cause

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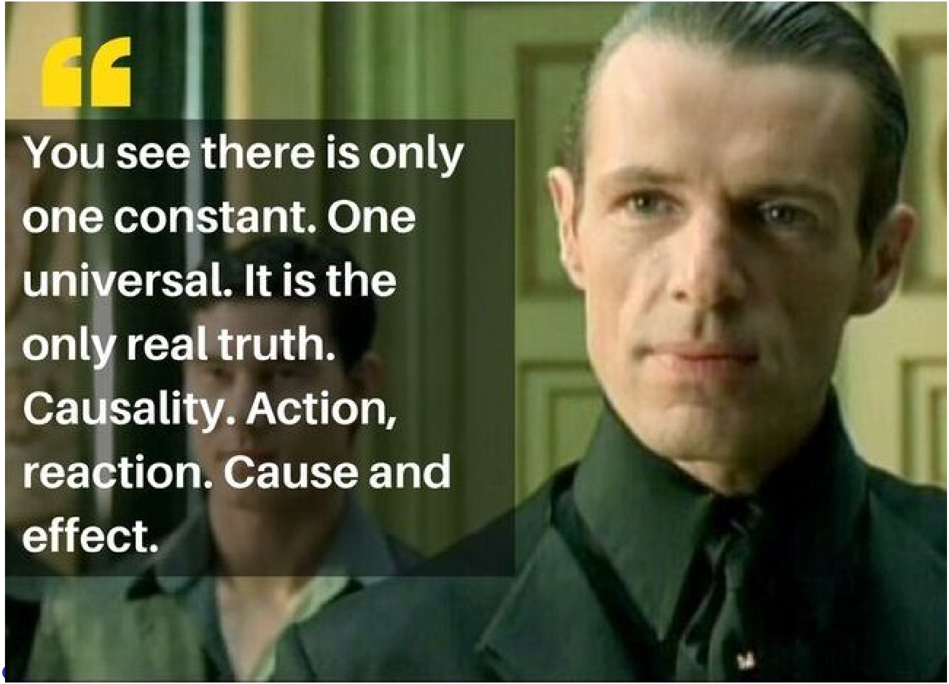
outline

[*] (elements of) research design: causality

endogeneity

ivreg

did


"
You see there is only one constant. One universal. It is the only real truth. Causality. Action, reaction. Cause and effect.

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research design

- bad res des doesn't violate ols assumptions
- but without some res des can't have causality
- causality is acheived with design, not stats (incl ols)!!
   - sure getting closer to it with multiple regressions, but cannot really get there with much confidence
   - multiple regression results themselves (without design or at very least much thought given to causal mechanism), are about as good as an educated guess

research design is a class itself

- here just few things that will be important for this class
- a quick, useful and applied reference is
  http://www.socialresearchmethods.net/kb/design.php
- a more in-depth treatment is Lawrence B. Mohr, Impact Analysis for Program Evaluation
  books.google.com/books?isbn=0803959362
- also see https://methods.sagepub.com/ eg can search 'causality'
  - (guess have to be on campus/vpn for free access)

causality

- much of research design is about causality
  - want to show X $\rightarrow$ Y
- correlation is necessary for causality
- but not sufficient
  - many correlations just by chance: `tylervigen.com`

INUS condition (Mackie, 1980)

- a useful way of thinking about causality: Insufficient but Non-redundant part of Unnecessary but Sufficient Condition
- many, if not most causes are INUS conditions
- eg a cigarette as a cause of forrest fire
  - it's Insufficient, because by itself it is not enough, eg you also need oxygen, dry leaves, etc
  - it is contributing to fire, hence Non-redundant
- and along with other stuff (oxygen, dry leaves etc) it constitutes Unnecessary but Sufficient Condition
  - it's not necessary for fire, it can be lightening, etc
  - but it's sufficient – it's enough to start the fire

basic concepts

- Y, DV, outcome
- X, IV, predictor
  - (T: (treatment), like X)
- Z: some other variable
- want to show $X \rightarrow Y$ (X affects (causes) Y)
  - and not the other way round ($Y \rightarrow X$)
  - and not $Z \rightarrow Y$; eg X(CO_2),Y(temp), Z(sun temp)
  - it is difficult to argue! (lots of Zs)
  - there are unknown unknowns (Zs we're unaware of)

The Problem: Unknown Unknowns

- known knowns: things we know that we know ($inc \rightarrow swb$)
- known unknowns: things that we now know we don't know ($genes \rightarrow swb$)
- unknown unknowns: things we do not know we don't know ($??? \rightarrow swb$)
- how do we deal with unknown unknowns?
- an experiment!

The Problem put another way: Counterfactual

- it all boils down to comparing:
  what happened to what would have happened had the treatment not happened
- eg got a new teacher and now kids perform better on SAT
  - to know whether the teacher caused better performance we would need to know what would have happened to SAT scores without this teacher (scores might have gone up due to Z (better book, students, etc)
  - and compare it to what actually happened

The Problem put another way: Counterfactual

- the problem is that we do not observe counterfactual (we can try to infer it though)
- counterfactual is the effect of all knowns/unknowns (incl. unknown unknowns)
- how do we deal with lack of counterfactual
- do an experiment!
- (or if you cannot, try to estimate it somehow)

the gold standard [need IRB]

- the experimental design eg med trails, MTO
- only here can confidently argue causality
- and it is because randomization takes care of the known and unknown predictors of the outcome
  - (draw a picture of 2 groups of people)
  - in other words, experiment establishes a counterfactual
- but mostly can't do it: unethical, politically incorrect etc eg can't randomly assign kids to bad school, smoking etc

`http://www.socialresearchmethods.net/kb/desexper.php`

internal validity

- internal validity is about causality
- you have internal validity if you can claim that X causes Y
  - eg some drug X causes some disease Y to disappear
  - http://knowledge.sagepub.com/view/researchdesign/n43.xml#n43
  - http://knowledge.sagepub.com/view/researchdesign/n192.xml#n192

threats to internal validity

- history, maturation, regression to the mean
  - something else happened that caused Y
  - things develop over time in a certain way
- selection bias, self selection
  - does smoking causes cancer?
  - maybe less healthy people select to smoke?
  - and other stuff goes with it: junk food, no exercise, etc
  - very few hit gym, eat organic, and enjoy Marlboro
- http://knowledge.sagepub.com/view/researchdesign/n192.xml#n192

spurious correlation

- you think that X causes Y, but actually it is Z
- global warming:
  - we have it–we can measure temperature
  - but what's the cause: CO_2 or Sun activity?

reverse causality

- related to spurious correlation
- here, instead of some other Z that causes Y instead of X
- we have Y causing X, as opposed to X causing Y
- eg my "Luxury car owners are not happier than frugal car owners"
  - not necessarily that luxury car makes you less happy than frugal car
  - it may be unhappiness causing shopping; if you are unhappy, you go shopping

reverse causality OR chicken-egg dilemma

- you may try to find some other X that measures the same or similar concept and that cannot be caused by Y
- eg instead of education $\rightarrow$ wage; do father's education$\rightarrow$ wage (your wage can reverse cause your education, but not your father's education)
- find some exogenous (external) shock: policing$\leftrightarrow$crime
- but terror attack/alert $\rightarrow$policing$\rightarrow$crime: then we know that policing$\rightarrow$crime; not the other way round
  - https://www.jstor.org/stable/10.1086/426877
- or dating and happiness–which comes first?
  - dating can cause happiness
  - but also happiness can cause dating: happy folks more likely to be dated!

natural experiment

- again most of the time you cannot have an experiment
- but there are natural experiments or exogenous shocks
- exogenous meaning that they are caused externally (like an experimenter's randomization) and somewhat randomly (at least with relation to a problem at hand
  - eg earthquake (any weather, eg storm); terrorist attack; policy change (less random)
- in model simply have dummy for U/As affected by storm, policy etc

causality without experiment?

- yes! well maybe but need to do some serious thinking
  - (INUS, endogeneity, etc)
- essentially you want to exclude alternative explanations
- so you act like a devil's advocate
- try to abolish your story / find an alt explanation
- if you cannot find any, then your story is right
  - until disproved
  - use regression and "control" for other vars BUT in addition do the thinking! (like today)
- there are some designs that improve our inference greatly over having no design at all (ex post facto, observational)

ex post facto: $X_1 Y_1$ (very common; *no* design)

- non-experimental, cross-sectional, observational, correlational; you'll most likey do this
- we start investigation "after the fact"
- no time involved, don't know whether X precedes Y
- both, X and Y are observed at the same time examples?
  - (but X must precede Y in order to be causal)
- practically impossible to argue causality here
- but cheap and big N, and good external validity
- still many "causes" discovered using ex post facto
- eg smoking→cancer was found out using ex post facto
- and then confirm using better designs
- http://knowledge.sagepub.com/view/researchdesign/n145.xml
- http://knowledge.sagepub.com/view/researchdesign/n271.xml#n271

before-after (pre-post) (OR treatment-control)

- measured Y, then do X, and then measured Y again
- eg measured readership at the library, buy some cool stats books; measured readership again
- eg measured crime rate, put more police on the streets; measured crime again
- eg measured soup consumption, changed soup; measured soup consumption again
- anyone did pre/post? eg working at school?
  - tried new programs, new approaches?
  - or simply pre-post without T, say to identify highest and lowest gain students

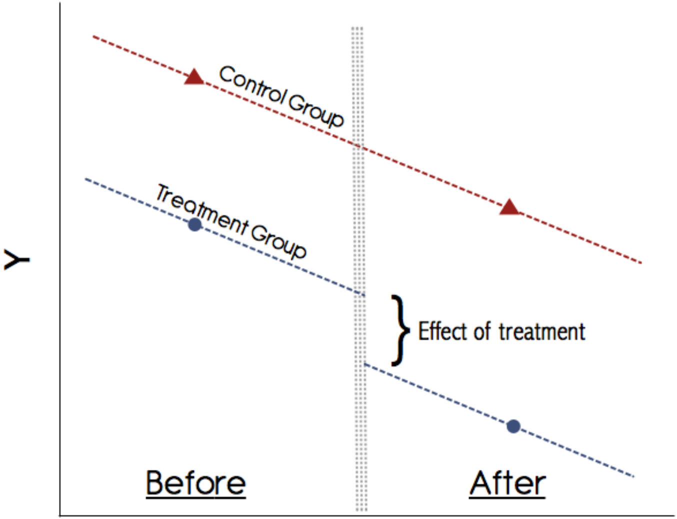
(2 group) comparative change: $\frac{Y_{E1} X_2 Y_{E3}}{Y_{C1} \quad Y_{C3}}$

- eg H_0 : police with better guns fights crime better
- 2010 measured crime in Camden (Y_{E1}) and Newark (Y_{C1})
  - 2011 give super guns to Camden cops (X_2), (not Newark)
  - 2012 measured crime in Camden (Y_{E3}) and Newark (Y_{C3})
- if crime dropped more in Camden than Newark: super guns worked
- stata: see so called DID http://www.princeton.edu/~otorres/DID101.pdf

DID (Difference In Difference)

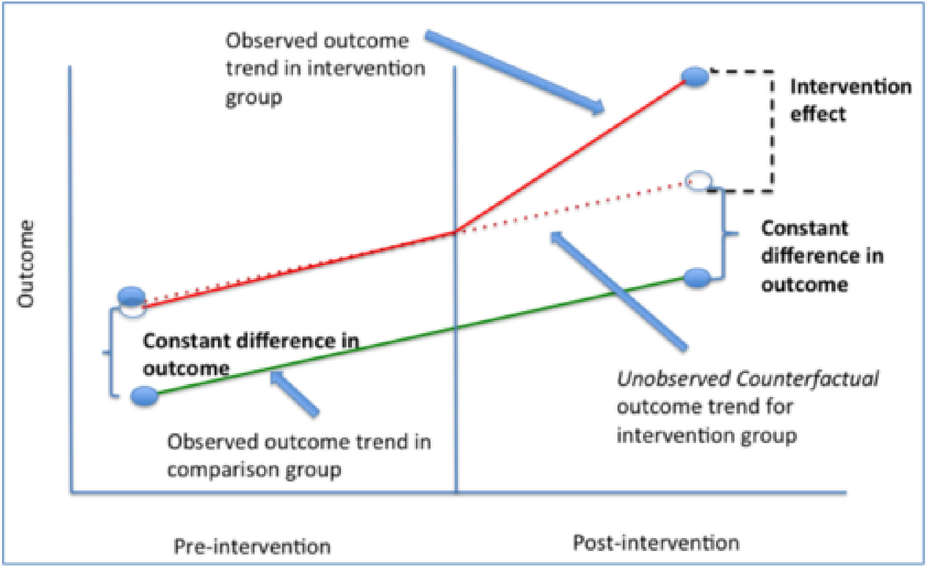
- just 'before after' with a comparison group
- did sth to one group, and not to the other group
  - over time (pre post) see if there is any difference

DID

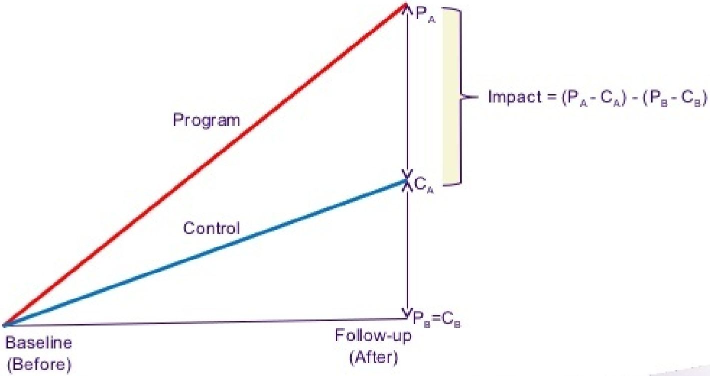

Control Group
Treatment Group
Y
Effect of treatment
Before
After

-

DID


Observed outcome trend in intervention group
Intervention effect
Outcome
Constant difference in outcome
Constant difference in outcome
Unobserved Counterfactual outcome trend for intervention group
Observed outcome trend in comparison group
Pre-intervention
Post-intervention

Illustrating Difference-in-Difference Estimate of Average Program Effect



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regression discontinuity analysis

- use when some rigid cutoff, say:
  - remedial program for F grades
  - prison sentence for a crime
- compare those who just barely made it (C-, or a ticket)
  - v those who didn't (F, prison)
- the cool thing is that the two groups are similar, especially:
  - not really any difference whatsoever with respect to cause of treatment!
  - so the treatment is arbitrary (random), so we have experiment! (kind of)

example: minorities in workforce

- new jersey state government workforce profile 2010
- `http://www.nj.gov/csc/about/publications/workforce/pdf/wf2010.pdf`
- p37: minorities in state govt over time
- how increase internal validity, eg say:
  - some program to recruit minorities $\rightarrow$ minorities empl
- compare to PA, DE, NY etc
- factor in minority population; applications
- do experiments! many already done! again, read lit
  - say people with black names apply for jobs
  - students with Asian names email professors
- and both, employers and professors discriminate against

tacit knowledge is the key

- if you know sth about state govt
  - you know that it is concentrated in Trenton
- hence, the key is population characteristics around Trenton!
- i did study on SJ not knowing anything about it
  - and misinterpreted many liquor stores/pc for much drinking/pc (by locals) (and its tourists!)

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closely related to design!

- if you have bad design, you'll have endogeneity
- curiously, economists are obsessed with it
- but other fields aren't
- a superb and readable reference is Sorensen (2012)

  `http://people.bu.edu/tsimcoe/code/Endog-PDW.pdf`

what is it

- technically, if x and error term are correlated
- so there is some Z that predicts Y and correlates with X
- so it can be just LOVB, or unobserved heterogeneity
- unobserved heterogeneity: Rumsfeld's unknown unknowns

simultaneity and self-selection

- but usually by endogenity we mean bigger problems
- simultaneity and self-selection
- and they are bigger problems because no amount of control vars helps!
- simultaneity not only $X \to Y$ but also $Y \to X$
  - could do Granger causality or IV
- but best do an experiment, or natural experiment
- think deeply about the relationship between X and Y
- one of the best ways to think deeply, i think, is to use INUS condition

the bottom line

- the bottom line is that in experiment U/As are assigned to levels of X at random
- think about whether that is the case in your study (after controlling for other Xs)
- or at least if that's the case to large degree
- you want to think about selectivity and self-selection early in the process: at the research design stage
- think about **source of variability** in X
  - or data generating process as pol sci would put it

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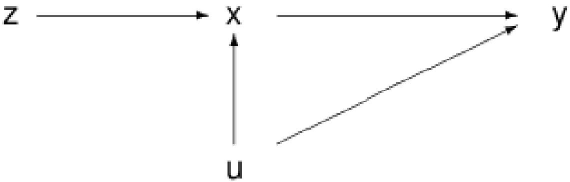
not so great / i dont like it

- indeed, beware: cure may be worse than disease
- often/usually doesnt make sense
- mostly used by economists; rare outside of economics
- some IV make sense especially if just lagged eg endogenous wage is instrumented with wage lagged; or person's education with father's education

educ$->$wage

- 

- but in error term u there may be stuff like iq that predicts wage but correlates with educ
- so eg instrument educ with father's education
- [*] http://fmwww.bc.edu/GStat/docs/StataIV.pdf

  https://www.stata.com/meeting/13uk/baumUKSUG2007.pdf baum is usually good

gellman's approach

- "find the IV first" approach cleaner: in this story, all causation flows from the IV
  https://statmodeling.stat.columbia.edu/2009/02/09/where_do_instru/
- "think of (T,y) as a joint outcome"
- https://statmodeling.stat.columbia.edu/2009/07/14/how_to_think_ab_2/
- [*] and then there is economist perspecitve
  https://www.aeaweb.org/articles?id=10.1257/jep.20.4.111

gellman's trick: think of (T,y) as a joint outcome

- z = iv, T = treatment, y = outcome
- causal model: z $->T->y$
- trick: think of (T,y) as a joint outcome
  - and think of the effect of z on each
- eg, an increase of 1 in z is associated with an increase of 0.8 in T and an increase of 10 in y.
- usual IV summary is to just say the estimated effect of T on y is 10/0.8=12.5
  - but rather just keep it separate and report the effects on T and y separately
- helpful to go back and see what i've learned from separately thinking about the corr(z,T), and corr(z,y)–that's ultimately what IV anal is doing

learn by example

- like with everything else probably most productive is to learn by example in your area
- ie find IVs in your/related research area
  - eg i found some happiness papers
    https://www.sciencedirect.com/science/article/pii/S0167487017302283
    https://www.sciencedirect.com/science/article/pii/S0014292113001232
- and now i have an idea for IV in my research:
  - use psid and IV urban with urban last wave
  - gss and IV with place size when 16
  - heck maybe even farm/fishery/forestry etc empl in gss [nah doesnt correlate with urbanicity for some reason]

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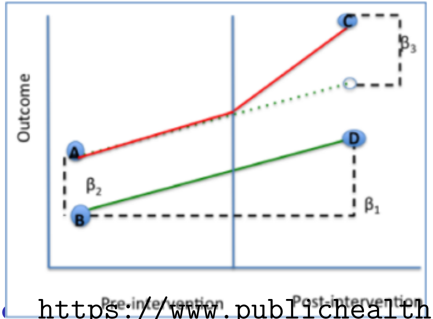
$$Y = \alpha + \beta_1 T + \beta_2 G + \gamma_1 TG \tag{1}$$

=treatment time

G=treatment group

$$Y = \beta 0 + \beta 1 * [\text{Time}] + \beta 2 * [\text{Intervention}] + \beta 3 * [\text{Time} * \text{Intervention}] + \beta 4 * [\text{Covariates}] + \varepsilon$$

Coefficient	Calculation	Interpretation
β_0	B	Baseline average
β_1	D-B	Time trend in control group
β_2	A-B	Difference between two groups pre-intervention
β_3	(C-A)-(D-B)	Difference in changes over time



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