2. Causal Effects

ECON8011 Microeconometrics

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- Main Question: What is the causal relationship of interest?
- Although purely descriptive research has an important role to play, we believe that the most interesting research in social science is about cause and effect, like the effect of class size on children's test scores.
- A causal relationship is useful for making predictions about the consequences of changing circumstances or policies; it tells us what would happen in alternative worlds.
- The second research FAQ is concerned with the experiment that could ideally be used to capture the causal effect of interest.
- But ideal experiments are most often hypothetical.

- Four questions to answer:

  1. What is the causal relationship of interest?
  2. What is the experiment that could ideally be used to capture the causal effect of interest?
  3. What is the identification strategy?
  4. What is the mode of inference?

1. What is the causal relationship of interest?

- Causal effect of class size of children's test scores
- Causal effect of schooling on wages
- Causal effect of democratic institutions heritage on growth.

2. What is the ideal experiment?

- Requires to identify:
  - the forces we want to manipulate
  - and those we would like to hold constant
- Running examples:
  - Assign otherwise identical children in classes of different size
  - Offering potential dropouts a reward for finishing school
  - Go back-in time and randomly assign different government structures to former colonies on their independance day
- We don't always get an ideal experiment

3)What is the identification strategy?

- "the manner in which a researcher uses observational data"
- Running examples:
  - Exogenous rules on class division (Angrist and Lavy, QJE 1999)
  - Change in compulsory school attendance; (Angrist and Krueger, QJE 1991)
  - Difference in mortality rates of settlers led to more or less extractive institutions. (Acemoglu, Johnson and Robinson, AER 2001)
- Some elements of the toolbox:
  - Randomized Control trial
  - Matching
  - Instrumental Variables
  - Regression Discontinuity Design

4) What is the mode of inference?

- What is the population of interest?
- How to draw a sample?
- What are the assumptions on the estimators and their standard errors

The Selection Problem

- The role experiments play in uncovering causal effects. $\rightarrow$ if-then question.
- Do hospitals make people healthier?
- The natural approach for an empirically-minded person is to compare the health status of those who have been to the hospital to the health of those who have not.

- The National Health Interview Survey (NHIS) in US and TURKSTAT Health Survey (THS) in Turkey contains the information needed to make this comparison.
- "During the past 12 months, was the respondent a patient in a hospital overnight?"
- "Would you say your health in general is excellent, very good, good, fair, poor?"

- The following table displays the mean health status (assigning a 1 to excellent health and a 5 to poor health) among those who have been hospitalized and those who have not (tabulated from the 2005 NHIS):

Group	Sample Size	Mean health status	Std. Error
Hospital	7774	2.79	0.014
No Hospital	90049	2.07	0.003

- The difference in the means is 0.71, a large and highly significant contrast in favor of the non-hospitalized, with a t-statistic of 58.9.

- People who go to the hospital are probably less healthy to begin with.
- Moreover, even after hospitilization people who have sought medical care are not as healthy, on average, as those who never get hospitalized in the first place, though they may will be better than they otherwise would have been.
- Think about hospital treatment as described by a binary random variable $D_i = \{0, 1\}$.

- Outcome of interest, a measure of health status, is denoted by Y_i.
- The question is whether Y_i is affected by hospital care.
- To address this question, we assume we can imagine what might have happened to someone who went to the hospital if they had not gone and vice versa.

- A naive comparison of averages by hospitalization status tells us something about potential outcomes.
- The comparison of average health conditional on hospitalization status is formally linked to the average causal effect by the equation below:

$$\underbrace{E[Y_i|D_i=0]}_{\text{observed difference in average health}} =$$

$$\underbrace{E[Y_{1i}|D_i=1]-E[Y_{0i}|D_i=1]}_{\text{average treatment effect on the treated}} + \underbrace{E[Y_{0i}|D_i=1]-E[Y_{0i}|D_i=0]}_{\text{selection bias}}$$

- The term $E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] = E[Y_{1i} - Y_{0i}|D_i = 1]$: is the average causal effect of hospitalization on those who were hospitalized.
- This term captures the averages difference between the health of the hospitalized, $E[Y_{1i}|D_i = 1]$, and what would have happened to them had they not been hospitalized $E[Y_{0i}|D_i = 1]$

- The observed difference in health status however, adds to this causal effect a term called **selection bias**.
- This term is the difference in average Y_{0i} between those who were and were not hospitalized.
- Because the sick are more likely than the healthy to seek treatment, those who were hospitalized have worse Y_{0i}'s making selection bias negative in this example.
- The selection bias may be so large (in absolute value) that it completely masks a positive treatment effect.
- The goal of most empirical economic research is to overcome selection bias, and therefore to say something about the causal effect of a variable like D_i.

Random Assignment Solves the Selection Problem

- Random assignment of D_i solves the selection problem because random assignment makes D_i independent of potential outcomes. To see this, note that:

$$\begin{aligned} E[Y_i|D_i = 1] - E[Y_i|D_i = 0] &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] \end{aligned}$$

  where the independence of Y_{0i} and D_i allows us to swap $E[Y_{0i}|D_i = 1]$ for $E[Y_{0i}|D_i = 0]$ in the second line.

- In fact, given random assignment, this simplifies further to

$$\begin{aligned} E[Y_{1i}|D_1 = 1] - E[Y_{0i}|D_i = 1] &= E[Y_{1i} - Y_{0i}|D_i = 1] \\ &= E[Y_{1i} - Y_{0i}] \end{aligned}$$

- The effect of randomly-assigned hospitalization on the hospitalized is the same as the effect of hospitalization on a randomly chosen patient.

- The main thing, however, is that random assignment of D_i eliminates selection bias.

- This does not mean that randomized trials are problem-free, but in principle they solve the most important problem that arises in empirical research.

STAR Experiment

- Labor economists and others have a long tradition of trying to establish causal links between features of the classroom environment and children's learning, an area of investigation that we call "education production".
- A key question in research on education production is which inputs produce the most learning given their costs.
- One of the most expensive inputs is class size - since smaller classes can only be had by hiring more teachers.
- It is therefore important to know whether the expense of smaller classes has a payoff in terms of higher student achievement.
- The STAR experiment was meant to answer this question.

- The experiment assigned students to one of three treatments: small classes with 13-17 children, regular classes with 22-25 children and a part-time teacher's aide, or regular classes with a full time teacher's aide.
- Schools with at least three classes in each grade could choose to participate in the experiment.
- The first question to ask about a randomized experiment is whether the randomization successfully balanced subject's characteristics across the different treatment groups.
- To assess this, it's common to compare pre-treatment outcomes or other covariates across groups.

Table 2.2.1: Comparison of treatment and control characteristics in the Tennessee STAR experiment

	Students who entered STAR in kindergarten				
	Variable	Small	Regular	Regular/Aide	Joint *P*-value
1.	Free lunch	.47	.48	.50	.09
2.	White/Asian	.68	.67	.66	.26
3.	Age in 1985	5.44	5.43	5.42	.32
4.	Attrition rate	.49	.52	.53	.02
5.	Class size in kindergarten	15.10	22.40	22.80	.00
6.	Percentile score in kindergarten	54.70	48.90	50.00	.00

Notes: Adapted from Krueger (1999), Table 1. The table shows means of variables by treatment status. The P-value in the last column is for the F-test of equality of variable means across all three groups. All variables except attrition are for the first year a student is observed, The free lunch variable is the fraction receiving a free lunch. The percentile score is the average percentile score on three Stanford Achievement Tests. The attrition rate is the proportion lost to follow up before completing third grade.

- Differences in these characteristics across the three class types are small and none are significantly different from zero. This suggests the random assignment worked as intended.

- Because randomization eliminates selection bias, the difference in outcomes across treatment groups captures the average causal effect of class size (relative to regular classes with a part-time aide).

- In practice, the difference in means between treatment and control groups can be obtained from a regression of test scores on dummies for each treatment group.

Table 2.2.2: Experimental estimates of the effect of class-size assignment on

Explanatory variable	(1)	(2)	(3)	(4)
Small class	4.82	5.37	5.36	5.37
	(2.19)	(1.26)	(1.21)	(1.19)
Regular/aide class	.12	.29	.53	.31
	(2.23)	(1.13)	(1.09)	(1.07)
White/Asian (1 = yes)	–	–	8.35	8.44
			(1.35)	(1.36)
Girl (1 = yes)	–	–	4.48	4.39
			(.63)	(.63)
Free lunch (1 = yes)	–	–	-13.15	-13.07
			(.77)	(.77)
White teacher	–	–	–	-.57
				(2.10)
Teacher experience	–	–	–	.26
				(.10)
Master's degree	–	–	–	-0.51
				(1.06)
School fixed effects	No	Yes	Yes	Yes
R^2	.01	.25	.31	.31

Note: Adapted from Krueger (1999), Table 5. The dependent variable is the Stanford Achievement Test percentile score. Robust standard errors that allow for correlated residuals within classes are shown in

- The small-class effect is significantly different from zero, while the regular/aide effect is small and insignificant.