

# Microeconometrics Module

## Lecture 8: Instrumental Variables

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[Course Link](#)

# Selection on Observables and Unobservables

## Understanding the Assumptions:

- Observables:

$$(Y_{0i}, Y_{1i}) \perp D_i \mid X_i$$

Assumes that all relevant variables influencing treatment assignment,  $X_i$ , are observed.

- Unobservables:

1.  $(Y_{0i}, Y_{1i}) \perp Z_i$
2.  $\text{Cov}(Z_i, D_i) \neq 0$

Moves beyond observable characteristics, relying on instruments ( $Z_i$ ) that affect treatment but are independent from the outcomes except through treatment.

# The Goals of Causal Inference

## Isolating Variation:

- We aim to separate the exogenous (good) variation in  $D_i$  from the endogenous (bad) variation that correlates with outcomes  $Y_{0i}$  and  $Y_{1i}$ .
- **Strategy:**
  - Use observables  $X_i$  to control for all observable confounding.
  - Utilize unobservables  $Z_i$  to capture the pure effects of  $D_i$  on  $Y_i$ , filtering out the confounding.

# Choosing the Right Approach

## Which approach better handles confounding?

1. **Observables:** Assumes perfect knowledge of confounders—challenging and often unrealistic in non-experimental settings.
2. **Unobservables (Instrumental Variables):** More plausible as it uses instruments to isolate exogenous variation, though it may sometimes be underpowered.

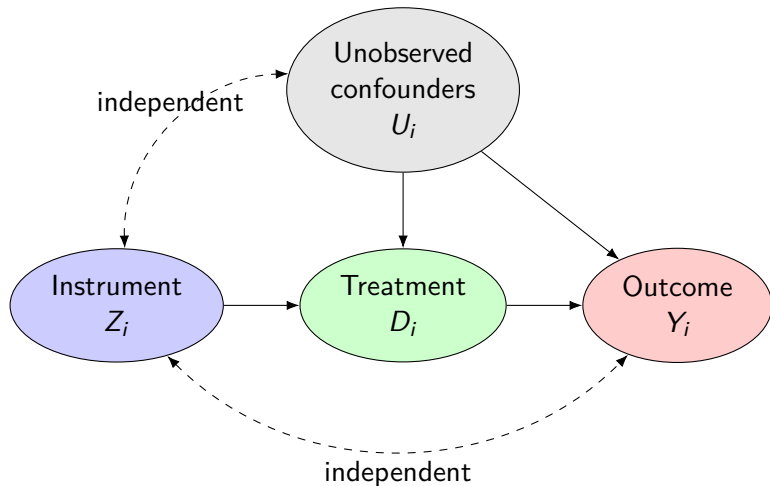
# Instrumental Variables: An Introduction

## Isolating Good Variation:

$$Y_i = \beta_0 + \beta_1 D_i + \varepsilon_i \quad (1)$$

- Instrumental Variables (IV) use tools or instruments ( $Z_i$ ) to ensure that  $\text{Cov}(D_i, \varepsilon_i) = 0$ .
- This approach allows us to estimate  $\beta_1$  consistently, avoiding the bias that occurs in ordinary least squares (OLS) when  $D_i$  is correlated with  $\varepsilon_i$ .

# Directed Acyclic Graph: Instrumental Variable Approach



# Defining a Valid Instrument

## Criteria for Instrument Validity:

1.  $\text{Cov}(Z_i, D_i) \neq 0$  — The instrument must influence the treatment.
2.  $\text{Cov}(Z_i, \varepsilon_i) = 0$  — The instrument must not be related to the outcome other than through the treatment.

These conditions ensure that  $Z_i$  is a suitable instrument for isolating the causal effect of  $D_i$  on  $Y_i$ .

First condition is easy to check. Second condition – known as **exclusion restriction** – can only be reasoned through. You cannot check it. Why?

# Two-Stage Least Squares (2SLS)

## Operationalizing IV:

- **First Stage:** Estimate the effect of  $Z_i$  on  $D_i$  (possibly with other covariates  $X_i$ ), obtaining  $\widehat{D}_i$ .
- **Second Stage:** Use  $\widehat{D}_i$  to estimate the causal effect on  $Y_i$ .

## Consistency:

$$\hat{\beta}_{2SLS} = (D'P_Z D)^{-1} (D'P_Z Y)$$

where  $P_Z = Z(Z'Z)^{-1}Z'$  is the projection matrix of  $Z$ . This estimator is consistent for  $\beta_1$ , assuming valid instruments.



# IV Estimation Essentials

## Key Considerations in Two-Stage Least Squares (2SLS) and IV Estimation:

- The controls ( $X_i$ ) must be consistent across both stages to maintain coherence in the model.
- With one instrument and one endogenous variable, 2SLS and IV yield identical results.
- Standard errors from the second stage are typically biased unless corrected for the procedures used in the first stage.

# Understanding the Reduced Form

## The Reduced Form Equation:

$$Y_i = \pi_1 Z_i + \pi_2 X_i + u_i$$

- This regression links the outcome directly to the instrument and control variables.
- It provides a consistent estimate of the instrument's effect on the outcome, bypassing endogeneity issues.

# The Value of the Reduced Form

## Advantages of the Reduced Form:

- Clarifies the source of identifying variation in the model.
- Avoids complications associated with weak instruments.
- Simplifies interpretation by directly estimating the effect of the instrument on the outcome.

$$\widehat{\beta}_1^{2SLS} = \frac{\widehat{\pi}_1}{\widehat{\gamma}_1}$$

This ratio illustrates the causal effect of treatment, scaled by the influence of the instrument on treatment.

# Intuitive Understanding of Reduced Form

## Estimating Impact via 2SLS:

$$\hat{\beta}_1^{2SLS} = \frac{\text{Reduced-form estimate}}{\text{First-stage estimate}} = \frac{\hat{\pi}_1}{\hat{\gamma}_1}$$

- $\hat{\pi}_1$ : Effect of the instrument on the outcome.
- $\hat{\gamma}_1$ : Effect of the instrument on the treatment.
- This ratio adjusts the direct instrument effect on the outcome to reflect its indirect effect via treatment.

# Reduced Form Example: Scholarship Impact on Income

## Scenario Analysis:

- Suppose 50% of lottery winners graduate due to the scholarship ( $\hat{\gamma}_1 = 0.50$ ).
- Reduced form estimate shows a \$5,000 income increase for winners ( $\hat{\pi}_1 = \$5,000$ ).
- Actual effect of graduation on income, when adjusted for the scholarship effect on graduation, is:

$$\frac{\$5,000}{0.50} = \$10,000$$

This calculation adjusts for the proportion of scholarship recipients who graduate, doubling the perceived income benefit.

# Deep Dive into IV Mechanics

**Further Insights:** Explore the nuances of IV estimation, focusing on the subtleties and implications of instrument strength and exogeneity.