THE WORLD BANK

IMPACT EVALUATION

Technical Track

Session IV

Instrumental Variables

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Beijing, China, 2009

An example to start off with…

- Say we wish to evaluate a voluntary job training program
  - Any unemployed person is elegible
  - Some people choose to register ("Treatments")
  - Other people choose not to register ("Comparisons")
- Some simple (but not-so-good) ways to evaluate the program:
  - Compare before and after situation in the treatment group
  - Compare situation of treatments and comparisons after the intervention
  - Compare situation of treatments and comparisons before and after

Voluntary job training program

Say we decide to compare outcomes for those who participate to the outcomes of those who do not participate:

a simple model to do this:

$$y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$$

Where D = 1 if person participates in training

D = 0 if person does not participate in training

x = control variables (exogenous & observable)

Why is this not working properly? 2 problems:

- ▹ Variables that we omit (for various reasons) but that are important
- ▹ Decision to participate in training is endogenous

Problem #1: Omitted Variables

Even in a well-thought model, we'll miss

▹ "forgotten" characteristics: we didn't know they mattered

▹ characteristics that are too complicated to measure

Examples :

▹ Varying talent and levels of motivation

▹ Different levels of information

▹ Varying opportunity cost of participation

▹ Varying level of access to services

The full "correct" model is: $y = \alpha + \gamma_1 D + \gamma_2 x + \gamma_3 M + \eta$

The model we use: $y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$

Problem #2: Endogenous Decision to Participate

- Participation is a decision variable? ➔ endogenous!
- (I.e. it depends on the participants themselves)

$$y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$$
$$D = \pi + \pi_2 M + \xi$$

$$=> y = \alpha + \beta_1(\pi + \pi_2 M + \xi) + \beta_2 x + \varepsilon$$
$$=> y = \alpha + \beta_1 \pi + \beta_2 x + \beta_1 \pi_2 M + \beta_1 \xi + \varepsilon$$

- <u>So</u>: in the two cases: we're missing the M term, which we need to estimate the correct model, but which we cannot measure properly.

- The “correct model is: $y = \alpha + \gamma_1 D + \gamma_2 x + \gamma_3 M + \eta$
- Simplified model: $y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$

- Say we estimate the treatment effect γ_1 with $\beta_{1,OLS}$
- If *M* is correlated with *D*, and we don’t include *M* in the simplified model, then the estimator of the parameter on *D* will pick up part of the effect of *M*. This will happen to the extent that *M* and *D* are correlated.
- Thus: our OLS estimator $\beta_{1,OLS}$ of the treatment effect γ_1 captures the effect of other characteristics (*M*) in addition to the treatment effect.
- This means that there is a difference between $E(\beta_{1,OLS})$ and γ_1

  → the expected value of the OLS estimator β_1 isn’t γ_1, the real treatment effect

  → $\beta_{1,OLS}$ is a biased estimator of the treatment effect γ_1.

- The “correct model is: $y = \alpha + \gamma_1 T + \gamma_2 x + \gamma_3 D + \eta$
- Simplified model: $y = \alpha + \beta_1 T + \beta_2 x + \varepsilon$

- This means that there is a difference between $E(\beta_{1,OLS})$ and γ_1

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- Why did this happen?
  - One of the basic conditions for OLS to be BLUE was violated:

- In other words $E(\beta_{1,OLS}) \neq \gamma_1$ (biased estimator)
- Even worse…..$plim(\beta_{1,OLS}) \neq \gamma_1$ (inconsistent estimator)

What can we do to solve this problem?

$$y = \alpha + \gamma_1 D + \gamma_2 x + \gamma_3 M + \eta$$

$$y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$$

- Try to clean the correlation between D and ε:
- Isolate the variation in D that is not correlated with ε through the omitted variable M
- We can do this using an instrumental variable (*IV*)

Basic idea behind IV

$$y = \alpha + \gamma_1 D + \gamma_2 x + \gamma_3 M + \eta$$

$$y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$$

- The basic problem is that *corr (D,M)* $\neq$ *0*
- Find a variable *Z* that satisfies two conditions:
  1. Correlated with *D*: *corr (Z , D)* $\neq$ *0*

     ---- *Z* and *D* are correlated, or *Z* predicts part of *D*
  2. *Z* is not correlated with *ε*: *corr (Z , ε) = 0*

     ----By itself, *Z* has no influence on *y*. The only way it can influence *y* is because it influences *D*. All of the effect of *Z* on *y* passes through *D*.
- Examples of *Z* in the case of voluntary job training program?

Two-stage least squares (2SLS)

Remember the original model with endogenous *D*:

$$y = \alpha + \beta_1 D + \beta_2 x + \varepsilon$$

Step 1: Regress the endogenous variable D on the instrumental variable(s) Z and other exogenous variables

$$D = \delta_0 + \delta_1 x + \theta_1 Z + \tau$$

▹ Calculate the predicted value of D for each observation: $\hat{D}$

▹ Since Z and x are not correlated with ε, neither will be $\hat{D}$.

▹ You will need one instrumental variable for each potentially endogenous regressor

Two-stage least squares (2SLS)

Step 2: Regress y on the predicted variable $\hat{D}$ and the other exogenous variables

$$y = \alpha + \beta_1 \hat{D} + \beta_2 x + \varepsilon$$

- ▹ Note: the standard errors of the second stage OLS need to be corrected because $\hat{D}$ is not a fixed regressor.
- ▹ In practice: use STATA ivreg command, which does the two steps . at once and reports correct standard errors.
- ▹ Intuition: by using Z for D, we cleaned D of its correlation with ε.
- ▹ It can be shown that (under certain conditions) IV yields a consistent estimator of γ_1(large sample theory)

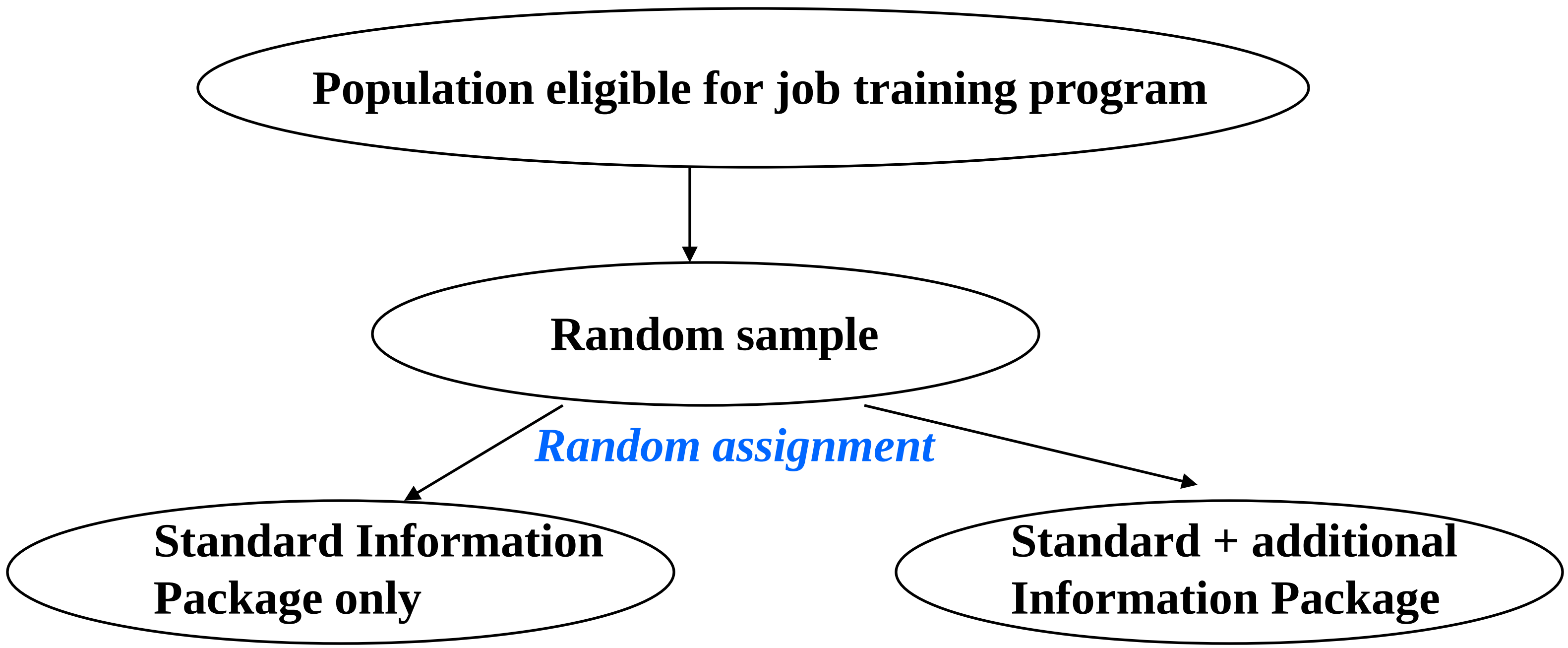
Uses of instrumental variables

- Simultaneity: X and Y cause each other
  - instrument X
- Omitted Variables: X is picking up the effect of other variables which are omitted
  - instrument X with a variable that is not correlated with the omitted variable(s)
- Measurement Error: X is not measured precisely
  - instrument X

Where do we find instrumental variables?

- Searching for one – hard!
- Creating one with information
  - If everyone is eligible to participate in treatment
  - But some have more information than others
    - Who has more information will be more likely to participate
  - Provision of "additional information" on a random basis

Example 1: voluntary job training program



Monthly income 1 year later = 700

Monthly income one year later= 850

30 percent takeup

90 percent takeup

Question: what is the impact of the job training program?

Standard Information Package only

Standard + additional Information Package

Monthly income 1 year later = 700

30 percent takeup

Monthly income one year later= 850

90 percent takeup

Question: what is the impact of the job training program?

- **Difference between the "well informed" and "not well informed" group**

  …………………………………

- **Corrected for the differential take-up rate**

  …………………………………

- **Practically: Impact = ……………………………**

Link back to the estimation formula

- Stage 1:
  - Regress the participation on training on a dummy for whether person received additional information package (linear model)
  - Compute predicted value of participation

- Stage 2:
  - Regress wages on the predicted value of participation

Example 2: School autonomy in Nepal

- Goal is to evaluate
  - A. Autonomous school management by communities
  - B. School report cards
- Data
  - You can include 1000 schools in the evaluation
  - Each community freely chooses to participate or not.
  - School report cards done by NGOs
  - Each comunity has exactly one school.
- Task: design the implementation of the program so it can be evaluated – propose method of evaluation.

School autonomy in Nepal

		Intervention B: School report card intervention by NGO		
		Yes	No	*Total*
Instrumental Variable for Intervention A: NGO visits community to inform on procedures for transfer of the school to community management	Yes	300	300	*600*
	No	200	200	*400*
	Total	*500*	*500*	*1000*

Reminder and a word of caution….

- *corr* $(Z,\varepsilon) = 0$
  - if *corr* $(Z, \varepsilon) \neq 0$ "Bad instrument" ¡Problem!
  - ¡Finding a good instrument is hard!
  - ¡Use both theory and common sense to find one!
  - We can think of designs that yield good instruments.

- *corr* $(Z,D) \neq 0$
  - "Weak instruments": the correlation between Z and D needs to be sufficiently strong.
  - If not, the bias stays large even for large sample sizes.