PS6 Lecture 8

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Agenda

- Causation
  - Association versus causation
  - Conditions for causation
- Statistical control
  - In an experimental context
  - Limitations

Thinking about causation

We've been looking at the relationship between year (i.e. time) and GDP/cap.

- does this mean that we think time **causes** changes in GDP/cap?
- if not, why is it that we observe a strong positive relationship between time and GDP/cap
- further, what does it mean for something to **cause** something?

Some vocab

We think about relationships as occurring between an outcome variable and 1 or more explanatory variables.

dependent variable: aka DV, response variable. The *outcome* we are interested in.

independent variable: aka IV, explanatory variable. The thing causing changes in our outcome of interest.

These ideas will be further elaborated on once we start learning about statistical regression.

Association v. causation

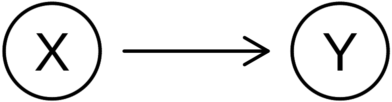
- Just because we observe correlation between 2 variables does not mean X causes Y.
- There are several potential explanations for why we observe some bivariate relationship.
- Some are 'causal' in the way we commonly think about it, while others only look the part.
- The deciding factor is theory.

Explaining observed association

There are at least 4 possible explanations for observing association between 2 (or more) variables:

- causation
- common response
- confounding
- chance

Causation



Causation

Causation is what we usually want.

- In statistical analysis, we tend to think of causation as "if X occurs, the probability of Y occurring is increased."
- an alternative is to use the **counterfactual** framework: "X occured, and as a result, Y *necessarily* occured. Further, if X hadn't occurred, Y would also not have occured."

Example: causation

I eat a hamburger (X) which causes me to feel full (Y)

X: amount of food I eat

Y: how hungry I am

Seems self-evident that X causes Y. . . but in the real-world is it necessarily true?

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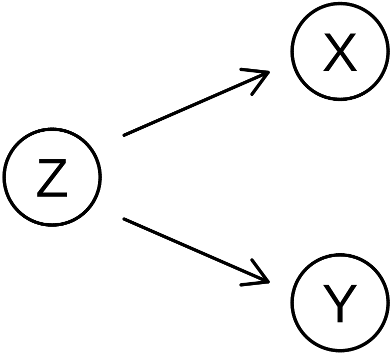
counterfactual: If I hadn't eaten that burger, would/could I still feel full?

Common response



Common response

In the **common response** scenario, a **lurking variable** affects both our purported IV and DV.

- **lurking variable:** a variable extraneous to the association we are focusing on (AKA unobserved/latent variable)
- We observe a relationship between X and Y because Z (the lurking variable) simultaneously affects both.
- In effect, the real IV is Z, and both X and Y are DVs with respect to Z.

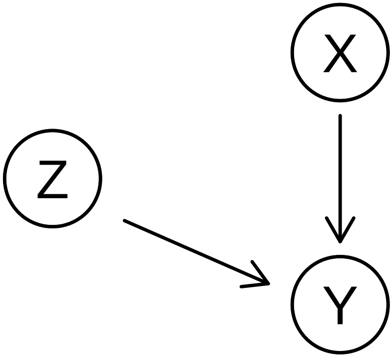
Example: common response

- I observe that my hunger level (Y) is associated with the amount of money I have in my wallet (X)
- Does this mean that X causes Y?

Example: common response

- I observe that my hunger level (Y) is associated with the amount of money I have in my wallet (X)
- Does this mean that X causes Y?
- Nope. We haven't accounted for Z: how much food I purchased and ate. Z is a lurking variable that causes both X and Y

Confounding



Confounding

When 2 variables are **confounded**, it's not possible to distinguish whether it's X or Z that causes changes in Y.

- the core issue is that X and Z share some kind of relationship that we have not accounted for in our analysis
- both X and Z may be affecting Y but it's not possible to assess the *extent* of each effect
- confounding can occur between a purported IV and an unobserved variable, or 2 (or more) IVs

Example: confounding

I often eat fast-food hamburgers (X) which causes me to gain weight (Y). However, my laziness, which motivates my dietary choices also keeps me from exercising as much as I should. My lack of exercise (Z) also increases my weight.

X: amount of food I eat

Y: amount of weight gain

Z: how much I exercise

Example: confounding

- We cannot tell whether it's my lack of exercise or my dietary choices that leads to weight gain.
- If we don't consider exercise, we could mistakenly attribute weight gain to diet when in fact, lack of exercise is also responsible.
- *Dietary choice is confounded by amount of exercise*.

We want causation. What conditions must typically be met to show that it's causation and not something else?

- temporally appropriate
- plausible argument
- valid counterfactual
- alternate explanations

Temporally appropriate

- X must have occurred before Y (duh).
- if there is some time dependent component to your explanation of the cause, the appropriate pattern must be observed

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- Cohort born immediate after RvW would have entered primo-criminal age in early 1990's.
- Roe v. Wade shrank disadvantaged portion of this cohort, so we observe decreasing crime rate in early 90's

- RvW (X) does occur before ↓ crime rate (Y)
- . . . but the theorized causal relationship would still not be supported if gap was not of appropriate size
- **Timing is key.**

Plausible argument

There must be a *plausible* argument that X causes Y

- typically a matter of common-sense.
- if there is some lengthy process leading X to cause Y (there usually is), it must be broken down into small enough steps such that each step is self-evident.

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On its own, each step is pretty "duh." In combination, they lead to a surprising conclusion and explain why we believe X causes Y.

Valid counterfactual

Assume we observe X occurs before Y, and there is a plausible explanation for how X causes Y.

- Does this mean X actually causes Y? **Not necessarily.**
- What if increase in X is associated with increase in Y, but decrease in X does NOT decrease Y?

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For X to cause Y, we must see $\Uparrow X \rightarrow \Uparrow Y$ AND $\Downarrow X \rightarrow \Downarrow Y$

E.g.: shortly after stimulus law, economic growth increases. Policymaker would have us believe law caused increase in growth

- temporally appropriate? Yep
- plausible enough? Sure

If the law had NOT been passed, would economic growth NOT have increased? If the answer is no (i.e. growth would have increased regardless), stimulus was probably not the cause[1].

[1] *How* we'd actually answer the question is a topic for a more advanced class.

Alternate explanations

Are there other explanations that would explain observed pattern?

- alternate explanations may eliminate yours
- they may be valid in addition to your explanation
- one of most common critiques of new theories in social science

Let's continue our stimulus example. What else could explain increased econ. growth?

- cyclicality
- a different policy
- socio-cultural change
- etc. etc.

- List can grow ad nauseam.
- Typically, it suffices to *account* for most commonly accepted alternate theories.
- **So how do we account for alternate explanations in our data analysis?**

Control

To account for alternate explanations, we **control** for them.

- Process for *holding constant* factors other than the one we are interested in
- Can be done at the time data are collected as well as when they are analyzed

Another concept that is easier to understand through illustration – we'll look first at control when data are collected

Suppose you wish to assess impact of a weight loss pill

Attempt 1:

- Give pill to 20 individuals
- Observe that, on average, they all lose weight
- Conclude the pill is effective

What's wrong here?

Problems:

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In attempt 1, we cannot answer any of these questions because we have not *controlled* for them.

Attempt 2:

- Increase participant pool to 40.
- Allow 20 participants to volunteer to take actual pill (i.e. treatment).
- Give placebo to remaining 20 (i.e. control).
- Observe that, on average, group given actual pills lost more weight than group given placebos.
- Conclude the pill is effective

Better, but still problematic.

- We've *tried* to address concern 1 (viz. would loss have occurred regardless the pill) by comparing people who took pill against those who did not
- . . . but what if some other factor were at play?

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e.g. the 20 who volunteered to take the pill are generally more serious about weight loss, so *on average*, they exercise and diet more effectively

Attempt 3:

- Choose 20 participants *at random* and give them actual pill.
- Give placebo to remaining 20.
- Everything else the same

Better.

Assigning participants at random ensures that the mix of people...

- on different diets,
- of diff. sexes
- with diff. beginning weights
- etc.

...is **the same on average** between the groups

- After randomization, the only difference between control and treatment groups *on average* is the pill.
- Because the pill is the only difference *on average*, we can attribute any changes in weight to the pill
- ...so with this design, we address the first concern (viz. weight loss would have occurred regardless the pill)

What about *other* alternative explanations?

- diet
- exercise regimen
- other medications

What would we need to do to control for these other factors?

To control for diet, examine following groups...

	control	treatment
diet		
no diet		

We'd need compare each cell against others; e.g.:

	control	treatment
diet	-5	-17
no diet	+1	-8

The diet group loses 12 more pounds with treatment, while the control group loses 9. We'd conclude that medicine is overall effective, but even more so with diet.

To control for diet & medication, examine following groups. . .

	no meds		meds	
	control	treatment	control	treatment
diet				
no diet				

To control for diet, medication, & exercise, examine following groups. . .

		no meds		meds	
		control	treatment	control	treatment
no exercise	diet				
	no diet				
exercise	diet				
	no diet				

- Each cell requires sufficient observations to keep std. error manageable
- We used limited number of categories for alt. explanations, but easy to imagine more categories which would increase number of cells, each requiring observations
- Observations cost resources
- Easy enough to see trouble in the offing

Takeways from this example

- Control at time of collection is useful but limited
- This was an experimental setting where we had complete control over our observations but...
- ...in social science, we often do not have such control

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If no to all (as is typical), where does that leave us??