

FOCs from last time:

$$1) [T(B')^{-1} - \bar{Y}'(\bar{Y}B + Z\Gamma)\Sigma^{-1}]'u = 0$$

$$2) [-Z'(\bar{Y}B + Z\Gamma)\Sigma^{-1}]'u = 0$$

$$3) [T\Sigma - (\bar{Y}B + Z\Gamma)'(\bar{Y}B + Z\Gamma)]'u = 0$$

We will do covariance restrictions. Without restrictions,

$$\hat{\Sigma} = \frac{u'u}{T}$$

Let some  $\sigma_{ij} = 0$

$$\Rightarrow [T(B')^{-1}\Sigma - \bar{Y}'(\bar{Y}B + Z\Gamma)\Sigma^{-1}]'u = 0$$

Let  $N_j$  be a set of indices  $m$  for the  $j^{\text{th}}$  row of  $\Sigma$

$$\text{s.t. } \sigma_{jm} = 0$$

$$[T(B')^{-1}\Sigma]_{ij} = T \sum_{\substack{k=1 \\ k_i \text{th elt of } (B')^{-1}}}^M \beta^{ki} \sigma_{kj} = (v_i' - \sum_{k \in N_j} \beta^{ki} u_k') u_j \text{ only}$$

for zero elements

$$\begin{aligned} \Rightarrow [T(B')^{-1}\Sigma - \bar{Y}'(\bar{Y}B + Z\Gamma)\Sigma^{-1}]_{ij} &= [v_i' - \sum_{k \in N_j} \beta^{ki} u_k - Z\pi_i - v_i]' u_j = 0 \\ &= -[Z\pi_i + b'_{ji} \hat{u}_i]' u_j \end{aligned}$$

The FOC becomes

$$- \{ [(B')^{-1}\Gamma'Z' + \tilde{V}'] (\bar{Y}B + Z\Gamma) \} \Sigma^{-1} u = 0$$

replaced  $\bar{Y}$  by  $\tilde{V}$ .  
uncorrelated residuals multiplied by  $B^{-1}$

- Imposing covariance restrictions in 3SLS does not improve asymptotic efficiency.

Hausman, Newey, Taylor:

A3SLS  $\hat{=} \text{FIML} > \text{3SLS}$

augmented 3SLS

- can use  $\hat{u}_j$  as instrument if  $\sigma_{ij} = 0$ .

## LIML

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} X_1 & 0 \\ 0 & I \otimes Z \end{bmatrix} \begin{bmatrix} \delta_1 \\ \pi_2 \end{bmatrix} + \begin{bmatrix} u_1 \\ v_2 \end{bmatrix} \quad V \begin{bmatrix} u_1 \\ v_2 \end{bmatrix} = \Psi \otimes I = \begin{bmatrix} \sigma_{11} & \Psi_{12} \\ & \Omega_{22} \end{bmatrix} \otimes I$$

- assume that eqn 1 is overidentified and that other eqns are just identified. Then FIML gives us LIML for eqn 1

FOCs:

$$\begin{bmatrix} (B')^{-1} \Gamma' Z' \\ -Z' \end{bmatrix} \begin{bmatrix} \Psi B_1 + Z \Pi_1 \\ \Pi_2 - Z \Pi_2 \end{bmatrix} \Psi^{-1} u = 0 \quad \text{FIML FOCs}$$

- $B_{11} = 1 \Rightarrow \log[\det(B)^{-1}] = \log 1 = 0$

- It is as if  $B$  is triangular

Stack the FOCs: Recall that 3SLS  $\equiv$  2SLS in this setup (since eqn 1 is overid and others are justid)

$$\Rightarrow \hat{\delta}_1 = (\hat{X}_1' \hat{X}_1)^{-1} \hat{X}_1' y_1 \quad \hat{\Sigma}_1 = \begin{bmatrix} Z \hat{\Pi}_2 \\ Z \hat{\Pi}_2 \end{bmatrix}$$

$$\hat{\Pi}_2 = (I \otimes (Z'Z)^{-1} Z') y_2 - [ \hat{\Psi}_{21} \hat{\sigma}'' \otimes (Z'Z)^{-1} Z' ] (y_1 - \hat{X}_1 \hat{\delta}_1)$$

$\Rightarrow$  LIML is just a special case of FIML

Since  $\text{plim } \hat{\pi}_2^{\text{LIML}} = \text{plim } \hat{\pi}_2^{\text{2SLS}}$

• For any bowl-shaped loss function, up to second-order, LIML is better than 2SLS.

• LIML is median-unbiased  $\Rightarrow$  approximately mean-unbiased

$$\begin{aligned} \text{plim } \sqrt{T} (\hat{\Sigma}_{\text{LIML}} - \hat{\Sigma}_{\text{2SLS}}) &= \text{plim} \left( \frac{\hat{\Sigma}'_{1,\text{LIML}} \Sigma_1}{T} \right)^{-1} \frac{\hat{\Sigma}'_{1,\text{LIML}} u_1}{\sqrt{T}} \\ &\quad - \text{plim} \left( \frac{\hat{\Sigma}'_{1,\text{2SLS}} \Sigma_1}{T} \right)^{-1} \frac{\hat{\Sigma}'_{1,\text{2SLS}} u_1}{\sqrt{T}} \end{aligned}$$

$$= \text{plim} \left( \frac{1}{T} \hat{\Sigma}'_{1,\text{2SLS}} \Sigma_1 \right)^{-1} \underbrace{\sqrt{T} (\hat{\pi}_{2,\text{LIML}} - \hat{\pi}_{2,\text{2SLS}})}_{O_p(1)} I_1 \underbrace{\left( \frac{\Sigma' u_1}{T} \right)}_{O_p(1)}$$

$$= 0$$

LIML as a k-class estimator

$$\hat{\Sigma}_1 = \begin{bmatrix} \hat{\Sigma}_1 \\ \Sigma_1 \end{bmatrix} = \left[ ((1-R)I + R P_Z) \Sigma_1 \quad \Sigma_1 \right]$$

LIML:  $R = \frac{1}{1-\hat{\lambda}}$  where  $\hat{\lambda}$  is smallest char. value of  $0 = |\Sigma_1' P_Z \Sigma_1 - \lambda \Sigma_1' \Sigma_1|$

• For consistency, need  $\text{plim } R = 1$

• For efficiency, need  $\text{plim } \sqrt{T}(R-1) = 0$

How to test overidentifying restrictions?

Full information

$$W_p^1 = -2 \log \left[ \frac{L(\hat{\Pi}_R, \hat{\Omega}_R)}{L(\hat{\Pi}_{UR}, \hat{\Omega}_{UR})} \right]$$

\* of overid.

$$= T \log \left[ \frac{\det \hat{\Omega}_R}{\det \hat{\Omega}_{UR}} \right] \xrightarrow{d} \chi^2(p)$$

where  $\hat{\Pi}_R = \hat{\Pi}_F \hat{\beta}_F^{-1}$

3SLS:  $W_p = \hat{u}_{3SLS}' \left( \hat{\Sigma}_{3SLS}^{-1} \otimes P_Z \right) \hat{u}_{3SLS} \xrightarrow{d} \chi^2(p)$

Limited information Let  $p_i$  = degree of overid for eqn 1

LIML:  $T(R-1) \sim \chi^2(p_i)$

ZSLS:  $\frac{(y_i - X_i \hat{\delta}_i)' P_Z (y_i - X_i \hat{\delta}_i)}{\hat{\sigma}_{ii}} \sim \chi^2(p_i)$

$$= TR^2$$

Omnibus test  $\frac{Z' \hat{\varepsilon}}{\sqrt{T}} \quad V = \left( \frac{1}{T} (Z' \Omega Z) \right)$

Test  $W = \frac{1}{T} \hat{\varepsilon}' Z V^{-1} Z' \hat{\varepsilon} \sim \chi^2(p_i)$

• This will work for conditional heteroskedasticity

Hausman test

$\hat{Z}_1$  - confident that these are instruments  
 $\hat{Z}_2$  - not sure

$\tilde{\delta}_1$  uses just  $\tilde{Z}_1$

$\hat{\delta}_1$  uses both  $\tilde{Z}_1$  and  $\hat{Z}_1$

$$\hat{q} = \tilde{\delta}_1 - \hat{\delta}_1$$

$$\text{Let } W = \frac{1}{\hat{\sigma}_{11}} \hat{q}' \left[ (\tilde{X}_1' P_{\tilde{Z}_1} \tilde{X}_1)^{-1} - (\tilde{X}_1' P_{\hat{Z}_1} \tilde{X}_1)^{-1} \right] \hat{q}$$

$$\text{dof} = \min\{p_1, k_1\}$$

• Biased towards rejection.

Nonlinear

$$f_1(y, Z, \alpha) \stackrel{\text{separable}}{=} u_1$$

nonseparable:  $f_1(y, Z, \alpha, u_1) = 0$   
• Matzkin

$$f_1(y, Z, \alpha) \approx \underbrace{f_1(y, Z, \alpha')}_{= u_1'} + \frac{\partial f_1}{\partial \alpha} (\alpha - \alpha')$$

$$= g_1' (\alpha - \alpha') + u_1'$$

It might be the case that  $\text{plim} \frac{g_1' u_1}{N} \neq 0$

$$\text{Let } \hat{\theta} = \underbrace{\alpha^2 - \alpha'}_{\text{difference after iterating}} = \underbrace{(W_1' g_1)^{-1} W_1' \hat{u}_1}_{\text{true IV}}$$

Can prove that  $\sqrt{N} (\hat{\alpha} - \alpha) \xrightarrow{d} X$

where  $X \sim N(0, \text{plim} \hat{\sigma}_{11} (W_1' g_1(\hat{\alpha}))^{-1} (W_1' W_1) (g_1(\hat{\alpha}) W_1)^{-1})$

Forbidden regression:

$$\min_{\alpha} \sum u_{1i}^2 = \min_{\alpha} \sum f_1(y_{1i}, \hat{y}_{1i}, Z_{1i}, \alpha)$$

$$y_1 = \beta_1 y_2^{\beta_2} + \sum \gamma_i + u_1$$

spse we replace  $y_2$  with  $y_2^1$

$$\Rightarrow y_1 = \beta_1 (y_2^1 + \hat{v}_2)^{\beta_2} + \sum \gamma_i + u_1$$

$$\approx \beta_1 y_2^{\beta_2} + \sum \gamma_i + u_1 + \beta_1 \log(y_2^1) \hat{v}_2^{\beta_2 - 1} + \beta_1 \log^2(y_2^1) \hat{v}_2^{\beta_2 - 2} \frac{1}{2}$$

In the linear case:

$$E[y_1] = E[\sum \gamma_i + \hat{v}] = E[\sum \gamma_i]$$

Nonlinear simultaneous equation systems are almost always identified, because if you have one exogenous variable, you can take all nonlinear functions of it to get infinite instruments

$$\alpha^2 = \alpha^1 + (\hat{W}_1' g_1)^{-1} \hat{W}_1' f_1(y, Z, \alpha^1)$$

$$= \alpha^1 + (g_1' \hat{W}_1 (\hat{W}_1' \hat{W}_1)^{-1} \hat{W}_1' g_1)^{-1} g_1' \hat{W}_1 (\hat{W}_1' \hat{W}_1)^{-1} \hat{W}_1' f_1(y, Z, \alpha^1)$$

$$\hat{W}_1 = P_{\hat{w}_1} g_1$$

Amemiya's nonlinear 2SLS (NL2SLS)

$$J = \min_{\alpha} f_1(y, Z, \alpha) \hat{W}' (\hat{W}' \hat{W})^{-1} \hat{W}' f_1(y, Z, \alpha) \Rightarrow J \approx \chi^2(p)$$

$$\sqrt{N}(\hat{\alpha} - \alpha) \xrightarrow{d} N(0, \text{plim} \frac{1}{N} \sigma_{11} (g_1' P_{\hat{w}_1} g_1)^{-1})$$

Let  $f_1(y, Z, \alpha) = u$        $V(u) = \sum \sigma_i^2 I$   
can then do NL3SLS