

## Three-Stage Least Squares (3SLS)

$$y^j = Y^j \delta^j + Z^j \gamma^j + \varepsilon^j, \quad j=1, \dots, M$$

$$= \begin{bmatrix} Y^j & Z^j \end{bmatrix} \begin{bmatrix} \delta^j \\ \gamma^j \end{bmatrix} + \varepsilon^j$$

$T \times 1$        $T \times r_j, r_j \times 1$        $T \times s_j, s_j \times 1$        $T \times 1$        $T \times 1$        $K_j = r_j + s_j$   
 $T \times K_j$        $K_j \times 1$

$$y^j = X^j \beta^j + \varepsilon^j, \quad j=1, \dots, M$$

$T \times 1$        $T \times K_j, K_j \times 1$        $T \times 1$

This is the same setup as the Seemingly Unrelated Regressors model, but now  $X^j$  includes a set of variables  $Y^j$  that are endogenous.

This is our simultaneous equations system with normalization and exclusion restrictions.

Let's stack the equations, as before:

$$\bar{X} = \begin{bmatrix} X^1 & & 0 \\ & \ddots & \\ 0 & & X^m \end{bmatrix}, \quad \bar{y} = \begin{bmatrix} y^1 \\ \vdots \\ y^m \end{bmatrix}, \quad \bar{\varepsilon} = \begin{bmatrix} \varepsilon^1 \\ \vdots \\ \varepsilon^m \end{bmatrix}, \quad \bar{\beta} = \begin{bmatrix} \beta^1 \\ \vdots \\ \beta^m \end{bmatrix}$$

$(T \times M, \sum_{j=1}^m K_j)$        $T \times M$        $T \times M$        $\sum_{j=1}^m K_j \times 1$

$$\Rightarrow \bar{y} = \bar{X} \bar{\beta} + \bar{\varepsilon}$$

To do system IV, we need an instrumental

variable  $\bar{W}$   $T \times \sum_{j=1}^m K_j$  so that  $\hat{\beta}_{IV} = (\bar{W}' \bar{X})^{-1} (\bar{W}' \bar{y})$

Where does  $\bar{W}$  come from? Note that

$$(\mathbf{I}_m \otimes \mathbf{Z})' \bar{\mathbf{E}} / T = \frac{1}{T} \begin{bmatrix} \mathbf{z}' & \mathbf{z}' & 0 \\ 0 & \dots & \mathbf{z}' \end{bmatrix} \begin{bmatrix} \mathbf{\varepsilon}' \\ \vdots \\ \mathbf{\varepsilon}^m \end{bmatrix} = \begin{bmatrix} \frac{1}{T} \mathbf{z}' \mathbf{\varepsilon}' \\ \vdots \\ \frac{1}{T} \mathbf{z}' \mathbf{\varepsilon}^m \end{bmatrix} \xrightarrow{P} 0$$

under the orthogonality assumption. So,

$\mathbf{I}_m \otimes \mathbf{Z}$  is the set of instruments to be used to form  $\bar{W}$ .  
 $m \times m$     $T \times k$   
 $(Tm \times km)$

We need  $mk \geq \sum_{i=1}^m k_i$ . This holds if each equation is identified since the order condition for the  $i$ 'th equation is  $k \geq q_i$ .

$$\bar{W}_{Tm \times \sum_{j=1}^m k_j} = (\mathbf{I} \otimes \mathbf{Z})_{Tm \times km} \bar{A}_{km \times \sum_{j=1}^m k_j}$$

What is the best  $\bar{A}$ ?

$$\bar{A} = (\hat{\Sigma}^{-1} \otimes \mathbf{I}) \cdot (\mathbf{I} \otimes (\mathbf{Z}'\mathbf{Z})^{-1} \mathbf{Z}') \bar{X} \quad \text{where}$$

$\text{Var}(\bar{\mathbf{E}}) = (\Sigma \otimes \mathbf{I})$  and  $(\hat{\Sigma}^{-1} \otimes \mathbf{I})$  is the inverse of the estimate of  $\text{Var}(\bar{\mathbf{E}})$ .

$$\begin{aligned} \bar{W} &= (\mathbf{I} \otimes \mathbf{Z}) \bar{A} = (\hat{\Sigma}^{-1} \otimes \mathbf{Z} (\mathbf{Z}'\mathbf{Z})^{-1} \mathbf{Z}') \bar{X} \\ &= (\hat{\Sigma}^{-1} \otimes P_Z) \bar{X} \end{aligned}$$

$$(1) \hat{\beta}_{3SLS} = [\bar{X}' (\hat{\Sigma}^{-1} \otimes P_Z) \bar{X}]^{-1} [\bar{X}' (\hat{\Sigma}^{-1} \otimes P_Z) \bar{y}]$$

Let's step back a minute and find the 3SLS estimator in a different way, relating it more to SUR.

Consider the IV estimator formed from

$$\bar{W} = \hat{\bar{X}} = \begin{bmatrix} Z(Z'Z)^{-1}Z'X^1 & 0 & \dots & 0 \\ 0 & Z(Z'Z)^{-1}Z'X^2 & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & & & Z(Z'Z)^{-1}Z'X^m \end{bmatrix}$$

$$= \begin{bmatrix} \hat{X}^1 & & 0 \\ & \hat{X}^2 & \\ 0 & & \hat{X}^m \end{bmatrix}$$

The IV estimator  $\hat{\beta}_{IV} = (\hat{\bar{X}}' \bar{X})^{-1} (\hat{\bar{X}}' \bar{Y})$  is nothing more than equation by equation 2SLS.

By analogy with the SUR model, we would expect this estimator to be less efficient than a GLS estimator. A natural candidate is

$$\hat{\beta}_{3SLS, \Sigma} = (\hat{\bar{X}}' (\Sigma^{-1} \otimes I) \bar{X})^{-1} (\hat{\bar{X}}' (\Sigma^{-1} \otimes I) \bar{Y})$$

Infeasible since  $\Sigma$  not known.

Plugging in an estimate for  $\Sigma$  gives

$$(2) \quad \hat{\beta}_{3SLS} = (\hat{\bar{X}}' (\hat{\Sigma}^{-1} \otimes I) \bar{X})^{-1} (\hat{\bar{X}}' (\hat{\Sigma}^{-1} \otimes I) \bar{Y})$$

Noting that  $\hat{\bar{X}}' (\hat{\Sigma}^{-1} \otimes I) = ((I \otimes P_Z) \bar{X})' (\hat{\Sigma}^{-1} \otimes I)$   
 $= \bar{X}' (\hat{\Sigma}^{-1} \otimes P_Z') = \bar{X}' (\hat{\Sigma}^{-1} \otimes P_Z)$ , the  
 3SLS estimator in Eqns (1) and (2) are identical.

The three-stages of computing the

3SLS estimator are:

1. Compute  $\hat{\bar{X}}$  by regressing each component of

$$\bar{X} \text{ on } Z: \quad \hat{\bar{X}} = \begin{bmatrix} Z(Z'Z)^{-1}Z'X' & 0 \\ 0 & Z(Z'Z)^{-1}Z'X^m \end{bmatrix}$$

2. Compute  $\hat{\beta}_{2SLS}^j$  for each equation  $j$  by doing  
 2SLS on each equation.

$$\begin{pmatrix} \hat{\beta}_{2SLS}^1 \\ \vdots \\ \hat{\beta}_{2SLS}^m \end{pmatrix} = \hat{\beta}_{2SLS} = (\hat{\bar{X}}' \hat{\bar{X}})^{-1} (\hat{\bar{X}}' y)$$

Define  $S_{ij} = \frac{\hat{\epsilon}^i \hat{\epsilon}^j}{T}$  where  $\hat{\epsilon}^i$  are the residuals

from equation  $i$ ,  $\hat{\epsilon}^i = y^i - X^i \hat{\beta}_{2SLS}^i$

$$3. \quad \hat{\Sigma} = S = \begin{pmatrix} S_{11} & S_{12} & \dots & S_{1m} \\ S_{21} & S_{22} & & \vdots \\ \vdots & & \ddots & \\ S_{m1} & \dots & \dots & S_{mm} \end{pmatrix}$$

$$\text{Compute } \hat{\beta}_{3SLS} = [\bar{X}' (S^{-1} \otimes P_Z) \bar{X}]^{-1} [\bar{X}' (S^{-1} \otimes P_Z) \bar{y}]$$

## Optimality of 3SLS

Let's find the variance of the general IV estimator using  $\bar{W} = (I \otimes Z) \bar{A}$

$$\sqrt{T} (\hat{\beta}_{IV} - \beta) = \left[ \frac{\bar{A}' (I \otimes Z)' \bar{X}}{T} \right]^{-1} \left[ \frac{\bar{A}' (I \otimes Z)' \bar{E}}{\sqrt{T}} \right]$$

$$(I \otimes Z)' \bar{E} / \sqrt{T} \xrightarrow{d} N(0, \text{plim} \frac{(I \otimes Z)' (\Sigma \otimes I) (I \otimes Z)}{T})$$

$$\xrightarrow{d} N(0, \text{plim} \Sigma \otimes \left( \frac{Z'Z}{T} \right))$$

$$\xrightarrow{d} N(0, \Sigma \otimes M_Z), \quad M_Z = \text{plim} \left( \frac{Z'Z}{T} \right)$$

$$\frac{\bar{A}' (I \otimes Z)' \bar{X}}{T} = \bar{A}' \begin{bmatrix} \frac{Z'X^1}{T} & & 0 \\ & \frac{Z'X^2}{T} & \\ 0 & & \dots & \frac{Z'X^m}{T} \end{bmatrix}$$

$$\frac{Z'X^j}{T} = \frac{1}{T} Z' [Y^j \quad Z^j] = \frac{1}{T} Z' [Z \pi_j + V_j, Z^j]$$

$$\xrightarrow{p} M_Z [\pi_j \quad C_j]$$

where  $\pi_j$  is the matrix of coefficients given from the reduced form for  $Y^j = Z \pi_j + V_j$  and

where  $C_j$  is a selection matrix that selects from  $M_Z$  the part that represents the

plim of  $\frac{1}{T} Z'Z^j$ .

Optimality of 3SLS (cont)

Let  $D_j = [\pi_j \quad c_j]$ ,  $A = \text{plim } \bar{A}$ .

Then 
$$\frac{\bar{A}'(I \otimes Z)' \bar{X}}{T} \xrightarrow{P} A' \begin{bmatrix} M_2 D_1 & & & 0 \\ & M_2 D_2 & & \\ & & \dots & \\ 0 & & & M_2 D_m \end{bmatrix}$$

$$= A' (I \otimes M_2) \begin{bmatrix} D_1 & & & 0 \\ & D_2 & & \\ & & \dots & \\ 0 & & & D_m \end{bmatrix}$$

$$= A' (I \otimes M_2) \bar{D}$$

Putting this together, we have

$$\sqrt{T} (\hat{\beta}_{IV} - \bar{\beta}) \xrightarrow{d} (A' (I \otimes M_2) \bar{D})^{-1} A' N(0, \Sigma \otimes M_2)$$

so that

$$A \text{Var}(\hat{\beta}_{IV}) = (A' (I \otimes M_2) \bar{D})^{-1} [A' (\Sigma \otimes M_2) A] (\bar{D}' (I \otimes M_2) A)^{-1}$$

For 3SLS,

$$\bar{A} = (\hat{\Sigma}^{-1} \otimes I) \begin{bmatrix} (Z'Z)^{-1} Z'X' & & & 0 \\ & 0 & & \\ & & \dots & \\ & & & (Z'Z)^{-1} Z'X'' \end{bmatrix}$$

$$= (\hat{\Sigma}^{-1} \otimes I) \begin{bmatrix} (Z'Z)^{-1} (Z'X') & & & 0 \\ & 0 & & \\ & & \dots & \\ & & & (Z'Z)^{-1} (Z'X'') \end{bmatrix}$$

$$\xrightarrow{P} (\Sigma^{-1} \otimes I) \begin{bmatrix} M_2^{-1} M_2 D_1 & & & 0 \\ & 0 & & \\ & & \dots & \\ & & & M_2^{-1} M_2 D_m \end{bmatrix} = (\Sigma^{-1} \otimes I) \begin{bmatrix} D_1 & & & 0 \\ & \dots & & \\ 0 & & & D_m \end{bmatrix}$$

## Optimality of 3SLS (Cont)

For 3SLS,

$$\bar{A} \xrightarrow{P} (\Sigma^{-1} \otimes I) \bar{D}$$

plugging in this plim for  $AVar(\hat{\beta}_{IV})$  gives

$$\begin{aligned} AVar(\hat{\beta}_{3SLS}) &= (\bar{D}' (\Sigma^{-1} \otimes Q) \bar{D})^{-1} (\bar{D}' (\Sigma^{-1} \otimes Q) \bar{D}) (\bar{D}' (\Sigma^{-1} \otimes Q) \bar{D})^{-1} \\ &= [\bar{D}' (\Sigma^{-1} \otimes Q) \bar{D}]^{-1} \end{aligned}$$

The final step to showing optimality is to show that

$$AVar(\hat{\beta}_{IV}) - AVar(\hat{\beta}_{3SLS}) \text{ is p.s.d.}$$

This is left as an (unnecessary) exercise.

## Comparing 2SLS, 3SLS

- When all equations are exactly identified, 2SLS  $\equiv$  3SLS. To see this, note:

$$\hat{\beta}_{3SLS} = \underbrace{[\bar{X}' (\hat{\Sigma}^{-1} \otimes P_z) \bar{X}]^{-1}}_{\downarrow} [\bar{X}' (\hat{\Sigma}^{-1} \otimes P_z) \bar{y}]$$

$$\bar{X}' (I \otimes Z)' (\hat{\Sigma}^{-1} \otimes I) (I \otimes (Z'Z)^{-1}) (I \otimes Z) \bar{X}$$

$$= \begin{bmatrix} X'Z & & 0 \\ & X'Z & \\ 0 & & X'X \end{bmatrix} (\hat{\Sigma}^{-1} \otimes I) (I \otimes (Z'Z)^{-1}) \begin{bmatrix} Z'X & & 0 \\ & Z'X & \\ 0 & & Z'Z \end{bmatrix}$$

Each of these blocks is square and invertible.

Comparing 2SLS, 3SLS (Cont)

So, when all equations are exactly identified,

$$\begin{aligned} \hat{\beta}_{3SLS} &= \begin{bmatrix} Z'X' & 0 \\ 0 & Z'X^m \end{bmatrix}^{-1} (I \otimes (Z'Z)) (\hat{\Sigma} \otimes I) \begin{bmatrix} X''Z & 0 \\ 0 & X^m'Z \end{bmatrix}^{-1} \\ &\quad \cdot \begin{bmatrix} X''Z & 0 \\ 0 & X^m'Z \end{bmatrix} (\hat{\Sigma}' \otimes I) (I \otimes (Z'Z)^{-1}) \begin{bmatrix} Z'y' \\ \vdots \\ Z'y^m \end{bmatrix} \\ &= \begin{bmatrix} (Z'X')^{-1} & 0 \\ 0 & (Z'X^m)^{-1} \end{bmatrix} \begin{bmatrix} Z'y' \\ \vdots \\ Z'y^m \end{bmatrix} \\ &= \begin{bmatrix} (Z'X')^{-1} Z'y' \\ \vdots \\ (Z'X^m)^{-1} Z'y^m \end{bmatrix} = \text{2SLS eqn. by eqn.} \end{aligned}$$

Also, as in the SUR model, you can see that misspecification in some equation affects in general the consistency in all equations. To see this, expand the term

$$\bar{X}' (\hat{\Sigma}^{-1} \otimes P_Z) \bar{E}$$

and argue as we did for the SUR estimator.