

$$y_i = \mathbb{Y}_i \beta_i + \mathbb{Z}_i \gamma_i + \varepsilon_i = \mathbb{X}_i \delta_i + \varepsilon_i$$

$$\text{IV estimator: } \hat{\delta}_i = (W_i' \mathbb{X}_i)^{-1} W_i' y_i$$

$$W_i = \mathbb{Z}_i A$$

$$\begin{aligned} \text{2SLS: } \hat{W}_i &= \mathbb{Z}_i \hat{A} = \mathbb{Z}_i (\mathbb{Z}' \mathbb{Z})^{-1} \mathbb{Z}' \mathbb{X}_i = P_{\mathbb{Z}} \mathbb{X}_i \\ &= [P_{\mathbb{Z}} \mathbb{Y}_i, P_{\mathbb{Z}} \mathbb{Z}_i] = [\hat{\mathbb{Y}}_i, \mathbb{Z}_i] = \hat{\mathbb{X}}_i \end{aligned}$$

$$\begin{aligned} \text{2SLS estimator: } \hat{\delta}_i &= (\hat{\mathbb{X}}_i' \hat{\mathbb{X}}_i)^{-1} \hat{\mathbb{X}}_i' P_{\mathbb{Z}} y_i \\ &= (\hat{\mathbb{X}}_i' \mathbb{X}_i)^{-1} \hat{\mathbb{X}}_i' y_i \\ &= (\hat{\mathbb{X}}_i' \hat{\mathbb{X}}_i)^{-1} \hat{\mathbb{X}}_i' y_i \end{aligned}$$

$$\text{Prove: } 0 = \text{plim} (\hat{\delta}_i - \delta_i) = \text{plim} (\hat{\mathbb{X}}_i' \hat{\mathbb{X}}_i)^{-1} \hat{\mathbb{X}}_i' \varepsilon_i$$

$$(1) \text{ plim} \left( \frac{1}{T} \hat{A}' \mathbb{Z}' [\mathbb{Y}_i, \mathbb{Z}_i] \right)$$

$$\text{assume } \text{plim} \frac{\mathbb{Z}' \mathbb{Z}}{T} = M$$

$$\text{plim } \hat{A} = A = (\Pi_i, I_i)$$

$$(1) = \text{plim} \frac{1}{T} \hat{A}' \mathbb{Z}' (\mathbb{Z} \Pi_i + V_i) = A' M \Pi_i$$

$$(2) = \text{plim} \frac{1}{T} \hat{\mathbb{X}}_i' \varepsilon_i = \text{plim} \frac{1}{T} \hat{A}' \mathbb{Z}' \varepsilon_i = \text{plim } \hat{A}' \underbrace{\text{plim} \frac{\mathbb{Z}' \varepsilon_i}{T}}_{=0}$$

$$\Rightarrow 0 = \text{plim} (\hat{\delta}_i - \delta_i)$$

- IV in general is biased, since you need to estimate  $A$ .
- In general, these estimators need not have moments
  - 2SLS has the same # of moments as degrees of overidentification.

Normality

$$\sqrt{T}(\hat{\delta}_1 - \delta_1) = \underbrace{\left[ \hat{A}' \frac{Z'}{T} [Y_1, Z_1] \right]^{-1}}_{\substack{P \\ \rightarrow R^{-1}}} \underbrace{\frac{\hat{A}' Z' \varepsilon_1}{\sqrt{T}}}_{e(1)}$$

$$e(1) = \frac{1}{\sqrt{T}} \hat{A}' Z' \varepsilon_1 = \hat{A}' \underbrace{\frac{Z' \varepsilon_1}{\sqrt{T}}}_{(2)}$$

need Lindberg-Feller or Lyapunov  $\rightarrow 2+8, \delta > 0$  moments must exist

$$(2) \frac{Z' \varepsilon_1}{\sqrt{T}} \xrightarrow{d} N(0, \sigma_{11} \text{plim} \frac{Z' Z}{T}) \stackrel{d}{=} N(0, \sigma_{11} M)$$

$$\Rightarrow \frac{\hat{A}' Z' \varepsilon_1}{\sqrt{T}} \xrightarrow{d} N(0, \sigma_{11} \hat{A}' M A)$$

$$\Rightarrow \sqrt{T}(\hat{\delta}_1 - \delta_1) \xrightarrow{d} N(0, \sigma_{11} \underbrace{R^{-1} \hat{A}' M A (R^{-1})'}_N)$$

$$\text{Let } \hat{A} = [\hat{\pi}_1, I_1] \Rightarrow \text{plim } \hat{A} = [\pi_1, I_1]$$

$$R = \begin{pmatrix} \pi_1' z' z \pi_1 & M_{11} \end{pmatrix}$$

$$N = \begin{pmatrix} \pi_1' z' z \pi_1 & I_1 z' z I_1 \end{pmatrix}$$

$$= \begin{pmatrix} \pi_1' z' z \pi_1 & M_{11} \end{pmatrix} = R$$

$$\Rightarrow \sqrt{T} (\hat{\delta}_1 - \delta_1) \xrightarrow{d} N(0, \sigma_{11} R^{-1} R R^{-1})$$

$$\stackrel{d}{=} N(0, \sigma_{11} R^{-1})$$

Need to estimate  $\hat{\sigma}_{11} = \frac{1}{T(R_1 + S_1)} (y_1 - z \hat{\delta}_1)' (y_1 - z \hat{\delta}_1)$

◦ This will be a downward biased estimate of  $\sigma_{11}$  if you actually do the two stages.

Minimum distance or minimum  $\chi^2$  interpretation

OLS:  $\min_{\delta} (y_1 - X_1 \delta_1)' I (y_1 - X_1 \delta_1)$  is inconsistent

ZSLS:  $\min_{\delta} (y_1 - X_1 \delta_1)' \underbrace{P_z}_{\text{eliminates the joint endogeneity}} (y_1 - X_1 \delta_1)$  is consistent

◦ minimum distance interpretation  
 ◦ transformation to orthogonality

$$\Leftrightarrow \min_{\delta} \frac{1}{\sigma_{11}} (y_1 - X_1 \delta_1)' P_z (y_1 - X_1 \delta_1)$$

The solution:  $\frac{\varepsilon_1' P_Z \varepsilon_1}{\sigma_{11}} \sim \chi^2 (K - K_1)$   $K_1 = r_1 + s_1$   
 degree of overidentification

• This is a test of overidentifying restrictions.  
 "  $E[\chi^2(K - K_1)] = K - K_1$  "

How to prove this is  $\chi^2$ ?

$$\frac{1}{\sigma_{11}} \varepsilon_1' B \varepsilon_1$$

$$B = P_Z - P_Z X_1 (X_1' P_Z X_1)^{-1} X_1' P_Z$$

$$= P_Z - P_{X_1} \quad X_1 = P_Z X_1 \text{ cspan } Z$$

B is symmetric and idempotent

$$\Rightarrow \text{Cochran's thm: } \frac{\varepsilon_1' B \varepsilon_1}{\sigma_{11}} \rightarrow \chi^2(\text{tr}(B))$$

$$\varepsilon_1 = Z\alpha + w \quad (*)$$

$$F: \alpha = 0 \quad \sim \chi^2(K - K_1)$$

"  $TR^2$  where  $R^2$  is from the regression (\*)

• Suppose this rejects. What instruments should you not have used? (Hopefully things will still be just identified.)

Prove that 2SLS is optimal among class of IV estimators. (under conditional homoskedasticity.)

$\hat{w}_1$  here uses  $\hat{A} = (Z'Z)^{-1}Z'X_1$

$$\hat{w}_1 = Z'\hat{A}$$

Consider  $\hat{\hat{w}}_1 = Z'D$

$$\text{Var}(\hat{\hat{\delta}}_1) = \sigma_{11} \left( \frac{W_1' X_1}{T} \right)^{-1} \left( \frac{\hat{w}_1' \hat{w}_1}{T} \right) \left( \frac{W_1' X_1}{T} \right)^{-1}$$

• Set  $T\sigma_{11} = 1$  (or else change units)

$$\text{Var}(\hat{\hat{\delta}}_1)^{-1} = \left( \frac{\hat{w}_1' X_1}{T} \right) \left( \frac{\hat{w}_1' \hat{w}_1}{T} \right)^{-1} \left( \frac{W_1' X_1}{T} \right) = (X_1' Z D) (D' Z' Z D)^{-1} (D' Z' X_1)$$

Choose any  $g \neq 0$   $g' [\text{Var}(\hat{\delta}_{2SLS})^{-1} - \text{Var}(\hat{\delta}_D)] g \geq 0$

$$g' (X_1' Z D) (D' Z' Z D)^{-1} (D' Z' X_1) g$$

$$\text{Let } Z'Z = NN', \quad h = N^{-1}Z'X_1 g$$

$$\Rightarrow h'h = g' X_1' Z (N^{-1})' Z' Z X_1 g$$

$$= g' X_1' Z (Z'Z)^{-1} Z' X_1 g$$

$$= g' [V(\hat{\delta}_{2S})]^{-1} g$$

$$g' (X_1' Z D) (D' Z' Z D)^{-1} (D' Z' X_1) g = h' N D (D' N' N D)^{-1} D' N' h$$

$$= h' G (G' G)^{-1} G' h \quad \text{where } G = ND$$

Thus, comparison:  $h' [I - G (G' G)^{-1} G'] h \geq 0$

$$h'h \geq h' P_G h$$

$$= M_G$$

$$\Rightarrow h' M_G M_G' h = (M_G' h)' (M_G' h) \geq 0$$

Thus,  $\text{Var}(\hat{\delta}_{2SLS}) \leq \text{Var}(\hat{\delta}_O)$

◦ Could nonlinear combinations of our instruments do better?

Third interpretation of 2SLS.

$$\text{plim} \frac{\sum \mathbb{Y}_i' \varepsilon_i}{T} \neq 0$$

$$\hat{\mathbb{Y}}_i^1 = \mathbb{Z} \hat{\pi}_i^1$$

$$\hat{\pi}_i^1 = (\mathbb{Z}'\mathbb{Z})^{-1} \mathbb{Z}' \mathbb{Y}_i$$

$$= (\mathbb{Z}'\mathbb{Z})^{-1} \mathbb{Z}' (\mathbb{Z} \pi + v_i)$$

$$= \pi + (\mathbb{Z}'\mathbb{Z})^{-1} \mathbb{Z}' v_i$$

$$\Rightarrow E[\hat{\pi}_i^1] = \pi + E[(\mathbb{Z}'\mathbb{Z})^{-1} \mathbb{Z}' v_i]$$

We know  $\text{plim} \hat{\pi}_i^1 = \pi$

$$\hat{\mathbb{Y}}_i^1 = \mathbb{Y}_i - v_i^1 \Leftrightarrow \mathbb{Y}_i = \hat{\mathbb{Y}}_i^1 + v_i^1$$

$$y_i = \hat{\mathbb{Y}}_i^1 \beta_1 + \mathbb{Z}_i \pi_1 + \varepsilon_i + v_i^1 \beta_1$$

OLS on this is 2SLS.

Need to have  $v_i^1$  orthogonal to  $\mathbb{Z}_i$

(it will be orthogonal to  $\hat{\mathbb{Y}}_i^1$  by construction.)

$$y_i = \hat{\mathbb{X}}_i^1 \delta_i + \underbrace{\varepsilon_i + v_i^1 \beta_1}_{w_i}$$

$$\Rightarrow \hat{\delta}_i^1 = (\hat{\mathbb{X}}_i^1' \hat{\mathbb{X}}_i^1)^{-1} \hat{\mathbb{X}}_i^1' y_i = (\mathbb{X}_i' P_{\mathbb{Z}} \mathbb{X}_i)^{-1} \mathbb{X}_i' P_{\mathbb{Z}} y_i = \hat{\delta}_{i,IV}$$

Test of over ID:

$$y_i = \hat{\alpha}_i \delta_i + \underbrace{\tilde{z}_i}_{Z \setminus Z_1} \mu + w$$

F:  $\mu = 0$        $K - K_1$  degrees of freedom