# INSTRUMENTAL VARIABLES
## Technical Track Session IV

**Sergio Urzua**
**University of Maryland**

# Instrumental Variables and IE

- Two main uses of IV in impact evaluation:
  1. Correct for difference between assignment of treatment and actual treatment
     - E.g. Randomized Assignment with non-compliers
     - E.g. Fuzzy Regression Discontinuity
  2. Look for exogenous variation (*ex-post*) to evaluate the impact of a program in absence of a prospective design.
- Here:
  - General Principles behind IV and an example with a focus on use (1)

# 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 ways to evaluate the program:
  - Random sample containing treatment status (P), exogenous controls (X) and outcome (Y).
  - First alternative: To compare situation of participants and non-participants after the intervention. We already learned this estimator would be biased!

# 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 would this not be correct? 2 problems:
  - Decision to participate in training is endogenous (e.g. based on an "unmeasurable" characteristic).
  - Variables that we omit (e.g. unmeasured) but that are important

**P and ε are correlated**

# What can we do to solve this problem?

- We estimate: $y = \beta_0 + \beta_1 x + \beta_2 \boldsymbol{P} + \boldsymbol{\varepsilon}$

- So the problem is the correlation between ***P*** and ***ε***

- Intuition of IV: How about we replace ***P*** with "something else" that is …
  - … similar to ***P***
  - … but is not correlated with ***ε***

# Back to the job training program

- ***P*** = participation
- ***ε*** = that part of outcomes that is not explained by program participation or by observed characteristics

- Instrumental variable will be a variable ***Z*** that is:

  (1) Closely related to participation *P*. *[i.e. Corr ( Z , P ) > 0]*
  (2) but doesn't directly affect people's outcomes *Y*, *except through its effect on participation. [i.e. Corr ( Z , ε ) = 0 ]*

- Hard to come up with such a variable *ex-post* … but if we anticipate this problem, we can plan for it

# “Generating” an instrumental variable

- **Encouragement design:**

- Say that a social worker visits 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) except from its effect through enrollment in the training program.

→ Randomized “encouragement” or “promotion” visits can be a useful 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.

- $Z$ therefore satisfies the conditions for being 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

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 *ε*, neither will be $\hat{P}$
- You will need one instrumental variable for each potentially endogenous regressor.

# Two-stage least squares *(2SLS)*

## Step 2

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

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

- Note: The standard errors of the second stage *OLS* need to be corrected because $\hat{P}$ is a "generated" regressor.
- In Practice: Use *STATA* ivreg command, which does the two steps at once and reports correct standard errors.
- Intuition: By using *Z* to predict *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)

# Example: Training & Earnings

Consider the model: $y = \beta_0 + \beta_2 P + \varepsilon$

- Random Sample of 10,000 observations
- Data contains (y , P , Z )
- 6,328 individuals with D=1 & 3,618 with D=0.

# Example: Training & Earnings

Consider the model: $y = \beta_0 + \beta_2 P + \varepsilon$

First Strategy (Participants vs. Non-participants)

- $E(Y1|D=1) = -0.227$
- $E(Y0|D=0) = 0.996$

•Thus, $\delta = E(Y1|D=1) - E(Y0|D=0) = -1.223^{***}$

•You might conclude then that the effect of the program is negative. Selection bias?

# Example: Training & Earnings

Consider the model:

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

- Let introduce the instrument Z:

- Corr(Z,D)=0.37***
- Pr(D=1|Z=1)=0.82
- Pr(D=1|Z=0)= 0.45

$$\frac{Cov(y,Z)}{Cov(P,Z)} = \frac{E(Y \mid Z=1) - E(Y \mid Z=0)}{E(P \mid Z=1) - E(P \mid Z=0)} = 0.210$$

# *Example: Was it real?*

Consider the model: $y = \beta_0 \; + \beta_2 \; P + \varepsilon$

- I generated the data:

Y1(u)=0.1 + 0.2 + $\varepsilon$1(u)

Y0(u)=0.1 +  + $\varepsilon 0$(u)

P = 1 if Z(u) – Y0(u)>0,  =0 otherwise

Y(u)  = Y1(u) * P(u) + Y0(u) * (1-P(u))

**THUS, I KNOW THE TRUE AVERAGE TREATMENT EFFECT**

# *Example: Was it real?*

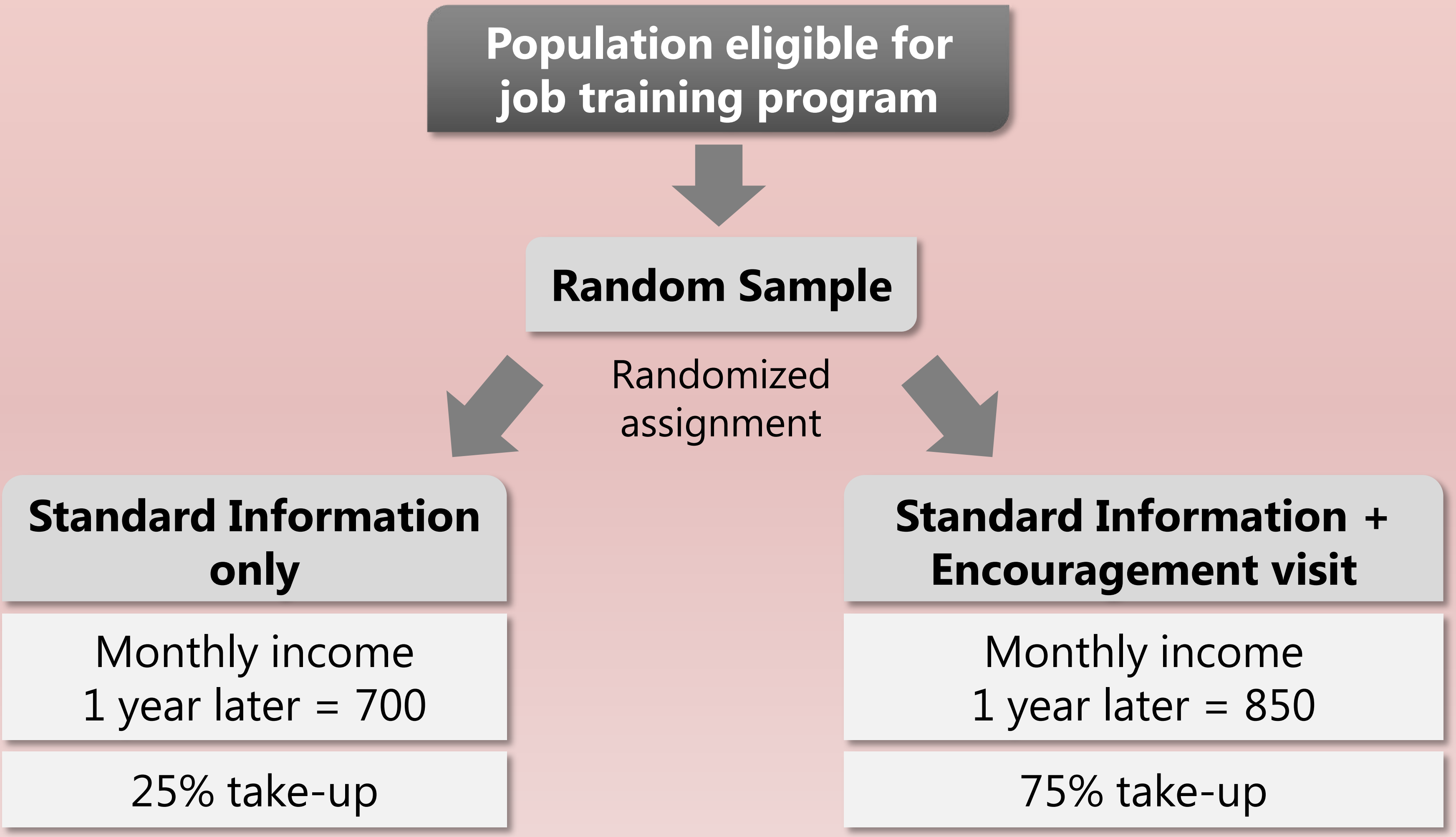
Consider the model: $y = \beta_0 + \beta_2 P + \varepsilon$

- In our fake data, we observe (D,Z,Y1,Y0,Y)

- **Treatment Effect= E(Y1|D=1)-E(Y0|D=1) = 0.2**
- **Selection Bias = E(Y0|D=1)-E(Y0|D=0) =-1.423**
- **δ = E(Y1|D=1)-E(Y0|D=0) = 0.2+(-1.423) = -1.22**

- IV got it right (IV=0.21)
- This is not rocket science!

# Non econometric intuition: Illustration from **voluntary job training program**




**Question: what is the impact of the job training program on the monthly income *of participants*?**

| Standard Information Package only | Standard + Additional Information Package |
| --- | --- |
| Monthly income 1 year later = 700 | Monthly income 1 year later = 850 |
| 25% take-up | 75% take-up |

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

Stage 1: Take-up difference between “well informed” and “not well informed”:

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Stage 2a: Income difference between the “well informed” and “not well informed” group:

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Stage 2b: Impact of participation: Income difference scaled by take-up difference:

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# Reminder and a word of caution…

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

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

# Reminder and a word of caution: Heterogeneity

- *It is possible to show that, in the context of heterogeneous effects, the IV approach might NOT provide meaningful results.*
- *However, we can still "evaluate" using structural models.*
- *Example: Evaluating the impact of financial intermediation*

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