6. Endogenous Selection Bias

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Review

- We use DAGs to check for non-parametric identification, using the adjustment criterion ("identification via conditioning")
    - There are other identification strategies besides covariate adjustment, some of which we'll get to later.
- Basic logic:
    - "No association without causation"
        - ⇒ For two variables to be associated, they must be linked via some <u>path</u> in the DAG. But: not all paths "transmit" association (i.e. some are "blocked").
    - Causal effect: the association flowing along "causal paths"
        - ⇒ Get rid of association flowing along non-causal paths (travelling at least one length against the direction of time)
        - Some non-causal paths are "naturally" blocked (containing unconditioned collider). Others need to be blocked by conditioning on non-collider
        - If all non-causal paths, and no causal paths, between treatment and outcome are blockable by {Z}, then the ACE of T on Y is non-parametrically identified conditional on {Z}.

Motivation

It’s well known that causal inference is threatened by many biases

- Selection bias
- Endogeneity bias
- Ascertainment bias
- Induced confounding
- Dependent censoring
- Non-response bias

These are usually discussed and addressed separately, with lots of algebra.

Goal

Show that these biases share a common underlying causal structure:

"Endogenous Selection"

Provide intuitive yet rigorous tool for recognizing and understanding the common underlying problem.

Goal

Specifically:

1. Use Pearl's DAGs and insights by Hernán, Robins, Greenland (2004) and others to show that many apparently disparate biases arise from the same underlying problem: <u>conditioning on a</u> "<u>collider</u>" (Elwert and Winship 2014).
2. Discuss many real social science examples

In the interest of time (as before), we

- …talk only about point-identification
- …won’t discuss estimation solutions
- …assume population level data
- …neglect issues of sampling error

Structure of the Problem: Conditioning on a Collider (Review)

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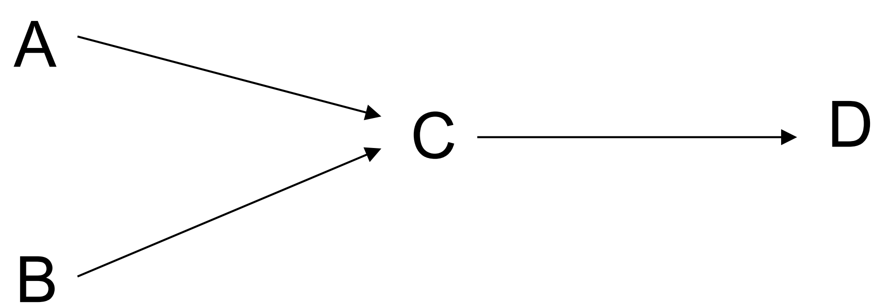
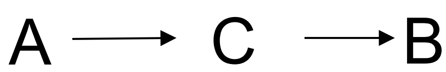
Colliders

A collider is a variable that is caused by two or more other variables (i.e., endogenous variable with two or more causes)

Recall: Colliders are path-specific—the same variable may be a collider on one path but not on another

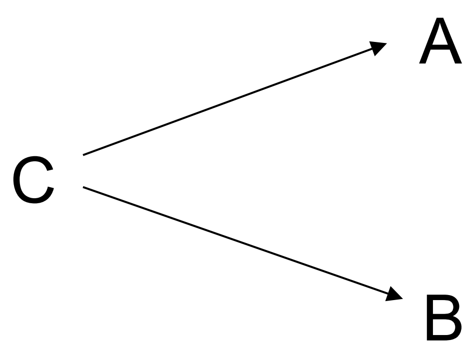


3 Sources of Association Between Two Variables A & B



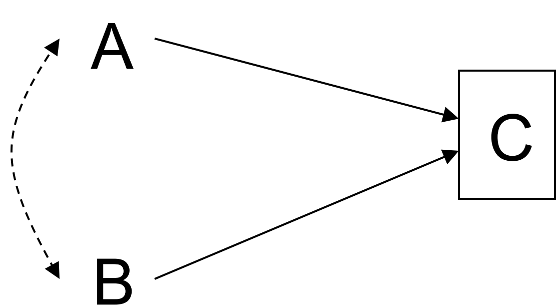
(1) Direct and indirect causation

$A \not\perp\!\!\!\perp B$ and $A \perp\!\!\!\perp B|C$



(2) Common cause confounding

$A \not\perp\!\!\!\perp B$ and $A \perp\!\!\!\perp B|C$



(3) Conditioning on a common effect ("collider"): Selection

$A \perp\!\!\!\perp B$ and $A \not\perp\!\!\!\perp B|C$

$\longleftrightarrow$: non-causal (spurious) association. $\square$: conditioning.

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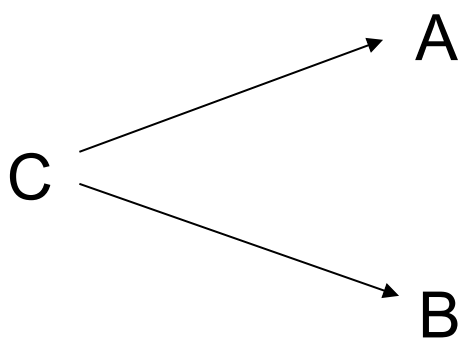
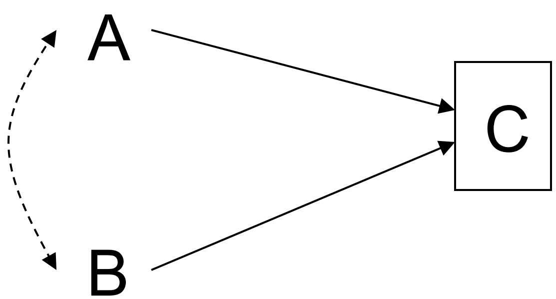
Confounding vs. Endogenous Selection



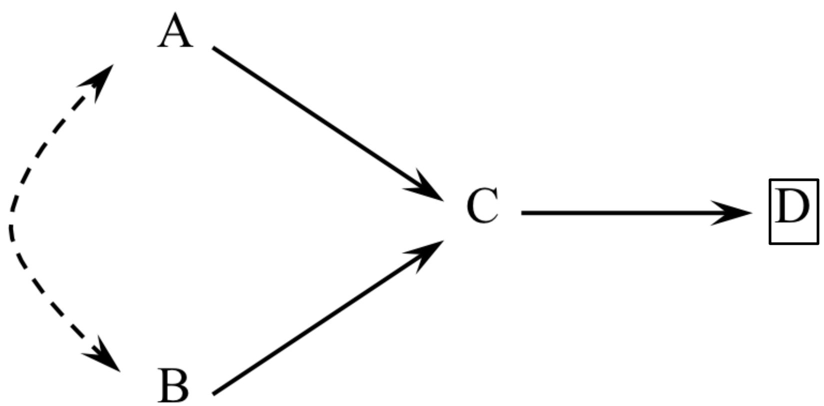
Confounding bias: <u>failure to condition</u> on a <u>common cause</u>



Endogenous selection bias: <u>mistaken conditioning</u> on a <u>common effect</u>.

Both confounding and selection are analytic mistakes.

Conditioning on a Descendant of a Collider



Same problem as outright conditioning on the collider itself

What Counts as "Conditioning"?

"Conditioning" on a variable means "introducing information about the variable in the analysis."

There are many ways to "condition" on a variable:

- Controlling (e.g. in regression)
- Stratification (e.g. crosstabs, survival analysis, log-linear models)
- Subgroup analysis (e.g. restrict analysis to employed women)
- Sample selection (e.g. only collect data on poor whites)
- Attrition, censoring, nonresponse (e.g., analyze only respondents or survivors)

Examples of Endogenous Selection Bias

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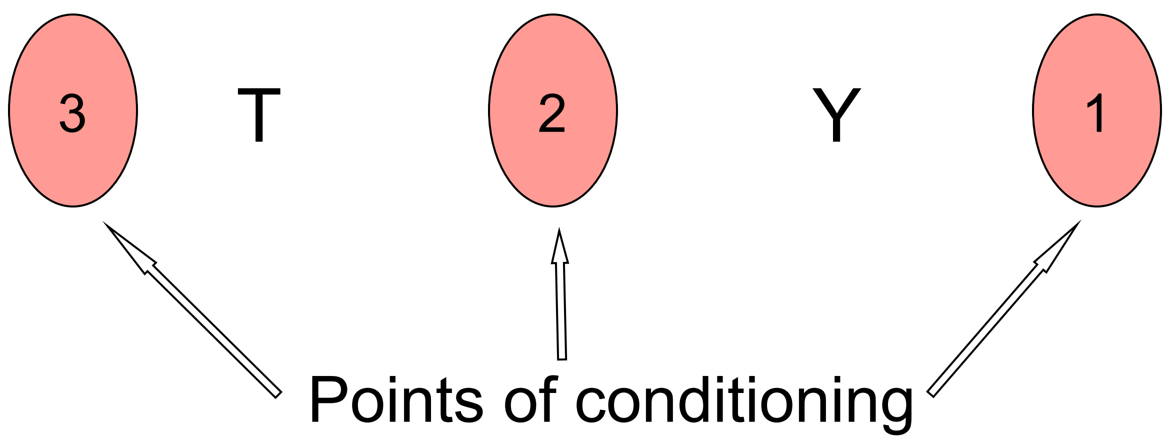
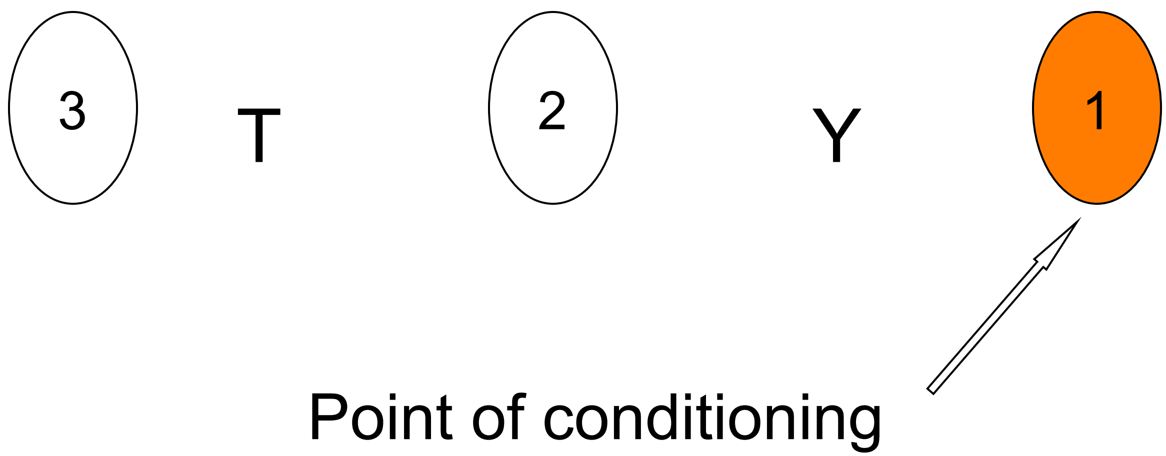
Conditioning on a Collider Anywhere Can Induce Bias

Timing of the collider relative to treatment, T, and outcome, Y, is irrelevant.



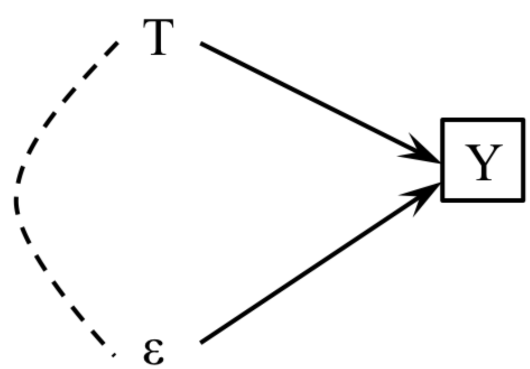
1. Conditioning on (Post-) Outcome Colliders



1.1 Conditioning on an Outcome Collider

Example: 1. Direct selection on the outcome

2. Outcome truncation



T: Treatment

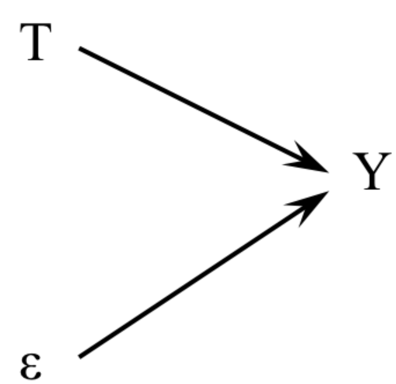
Y: Outcome

e: Error term (unobs.)

Cond. on Y creates assoc b/w T and e, and hence a new, non-causal connection b/w Y and T.

1.2 Conditioning on an Outcome Collider

Example: Direct selection on the outcome in the New Jersey Income Maintenance experiment (Hausman and Wise 1978)



T: Education

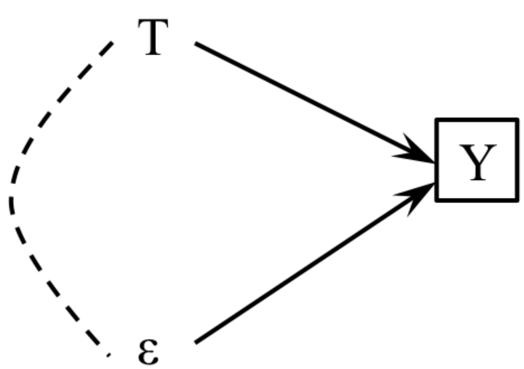
Y: Income

e: Error term (unobs.)

T is random. ACE of T on Y is identified.

1.2 Conditioning on an Outcome Collider

Example: Direct selection on the outcome in the New Jersey Income Maintenance experiment (Hausman and Wise 1978)



T: Education

Y: Income

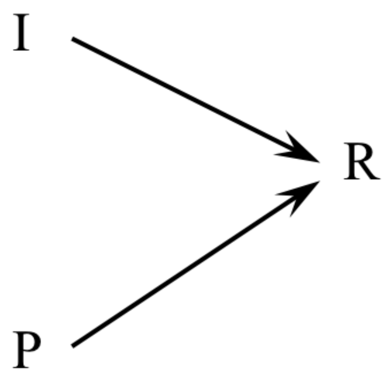
e: Error term (unobs.)

Sample restricted to low earners Y<$5000. Cond. on Y induces a non-causal assoc. b/w T and e,

(NB: Direct selection on the outcome works in case-control studies under restrictive conditions—not nonparametrically. Choice based sampling offers other parametric solutions.)

1.3 Conditioning on Post-Outcome Collider

Example: Selective non-response in a retrospective study



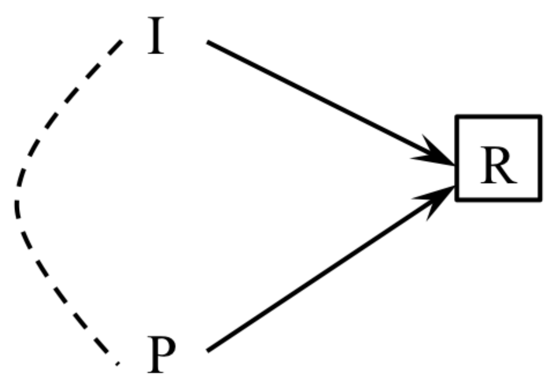
I: income

P: abortion

R: response

1.3 Conditioning on Post-Outcome Collider

Example: Selective non-response in a retrospective study



I: income
P: abortion
R: response

Analysis restricted to responding respondents => spurious association

1.4 Conditioning on Post-Outcome Collider

Example: Estimating the effect of commercial success on critical success (e.g. Alan and Lincoln 2004; Schmutz 2011)

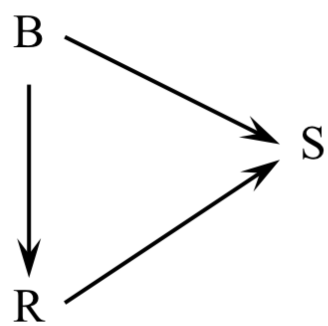
B: Billboard chart topper

R: Rolling Stone 500 Greatest Albums of All Time!

Find: Dramatic and counterintuitive negative effect of chart topping on inclusion in RS-500 list.

1.4 Conditioning on Post-Outcome Collider

Example: Estimating the effect of commercial success on critical success (e.g. Alan and Lincoln 2004; Schmutz 2011)



B: Billboard chart topper

R: Rolling Stone 500 Greatest Albums

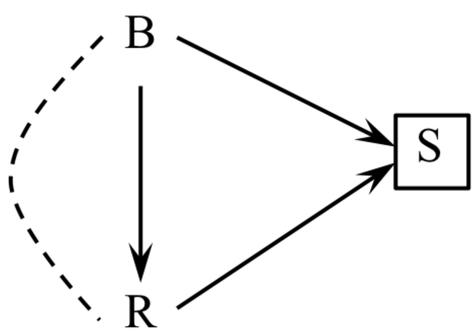
S: Sample inclusion

Sample includes all RS500 albums and 1100 albums that received other prizes, incl. chart topping

Dramatic and counterintuitive negative effect of chart topping on inclusion in the RS-500 list.

1.4 Conditioning on Post-Outcome Collider

Example: Estimating the effect of commercial success on critical success (e.g. Alan and Lincoln 2004; Schmutz 2011)



B: Billboard chart topper

R: Rolling Stone 500 Greatest Albums

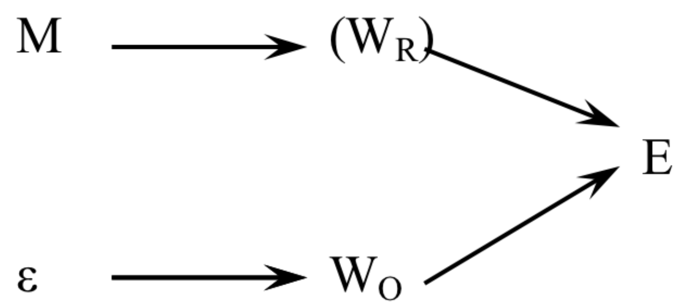
S: Sample inclusion

Sample includes all RS500 albums and 1100 albums that received other prizes, incl. chart topping

Dramatic and counterintuitive negative effect of chart topping on inclusion in the RS-500 list may be explained by endogenous election (flawed case-control design).

1.5 Conditioning on Post-Outcome Collider

Example: Motherhood wage penalty (Heckman selection bias)
Assume that there is no effect of M on W_O.



T: fertility

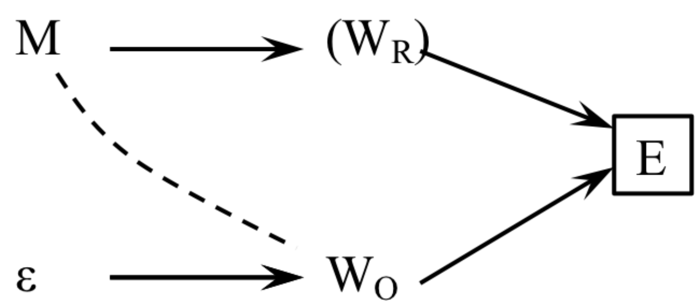
W_R: reservation wage (unobs.)

E: Employment

W_O: offer wage

1.5 Conditioning on Post-Outcome Collider

Example: Motherhood wage penalty (selection bias)
Assume that there is no effect of M on W_O.



T: fertility

W_R: reservation wage (unobs.)

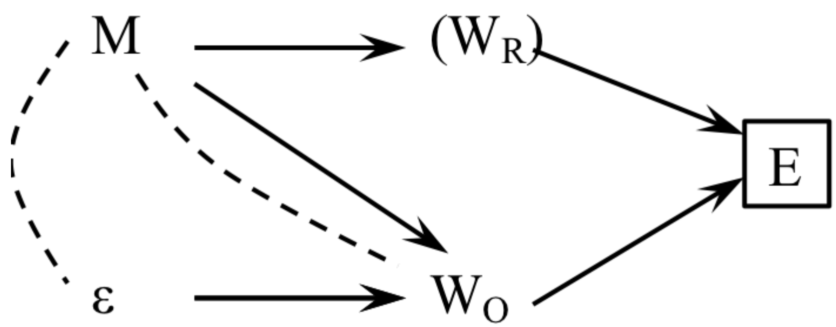
E: Employment

W_O: offer wage

Analysis restricted to employed women

1.5 Conditioning on Post-Outcome Collider

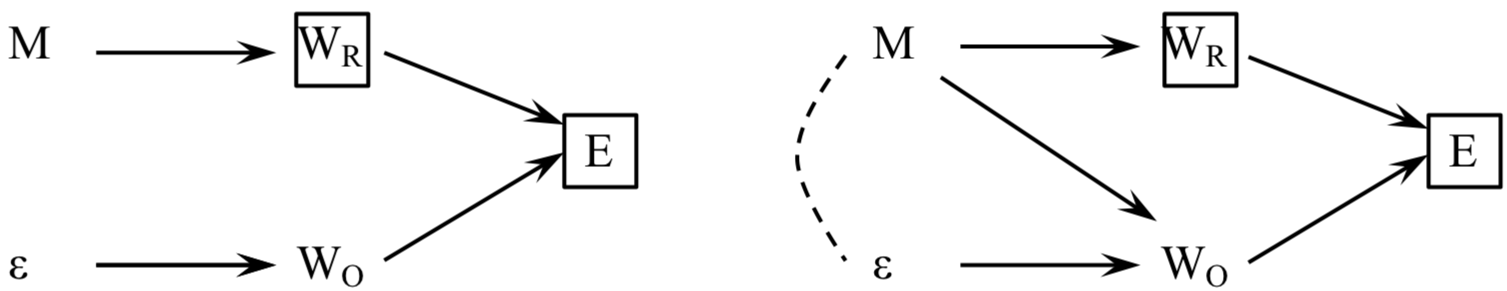
Example: Motherhood wage penalty (selection bias)
Now assume that there is an effect M→W_O.



This creates a second endogenous selection problem, because E now also amounts to conditioning on the descendant of the collider W_O.

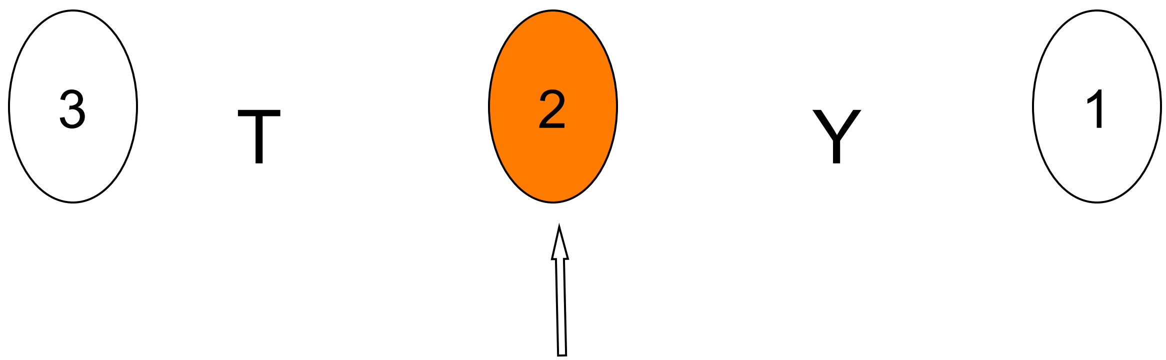
1.5 Conditioning on Post-Outcome Collider

Testing Null vs. estimating size of the effect:



If W_R is observed, one could nonparametrically test the Null of no effect of M→W_O. But the size of the effect, if there is one, remains non-identified because of endogenous selection.

2. Conditioning on an Intermediate Collider



Point of conditioning

2.1 Conditioning on an Intermediate Collider

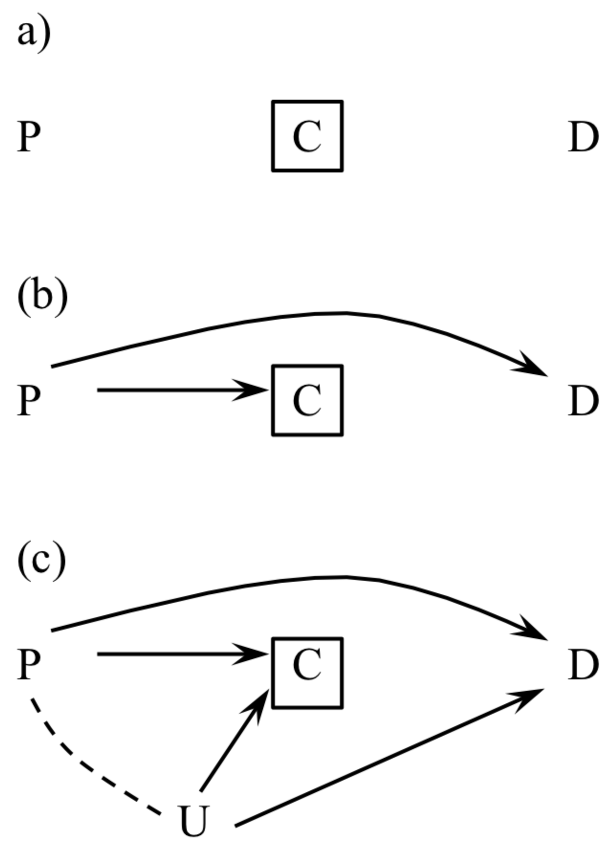
Example: Informative censoring in a prospective cohort study

P: poverty

D: divorce

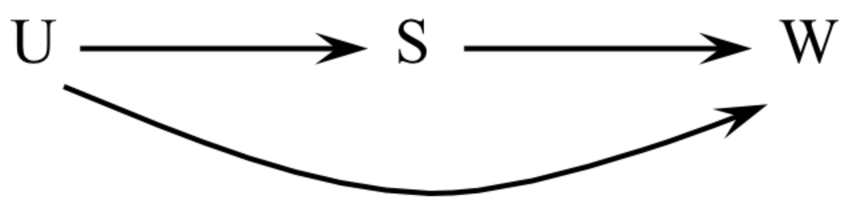
C: censoring/attrition

U: marital distress



2.2 Conditioning on an Intermediate Collider

Example: Endogenous ability bias in the effect of schooling on wages



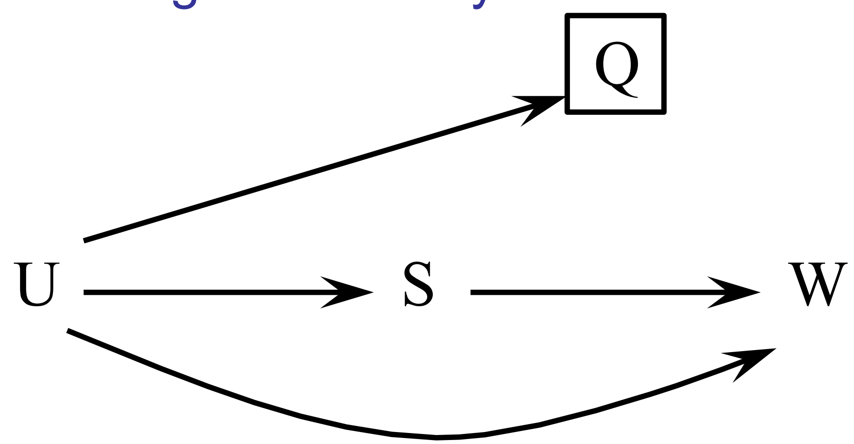
S: schooling
W: wages
U: innate ability

Problem: True ability unobserved
→ common cause confounding

[Girliches 1972; Chamberlain 1977; Angrist and Krueger 1999]

2.2 Conditioning on an Intermediate Collider

Example: Endogenous ability bias in the effect of schooling on wages

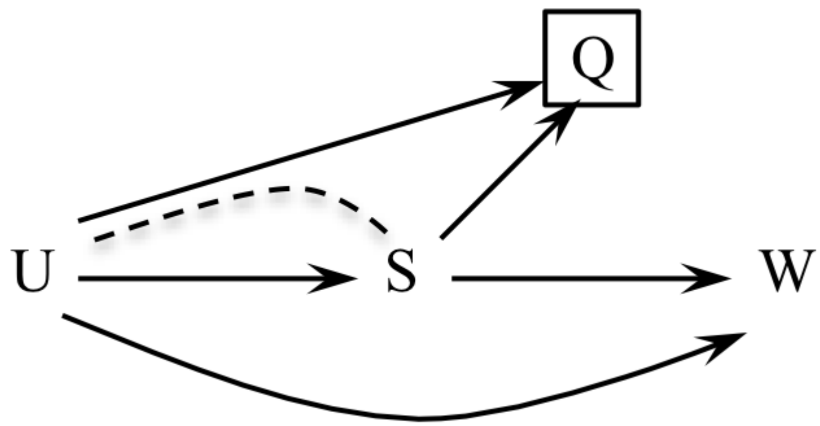


S: schooling
W: wages
U: innate ability (unobs.)
Q: IQ score

True ability is unobserved, but IQ is a good measured proxy. Conditioning on IQ will reduce, but not eliminate, bias. (First source of bias)

2.2 Conditioning on an Intermediate Collider

Example: Endogenous ability bias

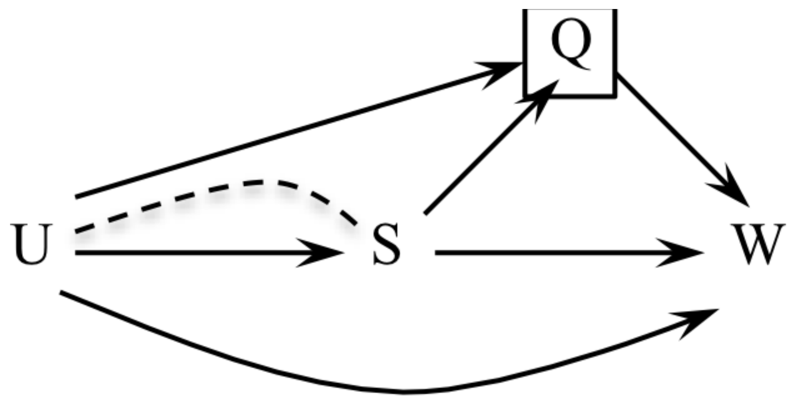


S: schooling
W: wages
U: innate ability (unobs.)
Q: IQ scores

But, IQ is itself affected by schooling. Conditioning on IQ leads to endogenous selection bias. (Second source of bias)

2.2 Conditioning on an Intermediate Collider

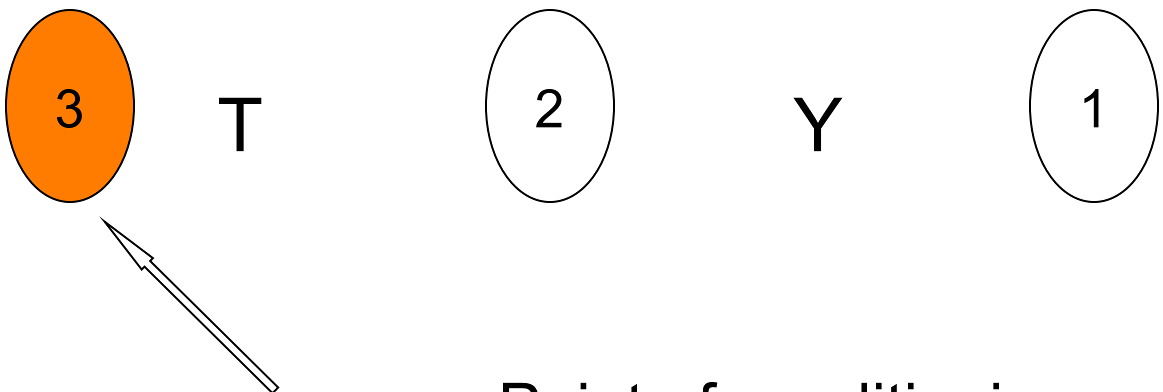
Example: Endogenous ability bias



S: schooling
W: wages
U: innate ability (unobs.)
Q: IQ scores

Finally, if IQ affects wages, then cond. on IQ will "control away" part of the causal effect of T on Y. (Third source of bias)

3. Conditioning on a Pre-Treatment Collider



Point of conditioning

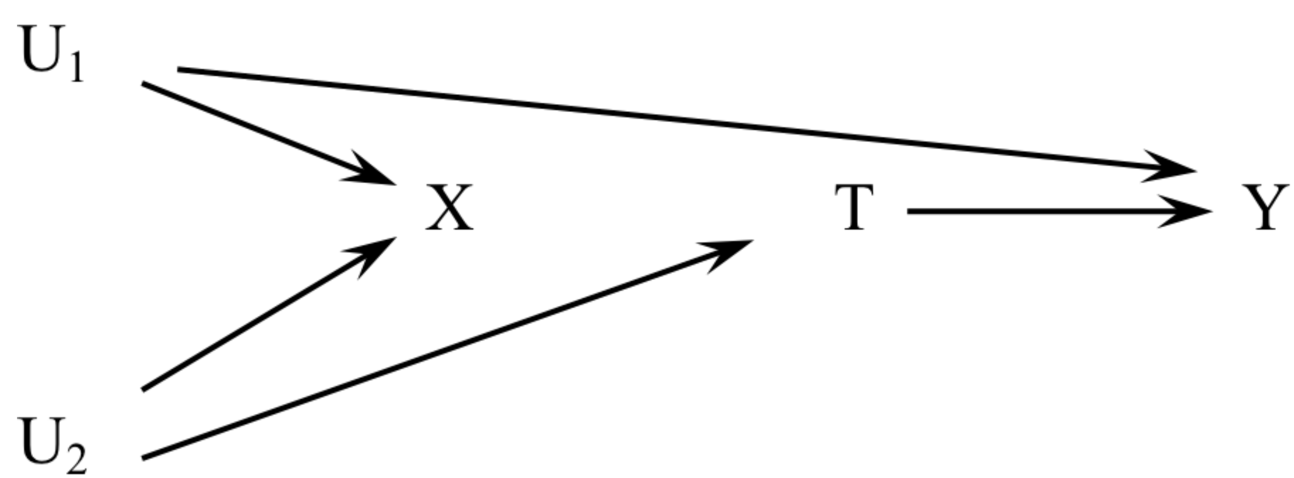
3. Conditioning on a Pre-Treatment Collider

Is condition on a pre-treatment variable always safe?

Standard practice suggests throwing pre-treatment “kitchen sink” of pre-treatment variables into regression or propensity score models.

3.1 Conditioning on a Pre-Treatment Collider

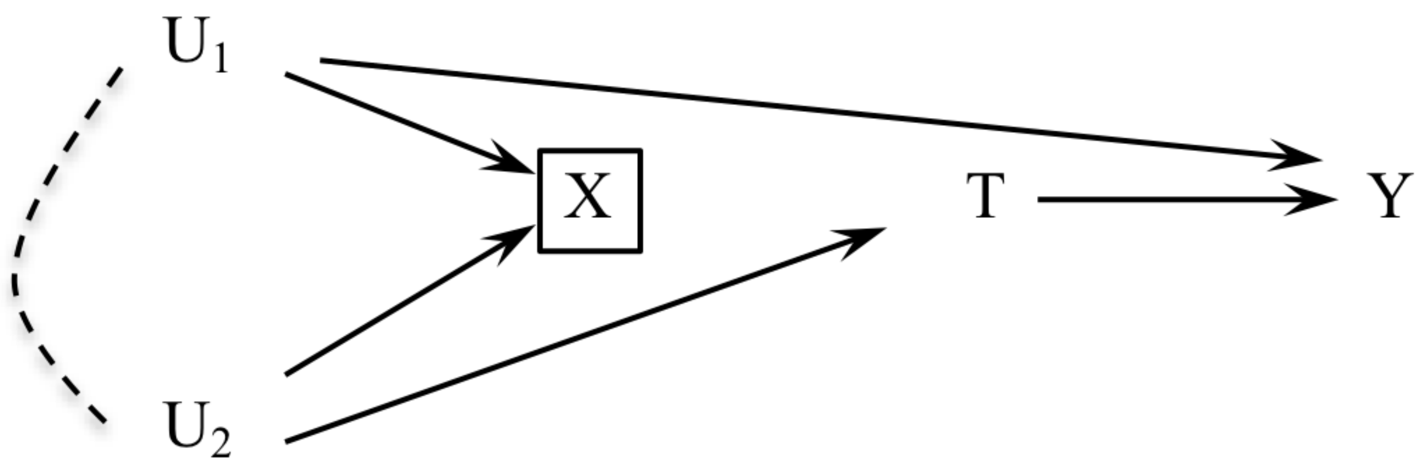
The basic problematic structure (Pearl 1995):



- Is the causal effect of T→Y nonparametrically identifiable?

3.1 Conditioning on a Pre-Treatment Collider

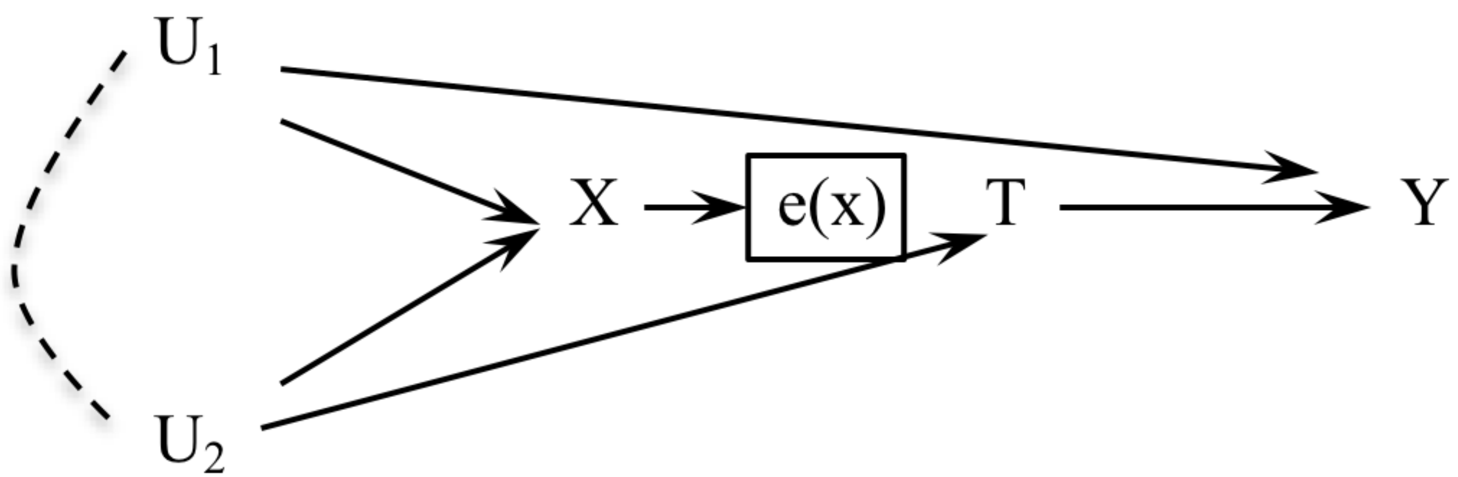
- The basic problematic structure:



- Is the causal effect of T→Y nonparametrically identifiable?
- Yes. But conditioning on pre-treatment X would ruin identification.

3.2 Conditioning on a Pre-Treatment Collider

- Propensity score estimation is not immune:



- Conditioning on the propensity score, e(x),—a descendant of the collider X—induces endogenous selection bias.

3.3 Latent Homophily Bias in Social Network Analysis

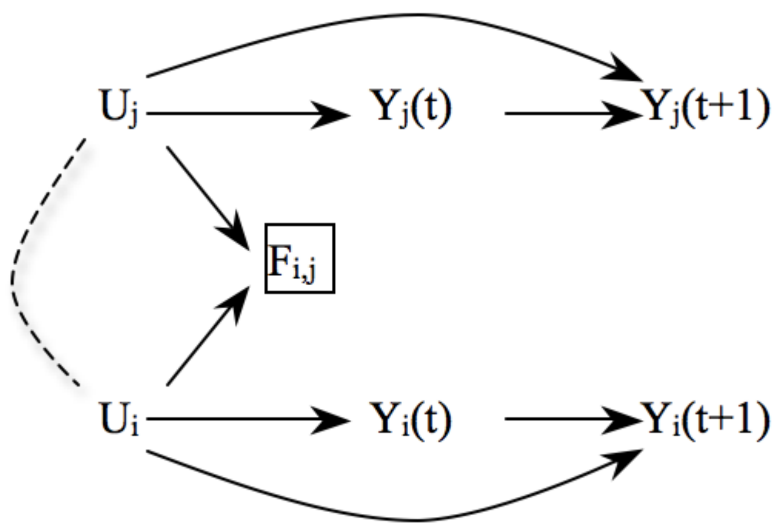
- Example: Social contagion—identify the influence of i's civic engagement at time t on j's civic engagement at t+1.

i,j: two individuals

Y: civic engagement

U: altruism

$F_{i,j}$: friendship



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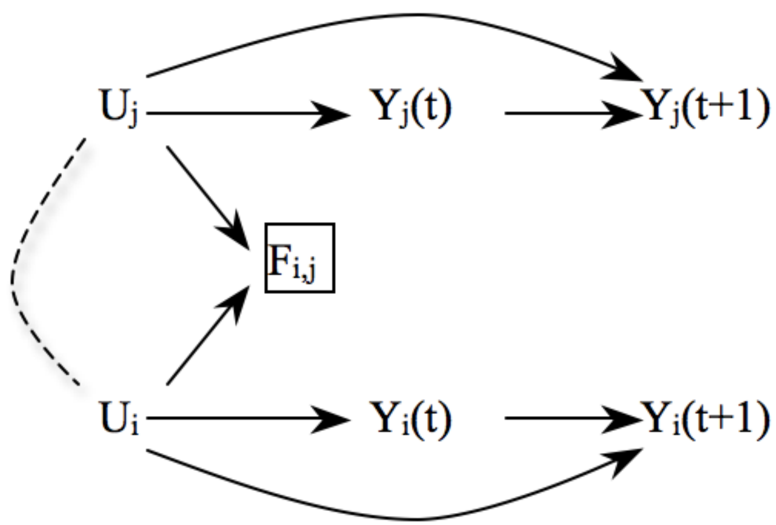
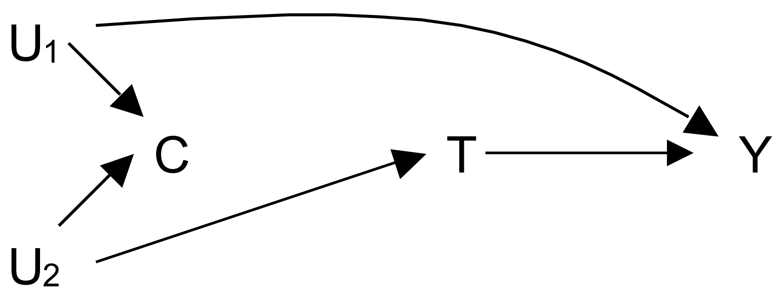


- Looking for associations among friends amounts to conditioning on F. Latent homophily generically biases study of social contagion (Shalizi and Thomas 2011). Latent homophily bias in network analysis is endogenous selection bias (Elwert 2013).
- (Bias will generally be small [Greenland 2003])

3.4 Confounding as a Causal Concept

Example: The associational definition of confounding is dangerous



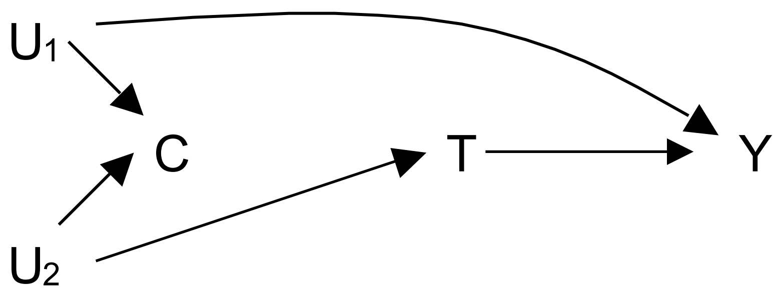
C fits conventional definition of confounding:

1. C is associated with T
2. C is associated with Y
3. C temporally precedes T

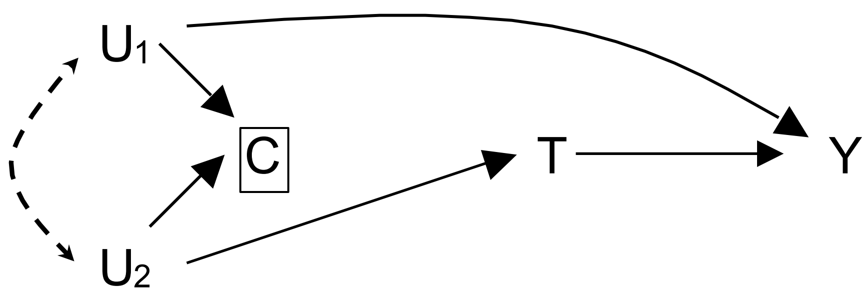
Yet T on Y is identified w/o conditioning on C

3.4 Confounding as a Causal Concept

Example: The traditional definition of confounding is dangerous



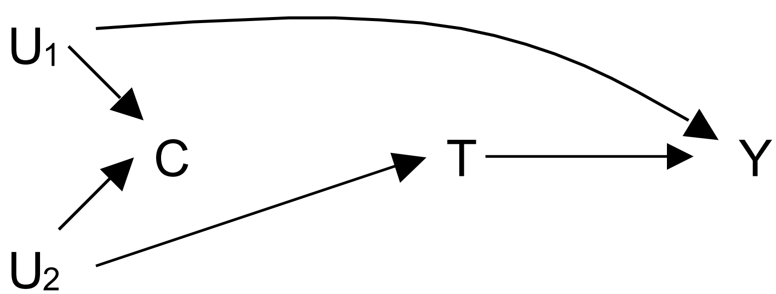
T on Y is identified w/o conditioning on C



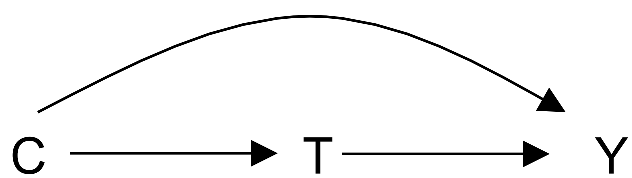
T on Y conditional on C is biased

3.4 Confounding as a Causal Concept

Two different DAGs -- observationally indistinguishable



Conditioning on C is unnecessary and harmful

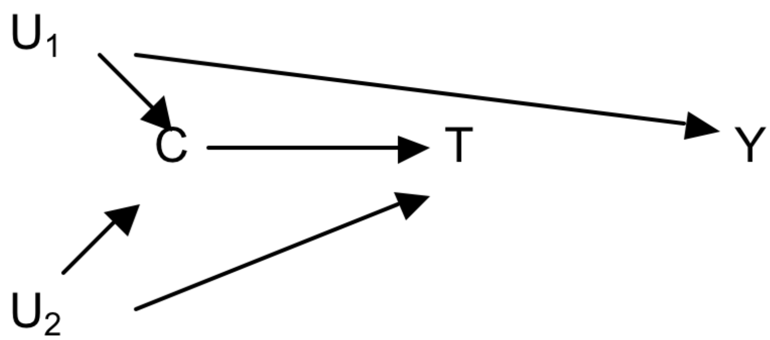


Conditioning on C is necessary and beneficial

The data cannot fully reveal what variables you should (should not) control for. We need strong theory. Confounding is a causal, not an associational concept (Greenland et al. 1999).

3.5 “Damned if you do, damned if you don’t”

What if a pretreatment variable is both a confounder and a collider?



T on Y cannot be estimated w/o conditioning on C

3.5 "Damned if you do, damned if you don't"

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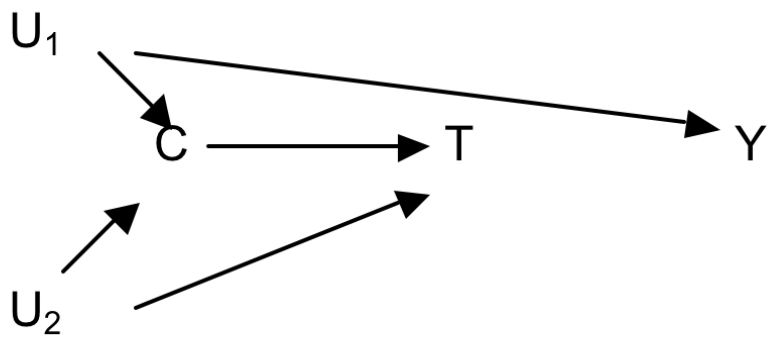
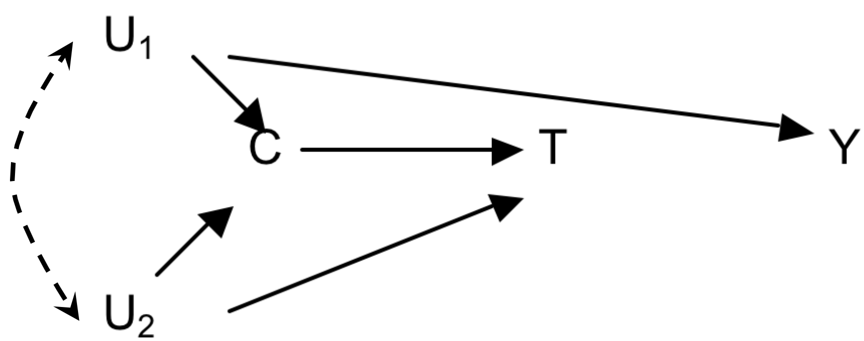


T on Y cannot be estimated w/o conditioning on C.

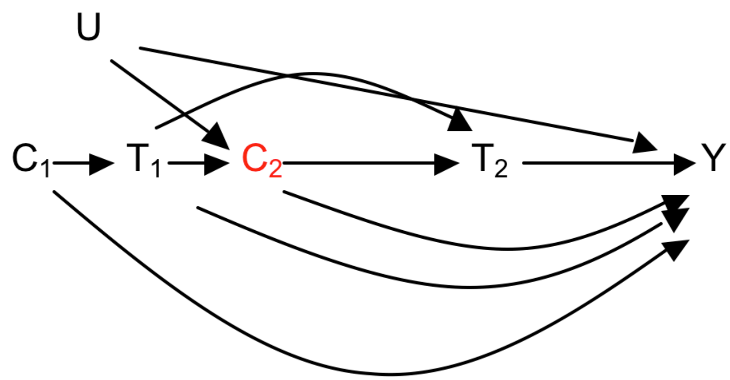


And T on Y cannot be estimated w/ conditioning on C either.

[Pearl 1995]

3.6 Time-Varying Treatments

Time-varying covariates often are both confounders and colliders.



T_t: tv treatment; C_t: tv confounder; U: unmeasured

How to estimate the joint causal effects of time-varying treatments, $\{T_t\}$, *e.g.* "always versus never treated"?

$$\delta = E[Y_{T=\{1,1\}} - Y_{T=\{0,0\}}]$$

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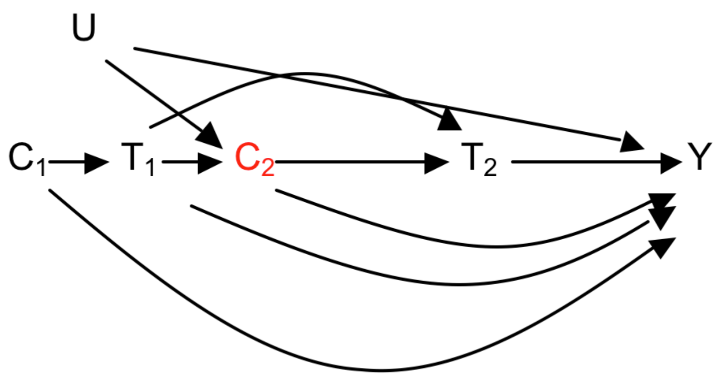
Ex.: Neighborhood Effects



Does growing up in a disadvantaged neighborhood affect high school graduation?

$Pr[Y_{T=\{1,1\}}=1] - Pr[Y_{T=\{0,0\}}=1] > 0$

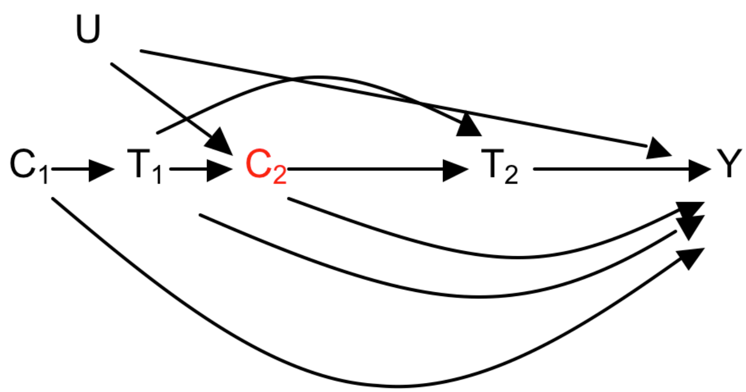
T: time-varying treatment

Residence in a disadvantaged neighborhood

C: time-varying confounder

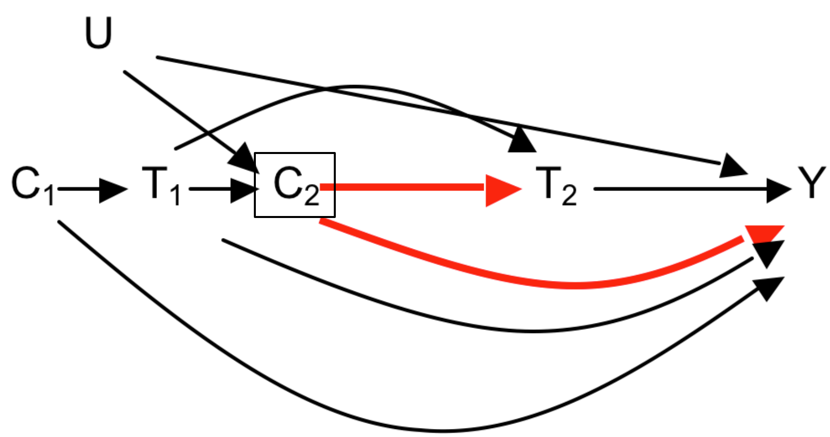
Parent's income=> residence=> parents' income

Failure of Standard Methods



Big Question: How do you handle C_2?

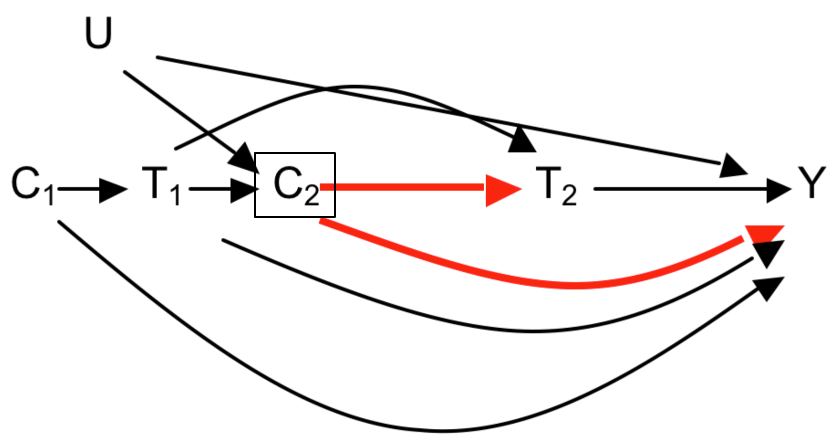
Failure of Standard Methods



Big Question: How do you handle C_2?

C_2 obviously a confounder for T_2 => Must control for C_2. But that…

Failure of Standard Methods



Big Question: How do you handle C_2?

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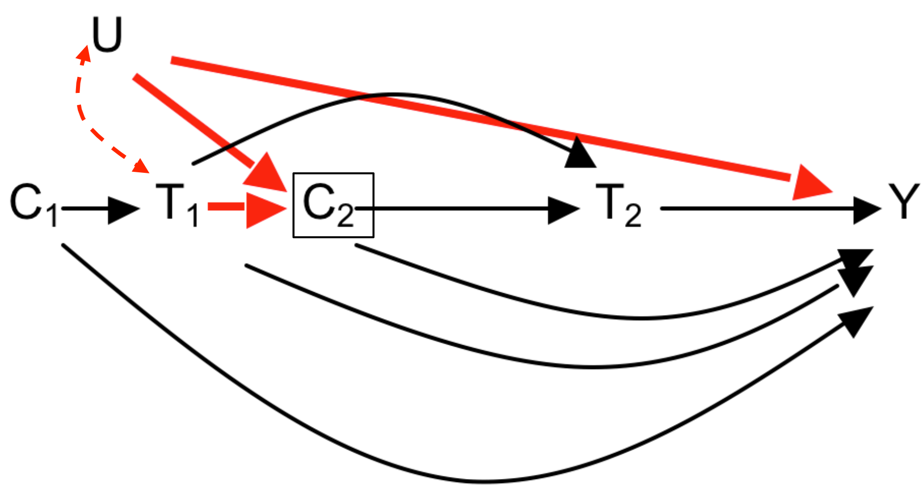

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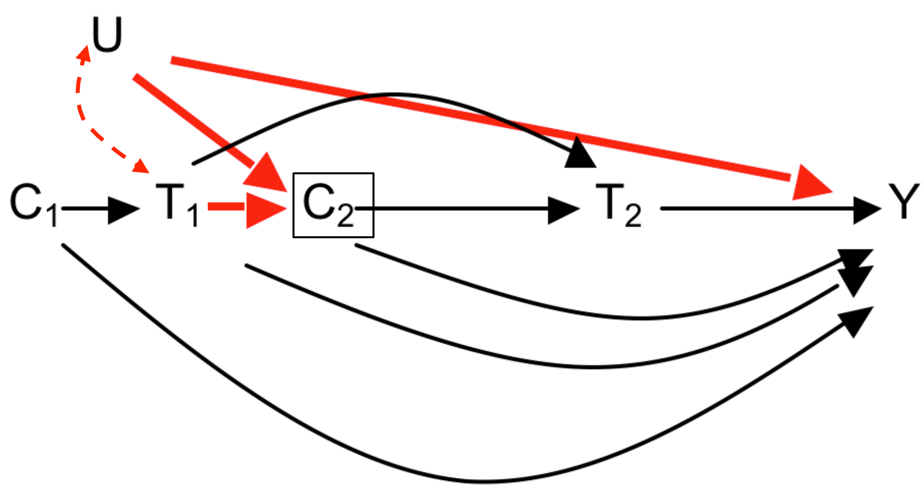

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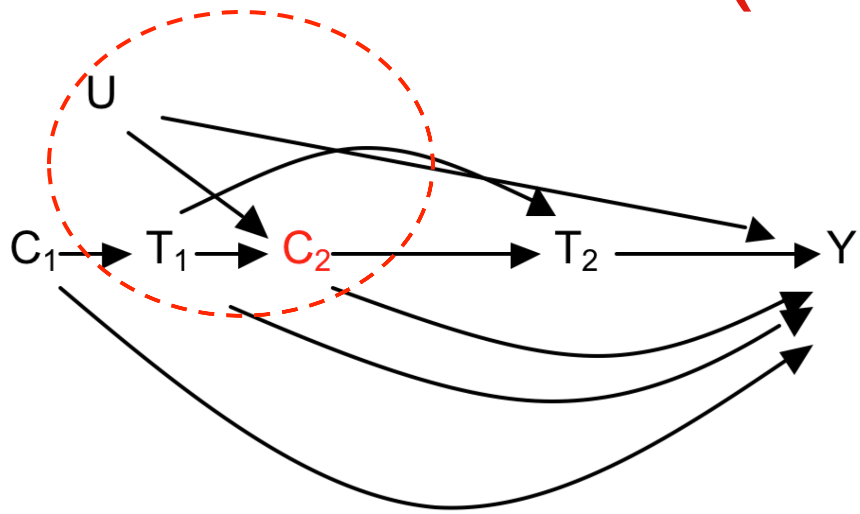
➔Looks like "damned if you do—damned if you don't": Conventional regression cannot handle time-varying confounding because it can't simultaneously control and not-control for C_2. This is <u>true even if all confounders, C_t, of T_t are observed</u>, i.e. there is no unobserved confounding.

General Problem (Robins 1986)



Standard methods for time-varying treatments may be biased if there is a time-varying confounder, C, that is

(1) a risk factor for future values of treatment, and

(2) affected by previous values of treatment,

even if there are no unobserved risk factors for treatment, ($T_t \coprod U|C_t$).

Needs more sophisticated solutions (e.g., Robins' marginal structural models, see Sharkey & Elwert (2011) for a sociological example.)

How Bad Is the Bias?

- Neither size nor direction of endogenous selection bias can generally be predicted without further parametric assumptions
- VanderWeele and Robins (2007) derive direction results under monotonic effects
- In certain binary systems where one must choose between confounding and selection bias (“damned if you do, damned if you don’t”), confounding dominates (Greenland 2003).
- In reality, all studies are biased. When parametric theory is unavailable (in sociology: almost always), a formal sensitivity analysis is advisable (VanderWeele 2011).

Conclusions

- Conditioning on a collider anywhere in the analysis (pre-treatment, post-treatment, or post-outcome) can create bias
- Causal inference requires causal assumptions

Conclusions

- Purely associational criteria of variable selection may lead analysts astray
- DAGs provide a unified perspective on a large number of biases
- DAGs are a useful tool for identifying and understanding the situations in which conditioning on a variable may bias an empirical analysis.

What Should One Condition On?

- Don’t condition on a collider (anywhere) if you can avoid it!
- Don’t condition on post-treatment variables (normally)
- Don’t condition on the outcome (unless it’s a properly executed case control study)
- Don’t condition on post-outcome variables (normally)
- If a variable is a collider and a confounder, you should probably condition on it.
- Be suspicious of pre-treatment variables that don’t credibly cause treatment or outcome—they’re likely colliders.
- If you can, only condition on pre-treatment variables that cause either treatment or outcome, or both. If any set of observable variables is sufficient to control for confounding, the variables that cause either treatment or outcome suffice also (VanderWeele and Shpitser 2011).

The End

Felix Elwert, version 05/2013