Statistics II

Week 5: **Instrumental Variables**

Lecture Review

Motivations

In experiments

It is often not possible to force subjects to comply with their assignment to treatment/control.

Those who choose to take the treatment may systematically differ from those who do not (selection bias)

In observational studies

Often the relationships between our variables of interest are affected by confounders that are unmeasured or unmeasurable. We can exploit natural experiments that generate (as if) random variation in our independent variable in order to estimate causal effects.

What is an IV?

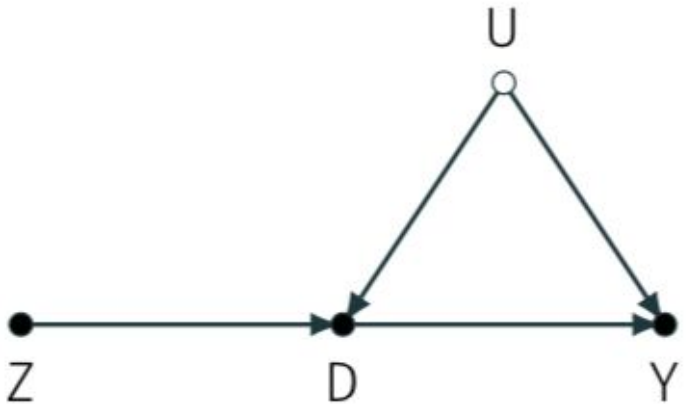
Basic idea:

In order to bypass the problems of non-compliance and confounders, use an exogenous variable (Z) that affects the treatment or independent variable (D) but is **not** affected by confounders (U)**.**

How does it work?

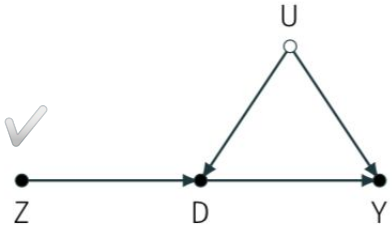
We split the variation of D into two parts:

- One potentially related to confounders (U), observed or unobserved.
- One **truly exogenous**

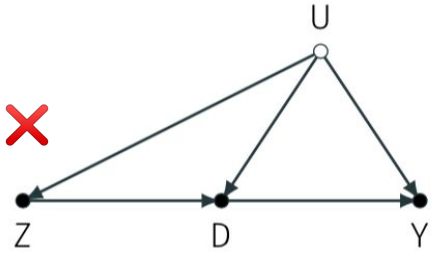


Requirements for valid IV

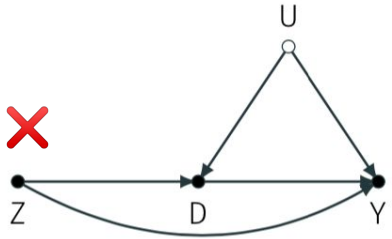
- Z must indeed affect D (**relevant**)



- Z must be **exogenous**, not a descendent of confounders. It must be as if randomly assigned.



- Z must only affect Y through D (**exclusion restriction**)



Intent to Treat Effect (ITT)

- ITT is the effect of the instrumental variable itself on the outcome, regardless of actual treatment. It only considers *assignment* to the treatment or control groups.

- Because Z is randomized, ITT is identified by the difference in means of the outcome of interest between those assigned to treatment and those not.

$$ITT = E(Y_i|Z_i = 1) - E(Y_i|Z_i = 0)$$

Compliance Types

- Some people will always take the treatment, regardless of whether they are in treatment or control (**always-takers**),
- and some never will (**never-takers**).
- Some will always do as their told (**compliers**),
- and some will always do the opposite (**defiers**).

	$Z_i = 0$	$Z_i = 1$
$D_i = 0$	Complier/Never-taker	Defier/Never-taker
$D_i = 1$	Defier/Always-taker	Complier/Always-taker

We cannot directly identify the group to which any particular respondent belongs.

IV Assumptions

Relevance, or nonzero average encouragement effect.

- Encouragement needs to make a difference.
- **Testable**: observe differences between treatment and control groups (**first stage**)

Exogeneity or ignorability of the instrument.

- Hypothetical potential outcomes must be independent from Z.
- Given by quasi-randomization of encouragement. Not empirically testable. A matter of plausibility.

IV Assumptions

Exclusion restriction: instrument affects outcome **only** via treatment.

- Implies zero ITT effect for always-takers/never-takers.
- Hardly testable! (placebo/falsification criterion)

Monotonicity: effect of treatment is only in one direction.

- Implies we assume there are no defiers.
- Also hardly testable; matter of plausibility

SUTVA: no spillovers

Homogeneity: constant treatment effect assumption

LATE (with binary D and Y)

- ITT can be decomposed into different subgroups:

ITT = The intent to treat for compliers + ITT for always-takers + ITT for never-takers + ITT for never-takers

- Under the monotonicity and exclusion assumptions, this simplifies as:

ITTcompliers × Pr(compliers)

- ITTc (for compliers) can then be interpreted as the Local Average Treatment Effect (LATE)

$$ITT_c = \frac{ITT}{Pr(compliers)} = LATE$$

However, compliers are defined in terms of principal strata, so we can never identify who they actually are.
Plus, different instruments yield different compliers.

Estimating LATE

"By hand"

Using the Wald estimator

$$\text{LATE} = \frac{\text{Cov}(Y_i, Z_i)}{\text{Cov}(D_i, Z_i)}$$

$$= \frac{E(Y_i|Z_i = 1) - E(Y_i|Z_i = 0)}{E(D_i|Z_i = 1) - E(D_i|Z_i = 0)}$$

(Be careful to weight the expected outcomes with the observed number of observations. See lecture slide no. 25 for an example)

or

Two-stage least squares (2SLS)

A sequence of two regressions

1. First stage: Regress treatment D on instrument Z → $D = \gamma_0 + \gamma_0 Z_i + v_i$

1.1 Calculate predicted values (D-hat) of first stage regression.

2. Regress outcome Y on predicted values (D-hat). → $Y_i = \beta_0 + \beta^{2sls}\hat{D} + u_i$

- The regression coefficient of D-hat is the LATE estimator. → β^{2sls}
- It only retains the variation in D that is generated by (as if) random variation in Z: the portion of the variation in D that we wanted to isolate!

Let’s see how to do this in R