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# **INSTRUMENTAL VARIABLES**

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## **Technical Track Session IV**

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# Instrumental Variables and IE

- Instrumental variables have many uses
- IV can be generated *ex ante*:
  - Randomized promotion (or encouragement design)
  - “Randomized offering” of a program
- IV can be used *ex post* to correct for non-compliance or conduct retrospective IE:
  - Correction for non-compliance to recover TOT from ITT
    - E.g. Randomized Assignment with non-compliers
    - E.g. Fuzzy Regression Discontinuity
  - Look for exogenous variation to evaluate the impact of a program in absence of a prospective design.
- Here:
  - General Principles behind IVs
  - Ex ante focus on randomized promotion
  - IV, non-compliance and randomized offering

# An example to start off with...

- Say we wish to evaluate a voluntary job training program
  - Any unemployed person is eligible (Universal eligibility)
  - Some people choose to register (Participants)
  - Other people choose not to register (Non-participants)
- Some simple (but not-so-good) ways to evaluate the program:
  - Compare before and after situation in the participant group
  - Compare situation of participants and non-participants after the intervention
  - Compare situation of participants and non-participants before and after (DD).

# 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:

$$y = \alpha + \beta_1 P + \beta_2 X + \varepsilon$$

$$P = \begin{cases} 1 & \text{If person participates in training} \\ 0 & \text{If person does not participate in training} \end{cases}$$

$X$  = Control variables (exogenous & observed)

- Why is this not working? **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 if we try to control for “everything”, we’ll miss:
  - (1) Characteristics that we didn’t know they mattered, and
  - (2) Characteristics that are too complicated to measure (not observables or not observed):
    - Talent, motivation
    - Level of information and access to services
    - Opportunity cost of participation
- Full model would be:

$$y = \gamma_0 + \gamma_1 X + \gamma_2 P + \gamma_3 M_1 + \eta$$

But we cannot observe  $M_1$ , the “missing” and unobserved variables.

# Omitted variable bias

- True model is:  $y = \gamma_0 + \gamma_1 x + \gamma_2 P + \gamma_3 M_1 + \eta$

- But we estimate:  $y = \beta_0 + \beta_1 x + \beta_2 P + \varepsilon$

- If there is a correlation between  $M_1$  and  $P$ , then the *OLS* estimator of  $\beta_2$  will not be a consistent estimator of  $\gamma_2$ , the true impact of  $P$ .

- Why?**

When  $M_1$  is missing from the regression, the coefficient of  $P$  will “pick up” some of the effect of  $M_1$

# Problem #2: Endogenous Decision to Participate

- True model is:

$$y = \gamma_0 + \gamma_1 X + \gamma_2 P + \eta$$

with

$$P = \pi_0 + \pi_1 X + \pi_2 M_2 + \xi$$

$M_2$  = Vector of unobserved / missing characteristics  
(i.e. we don't fully know why people decide to participate)

- Since we don't observe  $M_2$ , we can only estimate a simplified model:

$$y = \beta_0 + \beta_1 X + \beta_2 P + \varepsilon$$

- Is  $\beta_{2, OLS}$  an unbiased estimator of  $\gamma_2$ ?

# Problem #2: Endogenous Decision to Participate

- We estimate:

$$y = \beta_0 + \beta_1 x + \beta_2 P + \varepsilon$$

- But true model is:

$$y = \gamma_0 + \gamma_1 x + \gamma_2 P + \eta$$

with

$$P = \pi_0 + \pi_1 x + \pi_2 M_2 + \xi$$

- Is  $\beta_{2, OLS}$  an unbiased estimator of  $\gamma_2$ ?

$$\begin{aligned} \text{Corr}(\varepsilon, P) &= \text{corr}(\varepsilon, \pi_0 + \pi_1 x + \pi_2 M_2 + \xi) \\ &= \pi_1 \text{corr}(\varepsilon, x) + \pi_2 \text{corr}(\varepsilon, M_2) \\ &= \pi_2 \text{corr}(\varepsilon, M_2) \end{aligned}$$

- If there is a correlation between the missing variables that determine participation (e.g. Talent) and outcomes not explained by observed characteristics, then the OLS estimator will be biased.

# What can we do to solve this problem?

- We estimate:

$$y = \beta_0 + \beta_1 x + \beta_2 \mathbf{P} + \boldsymbol{\varepsilon}$$

- So the problem is the correlation between  $\mathbf{P}$  and  $\boldsymbol{\varepsilon}$
- How about we replace  $\mathbf{P}$  with "something else", call it  $\mathbf{Z}$ :
  - $\mathbf{Z}$  needs to be similar to  $\mathbf{P}$
  - But is not correlated with  $\boldsymbol{\varepsilon}$

# Back to the job training program

- $P$  = participation
- $\varepsilon$  = that part of outcomes that is not explained by program participation or by observed characteristics
- I'm looking for a variable  $Z$  that is:
  - (1) Closely related to participation  $P$
  - (2) but doesn't directly affect people's outcomes  $Y$ , *other than through its effect on participation.*
- So this variable must be coming from **outside.**

# Generating an outside variable for the job training program

- Say that a social worker visits unemployed persons to encourage them to participate.
  - She only visits 50% of persons on her roster, and
  - She randomly chooses whom she will visit
- If she is effective, many people she visits will enroll. There will be a correlation between receiving a visit and enrolling
- But visit does not have direct effect on outcomes (e.g. income) apart from its effect through enrollment in the training program.
- Randomized “encouragement” or “promotion” visits are an Instrumental Variable.

# Characteristics of an instrumental variable

- Define a new variable  $Z$

$$Z = \begin{cases} 1 & \text{If person was randomly chosen to receive the encouragement visit from the social worker} \\ 0 & \text{If person was randomly chosen not to receive the encouragement visit from the social worker} \end{cases}$$

- $Corr ( Z , P ) > 0$

People who receive the encouragement visit are more likely to participate than those who don't

- $Corr ( Z , \varepsilon ) = 0$

No correlation between receiving a visit and benefit to the program apart from the effect of the visit on participation.

- $Z$  is called an **instrumental variable**

# Two-stage least squares (2SLS)

Remember the original model with endogenous  $P$ :

$$y = \beta_0 + \beta_1 x + \beta_2 P + \varepsilon$$

## Step 1

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Regress the endogenous variable  $P$  on the instrumental variable(s)  $Z$  and other exogenous variables

$$P = \delta_0 + \delta_1 x + \delta_2 Z + \tau$$

- Calculate the predicted value of  $P$  for each observation:  $\hat{P}$
- Since  $Z$  and  $x$  are not correlated with  $\varepsilon$ , neither will be  $\hat{P}$ .
- You will need one instrumental variable for each potentially endogenous regressor.

# Two-stage least squares (2SLS)

## Step 2

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Regress  $y$  on the predicted variable  $P$  and the other exogenous variables

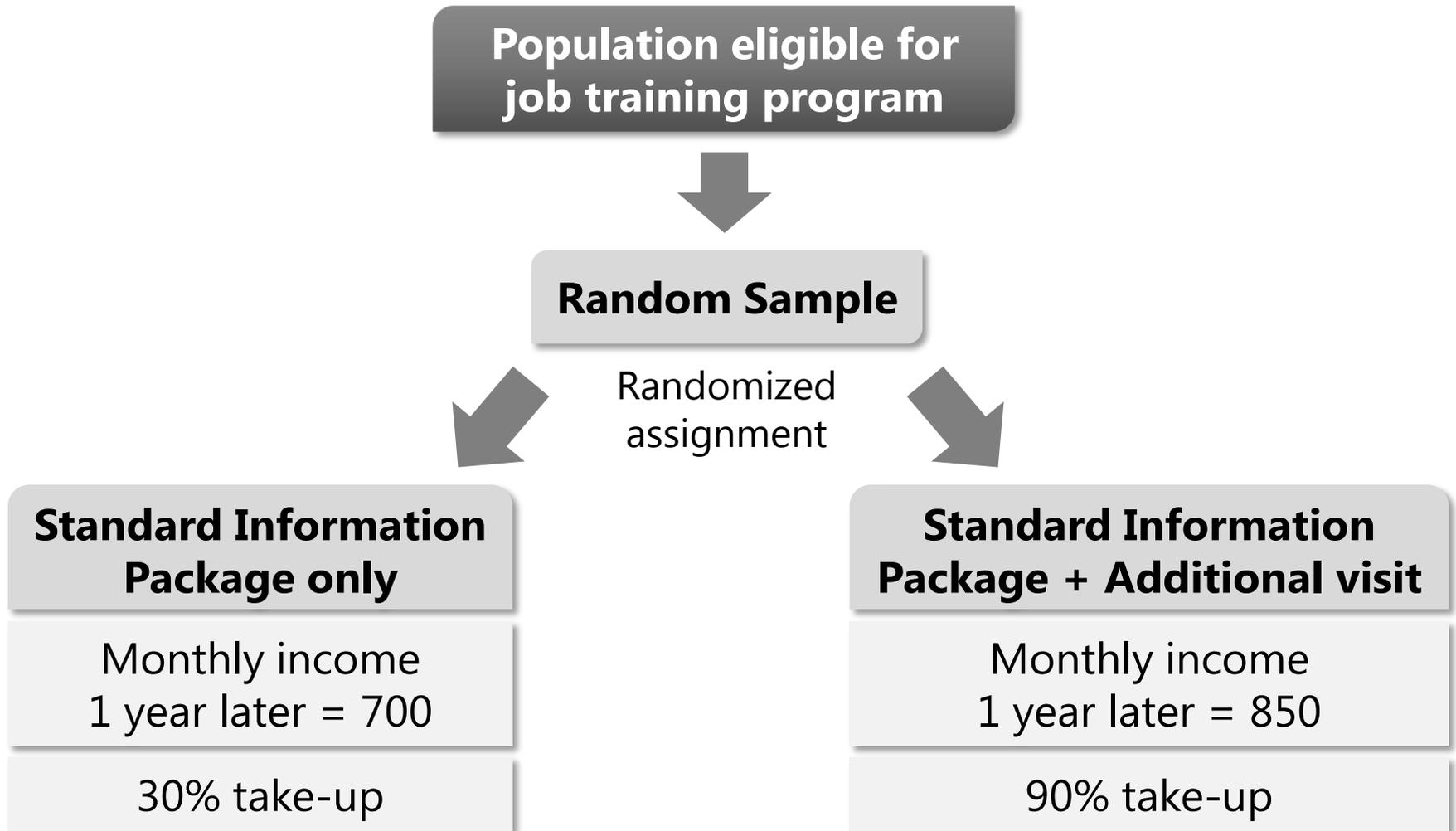
$$y = \beta_0 + \beta_1 x + \beta_2 P + \varepsilon$$

- **Note:** The standard errors of the second stage *OLS* need to be corrected because  $P$  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  $P$ , we cleaned  $P$  of its correlation with  $\eta$
- It can be shown that (under certain conditions)  $\beta_{2,IV}$  yields a consistent estimator of  $\gamma_2$  (large sample theory)

# Where do we find instrumental variables?

- Searching for an IV *ex post* ... Hard and risky!
- Generating an IV with information campaign designed *ex ante*
  - 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



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

**Standard Information Package only**

Monthly income  
1 year later = 700

30% take-up

**Standard + Additional Information Package**

Monthly income  
1 year later = 850

90% take-up

**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

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- Regress the participation on training on a dummy for whether person received additional visit (linear model)
- Compute predicted value of participation

## Stage 2

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Regress wages on the predicted value of participation

# Example 2: School autonomy in Nepal

## Goal

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To Evaluate:

- A. Autonomous school management by communities
- B. School report cards

## Data

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- You can include 1000 schools in the evaluation
- Each community freely chooses to participate or not
- School report cards done by NGOs
- Each community has exactly one school

## Task

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Design the implementation of the program so it can be evaluated –propose method of evaluation.

# School autonomy in Nepal

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

# Reminder and a word of caution...

- $corr(Z, \varepsilon) = 0$

- If  $corr(Z, \varepsilon) \neq 0$ , "Bad instrument"
- "Finding" a good instrument is **hard!**
- But you can build one yourself with a **randomized encouragement design**

- $corr(Z, P) \neq 0$

- "Weak instruments": the correlation between  $Z$  and  $P$  needs to be sufficiently strong.
- If not, the bias stays large even for large sample sizes.

# Recovering TOT from ATE in case of non-compliance

- Sometimes eligible units are selected randomly into the treatment group, are offered treatment, but not all of them accept it.
- Computing the Average Treatment Effect (ATE)  
Straight difference in average outcomes between the group to whom you offered treatment, and the group to whom you did not offer treatment
- Computing the Effect of Treatment on the Treated (TOT)  
Use the randomized offering as an instrumental variable ( $Z$ ) for whether people accepted the treatment ( $P$ )

# Note: IV is a 'local' effect

- IV methods identify the average gains to persons induced to change their choice by a change of the instrument (referred to as compliers)
  - ... however we cannot identify who these people are ("local average treatment effect" or LATE)
  - ... different instruments will identify different parameters and answer different questions
- Caution in extrapolating to the whole population

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**Thank You**



**Q & A**