



Office hours next week will be moved to :

Thursday (2/20) 12pm - 2pm

Agenda

- Review of IV
 - Binary IV
- Useful Things to Know
 - Dimensions
 - Identification
- Deriving IV from GMM
- Deriving IV from TSLS
- IV Asymptotics

Review of IV

Consider a linear model

$$Y = X'\beta + \epsilon \quad (\text{structural equation})$$

(structural param)

if β is the parameter of interest and $E[X\epsilon] \neq 0$

\Rightarrow there is endogeneity in the model

We can still perform a linear projection

$$Y = X'\beta^* + \underbrace{\epsilon^*}_{\text{projection error}}$$

where our projection coefficient is $\beta^* = E[XX']^{-1}E[XY]$
and $E[X\epsilon^*] = 0$ by construction.

However, the projection coefficient \neq structural parameter
 β^*

$$\begin{aligned}\beta^* &= (E[XX'])^{-1}E[XY] \\ &= (E[XX'])^{-1}E[X(X'\beta + \epsilon)] \\ &= \beta + (E[XX'])^{-1} \underbrace{E[X\epsilon]}_{\neq 0} \neq \beta \quad (\text{structural parameter}) \\ &\quad \text{under structural model}\end{aligned}$$

\Rightarrow Hence, OLS estimator is inconsistent for the structural parameter

$$\hat{\beta} \xrightarrow{P} (E[XX'])^{-1} E[XY] = \beta^* \neq \beta$$

For simplicity, consider the simple linear regression

$$Y = \beta_0 + \beta_1 X + \epsilon$$

where we cannot assert $E[X\epsilon] = 0$

Now suppose we observe RV Z w/ the following properties:

$$\text{cov}(Z, X) \neq 0 \quad (\text{relevance})$$

$$\text{cov}(Z, \epsilon) = 0 \quad (\text{validity})$$

$$\begin{aligned} \text{Then } \beta_{\text{INV}} &= \frac{\text{cov}(Z, Y)}{\text{cov}(Z, X)} = \frac{\text{cov}(Z, \beta_0 + \beta_1 X + \epsilon)}{\text{cov}(Z, X)} \\ &= \frac{\beta_1 \text{cov}(Z, X) + \text{cov}(Z, \epsilon)}{\text{cov}(Z, X)} \stackrel{0}{=} \beta_1 \end{aligned}$$

Binary IVs

$$Y = \beta_0 + \beta_1 X + \epsilon$$

where X is now a binary variable

If Z is a binary instrument for X , then

$$\beta_{1IV} = \frac{\text{Cov}(Z, Y)}{\text{Cov}(Z, X)} = \frac{E[Y|Z=1] - E[Y|Z=0]}{E[X|Z=1] - E[X|Z=0]}$$

Proof

$$\text{Cov}(Z, Y) = E[ZY] - E[Z]E[Y]$$

(A)

(B)

(C)

$$(A) \quad E[ZY] = E[LIE]$$

$0 \text{ since } Z=0$

$$\begin{aligned} E[ZY] &= E[E[ZY|Z]] \\ &= P(Z=1) E[ZY|Z=1] + P(Z=0) E[ZY|Z=0] \\ E[f(x)] &= \sum f(x) p(x) \quad \text{Def of } E(X) \\ &= P(Z=1) E[Y|Z=1] \end{aligned}$$

$$(B) \quad E[Z] = 1 \cdot P(Z=1) + 0 \cdot P(Z=0) \\ = P(Z=1)$$

$$\textcircled{c} \quad E[Y] = E[E[Y|Z]] \\ = P(Z=1) E[Y|Z=1] + P(Z=0) E[Y|Z=0]$$

$$\text{Then } \text{Cov}(Z, Y) = P(Z=1) E[Y|Z=1]$$

$$- P(Z=1) [P(Z=1) E[Y|Z=1] + P(Z=0) E[Y|Z=0]]$$

$$= P(Z=1) [E[Y|Z=1] (\underbrace{(1 - P(Z=1))}_{P(Z=0)} - P(Z=0) E[Y|Z=0])]$$

$$= P(Z=1) P(Z=0) [E[Y|Z=1] - E[Y|Z=0]]$$

If we repeat the above steps for $\text{Cov}(Z, X)$ and replace "Y" with "Z":

$$\text{Cov}(Z, X) = P(Z=1) P(Z=0) (E[X|Z=1] - E[X|Z=0])$$

$$\Rightarrow \beta_{IIV} = \frac{\text{Cov}(Z, Y)}{\text{Cov}(Z, X)} = \frac{P(Z=1) P(Z=0) (E[Y|Z=1] - E[Y|Z=0])}{P(Z=1) P(Z=0) (E[X|Z=1] - E[X|Z=0])}$$

$$= \frac{(E[Y|Z=1] - E[Y|Z=0])}{(E[X|Z=1] - E[X|Z=0])}$$

How can we think of binary β_{IIV} ?

Suppose

$$\text{Earnings} = \beta_0 + \beta_1 \cdot (\text{Private School}) + \epsilon$$

↳ use $Z = \text{lottery to attend}$

$$Z = \begin{cases} 1 & \text{won lottery} \\ 0 & \text{lost lottery} \end{cases}$$

↳ can assume lottery is random

$$\beta_{IIV} = \frac{(E[Y|Z=1] - E[Y|Z=0])}{(E[X|Z=1] - E[X|Z=0])} \quad (\text{Wald Estimator})$$

Difference in earnings for those
who won vs lost lottery

=

Difference in probability
of attending private school
between winners and losers

⇒ can be interpreted as LATE
(ie: only for compliers)

Useful Things to Know

- Dimensions

For the model

$$Y = X'\beta + e$$

with assumptions $E[Ze] = 0$ & $\text{rank}(EZX) = k$

vectors $\begin{cases} - Z : (l \times 1) \\ - X : (k \times 1) \end{cases}$ where $l = \# \text{ instruments}$
 $k = \# \text{ regressors}$

- Identification

- Just-identified ($l=k$)

↳ our assumption when dealing w/ IV

- Overidentified

↳ often dealt with in TSLS & GMM

Deriving IV as GMM Estimator

- Setup moment conditions

$$E[z\epsilon] = E[z(y - x'\beta)] = 0 \quad (\text{by validity assumption})$$

- Solve for $\hat{\beta}_{IV}$

$$E[zy] - E[zx'\beta] = 0$$

$$\Rightarrow \hat{\beta}_{IV} = (E_n[zx'])^{-1} (E_n[zy])$$

Note: This is only possible because $l = k$, so
 zx' is square

Deriving IV from TSLS

(Hansen p355)

- What is TSLS?

Exploiting variations in X due to Z !

1) Regress X on Z to obtain the fitted \hat{X}

$$X = Z\beta + u \quad \text{where} \quad \hat{\beta} = (Z'Z)^{-1}(Z'X)$$

2) Regress Y on \hat{X}

$$Y = \tilde{\beta}\hat{X}$$

$$\begin{aligned} \text{Note: } \hat{X} &= Z\hat{\beta} \\ &= Z(Z'Z)^{-1}(Z'X) \end{aligned}$$

Distributed transpose

$$\begin{aligned} \tilde{\beta}^{\text{TSLS}} &= (\hat{X}'\hat{X})^{-1}\hat{X}'Y \\ &= ((Z(Z'Z)^{-1}Z'X)'Z(Z'Z)^{-1}Z'X)^{-1}(Z(Z'Z)^{-1}Z'X)'Y \\ &= (X'Z(Z'Z)^{-1}Z'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'Y \\ &= (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'Y \\ &= (Z'X)^{-1}Z'Z(X'Z)^{-1}X'Z(Z'Z)^{-1}Z'Y \\ &= (Z'X)^{-1}Z'Y = \hat{\beta}_{IV}. \end{aligned}$$

\Rightarrow Hence, we've shown that IV is a special case of TSLS when $l=k$!

Note: In TSLS, it is possible to have $l \geq k$!

IV Asymptotics

1) IV estimator is consistent

$$\begin{aligned}
 \hat{\beta}_{IV} &= (\mathbb{E}_n[zx'])^{-1} \mathbb{E}_n[zy] \\
 &= (\mathbb{E}_n[z'x'])^{-1} \mathbb{E}_n[z(x'\beta + \epsilon)] \\
 &= (\mathbb{E}_n[z'x'])^{-1} \mathbb{E}_n[zx'\beta] + (\mathbb{E}_n[z'x'])^{-1} \mathbb{E}_n[ze] \\
 &= \beta + \underbrace{(\mathbb{E}_n[z'x'])^{-1} \mathbb{E}_n[ze]}_{\xrightarrow{P} 0}
 \end{aligned}$$

$$\Rightarrow \hat{\beta}_{IV} \xrightarrow{P} \beta$$

2) Cannot claim IV is unbiased, even if we assume $E[\epsilon|z] = 0$. Why?

$$\begin{aligned}
 E[\hat{\beta}_{IV}|z] &= E[\beta + (\mathbb{E}_n[zx'])^{-1} \mathbb{E}_n[ze]|z] \\
 &= \beta + E[\underbrace{(\mathbb{E}_n[zx'])^{-1} \mathbb{E}_n[ze]}_{\neq 0 \text{ bc } X, \epsilon \text{ correlated}}|z] \\
 &\Rightarrow \text{can't pass through } E
 \end{aligned}$$

Recall if X, Y indep, then

$$E[XY] = E[X]E[Y]$$

\Rightarrow However, since $E[ze] \neq 0$, we cannot split it into

$$E[\mathbb{E}_n[zx']^{-1}|z] \neq E[\mathbb{E}_n[ze]|z]$$

3) Asymptotics of Simple IV

$$\sqrt{n} (\hat{\beta}_{IV} - \beta_1) = \sqrt{n} \left(\frac{\sum (z_i - \bar{z})(y_i - \bar{y})}{\sum (z_i - \bar{z})(x_i - \bar{x})} - \beta_1 \right)$$

$$= \sqrt{n} \left(\frac{\sum (z_i - \bar{z}) y_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} - \beta_1 \right)$$

$$= \sqrt{n} \left(\frac{\sum (z_i - \bar{z})(\beta_0 + \beta_1 x_i + \epsilon_i)}{\sum (z_i - \bar{z})(x_i - \bar{x})} - \beta_1 \right)$$

$$= \sqrt{n} \left(\beta_0 \underbrace{\frac{\sum (z_i - \bar{z})}{\sum (z_i - \bar{z})(x_i - \bar{x})}}_{(*)} + \frac{\beta_1 \sum (z_i - \bar{z}) x_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} + \frac{\sum (z_i - \bar{z}) \epsilon_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} - \beta_1 \right)$$

$$(*) \quad \frac{\frac{1}{n} \sum (z_i - \bar{z})}{\frac{1}{n} \sum (z_i - \bar{z})(x_i - \bar{x})} = \frac{\frac{1}{n} \sum z_i - \frac{1}{n} \cdot n \bar{z}}{\frac{1}{n} \sum (z_i - \bar{z})(x_i - \bar{x})}$$

$$= \frac{\bar{z} - \bar{z}}{n} = 0$$

$$= \sqrt{n} \left(\frac{\sum (z_i - \bar{z}) \varepsilon_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} \right)$$

$$= \sqrt{n} \left(\frac{\sum ((z_i - E(z)) + (E(z) - \bar{z})) \varepsilon_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} \right)$$

$$= \sqrt{n} \left(\frac{\sum ((z_i - E(z)) \varepsilon_i)}{\sum (z_i - \bar{z})(x_i - \bar{x})} + \underbrace{\frac{\sum (E(z) - \bar{z}) \varepsilon_i}{\sum (z_i - \bar{z})(x_i - \bar{x})}}_{\text{constant}} \right)$$

$\rightarrow 0$ as $n \rightarrow \infty$ finite #

$$\sqrt{n} \left(\frac{(E(z) - \bar{z}) \sum \varepsilon_i}{\sum (z_i - \bar{z})(x_i - \bar{x})} \right) \xrightarrow{P} 0 \text{ as } n \rightarrow \infty$$

(A)

$$= \sqrt{n} \left(\underbrace{\frac{\frac{1}{n} \sum ((z_i - E(z)) \varepsilon_i)}{\frac{1}{n} \sum (z_i - \bar{z})(x_i - \bar{x})}}_B \right) + o_p(1)$$

(B)

Note: Assume all necessary moments exist

(A) Numerator looks like:

$$E[(z - E(z))\varepsilon] = E[z\varepsilon] - E[E(z)\varepsilon]$$

$$= E[z\varepsilon] - E(z)E(\varepsilon) \underset{\substack{\rightarrow \\ = 0}}{=} 0$$

$$\text{Var}[(z - E(z))\varepsilon] = E[(z - E(z))^2\varepsilon^2] - 0^2$$

$$= E[(z - E(z))^2\varepsilon^2]$$

$$= \sigma_z^2 \sigma^2 \quad \text{bc } z, \varepsilon \text{ indep}$$

$$\Rightarrow \text{By CLT, } \sqrt{n} \left(\frac{1}{n} \sum (z_i - E(z))\varepsilon_i \right) \xrightarrow{d} N(0, \sigma_z^2 \sigma^2)$$

(B) Denominator by WLLN

$$\frac{1}{n} \sum (z_i - E(z))(x_i - E(x)) \xrightarrow{P} E[(z - E(z))(x - E(x))]$$

$$= \text{cov}(z, x)$$

$$= \rho_{zx} \sigma_z \sigma_x$$

Combining everything

$$\sqrt{n}(\hat{\beta}_1 - \beta_1) \xrightarrow{d} N\left(0, \frac{\sigma_e^2 \sigma_x^2}{\rho^2 \sigma_e^2 \sigma_x^2}\right)$$

$$\rightarrow N\left(0, \frac{\sigma^2}{\rho^2 \sigma_x^2}\right)$$