

Inverse matrix:

$$\begin{bmatrix} (\bar{X}_1' (\sigma'' \otimes P_z) \bar{X}_1)^{-1} & (\bar{X}_1' (\sigma'' \otimes P_z \bar{X}_1)^{-1} \bar{X}_1' (\sigma'' \Psi_{12} \otimes Z(Z'Z)^{-1}) \\ \Omega_{22} \otimes (Z'Z)^{-1} - (\Psi_{21} \otimes I) \otimes (\Psi_{12} \otimes I) \end{bmatrix}$$

$$\sigma'' = \Psi'' + \sigma'' \Psi_{12} \Psi_{21}$$

$$\Psi'' \Psi_{12} \Omega_{22}^{-1} + \Psi_{12}'' = 0$$

$$\begin{aligned} \Rightarrow \hat{\beta}_{2SLS} &= (\bar{X}_1' (\sigma'' \otimes P_z \bar{X}_1)^{-1} \bar{X}_1' (\sigma'' \otimes P_z) y_1 \\ &= (\bar{X}_1' (I \otimes P_z) \bar{X}_1)^{-1} \bar{X}_1' (I \otimes P_z) y_1 \\ &= (\hat{\bar{X}}_1' \hat{\bar{X}}_1)^{-1} (\hat{\bar{X}}_1' y_1) \\ &= \hat{\beta}_{2SLS} \end{aligned}$$

$$\underline{\underline{Y}} B + Z \Gamma = U \quad U \sim N(0, \Sigma \otimes I)$$

$$\mathcal{L} = c + \frac{T}{2} \log[\det(\Sigma)]^{-1} - \frac{1}{2} \text{tr} \left[\frac{1}{T} \Sigma^{-1} U' U \right]$$

log likelihood of multivariate normal

$$= c + \frac{T}{2} \log[\det \Sigma]^{-1} + T \log |\det B|$$

$$B = \frac{\partial U}{\partial \beta}$$

$$- \frac{1}{2} \text{tr} \left[\frac{1}{T} \Sigma^{-1} (\underline{Y} B + Z \Gamma)' (\underline{Y} B + Z \Gamma) \right]$$

$B = I$ if no joint endogeneity

(*) What happens if we have a triangular system?

$(\underline{B}^u, \Gamma^u, \Sigma) \leftarrow$ maximize \mathcal{L} wrt this

unknown

$$\frac{\partial \log \det(A)}{\partial A} = (A')^{-1}$$

$$(i) \frac{\partial h}{\partial \beta^u} : \left[\underbrace{T(B')^{-1}}_{\text{Jacobian Term}} - \underbrace{Y'(\underbrace{YB + Z\Gamma}_{=u})\Sigma^{-1}}_{\text{wrt unknown elements}} \right]^u = 0$$

$$(ii) \frac{\partial h}{\partial \Gamma^u} : \left[-Z'(YB + Z\Gamma)\Sigma^{-1} \right]^u = 0$$

$$(iii) \frac{\partial h}{\partial (\Sigma^{-1})} : \frac{1}{2} [T\Sigma - (YB + Z\Gamma)'(YB + Z\Gamma)]^u = 0$$

$$\Rightarrow \Sigma = \frac{(YB + Z\Gamma)'(YB + Z\Gamma)}{T}$$

$$(i) \text{ becomes: } [(B')^{-1}\Sigma\Sigma^{-1} - \frac{1}{T}Y'u\Sigma^{-1}]^u = 0$$

$$\Leftrightarrow \left[\left\{ (B')^{-1}\Sigma - \frac{1}{T}Y'u \right\} \Sigma^{-1} \right]^u = 0$$

$$\text{It turns out } \text{plim } \frac{Y'u}{T} = (B')^{-1}\Sigma$$

$$\Rightarrow T(B')^{-1}\Sigma = (B')^{-1} \underbrace{u'u}_{YB + Z\Gamma} = Y'u + \frac{(B')^{-1}\Gamma'Z'u}{-\pi'Z'u}$$

$$\text{FOC: } [(B')^{-1}\Gamma'Z'(YB + Z\Gamma)\Sigma^{-1}]^u = 0$$

Thus, we have:

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

$$(ii) [-Z'(YB + Z\Gamma)\Sigma^{-1}]^u = 0$$

$$\text{Thus } \begin{bmatrix} (B')^{-1} \Gamma' z' \\ -z' \end{bmatrix} (\Gamma B + Z \Gamma) \Sigma^{-1} = 0$$

$B_{ii} = 1$ gives us (using the stacked form $y = \tilde{X} \delta + u$)

$$z_j [(\Sigma^{-1})_i \otimes I_T] y = z_j' [(\Sigma^{-1})_i \otimes I_T] x_i \delta$$

$$\text{and } \hat{y}_j [(\Sigma^{-1})_i \otimes I_T] y = \hat{y}_j' [(\Sigma^{-1})_i \otimes I_T] x_i \delta$$

$$\text{where } \hat{y}_j = (-Z \Gamma \hat{B}^{-1})_j$$

Thus, the stacked FOCs for FIML become

$$\hat{\delta}_{FIML} = (\hat{W}' \tilde{X})^{-1} \hat{W}' y$$

$$\text{where } \hat{W} = \hat{\tilde{X}}' (\hat{\Sigma} \otimes I)^{-1}$$

$$\hat{\tilde{X}}_F = \begin{bmatrix} \hat{\tilde{X}}_1 & 0 \\ 0 & \hat{\tilde{X}}_m \end{bmatrix}$$

$$\text{and } \hat{\tilde{X}}_i = [-Z (\Gamma \hat{B})^{-1}; Z_i]$$

FIML is "internally consistent" by the invariance principle.

• Need to iterate on FIML

$$\sqrt{T}(\hat{\delta}_{FIML} - \delta) \xrightarrow{d} N(0, \text{plim} [(\frac{1}{T} \tilde{X}' (\Sigma \otimes I)^{-1} \tilde{X})^{-1}])$$

$$\begin{aligned}
 \text{plim } \sqrt{T} (\hat{\delta}_{FIML} - \hat{\delta}_{3SLS}) &= \text{plim } \sqrt{T} (\hat{\delta}_F - \hat{\delta}_3) \\
 &= \text{plim} \left(\frac{1}{T} \hat{X}'_F (\hat{\Sigma}_F \otimes I)^{-1} \tilde{X} \right)^{-1} \frac{1}{\sqrt{T}} (\hat{X}'_F (\hat{\Sigma}_F \otimes I)^{-1} u) \\
 &\quad - \text{plim} \left(\frac{1}{T} \hat{X}'_3 (\hat{\Sigma}_3 \otimes I)^{-1} \tilde{X} \right)^{-1} \frac{1}{\sqrt{T}} (\hat{X}'_3 (\hat{\Sigma}_3 \otimes I)^{-1} u)
 \end{aligned}$$

use the facts that

$$1] \text{plim } \hat{\Pi}_F \hat{\beta}_F^{-1} = \text{plim } \hat{\Pi}_3 = \Pi$$

$$2] \text{plim } \hat{\Sigma}_F = \text{plim } \hat{\Sigma}_3 = \Sigma$$

Thus,

$$\begin{aligned}
 \text{plim } \sqrt{T} (\hat{\delta}_F - \hat{\delta}_3) &= \text{plim} \left(\frac{1}{T} \hat{X}'_3 (\hat{\Sigma}_3 \otimes I)^{-1} \tilde{X} \right)^{-1} \\
 &\quad \frac{1}{\sqrt{T}} \left[\hat{X}'_F (\hat{\Sigma}_F^{-1} \otimes I) - \hat{X}'_3 (\hat{\Sigma}_3^{-1} \otimes I) \right] u
 \end{aligned}$$

$$\text{but } \text{plim } \frac{Z'u}{T} = 0$$

$$\text{and } \begin{array}{l} \sqrt{T} (\hat{\Pi}_3 - \hat{\Pi}_F) \\ \sqrt{T} (\hat{\Sigma}_3 - \hat{\Sigma}_F) \end{array}$$

both have limiting distributions and are thus bounded in probability.

$$\Rightarrow \sqrt{T} (\hat{\delta}_F - \hat{\delta}_3) = o_p(1) \cdot O_p(1) = o_p(1)$$

$$\text{and } \sqrt{T} (\hat{\delta}_F - \hat{\delta}_3) \xrightarrow{P} 0 \text{ and thus } \sqrt{T} (\hat{\delta}_F - \hat{\delta}_3) \xrightarrow{d} 0,$$

so $\hat{\delta}_F$ and $\hat{\delta}_3$ are asymptotically equivalent.

Test of overid restrictions:

compare $\hat{\Pi}_R$ and $\hat{\Pi}_{UR}$

least squares eqn by eqn

$$\hat{\Pi}_R = - \hat{A} \hat{B}^{-1}$$

restricted estimates

$$\underline{LR} = 2 (\mathcal{L}_U - \mathcal{L}_R) \xrightarrow{P} \chi^2 (* \text{overid})$$

alternatively, can test using
check if $\alpha \neq 0$.

$$\hat{u}_3 = \bar{Z}\alpha + W$$

$$\text{var}(W) = \Sigma \otimes I$$

quasi-maximum likelihood

can do away with initial normality assumption

$$y_i = X_i \delta_i + u_i$$

$$\hat{y}_i = \bar{Y}_i - \hat{v}_i$$

$$\hat{\delta}_i = \begin{bmatrix} \bar{Y}_i \bar{Y}_i - \hat{v}_i \hat{v}_i & \bar{Y}_i Z_i \\ Z_i \bar{Y}_i & Z_i Z_i \end{bmatrix}^{-1} \begin{bmatrix} (\bar{Y}_i - \hat{v}_i) y_i \\ Z_i y_i \end{bmatrix}$$

$$\text{let } \hat{\bar{Y}}_i = \bar{Y}_i - K \hat{v}_i$$

$$\text{2SLS: } K=0$$

$$\text{OLS: } K=1$$

$$W_i = \begin{bmatrix} \hat{\bar{Y}}_i \\ Z_i \end{bmatrix}$$

Consistency $\Rightarrow K=1$

Need $\text{plim } K = I$ if K is stochastic

What if we want this to be as efficient as 2SLS?

Need $\sqrt{T}(K - I) \xrightarrow{d} 0$

Nagar: 2SLS is biased but consistent. Can do 2nd order Taylor expansion to get an unbiased estimator up to second order.

$$\bullet K = I + \frac{K - K_1}{T}$$

$K = \#$ instruments

$K_1 = \#$ rhs variables

$$\bullet \text{plim } \sqrt{T}(I - K) = - \text{plim } \left(\frac{K - K_1}{\sqrt{T}} \right) = 0 \Rightarrow \text{optimality}$$

suppose

$$\frac{K}{T} \rightarrow \alpha$$

(ie have many instruments)

bias doesn't go away

Bekker EMA 1994

\bullet many instruments problem.