Class 5. Research designs

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Advanced quantitative research methods, API6319
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Establishing causal relationships

Hurdles along the route to establishing causal relationships

- Most of our interesting research questions involve trying to understand whether changes in one variable (X, the *independent variable*) *cause* changes in another variable (Y, the *dependent* variable). ($X \rightarrow Y$):
    - Does increased development aid *cause* increase in growth rates? (How much?)
    - Does more education *cause* higher incomes? (How much?)
    - Do smaller class sizes in primary school *cause* improved grades? (How much?)
- But establishing causality is difficult.

Establishing causal relationships is difficult

Probabilistic vs. deterministic relationships

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  - Turn on a switch $\rightarrow$ Light goes on (every time).
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- In contrast, cause and effect relationships in the social sciences are *probabilistic*.
  - Increase in gasoline prices $\rightarrow$ Some people purchase more fuel efficient vehicles. (Average fuel efficiency improves.)
  - Increase in micro-lending $\rightarrow$ Income of some women goes up. (Average income of women increases.)
  - Increase in development aid $\rightarrow$ Growth rate of some countries increases. (On average, growth rate increases.)
- We need to learn to think in terms of averages rather than anecdotes.

Establishing causal relationships is difficult

Multiple things affect outcome

- Almost all of our theories in the social sciences involve a *bivariate* relationship: one (independent) variable *causes* changes in another (dependent) variable
  - For example: The availability of micro-lending helps to raise the incomes of poor women
- In reality, there are many things that affect the dependent variable
  - For example: incomes of poor women depend on culture, education, government policies, etc.
- It is often difficult to isolate the causal relationship of interest from the web of relationships

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  - Fred's parents arrived late. It was a sunny day. Fred was angry.
- System 1 brain is "a machine for jumping to conclusions"
- We need to train our System 2 brain to carefully scrutinize System 1 conclusions, and avoid confirmation bias. Social scientists look for reasons to refute claims, not support them.

Hurdles to establishing causality

- We typically want to establish whether some variable X *causes* changes in some other variable Y.
- To do so, we need to carefully consider the answers to the following questions:
  1. Is there a credible causal mechanism that connects X to Y?
  2. Can we rule out the possibility that Y could cause X?
  3. Is there covariation between X and Y?
  4. Are there *confounding factors* X that might be responsible for the perceived covariation between X and Y?

Is there a credible causal mechanism that links X to Y?

- This logically about whether X could cause Y
- It is important to have some theory about why changes in X could cause changes in Y.
- It can be helpful to think through the *mechanism* via which the relationship takes place
- We want to avoid "shots in the dark" where we are mining data to find random relationships between variables (this is the domain of *machine learning* and not part of the *scientific method*)

Can we rule out the possibility that Y could cause X?

- In evaluating the claim that X *causes* Y, we will look at data to see if the two variables are related.
- One reason the two variables could be related is if X causes Y
- Another reason the two variables could be related is if Y causes X
- We need to distinguish between these two possibilities. Typically, there is no statistical test for claim, and we need to think it through logically.
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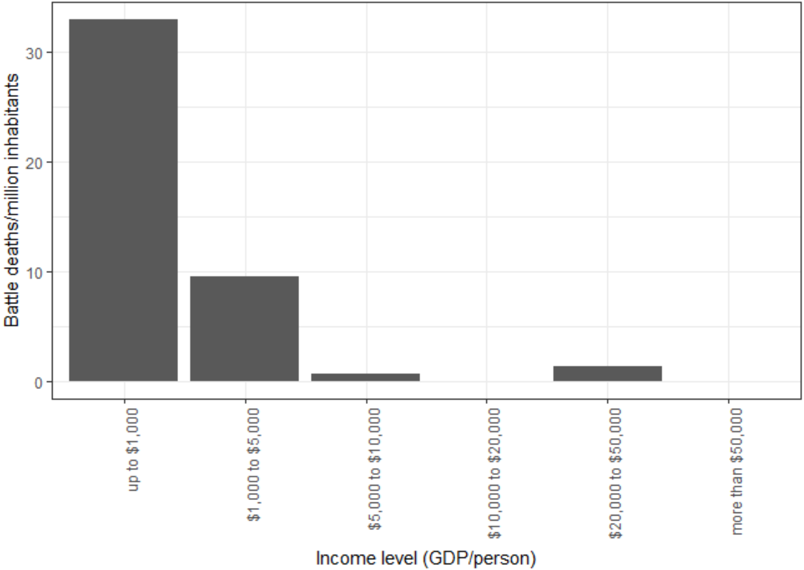
    - Example: Does paid parental leave improve infant health? Data on children's health from before and after parental leave policy

Deaths and incomes



Is there covariation between X and Y?

- In order to validate our theory about the causal effect of X on Y, we will collect data on these two variables
- We will learn how to implement statistical tests to see if these variables move together

  positive relationship More of X is associated with more of Y

  negative relationship More of X is associated with less of Y
- It is important to note that "correlation does not imply causation." However if there is a causal relationship between X and Y, the two variables will also be correlated.
- Sometimes another variable changes at the same time as X (call it Z). We may only observe correlation between X and Y once we "control for" Z.

Are there *confounding factors* X that might be responsible for the perceived covariation between X and Y?

- Our theories are typically *bivariate* - that is they relate a single independent variable (X) to a dependent variable (Y)
- In the real world, many factors can affect Y
- When we are looking for a relationship between X and Y, we therefore need to take account of these other factors. If we don't, our results will probably be misleading.
  - Example: we are interested in finding out if there is a relationship between education (X) and income (Y). We gather data on individuals from the Census, and find out the two variables are related. Is this evidence that education *causes* higher incomes?
- We will learn techniques for "controlling for" other variables in looking at a relationship between X and Y.

Establishing causality

- If one of the hurdles isn't passed, we need to be wary of claims that X causes Y.
- You need to think critically about research design, in your own work and when looking at that of others.
- We will be going through different *research designs* that can help us clear some of the hurdles.

Example 1: Do hospitals make people healthier?

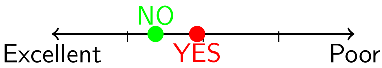
- Suppose we are interested in a causal question: "Do hospitals make people healthier?"
- We might think to answer this question by gathering data on groups of individuals that gone to hospital, and comparing to other individuals that have been in hospital.
- The 1991 wave of the General Social Survey asks two relevant questions:
    1. Did you spend any nights as a patient in a hospital nursing home or convalescent home during the last 12 months?
    2. Compared to other people your age, how would you describe your state of health? [1=excellent;5=poor]

Example 1 (con't)

- Taken at face value, the data in the table below suggest that spending time in hospital causes a deterioration in health outcomes.
- Is this plausible? What else might be going on? Think about four hurdles.

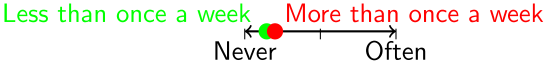
Time spent in hospital in last 12 months?	Mean self-reported health
YES	2.92
NO	2.37

Table: 1991 General Social Survey. [1=excellent;5=poor]



Example 2: Video games and violence

- Suppose we are interested in a causal question: "Does playing video games cause violent behaviour?"
- We might try to answer this question by comparing rates of fighting in kids that play video games with kids that don't play video games.
- The 1998-9 National Longitudinal Survey of Children and Youth asks two relevant questions (10-15 year olds):
  1. How often do you play video games?
  2. How often do you get into fights?
- Is this evidence that video games cause violent behaviour? (Think of four hurdles)



Examples

- Recall the four hurdles to establishing causality:
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  3. Recent college grads had a lower unemployment rate than their counterparts with only high school diplomas
  4. Evidence mounts that eating as a family can protect children from all sorts of harm, experts say

Police

Figure: Data on crime rates and police officers in 250 US cities.

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- Fundamental problem of causal inference: we can never observe the same person/country/etc. at the same time with different 'treatments'
- We need to design our research effectively. Effective research design rules out these competing explanations.

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- Effective research designs aim to satisfy the four hurdles that make it difficult to draw causal inferences.

Establish causal relationships by comparison

- We seek to understand whether some X *causes* Y.
- The obvious way to find out is to compare some individual with X to some individual without X and see how Y differs between the two individuals.
- Comparison is the basis for establishing our empirical understanding of causal relationships.
- Yet a simple comparison may be misleading, since it does not account for competing explanations.
    - Think of causal hurdles/fundamental problem of causal inference.
- Designing research effectively involves carefully specifying what type of comparison would be most useful.

Example: a simple comparison

- The data shows that higher access to electricity seems to be associated with better nutritional outcomes. Can we say that access to electricity causes better nutritional outcomes?

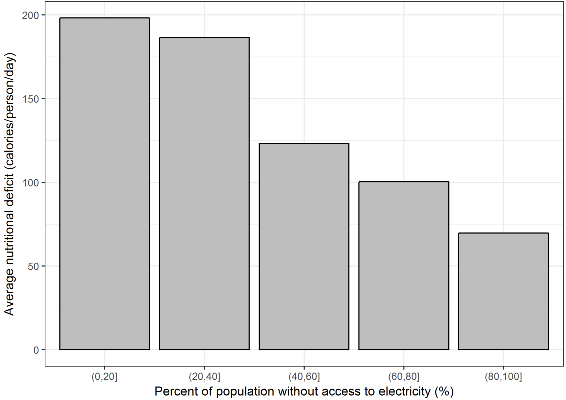

Figure: Based on data from World Bank for year 2010.

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- We need a research design that carefully considers these threats to validity

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  3. observes Y in the control and treatment groups. The difference is the causal effect of X.

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	Random assignment	Non-random assignment
Random sampling	Externally valid and internally valid	Externally valid but not internally valid
Non-random sampling	Internally valid but not externally valid	Not internally valid or externally valid

Experiments in medicine

- The conventional way to test new drugs and treatments is with a randomized controlled trial (RCT). Research question - is some new drug X effective at reducing some disease Y?
    1. Participants are recruited
    2. Participants are **randomly assigned** into two groups - a treatment group and a control group
    3. The treatment group is given the new treatment. The control group is given a placebo
    4. The two groups are compared (e.g., disease rates).
    5. The difference in outcomes (Y) is the effect of the treatment (X).
- The analyst controls who is assigned to treatment, and assigns treatment randomly.

Experiments in science

- The conventional way to test new scientific theories is with an experiment. Research question - does air pollution (X) lead to aggression (Y)?
  1. Get some rats.
  2. Rats are divided **randomly** into two groups - a treatment group and a control group.
  3. The treatment group is put in a room with elevated levels of pollution; the control group is put into another room that is otherwise similar.
  4. The behaviour of the two sets of rats is compared.
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- Can cash transfers eliminate poverty

Field experiments in social science: examples

Does micro-lending reduce poverty?

- Microcredit has generated considerable enthusiasm and hope for fast poverty alleviation.[1]
- In 2006, Mohammad Yunus (founder of Grameen Bank) and the Grameen Bank (micro-credit institution) were awarded the Nobel Prize for Peace, for their contribution to the reduction in world poverty.
- Yet there is substantial doubt as well: concerns about large profits made from the poor. Concerns about lenders pushing their clients to accept debt.
- How might we provide evidence to know whether micro-lending improves lives (e.g., reduces poverty)?

[1] See this study for more background.

Example: Does job micro-lending reduce poverty in Indian women?

- There is interest in knowing whether micro-lending can help reduce poverty
- Imagine that we collect data on two groups of women in India - some that have received micro-loans and others that have not. We compare poverty rates in these two groups. Does this comparison tell us about the causal effects of micro-loans on poverty?

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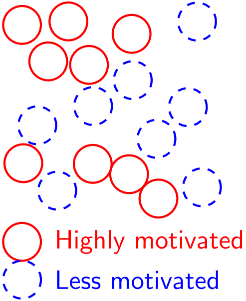
- Imagine that we collect data on two groups of women in India - some that have received micro-loans and others that have not. We compare poverty rates in these two groups. Does this comparison tell us about the causal effects of micro-loans on poverty?
    1. Is there a credible causal mechanism that connects X to Y?
    2. Can we rule out the possibility that Y could cause X?
    3. Is there covariation between X and Y?
    4. Are there *confounding factors* X that might be responsible for the perceived covariation between X and Y?
- This comparison is problematic especially because of confounding factors: there are likely to be other factors Z that influence poverty rates.
- One example is motivation (e.g., more motivated women more likely to apply for loan; less likely to be in poverty).

Randomized controlled trials vs. observational studies

Does job micro-lending reduce poverty in Indian women?



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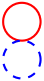
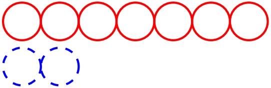


Highly motivated

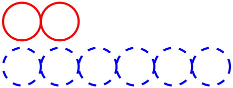
Less motivated

Observational study

Treatment group (micro-loans)



Control group (no micro-loans)



Problem: Highly motivated women select into micro-lending programs.

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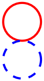

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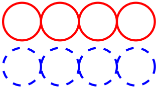
Experimental study

Treatment group (micro-loans)



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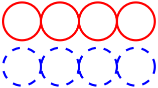

Solution: Micro-loans are randomized, so highly motivated women are just as likely to receive a micro-loan as not.

What did the experiment do?

The experiment was conducted as follows. In 2005, 52 of 104 poor neighborhoods in Hyderabad were randomly selected for opening of an MFI branch by one of the fastest-growing MFIs in the area, Spandana, while the remainder were not. Hyderabad is the fifth largest city in India, and the capital of Andhra Pradesh, the Indian state were microcredit has expanded the fastest. Fifteen to 18 months after the introduction of microfinance in each area, a comprehensive household survey was conducted in an average of 65 households in each neighborhood, for a total of about 6,850 households.

- After 12 months, we see no difference in monthly per capita consumption and monthly non-durable consumption. We do see significant positive impacts on the purchase of durables ... households have reduced expenditures on what that they themselves describe as "temptation goods."
- Fifteen to 18 months after gaining access, households are no more likely to be entrepreneurs
- For all but the largest businesses, there is no difference in the profits of the businesses... contrary to most people's belief, to the extent microcredit helps businesses, it may help the larger businesses more
- We do not find any effect on any of the women's empowerment or human development outcomes either after 18 or 36 months

Experiments as a solution to fundamental problem of causal inference

- Experiments help to solve the fundamental problem of causal inference
- Because the experimenter assigns the treatment (X) to the subjects (randomly), it is clear that Y did not cause X. If there is a relationship between X and Y, it must be because X causes Y.
- Because the experimenter assigns the treatment randomly, there is no systematic relationship between other variables (Z) and X.
- Z can be anything — we might not even know what Z is. A well-conducted experiment will still balance Z between treatment and control groups.
- Therefore, in a well-conducted experiment, comparing the dependent variable Y for subjects with different levels of X yields the causal impact of X on Y.

An example of an experiment

Blattman, C. and Dercon, S. More sweatshops for Africa?

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- Approach: Randomly hire applicants to sweathshops. Compare hired group with non-hired group.
- Result: Sweatshop jobs did not lead to improved wages, or increased likelihood of long-term employment.

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- Experiments often cannot tell us about *general equilibrium* effects (i.e., what would happen if we scaled up program to apply to everyone?)

Esther Duflo - fighting poverty with experiments

Video

Nature News on experiments and global poverty: article

Observational (non-experimental) studies

- Experimental research designs are limited to those in which the analyst can choose the treatment (X)
- This leaves out a large number of topics of interest in the social sciences
- For these other topics, we have to rely on observational studies to understand the effect of X on Y. An **observational study** is one in which the researcher does not manipulate the treatment (X), but instead just passively observes outcomes (Y) for subjects with different treatments (X).

Observational studies

- The basic idea of an observational study is the same as in an experimental study: the researcher *compares* the outcomes (Y) of individuals with different treatments (X). But now we have to be aware that:
  1. It is possible that even if there is a relationship between X and Y, it is not due to the effect of X on Y, but rather due to some other variable Z.
  2. It is possible that even if there is a relationship between X and Y, it is not because X causes Y but instead because Y causes X.
- For these reasons, we have to be cautious in conducting and interpreting results of observational studies.
- However, if we are careful about research design, observational studies can provide high-quality information about causal effects.

Observational studies can yield credible estimates of the causal effect of X on Y if done carefully

- Careful research design aims to rule out the possibility that Y causes X and aims to rule out the possibility that Y is caused by some other factor Z
- All studies are based on comparison of Y for different values of X
- It is necessary to design research in such a way that the comparison is fruitful in telling us about the causal effect of X on Y
- Researchers have developed a number of techniques for doing this
- All are focused on the *fundamental problem of causal inference*: it is not possible to observe the same subject at the same time in both treated and untreated states.

Some advanced observational research designs

A basic observational research design compares Y for individuals with different levels of X. This may lead to problems with interpretation (four hurdles). More advanced research designs try to get over these hurdles.

- Control for other variables/Multiple regression
- Natural experiment
- Regression discontinuity design
- Instrumental variable

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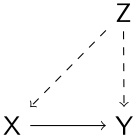
- When we learn *multiple regression* we will learn how to 'control for' confounding variables statistically.
- This is like looking for a relationship between X and Y in groups with similar Z

Controlling for other variables

- Suppose we suspect that the relationship we find between X and Y is actually due to a third variable Z



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$$\begin{tikzcd}
& Z \arrow[dl, dashed] \arrow[d, dashed] \\
X \arrow[r] & Y
\end{tikzcd}$$

- We can 'control for' Z. For example, we could look at the relationship between X and Y for different subsets of Z

Only with $Z = Z_1$

$$X \longrightarrow Y$$

Only with $Z = Z_2$

$$X \longrightarrow Y$$

Example: Flossing and oral health

Feeling Guilty About Not Flossing? Maybe There's No Need

- NY Times article claims that there is no (or only very weak) evidence that flossing improves oral health. As a result, US gov has stopped advising Americans to floss.

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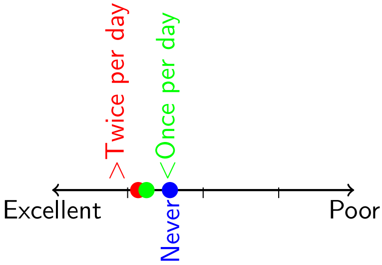
- Why not do an experiment on flossing?
- It is difficult to do randomized controlled trials on flossing—it is a long-term behavioural change; people may not stick with experimental protocol.

Example: Flossing and oral health

- But studies exist that link flossing to oral health. For example, in a recent Canadian survey[2] Canadians were asked about the state of their oral health and their frequency of flossing



- Is this evidence that flossing causes improved oral health? Why? Why not?

[2] Canadian Community Health Survey, 2009, Healthy Aging.

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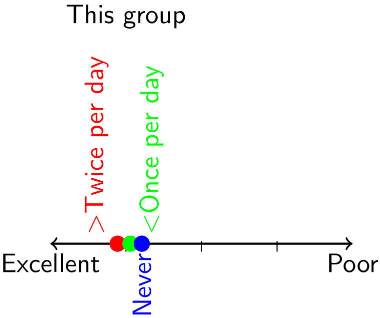

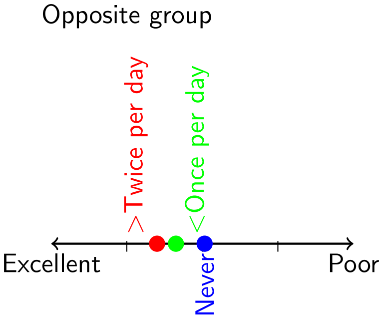

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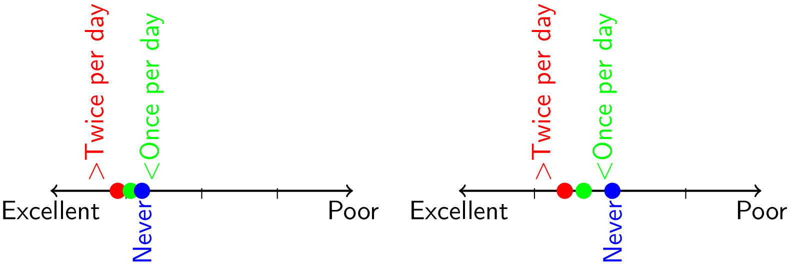
This group | Opposite group



- Have we eliminated all factors Z that could cause X? Can we?
- We can only 'control for' factors that we can measure. There may be other factors that we can't measure that confound the relationship between X and Y.

Does Y cause X?

Does oral health cause flossing?

- We are interested in testing whether more flossing causes improved oral health
- We do so by looking for a relationship in the data between oral health and flossing
- But the presence of a relationship could imply that differences in oral health are responsible for differences in flossing, not the reverse
- Our approach that controls for Z does not shed any light on the direction of causality. (in this case)

Multiple regression

- Later in the course, we will cover multiple regression.
- This is a formal statistical tool for "controlling" for other variables when drawing a conclusion about the link between X and Y
- Similar in concept to stratifying the sample, as described above.
- Same strengths and weaknesses as above:
  - We can control for other variables that we think might confound the relationship between X and Y if we can measure them.
  - We can't control for things that we can't measure or can't observe
  - We still need to be concerned about reverse causality.

Other observational research designs

- Regression discontinuity
- Matching
- Synthetic control
- Natural experiments
- Instrumental variables

Two good resources:

- Scott Cunningham. Causal inference: The mixtape. https://www.scunning.com/mixtape.html
- Angrist and Pischke. Mastering Metrics.

Wrapping up

- Any time we evaluate a study (or propose our own), we need to develop a *research design* that is capable of providing an estimate of the causal effect we are interested in
- Four causal hurdles
- Experiment - gold standard
- But all is not lost if we can't do an experiment
- Just need to think carefully about how our observational study may be compromised
- In any case, an experiment is a useful benchmark - think like an experiment.
- Beware country-level studies. Why?