POLS 205 Political Science as a Social Science

Evaluating Causal Theories

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Outline

Defining correlation & casusation Writing causal theories as models

Testing causal theories



http://xkcd.com/552/

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 - This is FALSE. Correlation may not be sufficient evidence to conclude causation, but it is a clue!

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Can we test this hypothesis?

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- Causation is directional. $X_i \Rightarrow Y_i$ does not imply $Y_i \Rightarrow X_i$

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Suggests we need a lot of observations to study causality

Correlation examples



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How can we solve this problem? Compare countries with similar ex ante debt levels: Control for debt

A simple causal model

Regular Exercise What is the causal relationship here?

Health
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> What is missing from this path diagram?







(why?)







Х

A simple causal model



In most path diagrams, we will leave out random effects to reduce clutter

What other variables might fit this pattern?

arm length

genes

What is the causal relationship here?

leg

length

arm length

genes

What is the causal relationship here? length Which variables are correlated?

leg













per capita gross domestic product Female education

> What is the causal relationship Fertility here? rate

per capita gross domestic product

Female education

> What is the causal relationship Fertility here? Which variables are correlated?

rate

Chris Adolph (UW)











Democratic Governor

Democratic Legislature What is the causal relationship here?

Welfare

Spending

Democratic Governor

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Which variables are correlated?





Effect of Democratic governors depends on party in control of leg, & vice versa

Welfare might stay low unless Democrats have united control







Campaign Contributions

> What is the causal relationship Expected Vote Percentage

Campaign Contributions

> Expected here? Vote Percentage Which variables are correlated?

Reciprocal Causation



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Can we think of other variables that have a reciprocal causal relationship?













If Party ID and ideology mutually cause each other for subjects, they should mutually cause for parents

Any other missing arrows?











Income a likely cause of subject's income Parents' Income should shape Parents' Ideol. & Party ID

Parents'

Other missing variables?



How about subject's Education? (Is this a simple relationship?)

Are we missing any arrows?



Lots: Education should influence income, ideology, and Party ID

You can probably guess the last variable in our diagram



Once again, we include the parents' characteristics

What happens if we omit?

Misattribute effects of parental education!



What's causally related in this diagram?

What is (and isn't) correlated?

How do we test causal theories?

To tease out the difference between correlation & causation, we'll need some notation:

Definitions	
Y _i	dependent variable observed for case <i>i</i>
Xi	treatment variable, as assigned for case <i>i</i>
Z _i	a confounding variable for case <i>i</i> ; it may or may not be observed
E(A B=b)	expected value of A when $B = b$

Correlation redux

Finding whether two variables are correlated is easy

Simple formula for correlation (we'll discuss at much greater length when we get to quantitative methods):

$$\operatorname{corr}(X, Y) = \frac{\operatorname{E}\left((X - \operatorname{E}(X))\left(Y - \operatorname{E}(Y)\right)\right)}{\sqrt{\operatorname{var}(X)}\sqrt{\operatorname{var}(Y)}}$$

where

$$\operatorname{var}(X) = \operatorname{E}\left(\left(X - \operatorname{E}(X)\right)^{2}\right)$$

Finding whether two variables are causally related is hard

Correlation examples



Fundamental problem of causal inference

Average causal effect of
$$X_i$$
 on $Y_i = E(Y_i|X_i = 1) - E(Y_i|X_i = 0)$

In words, the effect of X_i is the difference between Y_i when X_i is present and Y_i when X_i is absent

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But we only ever observe one of these!

The other is *counterfactual*, and can only be estimated

Why are we taking expectations? Because there is random noise around each case We're interested in the *average* causal effect, which removes the random noise

Fundamental problem of causal inference

Would the economy be better or worse had Obama and the Democratic Congress not implemented last year's stimulus package?

If we could rerun time like a tape (er, DVD? Blu-Ray? Video file?), we could change X_i for the same unit and see the change in Y_i

That is, we could remove the stimulus package, and track unemployment over the last year

Lacking a time machine, and the power to change history, FPC is unsolvable

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- Points to importance of controls for selection process in observational studies

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Unit homogeneity is at least partly testable with enough data

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May solve, but never certain. Similar vulnerabilities as Matching.

Can we imagine applying these methods to the effectiveness of Keynesian stimulus?



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