Causal Models in Economics

Causal Diagrams/Directed Acyclic Graphs (DAG)

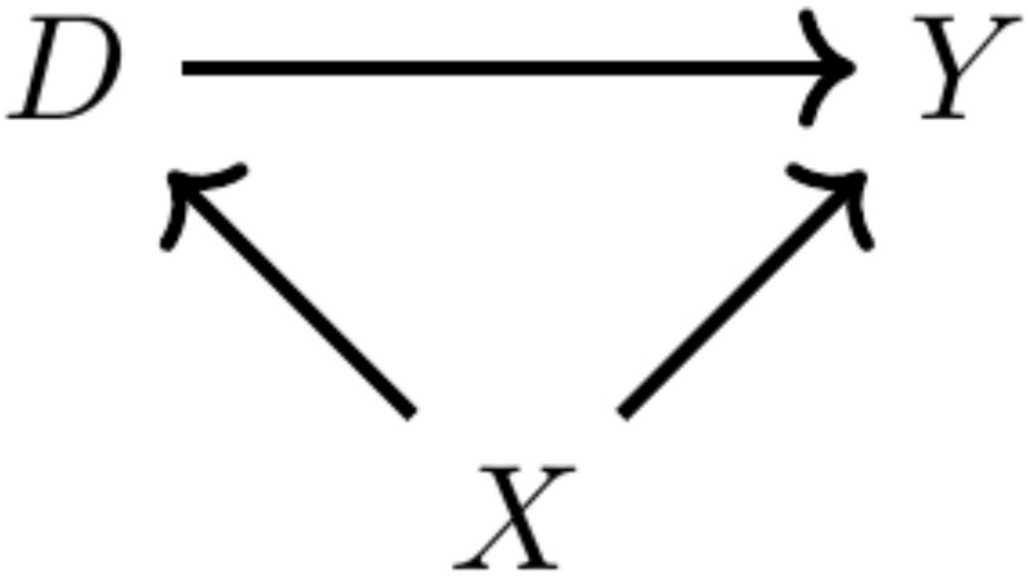
Causal Diagrams

A causal diagram contains two things:

1. The variables , represented by nodes in the diagram
2. The causal relationships, each represented by an arrow from the cause variable to the caused variable

Let’s start with the most basic

- D: treatment (honors class)
- Y: outcome (grades)
- X: Confounder (ability)

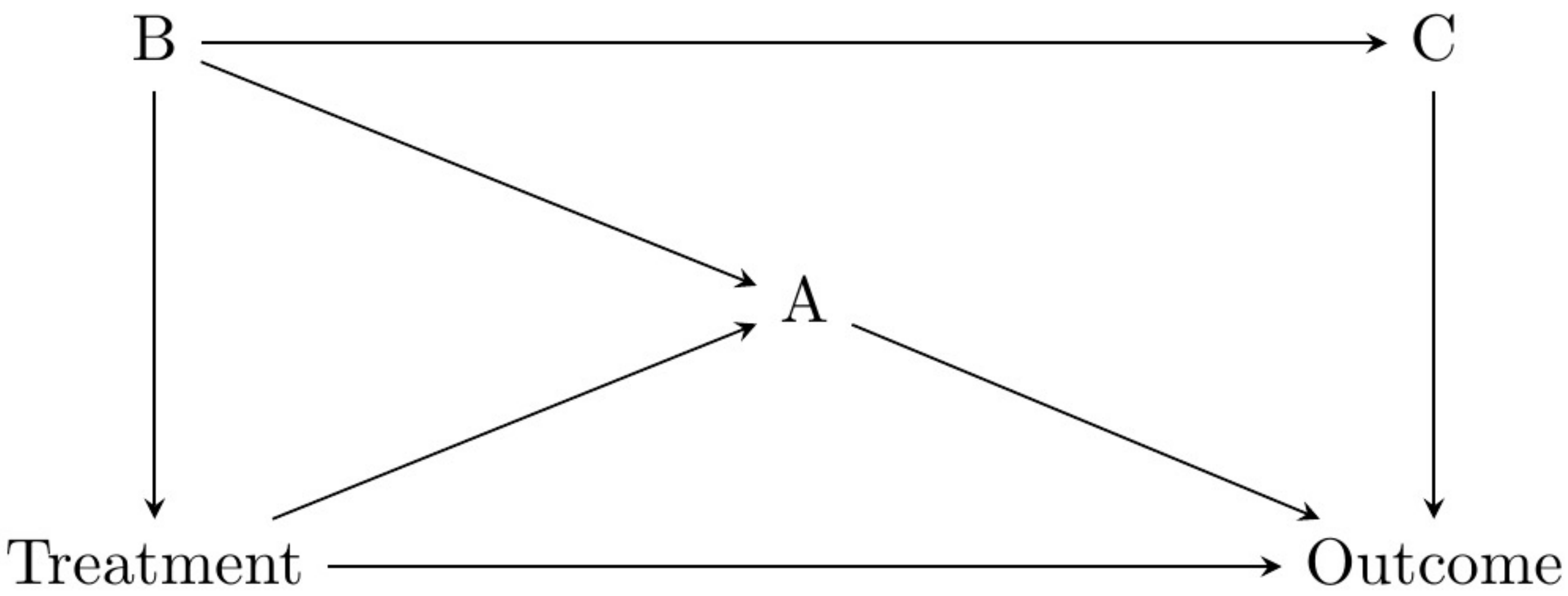


Paths

- A path between two variables on a causal diagram is a description of the set of arrows and nodes you visit when “walking” from one variable to another.

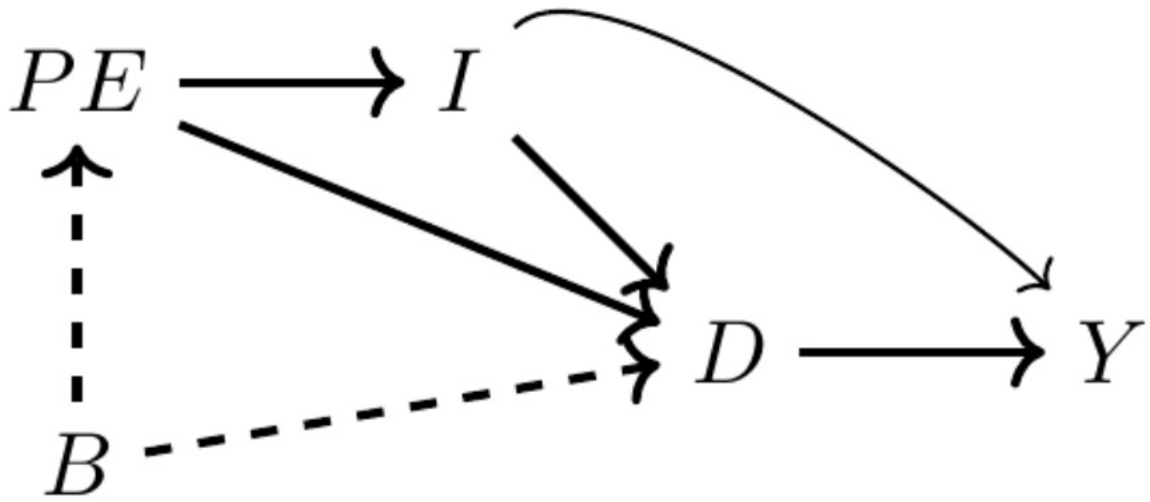
- However, A DAG graph cannot have cycles!

Find the paths in this diagram



A more complicated example

- PE: parental education
- I: family income
- B: unobserved confounders
- D: treatment (college education)
- Y: outcome (earnings)



Find all the paths

Front Door and Backdoor Paths

Every path in which all the arrows face away from Treatment are Front Door Paths, the rest are Backdoor Paths.

We want to control variables to close the backdoor paths but leave front door paths open.

Closed and Open Paths

A path is OPEN if all the variables along that path are allowed to vary.

A path is CLOSED if at least one of the variables along that path has no variation.

Colliders and Confounders

A variable is a *collider* on a particular path if, on that path, both arrows point to it.

Colliders are being caused by the variables to its left and right. It closes a path by default.

A variable is a confounder is both arrows point away from it.

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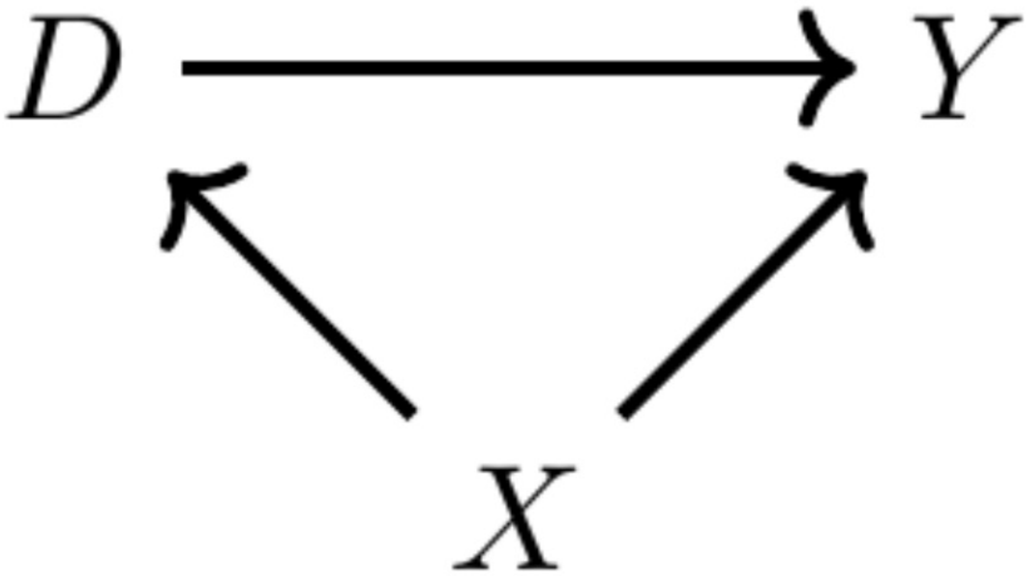
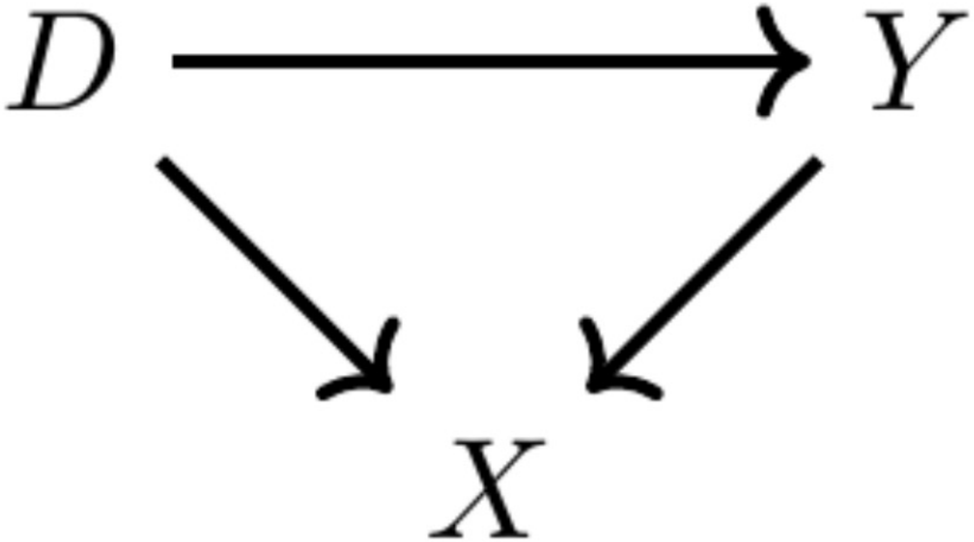


- One should control for confounders

Collider bias

- D: treatment (baby nutrition intake)
- Y: outcome (health status)
- X: collider (baby weight)

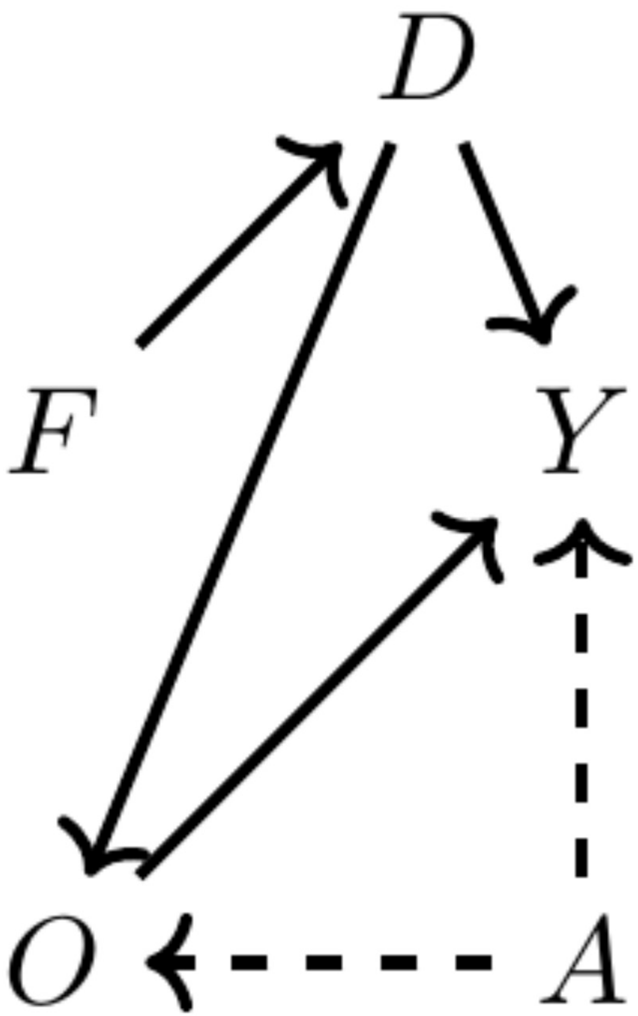


- One should NOT control for colliders

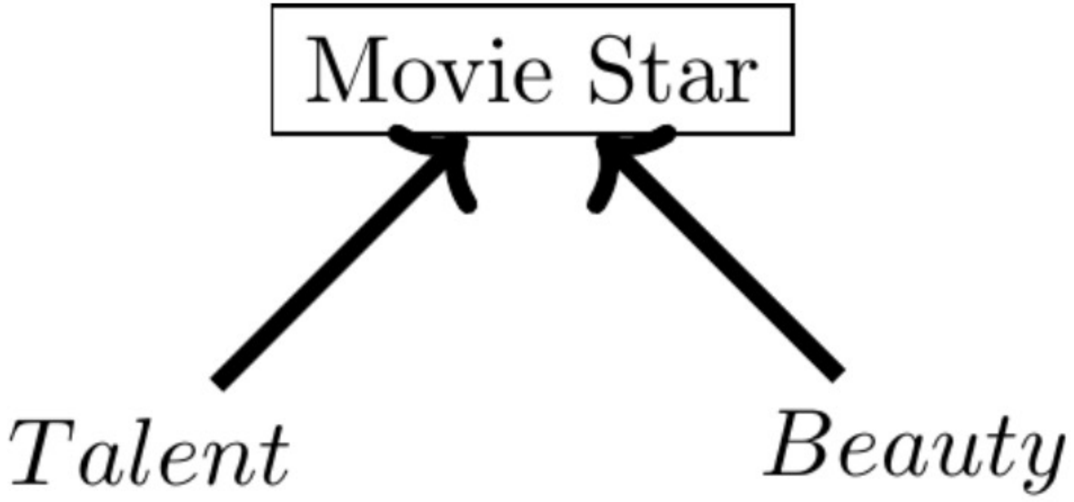
More complex examples

- F: gender
- D: discrimination
- Y: income
- O: occupation
- A: ability

- Should we control for O?



Collider bias from sampling



A real application: Policing and race

- Fryer 2019 found that conditional on suspect demographics, officer demographics, encounter characteristics, suspect weapon, and year fixed effects, blacks are 27 percent less likely to be shot at by police than are nonblack non-Hispanics. (which is not significant)
- Does it mean that race has no effect on policing?

A possible explanation