
Covariance (Cov)	$\sigma_{t,u} = \frac{\sum_{i=1}^{M} (t_i - \mu_t)(u_i - \mu_u)}{M}$	$\hat{\sigma}_{t,u} = \frac{\sum_{i=1}^{N} \left(t_i - \bar{t}\right)(u_i - \bar{u})}{N-1}$
Correlation (Corr)	$\rho_{t,u} = \frac{\text{Cov}(t,u)}{\sqrt{\text{Var}(t)\,\text{Var}(u)}} = \frac{\sigma_{t,u}}{\sigma_t \sigma_u}$	$\hat{\rho}_{t,u} = \frac{\widehat{\text{Cov}}(t,u)}{\sqrt{\widehat{\text{Var}}(t)\,\widehat{\text{Var}}(u)}} = \frac{\hat{\sigma}_{t,u}}{s_t s_u}$

2 Correlation and causation

You may have heard the phrase "correlation does not imply causation." What exactly does this mean, and why is it so important?

2.1 What is causality?

Causality, simply defined is the claim that, if when we change a policy, then some specific outcome is going to happen. In other words, the outcome changed *because of* the policy, and only because of the policy.

2.2 Examples of causal claims

- "Attending a private school increases one's chances of getting into an Ivy League college." Implication: a student would have lower chances if he or she went to a public school.
- "Majoring in science causes higher earnings." Implication: a student would earn less if he or she majored in something besides science.
- "Smoking causes weight loss." Implication: a smoker would weigh more if he or she had not been smoking.

2.3 Measuring causality

To measure causality, we need to collect data and measure these concepts in some way. There are three types of variables that we will need to identify in our data set:

1. **Outcome variable.** This is the characteristic that we want to affect. From the above examples, it is respectively "likelihood of admission," "earnings," and "weight."
2. **Treatment variable.** Also known as the *policy variable*, it is the characteristic that we use to create changes. From the above examples, it is "attending private school," "college major," and "smoking."
3. **Control variables.** Also known as *pre-treatment variables*, these are characteristics that affect the outcome, but that we cannot change. For example, demographic variables such as gender or ethnicity or family background. These may also include outcomes that happened in the past, such as SAT scores or GPA.

When we want to measure causality, we need to decide on two additional considerations:

1. *What is the unit of analysis?* Is it a city, an individual, a family, a household, a firm, a country?

2. *How are we going to measure the outcome and the treatment?* In other words, what is the definition of "smoking"? Is it one pack of cigarettes per day? Is weight measured in pounds or as body mass index? Is a science major restricted to the traditional natural sciences, or does it also include engineering and computer science? How does one measure likelihood of admission into a selective university? These are all questions that are up to the researcher to decide. When critically evaluating a causal claim, it is important to keep in mind what is being measured!

2.3.1 The need for variation

We also need variation in our data to measure causality. If all observations in our data set have the same value for the treatment variable, we won't be able to say anything about causality. For example, suppose every student in our data set was admitted to Yale, and that all students attended elite boarding schools. We wouldn't be able to say anything about what would have happened if these students had attended their neighborhood public school.

We need variation in both the outcome variable and the treatment variable to make causal claims!

2.4 "Correlation does not imply causation"

In other words, if the treatment variable and the outcome variable are correlated, that does not imply that the treatment variable has a causal impact on outcomes.

2.4.1 Examples

1. A hotel notices that when it charges a higher price, it tends to sell out its rooms.
   - Is this a causal effect?
   - If it were, then the hotel should increase its price to attract more customers.
   - But we know that demand curves are downward-sloping. What's going on here?
   - This is a case of reverse causation: When the hotel is popular (e.g. during busy seasons), it can charge a higher price and still sell out all of its rooms.
2. A student hears an advertisement by the College of Arts and Sciences that students who major in natural sciences earn 20% higher wages after college.
   - Is this a causal effect?
   - If it were, then the student who heard the advertisement should change her major!
   - What else could explain this?
   - A case of selection bias: Perhaps, for whatever reasons, natural science graduates earn more than other college students. In fact, these students would make just as much if they majored in studio art.

2.4.2 The selection problem

When units are allowed select their own value of the policy variable, any correlations with outcomes are unlikely to be causal.

Revisiting the college major example, college major may not have an impact on earnings because students are free to choose their major. How might this work? A student who majors in biology might really want to work as a scientist after college. So even if that student majored in studio art, she may still "do what it takes" to qualify for a scientist job. On the other hand, someone who is interested in English who decides to switch to biology may not be happy as a lab technician, and hence would not do as good of a job or would end up choosing an occupation with lower pay.

Now, there is a possibility that college major causes earnings to be higher or lower. The story for that would be if a student learns specific skills in the classes that are required for that major and ends up in a higher-paying job as a result.

2.4.3 When correlation *does* imply causation

When does correlation imply causation? When, after applying appropriate techniques, we see that there is still a correlation between the treatment variable and the outcome variable. What are these "appropriate techniques"? I will introduce them over the next several lectures.

It is also important to understand that, for almost every question we will examine in this class, causality is not black and white. In other words, for most questions, the answer is "this effect is 75% causation and 25% selection."

3 Counterfactual outcomes and treatment effects

The way to infer causality is to compare two potential outcomes for each unit in our data set: the *observed outcome* and the *counterfactual outcome*. We call the difference in these outcomes the **treatment effect**.[1]

For example, let's examine the effect of completing an additional grade of high school on a student's earnings. (The textbook calls this student Larry, so we'll follow suit.) Let Y indicate Larry's potential earnings. Y can take on two values: Y_T and Y_C. Y_T is Larry's earnings if he were treated (i.e. if he completed the next grade), and Y_C is Larry's earnings if he did not. (Here T stands for **treatment group** and C stands for **control group**.) We see in the data that Larry completed the extra year of schooling, so he is in the treatment group. However, we cannot see what Larry's earnings *would have been* if he had not completed school. Thus, in this example, Y_C is a **counterfactual outcome**.

Putting into math the definition of the treatment effect:

$$\textbf{Treatment effect} = Y_T - Y_C$$

[1] Why is it called a treatment effect? This stems from medical research, in which some patients in an clinical trial are treated with a certain remedy, while others are placed in a control group. Saying the phrase "treatment effect" is tantamount to saying "causal effect."

Causality boils down to comparing the actual outcome with the counterfactual outcome, or *what would have happened* if the treatment variable were different.

The main problem here is that we can never observe the counterfactual outcome. What causal inference does is give a set of assumptions under which we can plausiby say what the counterfactual outcome would have been. As we'll discuss later, one major assumption is that we won't be able to say much, if anything, about individual treatment effects. Instead, we will only be able to say what the counterfactual is for the treatment group *as a whole*.

3.1 Confounding variables

A confounding variable (also sometimes called a confounder, a lurking variable, or a hidden variable) is any variable that affects the outcome and is not constant across the treatment group and the control group.

What does this mean? Well, there is only one Larry, and we only observe his earnings when he is in the treatment group. To know what Larry's earnings would have been if he were in the control group, we would need to find a different student in the control group who has the exact same characteristics as Larry, except for not completing the additional grade in school. This is impossible, because there are over 10,000 different characteristics that make Larry who he is. And our data set only keeps track of 20 of them. Thus, there are likely to be additional characteristics that determine what Larry's earnings will be, but which are not included in our data set.

The fact that Larry is a unique individual means that we are likely going to be confounded by some variable. For example, maybe we find a person in the data set who is in the control group but who matches Larry on all other 20 characteristics that we can see. But maybe that person is much more social than Larry, and who does much better in job interviews than Larry does. Hence Larry's control group counterpart is more likely than Larry to be employed at a higher-paying job. In this case, "social skills" would be a confounder to our causal inference, because it overstates what Larry's earnings would have been if he had not completed school.

3.1.1 Confounders and the selection problem

You can think of the selection problem as a case of confounding: because individuals are able to select their value of treatment, this will result in the treatment group and control group being very different.

3.2 Counterfactual analysis (and hence, causal inference) is everywhere

Our course will focus mainly on how to quantify causality in educational institutions, but the practice of conducting counterfactual analysis is everywhere. Some examples:

- In July 2017, Nate Silver wrote an essay documenting how life was on "Earth 2"—the world in which Hillary Clinton defeated Donald Trump in the 2016 US presidential election. His point was to make a causal inference about the election of President Trump on a variety of outcomes: healthcare, foreign policy, etc.

- Many OU football fans will likely make counterfactual comparisons about how different the 2017 Oklahoma football season would have been if Bob Stoops had remained head coach instead of retiring. Perhaps the Sooners would have won the national championship instead of losing in the semifinals? Or maybe OU would have lost at some other point in the season?

- Any scenario in which a person asks “What If?” is a counterfactual comparison

3.3 How do I know if a counterfactual is plausible?

Counterfactuals are irrefutable by definition! A policy researcher’s job is to convince her audience that her counterfactual is the one that is *most likely* to have happened.

Fortunately, there are a number of tried-and-true methods for quantifying causality. These are:

1. Randomized Control Trials (RCTs), also called Randomized experiments
2. Regression analysis
3. Difference-in-differences
4. Fixed effects
5. Instrumental variables
6. Regression discontinuity

Video links

- https://www.youtube.com/watch?v=FNpcwiOme1g
- https://www.youtube.com/watch?v=4RZiWZXdbTw
- https://www.youtube.com/watch?v=K12qDIHAK54
- https://www.youtube.com/watch?v=vtSCZcKXw1w
- https://www.youtube.com/watch?v=9j_HWkrSxzI