Causal inference from observational data

SICSS

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We can’t all be experimentalists

- Ethics
- Cost
- Omnipotence
- Time

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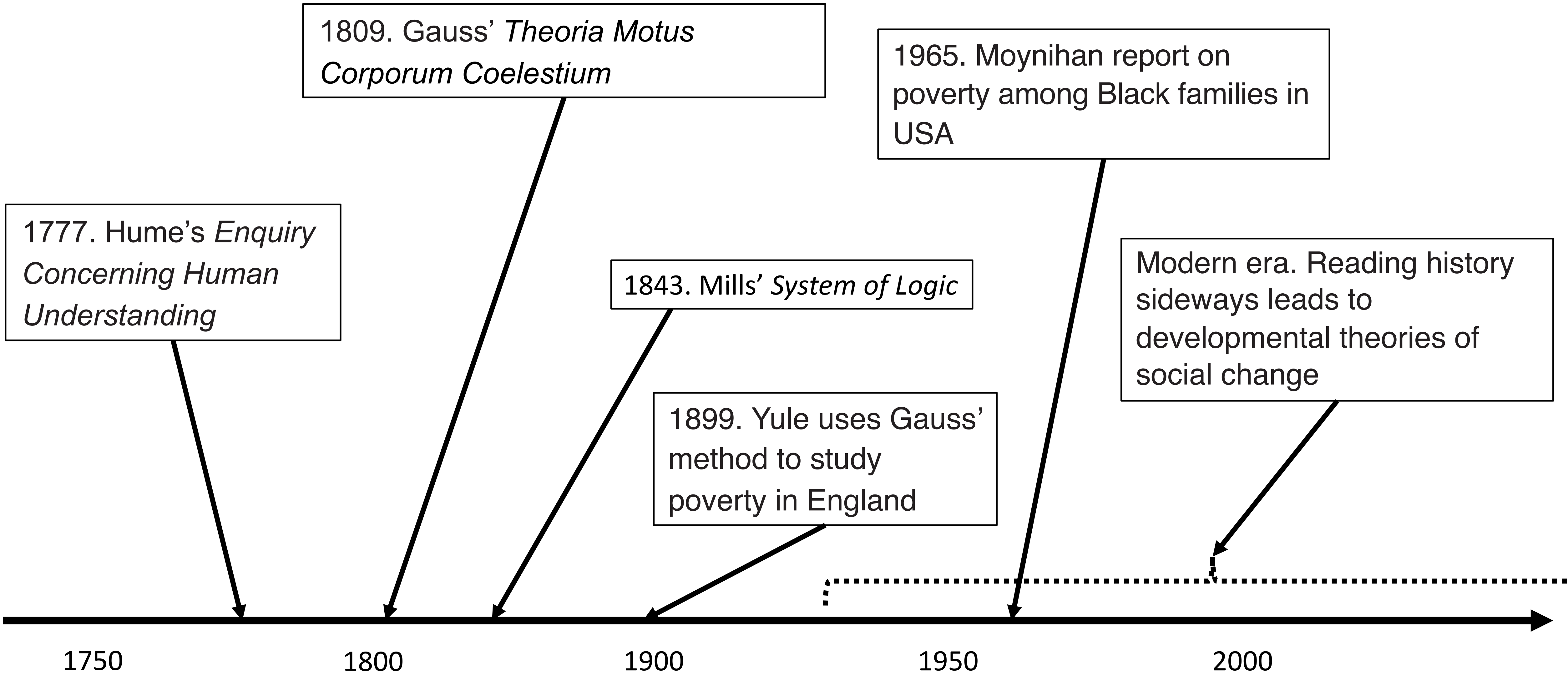
But we can all analyze data

- Traces
- Registries
- Administrative
- Surveys

So many ways to go wrong

- Sample selection on dependent variable
- Conditioning on exogenous variable
- Correctly addressing colliders
- Confounding
- Selection
- Measurement error
- Simpson’s paradox
- Ecological fallacy



1809. Gauss' *Theoria Motus Corporum Coelestium*
1965. Moynihan report on poverty among Black families in USA
1777. Hume's *Enquiry Concerning Human Understanding*
1843. Mills' *System of Logic*
Modern era. Reading history sideways leads to developmental theories of social change
1899. Yule uses Gauss' method to study poverty in England
1750
1800
1900
1950
2000

A very brief survey of ways to avoid that stuff

- Counterfactual framework
- Directed acyclic graphs
- Empirical methods
  - Regression and conditioning
  - Regression discontinuity
  - Instrumental variables
  - Matching
  - Difference-in-differences

Counterfactuals and potential outcomes

Effect = (🌏|cause occurs) − (🌏|cause does not occur)

Counterfactuals and potential outcomes

Y_i^c outcome for person *i* if they **do not** receive the treatment

Y_i^t outcome for person *i* if they **do** receive the treatment (controls)

Then, for person *i*, the effect of the treatment on Y is

$$\delta_i = Y_i^t - Y_i^c$$

Counterfactuals and potential outcomes

For most outcomes Y and treatments T, we cannot observe both Y_i^t and Y_i^c for any individual *i*

Luckily, many research questions are about average or population-level effects, not the effect on an individual

Therefore, we estimate the average treatment effect by comparing the outcome among the treated and the untreated

$$\bar{\delta} \quad = \overline{Y^t} - \overline{Y^c}$$

Counterfactuals and potential outcomes

In reality, this is usually

$$\bar{\delta} \quad = \overline{Y_{i\in T}^{t}} - \overline{Y_{i\in C}^{c}}$$

Or even more realistically

$$\hat{\bar{\delta}} = \overline{\widehat{Y_{i\in T}^{t}}} - \overline{\widehat{Y_{i\in C}^{c}}}$$

Directed Acyclic Graphs

- A set of nodes (variables) and directional edges (relationships) in which no feedback loops or cycles are present

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Teen childbearing $\longrightarrow$ *Midlife poverty*

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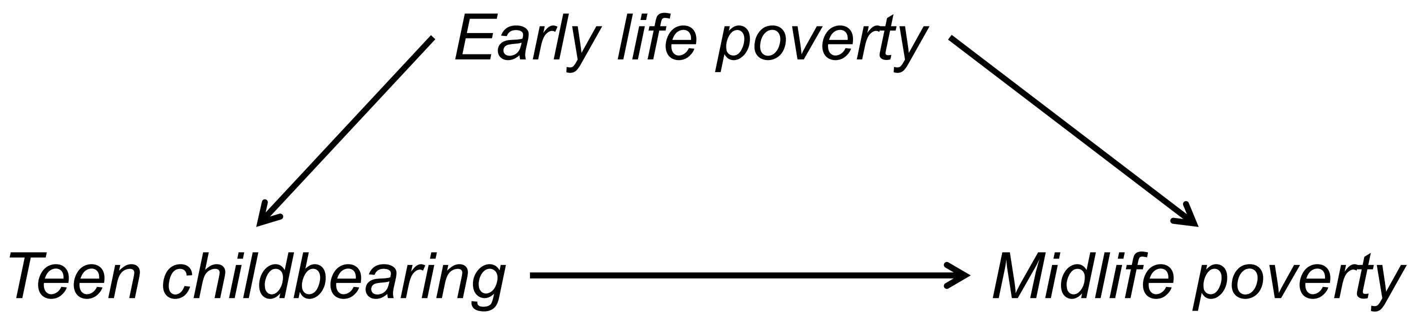

Directed Acyclic Graphs

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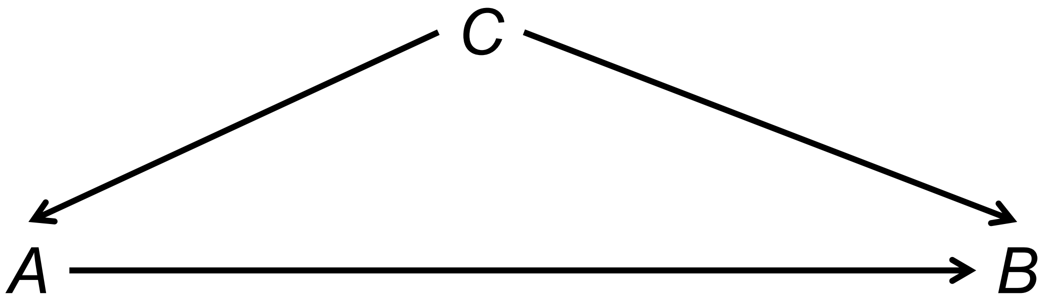
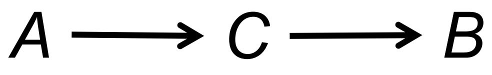
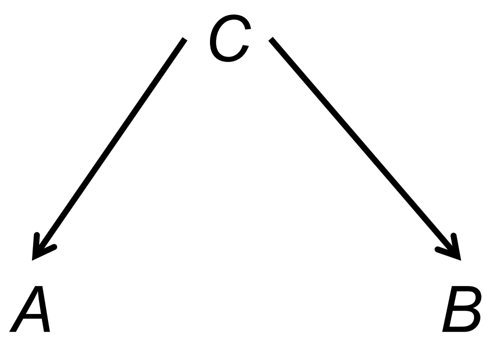


Basic patterns of causal relationships for 3 variables



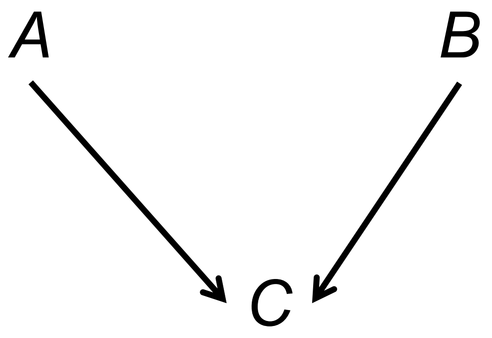
Mediation

chain



Mutual dependence

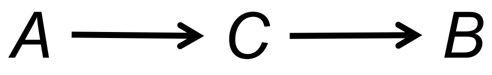
fork



Mutual causation

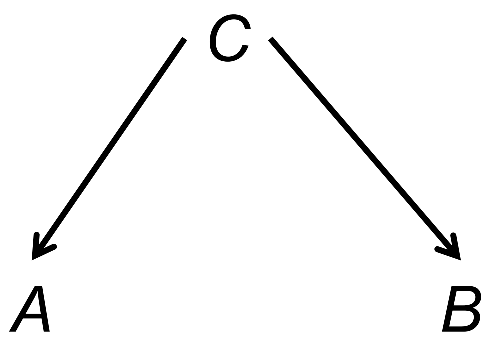
Inverted fork

Basic patterns of causal relationships for 3 variables



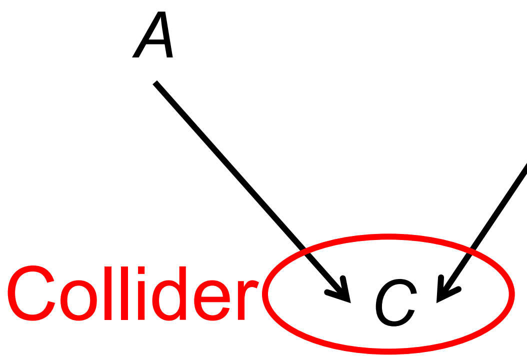
Mediation

chain



Mutual dependence

fork

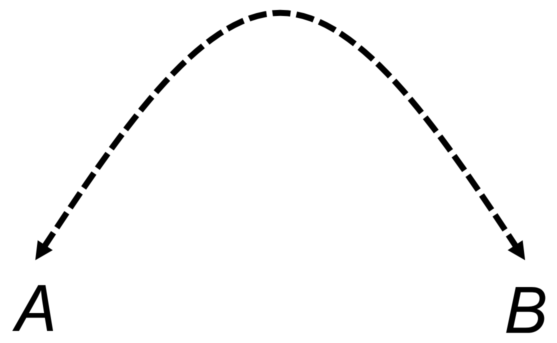


Mutual causation

Inverted fork

Joint dependence

DANGER! Almost all social phenomena share complex and unmeasured background causes.



Causal paths

$$A \longrightarrow C \longrightarrow D \longrightarrow B$$

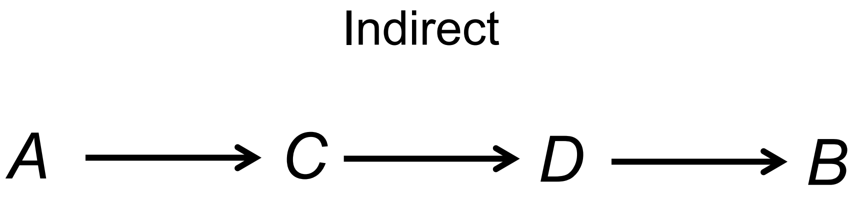
$$A \longrightarrow B$$

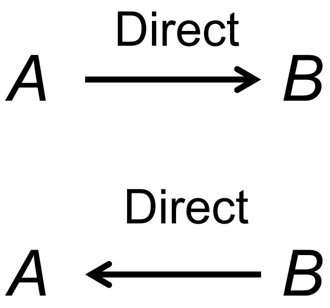
$$A \longleftarrow B$$

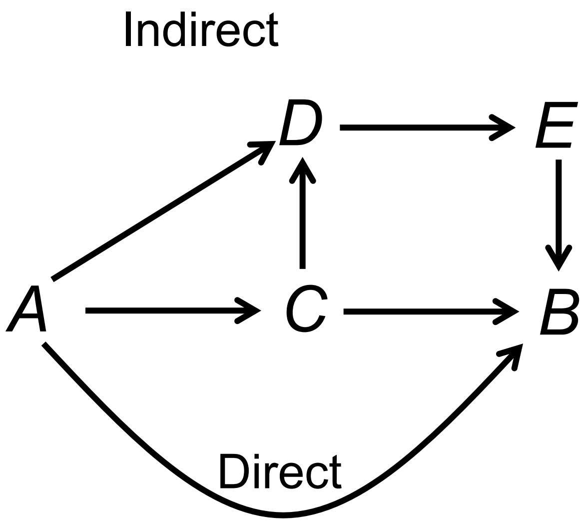
$$\begin{tikzcd}
 & D \arrow[r] & E \arrow[d] \\
A \arrow[ur] \arrow[r] \arrow[rr, bend right] & C \arrow[u] \arrow[r] & B
\end{tikzcd}$$

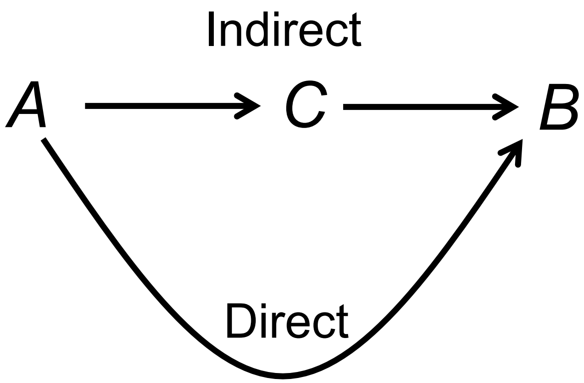
$$\begin{tikzcd}
A \arrow[r] \arrow[rr, bend right] & C \arrow[r] & B
\end{tikzcd}$$

Causal paths



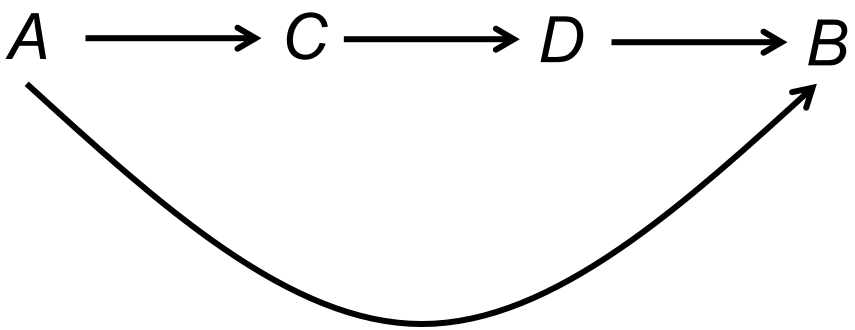


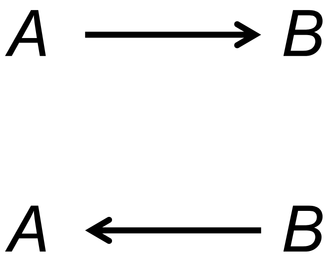




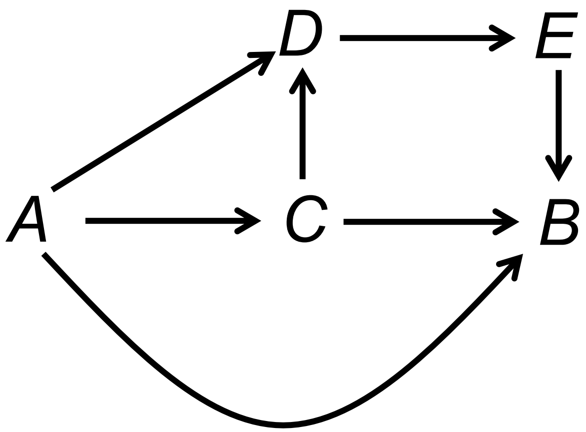
Causal paths

Backdoor

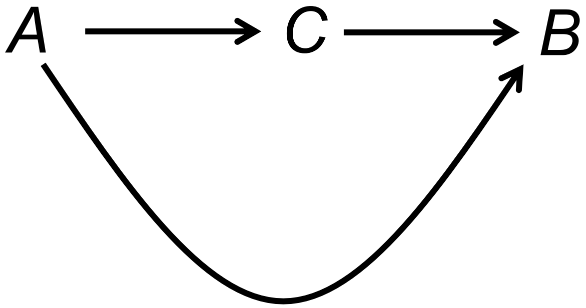




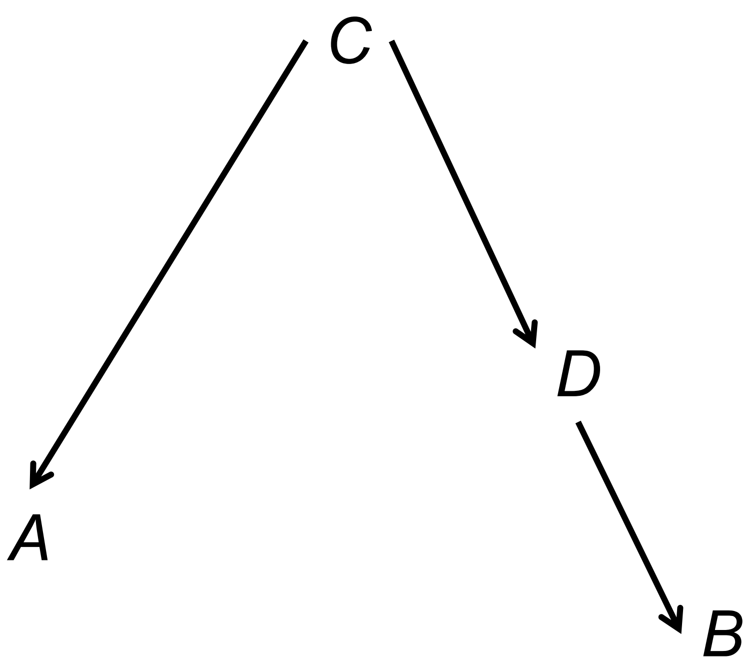
Backdoors

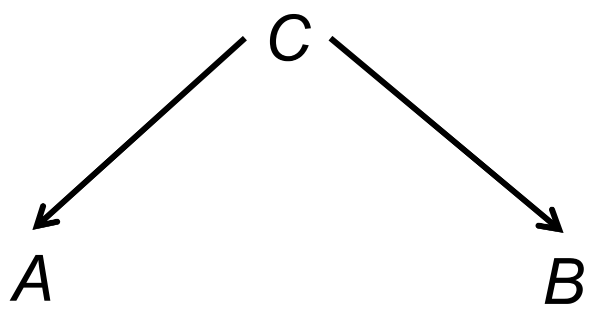


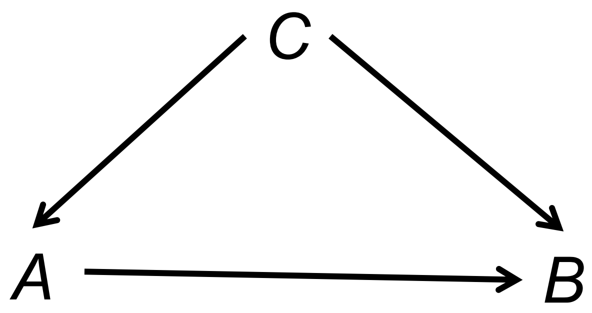
Back door



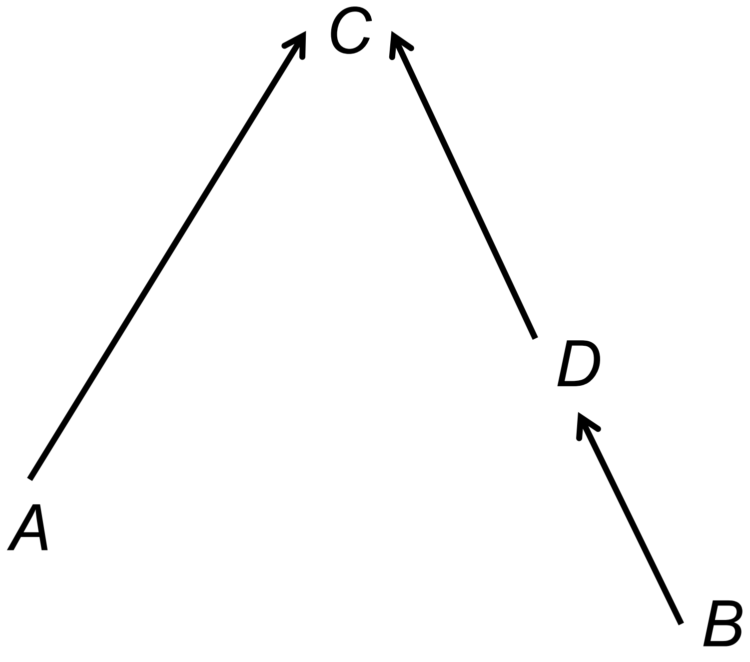
Confounded paths

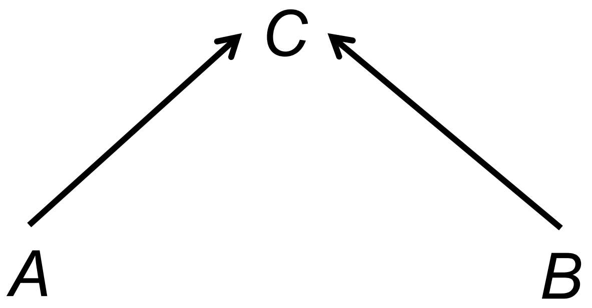


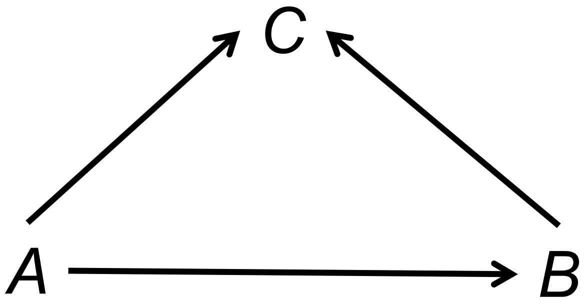




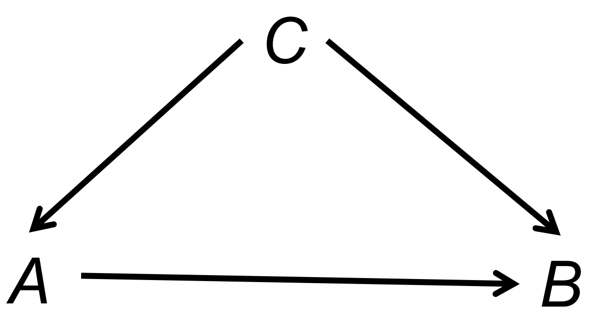
Colliding paths

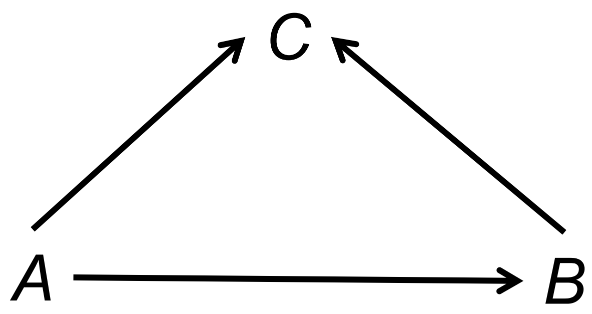


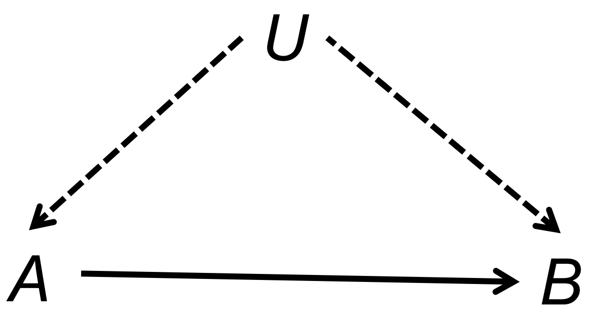




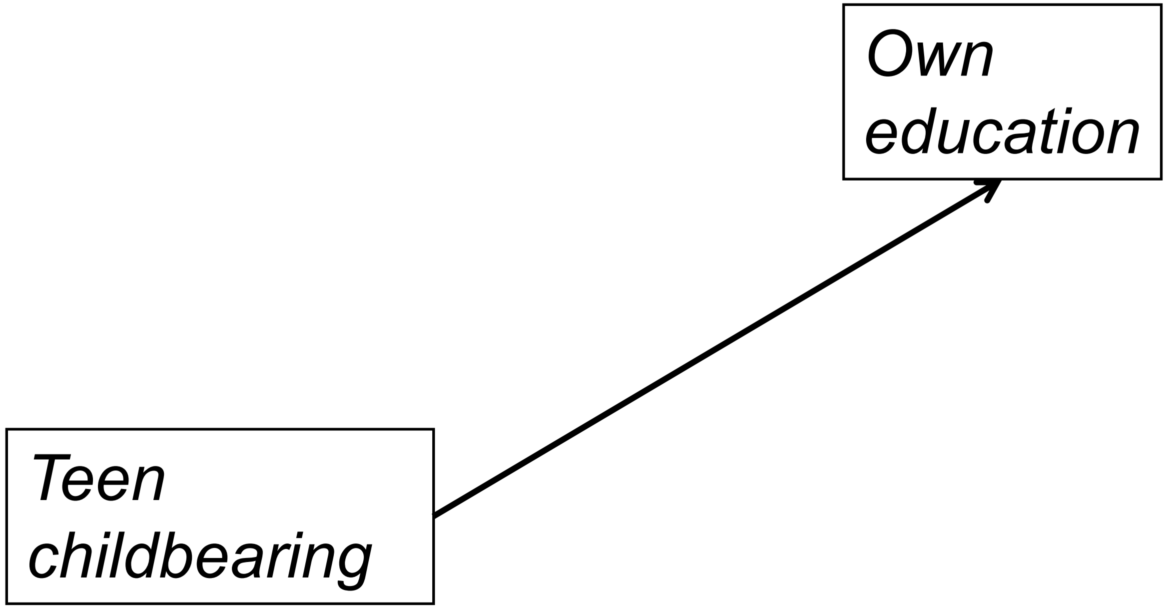
Open vs. closed backdoor paths

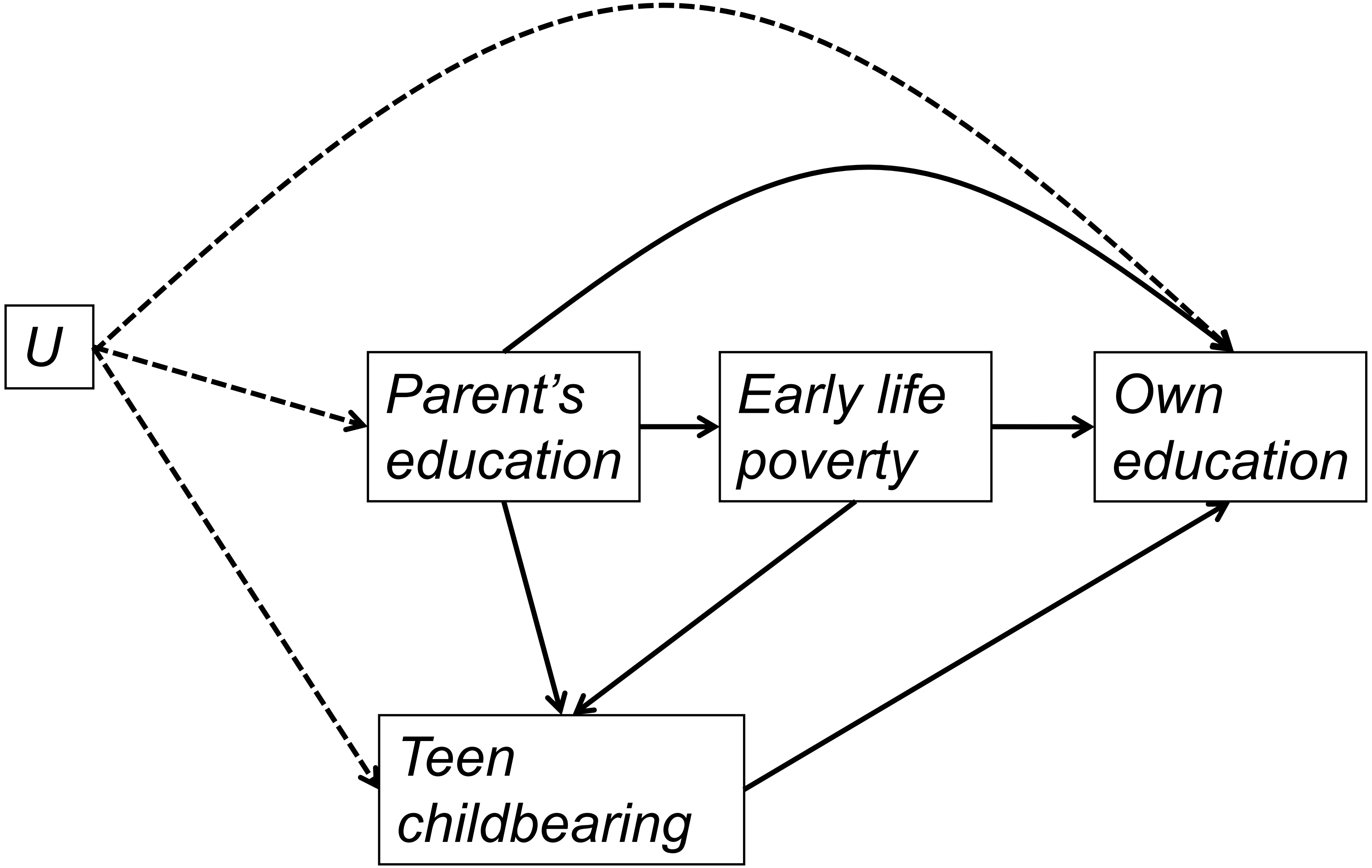






An example



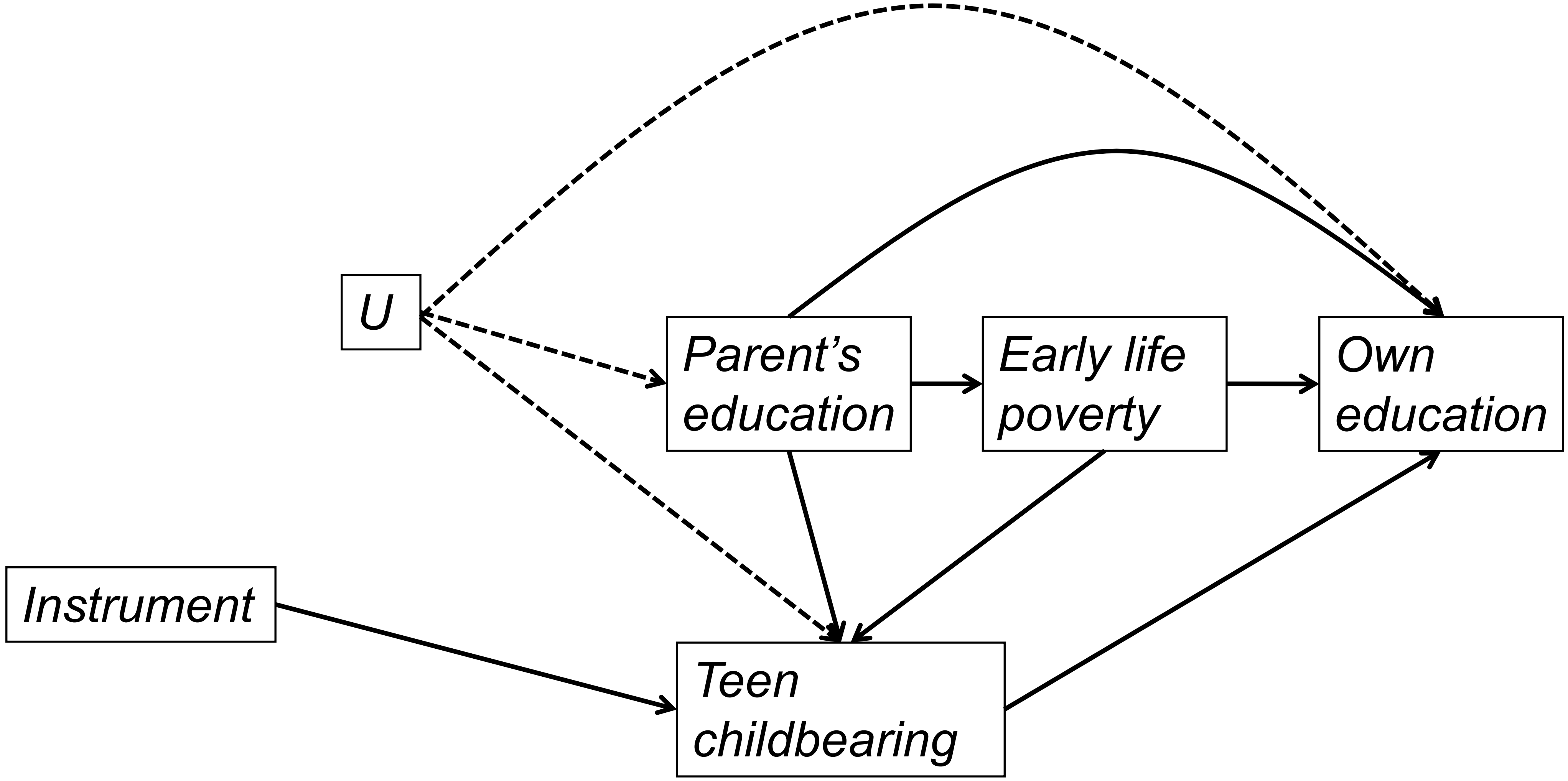

U
Parent's education
Early life poverty
Own education
Teen childbearing

Limitations of DAGs

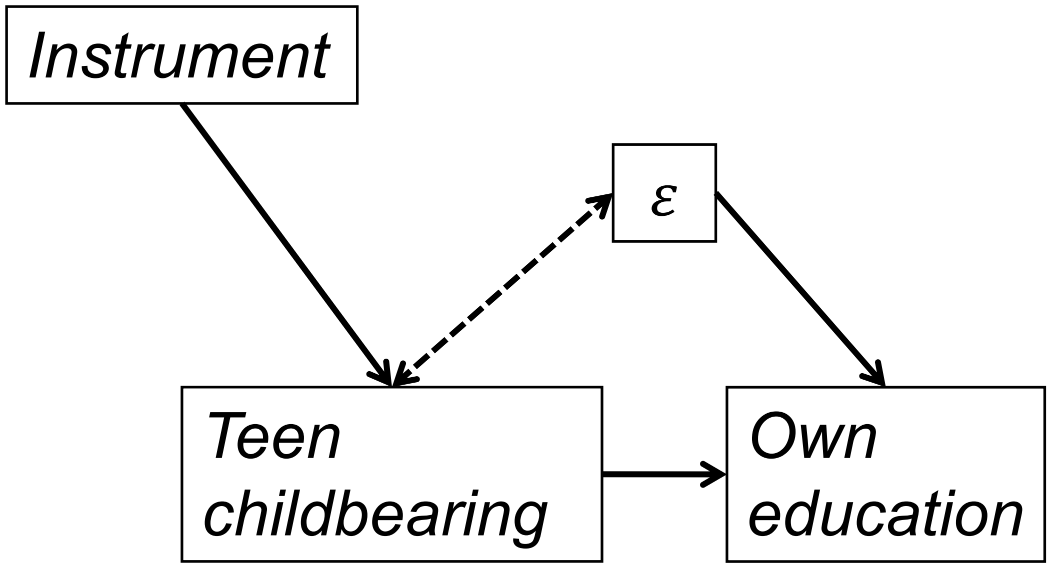
- You **must** have a theory and you're kind of betting the farm on it
- Not all potential outcome statements may be represented (time, for example is tough)
- Implicit focus on average treatment effects (ATEs)

Empirical methods

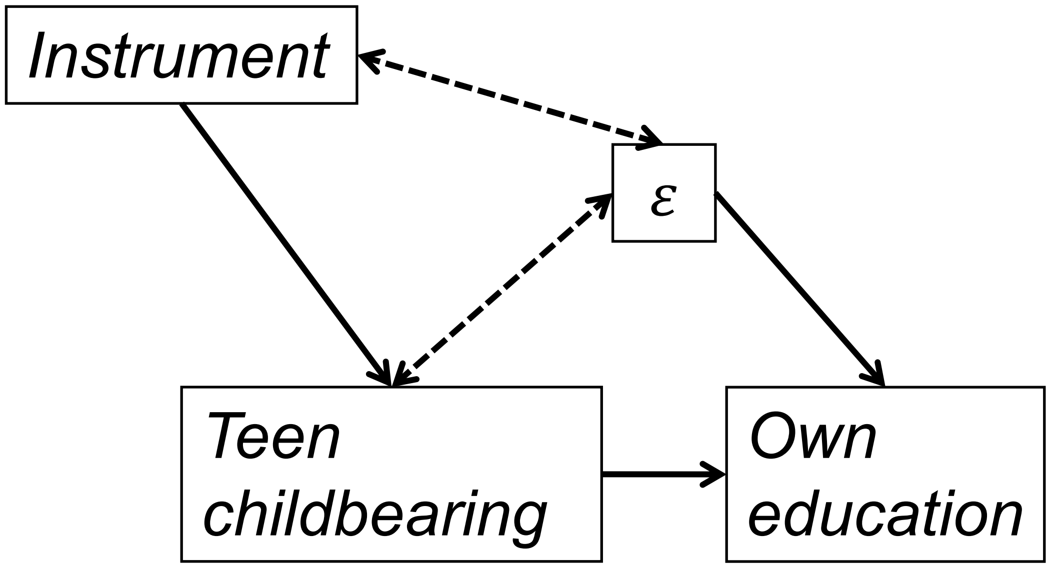
Instrumental variables



Instrumental variables



Valid instrument



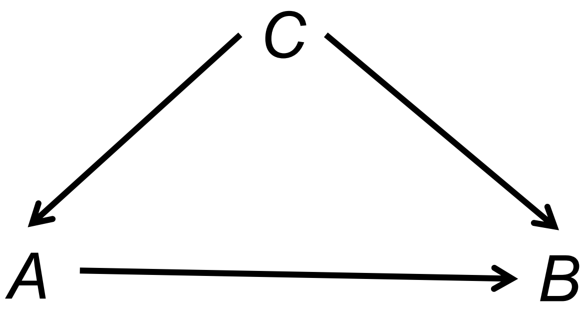
Invalid instrument

Instrumental variables

- Related to two-stage, latent variable selection, and control function models
  - Estimating the effect of a causal variable by estimating its effect through an exhaustive (closed) path

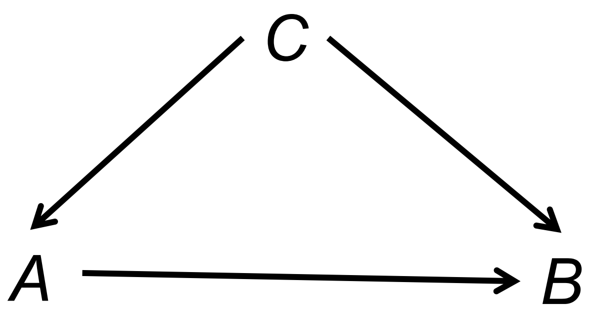
Regression and conditioning

- If your DAG tells you that the relationship between A and B is confounded by C and you can estimate $\hat{\bar{\delta}}$ separately by levels of C, then conditioning or regression may recover a valid estimate of ATE.
- Conditioning or stratification: Estimate $\hat{\bar{\delta}}$ separately by groups or strata of C and then weight the subgroup estimates to represent the population distribution.

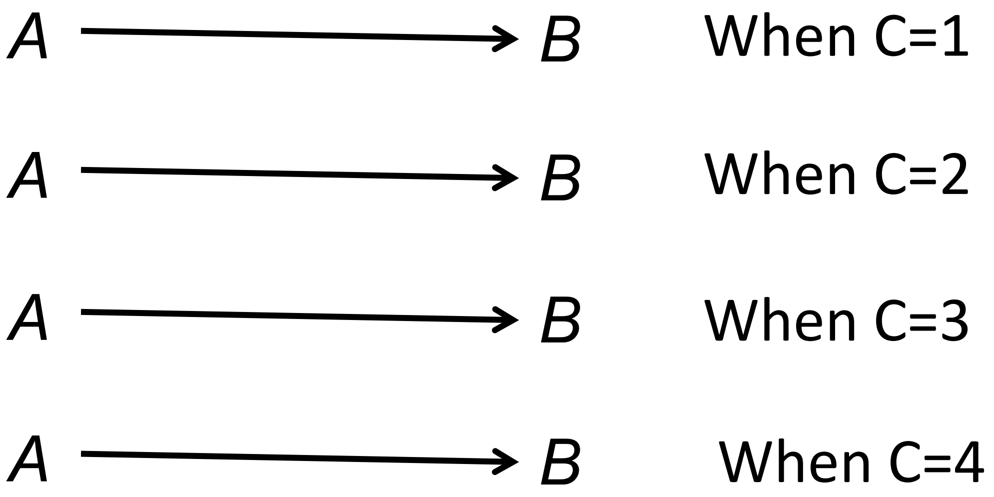


Regression and conditioning

- Conditioning removes nodes from your DAG, potentially simplifying your model and addressing confounding to allow the direct estimation of $\bar{\delta}$.



Becomes



Regression and conditioning

- But if you condition on a collider, your regression-based estimate may be wildly wrong.

- Regression is all about the error (what you can't measure)
  - Works when you can include $\overline{X}_i$ such that you minimize the correlation between treatment assignment T_i and the error term v_i

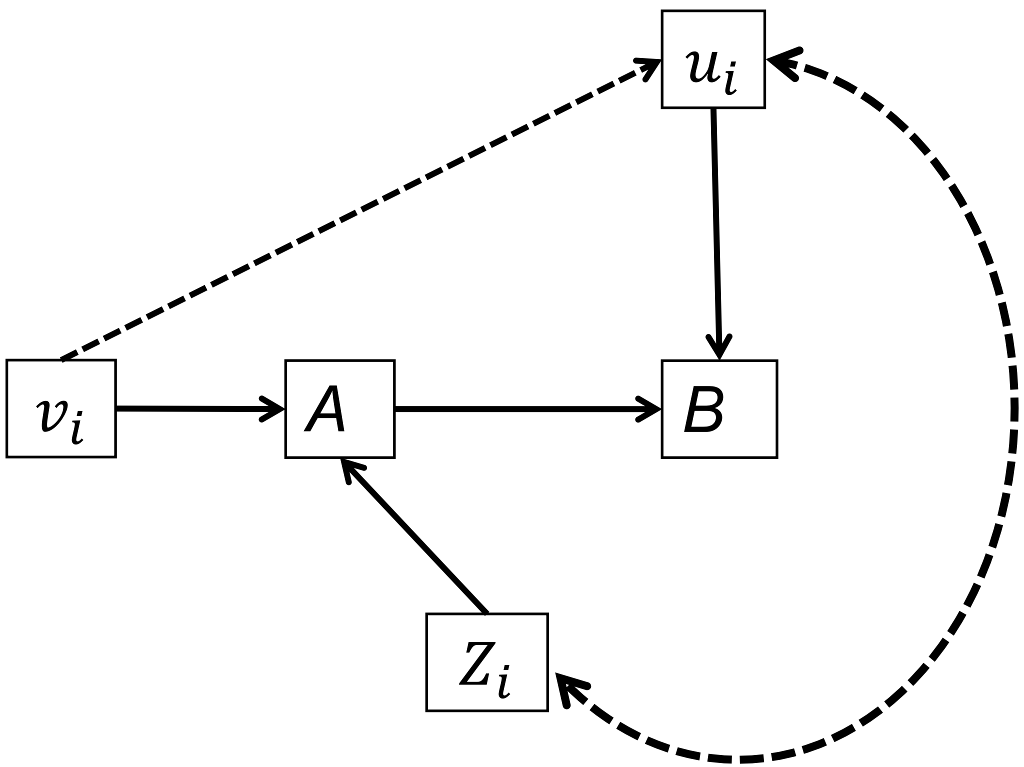
Matching

- Matching is a direct attempt to find counterfactuals at the individual level so that you can actually estimate $\delta_i = Y_i^t - Y_i^c$
- The basic approach is to find individuals *i* and *i** in the treatment and control group such that $Y_i^t = Y_{i*}^t$ and $Y_i^c = Y_{i*}^c$
- Then, $\delta_i = Y_i^t - Y_{i*}^c$ and $\delta_{i*} = Y_{i*}^t - Y_i^c$

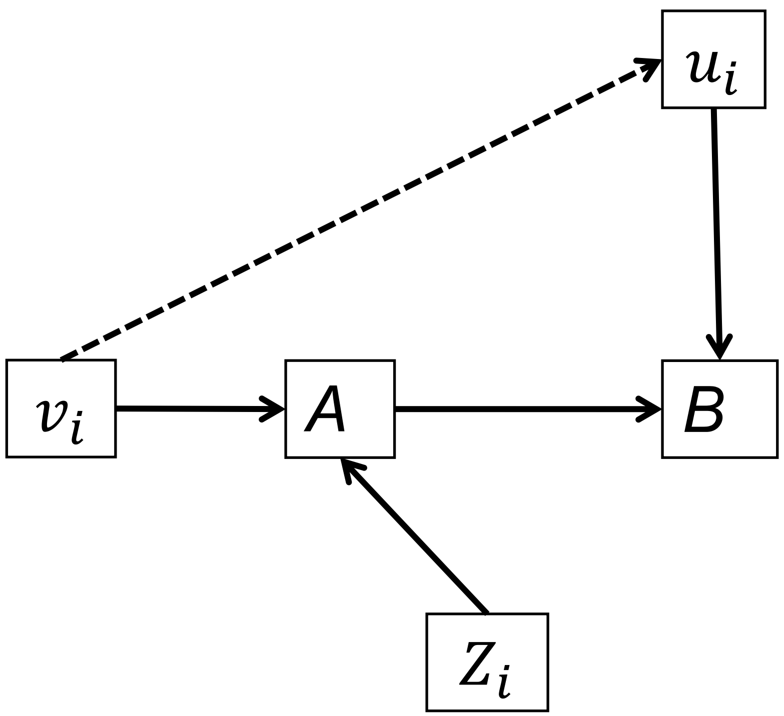
Matching

- Exact matching
  - i and i^* selected based on a full set of covariates $\bar{X}$ such that $\bar{X}_i = \bar{X}_{i^*}$
- Nearest neighbor matching
  - i and i^* selected such that $\bar{X}_i - \bar{X}_{i^*}$ is minimized
- Propensity score matching
  - $P(Z_i) = Prob(T = 1|Z_i)$

Matching



Most realities



The assumption made by matching

Matching

- Common support
  - Factors associated with treatment assignment needs to be relatively well-distributed across T and C
  - You usually need a lot of data

- No assumption about functional form of effect!
- Statistical efficiency

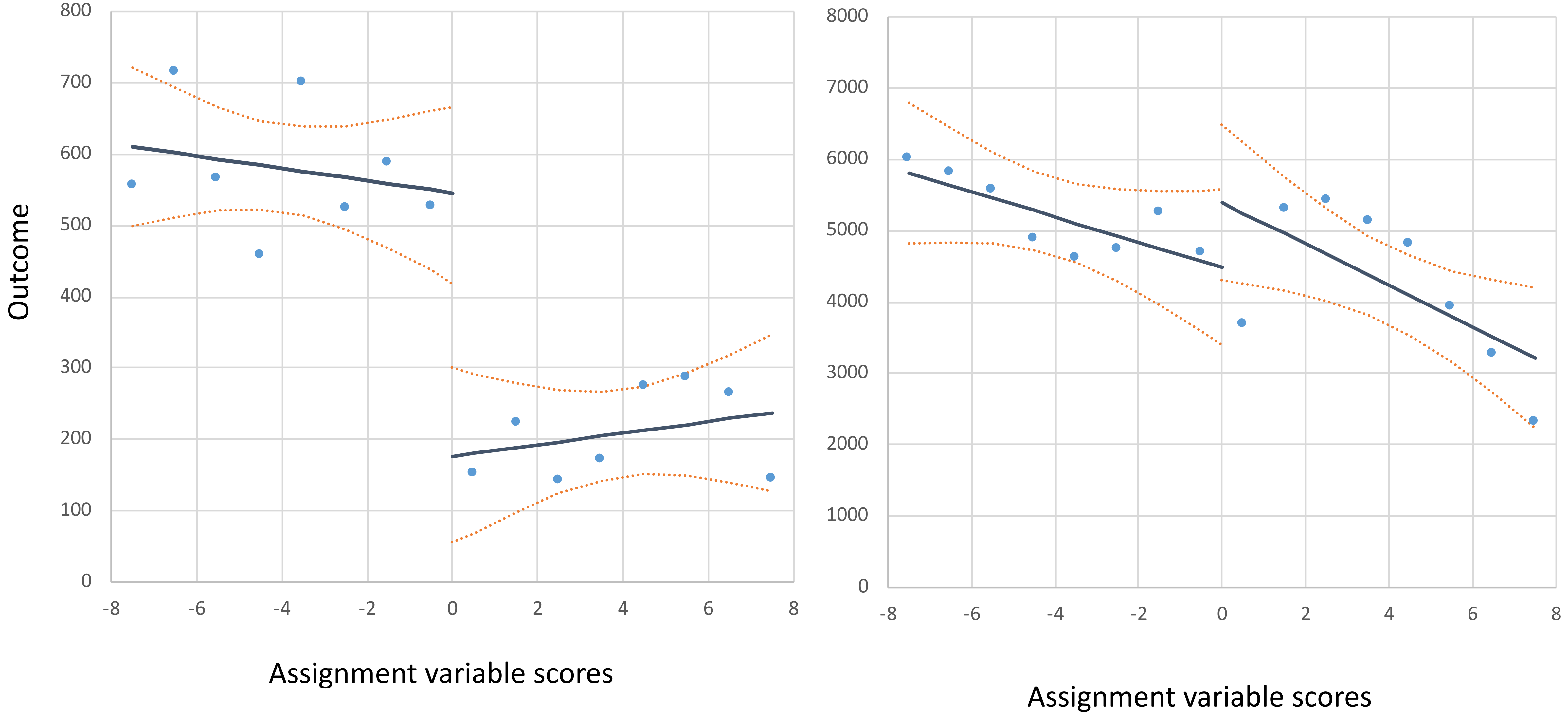
Regression discontinuity

- Requires an exogenous selection into treatment determined by an arbitrary cutoff in a running variable or assignment variable
  - Eligibility thresholds
  - Policy implementation on a specific date

- Must be able to model the running/assignment variable (poverty, time, etc.) on the outcome.

- Practically, easy to implement and provides a vivid illustration of effect

Regression discontinuity



Regression discontinuity

- Common problems:
  - Cutoffs aren’t actually strictly followed
  - Functional form of underlying relationship between running variable and outcome incorrectly specified
  - Only generates local area treatment effect (LATE)

Difference-in-differences

- Variation may function like an experiment if it is exogenous
- May be conducted as panel fixed effects, or repeated cross-sections

	Change over time		Difference-in-differences (DID)	P-value
	Intervention	No intervention		
Outcome	A=pre-post	B=pre-post	A-B	

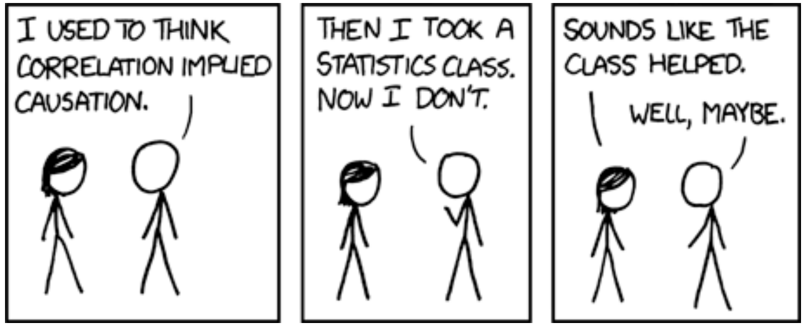
Some recommended further reading

Morgan, Stephen L., and Christopher Winship. *Counterfactuals and causal inference*. Cambridge University Press, 2015.

Pearl, Judea. *Causality*. Cambridge university press, 2009.

Cunninham, Scott. *Causal inference: the Mixtape*. V.1.7. http://scunning.com/cunningham_mixtape.pdf

Winship, Christopher, and Stephen L. Morgan. "The estimation of causal effects from observational data." *Annual review of sociology* 25.1 (1999): 659-706.



You already love xkcd, right?
https://xkcd.com/552/

Pearl’s three basic methods for identifying causal effects

- Condition on all backdoor paths
- Condition on variables in order to estimate by a mechanism
- Estimate effect using exogenous shock to cause