Introduction to Causal Inference and Causal Data Science

Instrumental Variables and Mediation

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Instrumental Variables

In our lectures so far we have considered different **identification** and **estimation** strategies

Blocking back-door paths (conditioning on confounders)

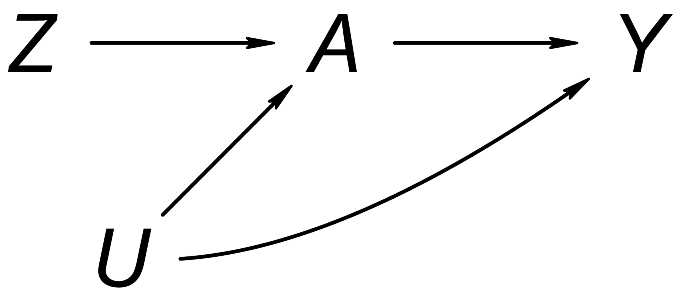
- Stratification, matching, regression adjustment

Creating “pseudo-populations”

- IP weighting, G-methods

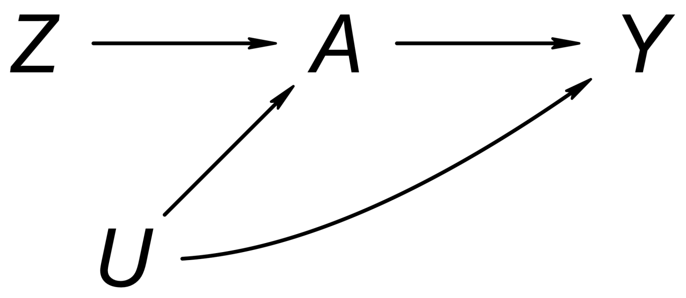
Instrumental Variables

Instrumental Variables (IV) methods are a different identification strategy, which relies on exploiting a particular structure that may occur in a DAG

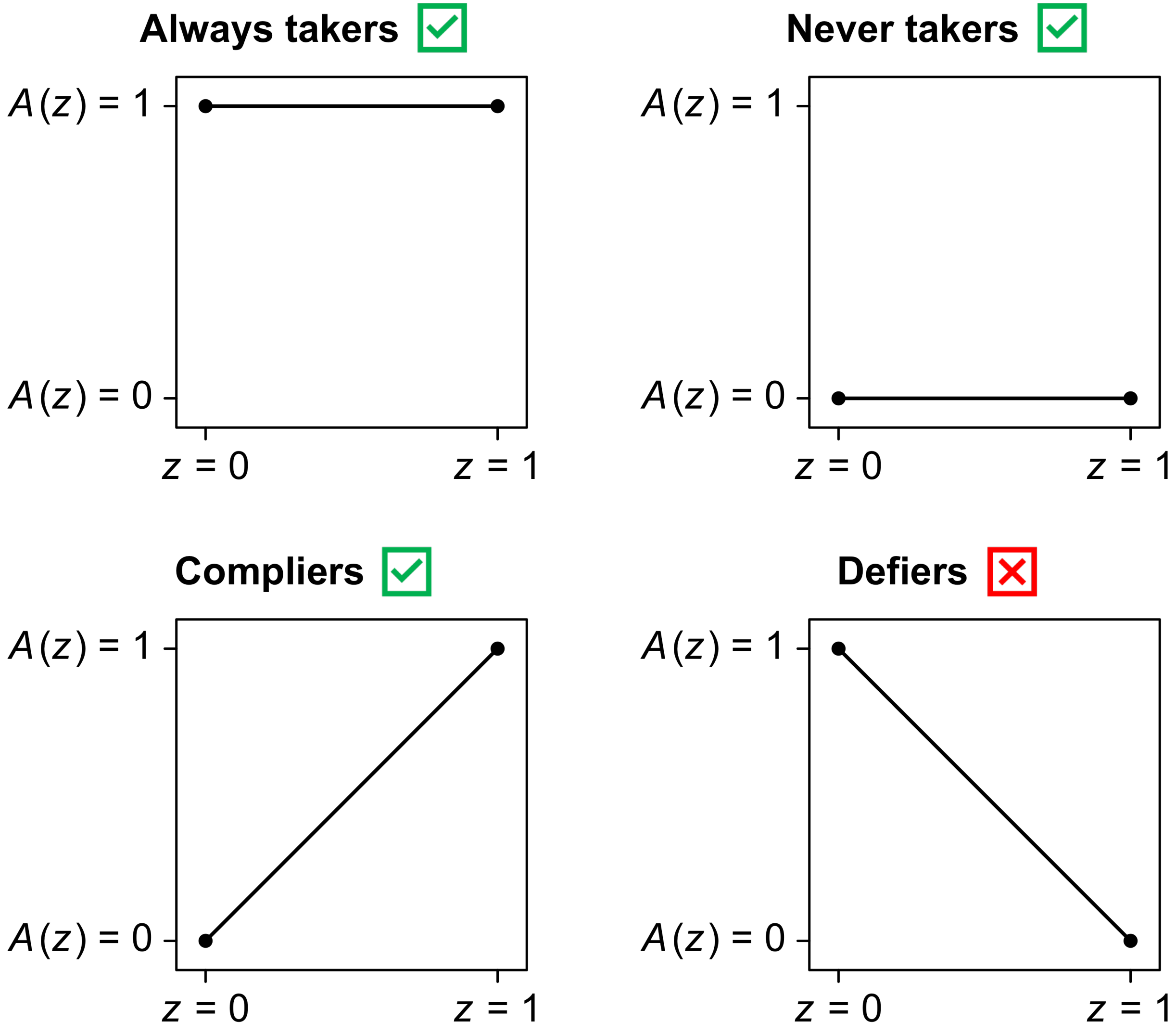


Z is an instrumental variable (IV) for treatment *A* and outcome *Y* if

- Cov(*Z*,*A*) ≠ 0 (**relevance**)
- *Y*(*z*,*a*) constant across levels of *z* (no direct effect of IV on *Y*; **exclusion restriction**)
- IV **exchangeability**
  - E.g., no causes shared by *Z* and *Y* or by *Z* and *A*



A fourth assumption: monotonicity



Suppose instrument Z and treatment A are binary
and, in addition to **consistency** and **positivity**, the following assumptions hold:

- **Relevance**
- **Exclusion restriction**
- **Exchangeability**: $Y(z,A(z))$ and $A(z)$ are both independent of Z, for all z
- **Monotonicity**: there are no defiers

Then, the mean per-protocol effect among compliers, $E[Y(1) - Y(0) \mid \text{Compliers}]$, equals $\text{Cov}(Y,Z) / \text{Cov}(A,Z)$ or, equivalently,

$$\frac{E[Y \mid Z = 1] - E[Y \mid Z = 0]}{E[A \mid Z = 1] - E[A \mid Z = 0]}$$

Critiques of IV methods

- IV methods in particular are/were very popular in economic fields

- Main critique of this is: How often can you actually find a true instrument / instrumental variable?
  - Highly context dependent!
  - In health sciences many have argued that this is quite rare

Mediation

For most of this week we have focused on estimating **total effects**

- Even though we often did not use that term directly

The distinction between a “total” and a “direct” effect becomes relevant in situations where a target variable A can effect the outcome Y through many distinct pathways

$$\begin{tikzcd} A \arrow[r] \arrow[rr, bend left] & M \arrow[r] & Y \end{tikzcd}$$

Direct Effects

Mediation analysis has a long (and controversial) history across many traditions

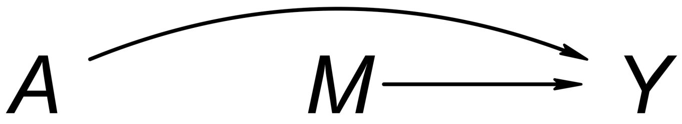
- E.g., in social sciences, tied up with the idea of using linear regression models, taking product terms of coefficients, etc.

There has also been much debate about this in the causal inference literature, and many different frameworks of how to give “mediation analysis” a firm causal foundation

Many debates focus around the **definition** of a direct effect and its relevance for real life decision making

Controlled vs Natural Direct Effects

The **controlled direct effect** (CDE) represents the effect of an intervention on **A,** combined with an intervention to keep **M** <u>fixed at a certain value</u> (say m)

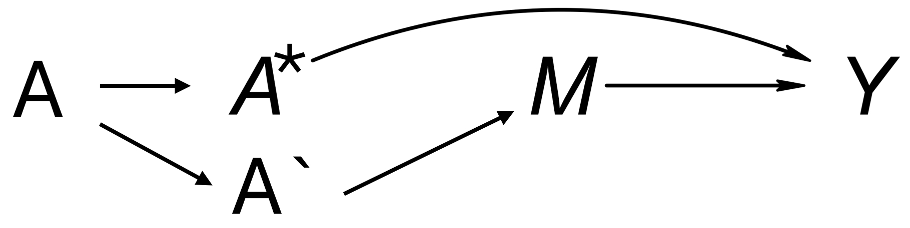


Can often be estimated by **conditioning** on M = m.

What is the effect of smoking on lung cancer, if we could force smokers and non-smokers to have the same tar levels in their lungs?

Natural Direct Effects

The **natural direct effect** (NDE) represents the effect of an intervention on **A,** combined with an intervention that **ensures M takes on** whatever value it “naturally” would have without that intervention



Estimation requires a model for the A -> M relationship

Imagine we can make everyone smoke, but we can create “tar free” cigarettes, and a “tar creation” mechanism

Direct Effects and Policy Relevance

Many causal questions that people come up with can be framed as total effects, or as CDE or NDE questions

- Related to “intention to treat” and “per protocol” effects in TTE

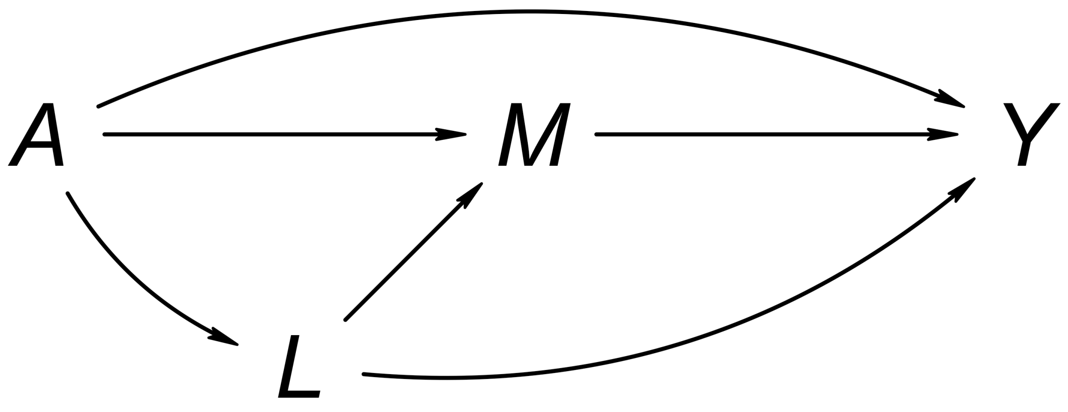
But, they may still be of more or less questionable policy relevance.

Covid Vaccination (A), Death (M) and Experiencing Covid (Y)

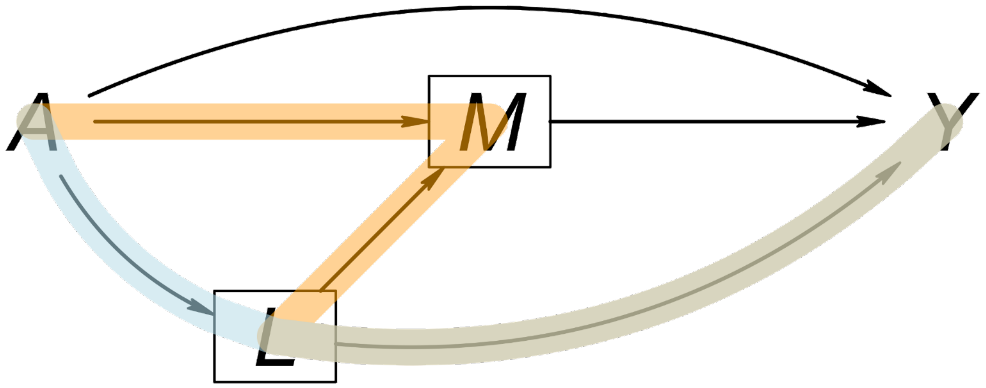
CDE: What is the effect of vaccination on covid-risk given we could keep vaccine takers alive?

NDE: What is the effect of vaccination on covid-risk given that we can ensure that vaccine takers would have the same risk of death as they would have in the absence of vaccination?

CDEs and Estimation: Confounder-feedback

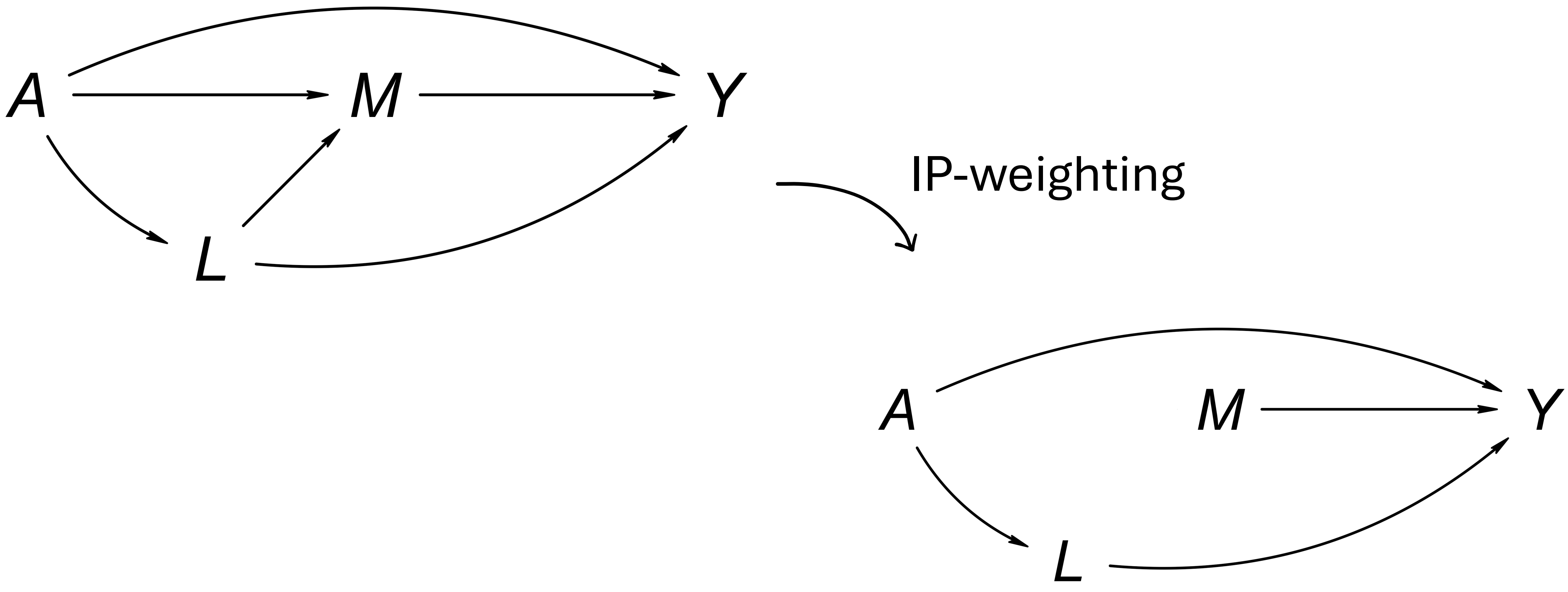


Conditioning



Collider bias!

CDEs and Estimation: Confounder-feedback



Longitudinal Settings

These concerns become especially important in **longitudinal settings**

- We may have **baseline confounding** and **post-baseline confounding**
- Survival models / approaches; known as **informative censoring**