

Consider the system

$$\underset{\text{mixm}}{\Gamma} \begin{pmatrix} y_{1i} \\ \vdots \\ y_{mi} \end{pmatrix}_{\text{mixl}} = \underset{\text{mixe}}{B} \begin{pmatrix} z_{1i} \\ \vdots \\ z_{li} \end{pmatrix}_{\text{exl}} + \begin{pmatrix} u_{1i} \\ \vdots \\ u_{mi} \end{pmatrix}_{\text{mixl}}$$

endogenous                                  exogenous

$$\Gamma Y_i = B Z_i + U_i$$

$$\text{and } E \underset{\text{exl}}{Z_i} \underset{\text{num}}{U_i}' = 0 \underset{\text{exm}}{}$$

In this case the first equation is

$$\sum_{j=1}^m \Gamma_{ij} y_{ji} = \sum_{j=1}^l B_{ij} z_{ji} + u_{ii}$$

$$\text{Normalize } \Gamma_{jj} = 1$$

$$y_{ii} + \sum_{j=2}^m \Gamma_{ij} y_{ji} = \sum_{j=1}^l B_{ij} z_{ji} + u_{ii}$$

Becomes the dependent variable.

Provided  $\Gamma^{-1}$  exists we can rewrite

$$Y_i = \underset{\text{mixl}}{\Gamma^{-1} B} \underset{\text{exl}}{Z_i} + \underset{\text{mixl}}{\Gamma^{-1} U_i} \quad (\text{reduced form})$$

$$\text{and } E \underset{\text{exl}}{Z_i} \underset{\text{mixl}}{V_i}' = E \underset{\text{exl}}{Z_i} \underset{\text{mixl}}{U_i}' (\Gamma^{-1})' = 0$$

Notice that we can estimate  $\Pi$  from an OLS regression.

We can focus without loss of generality on the first equation

$$\underset{\text{mixm}}{\Gamma} \underset{\text{mixe}}{\Pi} = \underset{\text{mixe}}{B}$$

$$\begin{pmatrix} 1 & -\gamma_1' & 0' \\ \Gamma_1 & \Gamma_2 & \Gamma_3 \end{pmatrix} \begin{pmatrix} \pi_1 & \pi_2 \\ \pi_L & \pi_2 \\ \pi_3 & \pi_4 \end{pmatrix} = \begin{pmatrix} \beta_1' & 0' \\ \beta_L & \beta_2 \end{pmatrix}$$

where  $\ell_1$  are the number of exogenous regressors and  $m_L$  the number of endogenous regressors included.

$$1 \pi_1 - \gamma_1' \pi_1 = \beta_L' \quad (1)$$

$$1 \pi_2 - \gamma_1' \pi_2 = 0' \Rightarrow \pi_2 = \gamma_1' \pi_1 \quad (2)$$

We recover  $\gamma_1'$  from (2) which we use in (1) to recover  $\beta_L$ .

Therefore, the first equation looks like

$$(1 \ -\gamma_1' \ 0') \begin{pmatrix} y_{1i} \\ y_{1i} \\ y_{1i}^* \end{pmatrix} = (\beta_1' \ 0') \begin{pmatrix} z_{1i} \\ z_{1i}^* \end{pmatrix} + u_{1i}$$

$\underbrace{z_{1i}}_{m_2}$

$$y_{1i} - \gamma_1' y_{1i} = \beta_1' z_{1i} + u_{1i}$$

$$\underset{m_1}{y_{1i}} = \underset{m_1 \times m_1}{\gamma_1' y_{1i}} + \underset{m_1 \times 1}{\beta_1' z_{1i}} + \underset{m_1}{u_{1i}}$$

We need at least  $m_2$  instruments for the endogenous regressors included. This is the same as

$$l - l_1 \geq m_2 \quad (\text{Necessary condition})$$

This relied on the fact that we could use (2) to recover  $\gamma_1'$ :

$$\underset{(l-l_1) \times m_1}{\pi_2} = \underset{m_1 \times m_1}{\gamma_1' \pi_2} \underset{m_2 \times (l-l_1)}{\pi_2 \times (l-l_1)}$$

$$\Rightarrow \underset{(l-l_1) \times m_1}{\pi_2' \gamma_1} = \underset{(l-l_1) \times 1}{\pi_2' \pi_2} \quad \text{rewritten as a linear system.}$$

Therefore, the sufficient condition is that  $\pi_2'$  is full column rank so that

$$\text{rank}(\pi_2') = m_2 \quad (\text{Sufficient Condition})$$

and

$$\hat{\gamma}_1^{\text{ILS}} = (\pi_2')^+ \hat{\pi}_2' = (\hat{\pi}_2 \pi_2')^+ \hat{\pi}_2 \hat{\pi}_2'$$

Moreover, recall the reduced form

$$\begin{pmatrix} y_{1i} \\ y_{1i} \\ y_{1i}^* \end{pmatrix} = \begin{pmatrix} \pi_1 & \pi_2 \\ \pi_1 & \pi_2 \\ \pi_3 & \pi_4 \end{pmatrix} \begin{pmatrix} z_{1i} \\ z_{1i}^* \end{pmatrix} + \begin{pmatrix} v_{1i} \\ v_{1i} \\ v_{1i}^* \end{pmatrix}$$

$$y_{1i} = \pi_1 z_{1i} + \pi_2 z_{1i}^* + v_{1i} \quad (\text{"Reduced Form"})$$

$$y_{1i} = \pi_1 z_{1i} + \pi_2 z_{1i}^* + v_{1i} \quad (\text{"First stage"})$$

$$y_{1i}^* = \pi_3 z_{1i} + \pi_4 z_{1i}^* + v_{1i}^*$$

(\*) That's why  $\pi_2$  is very important, since it captures the exogenous variation onto the endogenous regressors.

We can also rewrite the structural equation (for the first eq) as

$$\begin{aligned}
 y_{ii} &= \underbrace{y_{ii}'}_{\text{exogenous}} + \underbrace{z_{ii}'}_{\text{instruments}} \beta_1 + u_{ii} \\
 &= (y_{ii}', z_{ii}') \begin{pmatrix} \delta_{1,\text{exogenous}} \\ \beta_1 \end{pmatrix} + u_{ii} \\
 &= \underbrace{x_{ii}'}_{\text{exogenous}} \delta_{1,\text{exogenous}} + u_{ii}
 \end{aligned}$$

And our instruments are  $z_i = (z_{ii}, z_{i*})$ , so that  $E u_{ii} z_i = 0$ .

This looks like the linear IV models that we're used to. Then, we require

$$E z_i x_{ii}' \text{ is full rank} \Rightarrow \text{rank}(E z_i x_{ii}') = \underbrace{m_i + l_i}_{l \times (m_i + l_i)} = k_L$$

Write

$$\begin{aligned}
 E z_i x_{ii}' &= E \begin{pmatrix} z_{ii} \\ z_{i*} \end{pmatrix} (y_{ii}', z_{ii}') = E \begin{pmatrix} z_{ii} \\ z_{i*} \end{pmatrix} ((z_{ii}' \pi_1' + z_{i*}' \pi_2' + v_{ii}') z_{ii}') \\
 &\quad \xrightarrow{\text{plug in the First Stage}}
 \end{aligned}$$

$$\begin{pmatrix} E z_{ii} z_{ii}' \pi_1' + E z_{ii} z_{i*}' \pi_2' & E z_{ii} z_{i*}' \\ E z_{i*} z_{ii}' \pi_1' + E z_{i*} z_{i*}' \pi_2' & E z_{i*} z_{i*}' \end{pmatrix}$$

$\rightarrow$  non-zero!

If it's not full rank then  $\exists \theta$  s.t.

$$E z_i x_{ii}' \theta = \begin{pmatrix} E z_{ii} z_{ii}' \pi_1' \theta_1 + E z_{ii} z_{i*}' \pi_2' \theta_1 + E z_{ii} z_{i*}' \theta_2 \\ E z_{i*} z_{ii}' \pi_1' \theta_1 + E z_{i*} z_{i*}' \pi_2' \theta_1 + E z_{i*} z_{i*}' \theta_2 \end{pmatrix} = 0$$

$$\begin{pmatrix} E z_{ii} z_{ii}' & E z_{ii} z_{i*}' \\ E z_{i*} z_{ii}' & E z_{i*} z_{i*}' \end{pmatrix} \begin{pmatrix} \pi_1' \theta_1 + \theta_2 \\ \pi_2' \theta_1 \end{pmatrix} = 0$$

$\xrightarrow{\text{P.d. matrix of second moments}}$        $\xrightarrow{\text{must be 0}}$

Then

$$\pi_1' \theta_1 = -\theta_2$$

\* Both  $\theta_1$  and  $\theta_2 \neq 0$  because if one is 0 the other is also 0.

$$\pi_2' \theta_1 = 0$$

There's a nonzero vector that is mapped to 0, i.e.  $\text{rank}(\pi_2') < m_1$ .

This implies that  $\text{rank}(EZ_i X_{ii}')$   $\leq k_i \Rightarrow \text{rank}(T_{i2}') \leq m_2$ .  
 Now suppose  $\text{rank}(T_{i2}') < m_2$ . Then such  $\theta_1$  exist and we can find a  $\theta_2 = -T_{i1}'\theta_1$  so that  $EZ_i X_{ii}' = 0$ , i.e.  $\text{rank}(EZ_i X_{ii}') = 0$ .

In other words,

$$\text{rank}(EZ_i X_{ii}') = k_i \Leftrightarrow \text{rank}(T_{i2}') = m_2.$$

### Multiple Equation GMM

Suppose  $M$  equations are identified:

$$\begin{aligned} y_{i1} &= \underset{\text{size}}{X_{i1}'} \underset{\text{size}}{d_1} + \underset{\text{size}}{u_{i1}} \\ &\vdots \\ y_{iM} &= \underset{\text{size}}{X_{iM}'} \underset{\text{size}}{d_M} + \underset{\text{size}}{u_{iM}} \quad \text{where } E \underset{\text{size}}{Z_i} \underset{\text{size}}{u_{ji}} = 0 \\ &\quad \text{rank}(E \underset{\text{size}}{Z_i} \underset{\text{size}}{X_{ji}'}) = n_j \end{aligned}$$

In matrix form can be written as

$$\begin{aligned} y_1 &= \underset{\text{size}}{X_1} \underset{\text{size}}{d_1} + \underset{\text{size}}{u_1} \\ &\vdots \\ y_M &= \underset{\text{size}}{X_M} \underset{\text{size}}{d_M} + \underset{\text{size}}{u_M} \quad \text{where } X_j = \begin{pmatrix} X_{j1}' \\ \vdots \\ X_{jn}' \end{pmatrix}. \end{aligned}$$

$$\Rightarrow y = \begin{pmatrix} x_1 & \dots & 0 \\ 0 & \ddots & x_M \end{pmatrix} \begin{pmatrix} d_1 \\ \vdots \\ d_M \end{pmatrix} + u$$

where  $K = k_1 + \dots + k_M$

$$y = \underset{\text{size}}{X} \underset{\text{size}}{d} + \underset{\text{size}}{u}$$

The population moment conditions are

$$E \begin{pmatrix} z_i u_{i1} \\ \vdots \\ z_i u_{iM} \end{pmatrix} = E \begin{pmatrix} u_{i1} \otimes z_i \\ \vdots \\ u_{iM} \otimes z_i \end{pmatrix} = 0$$

The sample moment conditions are

$$\begin{aligned} \begin{pmatrix} z' u_1 \\ \vdots \\ z' u_M \end{pmatrix} &= \begin{pmatrix} z' & \dots & 0 \\ 0 & \ddots & z' \end{pmatrix} \begin{pmatrix} u_1 \\ \vdots \\ u_M \end{pmatrix} \\ &= (I_m \otimes z') \begin{pmatrix} u_1 \\ \vdots \\ u_M \end{pmatrix} \\ &= \underbrace{(I_m \otimes z')'}_{m \times K \text{ min}} u = (I_m \otimes z')' (y - Xd) = 0 \end{aligned}$$

We can solve the system as with a regular GMM estimator

$$\hat{\delta}_n = \underset{d \in \mathbb{R}^K}{\operatorname{argmin}} (Y - X_d)' (I_m \otimes Z) W_n (I_m \otimes Z)' (Y - X_d)$$

$$= [X' (I_m \otimes Z) W_n (I_m \otimes Z)' X]^{-1} X' (I_m \otimes Z) W_n (I_m \otimes Z)' Y$$

Recall the sample criterion function

$$\begin{aligned} & \underbrace{(Y - X_d)' (I_m \otimes Z)' W_n (I_m \otimes Z)' (Y - X_d)} \\ &= \begin{pmatrix} Z' (Y_1 - X_1 d_1) \\ \vdots \\ Z' (Y_m - X_m d_m) \end{pmatrix}' \begin{pmatrix} W_{11} & \cdots & W_{1m} \\ \vdots & \ddots & \vdots \\ W_{m1} & \cdots & W_{mm} \end{pmatrix} \begin{pmatrix} Z' (Y_1 - X_1 d_1) \\ \vdots \\ Z' (Y_m - X_m d_m) \end{pmatrix} \\ &= \begin{pmatrix} (Y_1 - X_1 d_1)' Z \\ \vdots \\ (Y_m - X_m d_m)' Z \end{pmatrix} \begin{pmatrix} W_{11} & \cdots & W_{1m} \\ W_{m1} & \cdots & W_{mm} \end{pmatrix} \begin{pmatrix} Z' (Y_1 - X_1 d_1) \\ \vdots \\ Z' (Y_m - X_m d_m) \end{pmatrix} \\ &= (Y_1 - X_1 d_1)' Z W_{11} Z' (Y_1 - X_1 d_1) + (Y_1 - X_1 d_1)' Z W_{12} Z' (Y_1 - X_1 d_1) + \dots + (Y_m - X_m d_m)' Z W_{mm} Z' (Y_m - X_m d_m) \end{aligned}$$

④ If  $W_{ij} = 0$  for  $i \neq j$  this becomes the sum of the individual criterion functions!

$$\hat{\delta}_n - \delta = [\underbrace{X' (I_m \otimes Z)}_n W_n \underbrace{(I_m \otimes Z)' X}_n]^{-1} \underbrace{X' (I_m \otimes Z)}_n W_n \underbrace{(I_m \otimes Z)' U}_n$$

$$\cdot \frac{(I_m \otimes Z)' X}{n} = \frac{1}{n} \begin{pmatrix} Z' \cdots 0 \\ 0 \cdots Z' \\ \vdots n \end{pmatrix} \begin{pmatrix} x_1 & \cdots & 0 \\ 0 & \cdots & x_m \\ \vdots & \ddots & \vdots \end{pmatrix} = \begin{pmatrix} \frac{Z' x_1}{n} & \cdots & 0 \\ 0 & \cdots & \frac{Z' x_m}{n} \\ \vdots & \ddots & \vdots \end{pmatrix} \rightarrow \begin{pmatrix} 0_1 & \cdots & 0 \\ 0 & \cdots & 0_m \end{pmatrix} := C$$

$$\cdot \frac{(I_m \otimes Z)' U}{n} = \frac{1}{n} \begin{pmatrix} Z' u_1 \\ \vdots \\ Z' u_m \end{pmatrix} = \frac{1}{n} \sum_{i=1}^n \begin{pmatrix} z_i u_{ic} \\ \vdots \\ z_i u_{im} \end{pmatrix} = \frac{1}{n} \sum_{i=1}^n (u_i \otimes z_i)$$

$$\text{Then } \sqrt{n}(\hat{f}_n - f) = \left[ X' \underbrace{(I_m \otimes Z)}_n W_n \underbrace{(I_m \otimes Z)' X}_n \right]^{-1} X' \underbrace{(I_m \otimes Z)}_n W_n \underbrace{(I_m \otimes Z)' U}_{\sqrt{n}}$$

$$\bullet \frac{(I_m \otimes Z)' U}{\sqrt{n}} = \frac{1}{\sqrt{n}} \sum_{i=1}^n (U_i \otimes Z_i) \xrightarrow{\xi_i} N(0, E[\xi_i \xi_i']) \\ = N(0, E[U_i U_i' \otimes Z_i Z_i'])$$

$$\bullet E[U_i U_i' \otimes Z_i Z_i'] = E \left[ \begin{pmatrix} U_{ii} U_{ii} & \dots & U_{ii} U_{mi} \\ \vdots & \ddots & \vdots \\ U_{mi} U_{ii} & \dots & U_{mi} U_{mi} \end{pmatrix} \otimes Z_i Z_i' \right]$$

$$= E \left[ \begin{matrix} U_{ii}^2 Z_i Z_i' & \dots & U_{ii} U_{mi} Z_i Z_i' \\ \vdots & & \vdots \\ U_{mi} U_{ii} Z_i Z_i' & \dots & U_{mi}^2 Z_i Z_i' \end{matrix} \right]$$

To have  $\sigma^2$  finite we need that every sub-matrix is finite.  
Then

$$\bullet E \|U_{ji} Z_i Z_i'\| \leq (E U_{ji}^4 \underbrace{E \|Z_i Z_i'\|^2}_{\text{Cauchy-Schwarz}})^{1/2}$$

Known as Frobenious Norm

$$= E [\text{trace}(\underbrace{Z_i Z_i'}_{\text{vec}} \underbrace{Z_i Z_i'}_{\text{vec}})]$$

$$= E [\text{trace}(\underbrace{Z_i Z_i'}_{\text{vec}} \underbrace{Z_i Z_i'}_{\text{vec}})]$$

$$= E [Z_i' Z_i \text{trace}(Z_i Z_i')] \quad \text{scalar = trace}$$

$$= E [\text{trace}(Z_i Z_i) \text{trace}(Z_i' Z_i)] \quad \text{trace}(A) = \text{trace}(A')$$

$$= E [(\text{trace}(Z_i Z_i))^{1/2}] = E [\|Z_i\|^4]$$

Then we require  $E U_{ji}^4 < \infty$  and  $E \|Z_i\|^4 < \infty$ .

$$\bullet E \|U_{ji} U_{si} Z_i Z_i'\| \leq (E U_{ji}^2 U_{si}^2 \underbrace{E \|Z_i Z_i'\|^2})^{1/2}$$

$$\leq (E U_{ji}^4 \cdot E U_{si}^4)^{1/2}$$

so we don't require further assumptions.

• Alternative way : Consider how  $E U_{ji}^2 Z_i Z_i'$  looks

$$E U_{ji}^2 Z_i Z_i' = E \left[ U_{ji}^2 \begin{pmatrix} Z_{ii} Z_{ii} & \dots & Z_{ii} Z_{ei} \\ \vdots & \ddots & \vdots \\ Z_{ei} Z_{ii} & \dots & Z_{ei} Z_{ei} \end{pmatrix} \right]$$

consider an arbitrary element in the  $(r,s)$  position

$$\begin{aligned} E(U_{ji}^2 Z_{ri} Z_{si}) &\leq (E U_{ji}^4 E Z_{ri}^2 Z_{si}^2)^{1/2} \\ &\leq (E U_{ji}^4 (E Z_{ri}^4 E Z_{si}^4)^{1/2})^{1/2} \end{aligned}$$

and we reach the same conditions, since  $E Z_{ri}^4 \leq 00$  implies  $E \|Z_i\|^4 \leq 00$ . However, these are a set of more primitive assumptions.

When  $E(U_{lli} Z_i Z_i')$  is block diagonal i.e.  $E U_{lli} U_{ri} Z_i Z_i' = 0$  exe, then the efficient weighting matrix  $W_h$  is

$$Q^{-1} = \begin{bmatrix} E U_{ii}^2 Z_i Z_i' & & & & 0 \\ & \ddots & & & \\ 0 & & \ddots & & E U_{mi}^2 Z_i Z_i' \end{bmatrix}^{-1}$$

$$= \begin{bmatrix} (E U_{ii} Z_i Z_i')^{-1} & & & & 0 \\ & \ddots & & & \\ 0 & & \ddots & & (E U_{mi}^2 Z_i Z_i')^{-1} \end{bmatrix}$$

$$= \begin{bmatrix} Q_{ii}^{-1} & & & & 0 \\ & \ddots & & & \\ 0 & & \ddots & & Q_{mm}^{-1} \end{bmatrix}$$

so the criterion function will be the sum of the single equation criterion functions since  $W_h$  is block diagonal. Intuitively, there are no efficiency gains since the other equations don't provide information to the equation that we're interested.

( 2 step GMM as efficient dimension reduction )

Consider the IV model

$$Y_i = X_i' \beta + U_i \quad , \quad \beta \in \mathbb{R}^K \text{ and } Z_i \text{ is } l \times l \text{ with } l > K$$

$$E Z_i U_i = 0$$

Suppose we use a matrix  $B_{n \times l}$  that has rank  $K$  to linearly transform  $Z_i$  into a vector of  $K$  instruments  $W_i := B_{n \times l} Z_i$ . We then run IV with  $W_i$ .

$$\tilde{\beta}_n(B) = \left( \sum_{i=1}^n W_i X_i' \right)^{-1} \sum_{i=1}^n W_i Y_i = (W' X)^{-1} W' Y$$

$$\textcircled{*} \quad W = \begin{pmatrix} W_1' \\ \vdots \\ W_n' \end{pmatrix} = \begin{pmatrix} Z_1' \\ \vdots \\ Z_n' \end{pmatrix} B' = Z B'$$

$$\tilde{\beta}_n(B) - \beta = (\frac{W' X}{n})^{-1} \frac{W' U}{n}$$

$$\sqrt{n}(\tilde{\beta}_n(B) - \beta) = (\frac{W' X}{n})^{-1} \frac{W' U}{\sqrt{n}} = (B \frac{Z' X}{n})^{-1} B \frac{Z' U}{\sqrt{n}}$$

$$\bullet \quad \frac{Z' U}{\sqrt{n}} = \frac{1}{\sqrt{n}} \sum_{i=1}^n U_i Z_i \xrightarrow{P} N(0, E U_i^2 Z_i Z_i')$$

$$\bullet \quad \frac{Z' X}{n} \xrightarrow{P} E Z_i X_i' = Q$$

by Slutsky's theorem  $(B \frac{Z' X}{n})^{-1} \xrightarrow{P} (B Q)^{-1}$

Then

$$\sqrt{n}(\tilde{\beta}_n(B) - \beta) \xrightarrow{d} N(0, (B Q)^{-1} B \Sigma B' (Q' B')^{-1})$$

$$\textcircled{*} \quad (ABC)^{-1} = C^{-1} B^{-1} A^{-1}$$

$$= N(0, (Q' B' (B \Sigma B')^{-1} B Q)^{-1})$$

Recall that the Asy-var of the efficient GMM is  $V^* = (Q' \Sigma^{-1} Q)^{-1}$ .  
Then we want to show

$$\begin{aligned} V(B) - V^* \text{ p.s.d.} &\Leftrightarrow V^{*-1} - V(B)^{-1} \text{ p.s.d.} \\ &= Q' \Sigma^{-1} Q - Q' B' (B \Sigma B')^{-1} B Q \\ &= Q' \underbrace{\Sigma^{-1/2}}_{\text{use } \Sigma^{-1/2}} \left( I_l - \underbrace{\Sigma^{1/2} B' (B \Sigma B')^{-1} B \Sigma^{1/2}}_{H} \right) \underbrace{\Sigma^{-1/2}}_{\text{use } \Sigma^{-1/2}} Q \\ &\quad \underbrace{\text{projection matrix}}_{\text{use } H} \end{aligned}$$

Therefore, it is p.s.d.

Notice that we can find the  $B$  such that it attains the lower bound  $V^*$ .

$$(Q' B' (B \cdot Q B')^{-1} B Q) = Q' \cdot R^{-1} \cdot Q$$

we want this to cancel each other      this should be this

$\Rightarrow \{ B^* = Q' \cdot R^{-1} \}$  and plug it to confirm :

$$Q' \cdot R^{-1} \cdot Q \cdot (Q' \cdot R^{-1} \cdot Q B' (B \cdot Q B')^{-1} B Q)' \cdot Q' \cdot R^{-1} \cdot Q$$

$$= V^* \text{ as desired.}$$

We can estimate it as

$$B_n = \frac{X' Z}{n} \cdot \hat{\Omega}_n^{-1} = \sum_{i=1}^n \frac{X_i Z_i'}{n} \cdot \hat{\Omega}_n^{-1}$$

$$\text{where } \hat{\Omega}_n = \frac{1}{n} \sum_{i=1}^n (Y_i - X_i' \hat{B}_n)^2 Z_i Z_i'$$

Is some consistent estimator of  $\Omega$

Finally, we can write

$$\begin{aligned} \hat{B}_n (B_n) &= \left( B_n \sum_{i=1}^n Z_i X_i' \right)^{-1} B_n \sum_{i=1}^n X_i Y_i \\ &= \left( \sum_{i=1}^n X_i Z_i' \cdot \hat{\Omega}_n^{-1} \sum_{i=1}^n Z_i X_i' \right)^{-1} \sum_{i=1}^n X_i Z_i' \cdot \hat{\Omega}_n^{-1} \sum_{i=1}^n Z_i Y_i = \hat{\beta}_{\text{2step}} \end{aligned}$$

( Testing on Structural Parameters without assuming identification )

$$y_i = \underset{n \times 1}{x_i}' \underset{K \times K}{\pi} + \underset{n \times 1}{u_i}$$

$$\underset{n \times 1}{x_i} = \underset{K \times K}{\pi}' \underset{K \times 1}{z_i} + \underset{n \times 1}{v_i}$$

which can be rewritten into matrix form by defining

$$\underset{K \times K}{\pi} = \begin{pmatrix} \pi_1 & \pi_2 & \dots & \pi_K \\ \text{exl} & \text{exl} & \dots & \text{exl} \end{pmatrix}_{K \times K}, \quad \underset{K \times K}{X} = \begin{pmatrix} x_1' \\ x_2' \\ \vdots \\ x_n' \end{pmatrix}_{n \times K}$$

Structural Eq :  $y = \underset{n \times 1}{X} \underset{K \times K}{\gamma} + \underset{n \times 1}{u}$

First Stage Eq :  $\underset{n \times K}{X} = \underset{K \times K}{Z} \underset{K \times K}{\pi} + \underset{n \times K}{V}$

Reduced Form Eq :  $y = \underset{n \times 1}{Z} \underset{K \times K}{\pi} \gamma + \underbrace{\underset{n \times K}{V} \gamma + \underset{n \times 1}{u}}_{W}$

Vectorize the first stage equation

$$\text{vec}(X) = \text{Vec}(Z \pi \underset{K \times K}{I}) + \text{vec}(V)$$

$$\begin{pmatrix} x_1' \\ \vdots \\ x_n' \end{pmatrix}_{n \times K} = (\underset{K \times K}{I} \otimes Z) \underset{K \times K}{\text{vec}(\pi)} + \begin{pmatrix} v_1 \\ \vdots \\ v_K \end{pmatrix}_{n \times 1}$$

$$\tilde{X} = \tilde{Z} \underset{K \times K}{\text{vec}(\pi)} + \tilde{V}$$

Then we get

$$\cdot \hat{\pi} = \pi + (Z' Z)^{-1} Z' W$$

$$\sqrt{n} (\tilde{\pi} - \pi) = (\frac{Z' Z}{n})^{-1} \frac{Z' W}{\sqrt{n}} = (\frac{Z' Z}{n})^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n (Z_i' W_i)_{K \times 1}$$

$$\cdot \text{vec}(\hat{\pi}) = \text{vec}(\pi) + (\tilde{Z}' \tilde{Z})^{-1} \tilde{Z}' V$$

$$\sqrt{n} (\text{vec}(\hat{\pi}) - \text{vec}(\pi)) = (\frac{\tilde{Z}' \tilde{Z}}{n})^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n (\tilde{V}_i \otimes Z_i)_{K \times 1}$$

Consider them jointly

$$\begin{aligned} \sqrt{n} \begin{pmatrix} \hat{\pi} - \pi \\ \text{vec}(\hat{\pi}) - \text{vec}(\pi) \end{pmatrix} &= \begin{pmatrix} \left( \frac{Z'Z}{n} \right)^{-1} \\ \left( \frac{\tilde{Z}'\tilde{Z}}{n} \right)^{-1} \end{pmatrix} \frac{1}{\sqrt{n}} \sum_{i=1}^n \begin{pmatrix} z_i w_i \\ \tilde{v}_i \otimes z_i \end{pmatrix} \\ &\xrightarrow{d} N(0, \begin{pmatrix} Q_z^{-1} & E z_i z_i' (Q_z^{-1} Q_z^{-1}) \\ Q_{\tilde{z}}^{-1} & \end{pmatrix} \underbrace{\Omega}_{\text{cov}}) \\ &= N(0, \begin{pmatrix} Q_z^{-1} & (Q_z^{-1} \otimes I_d) \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} (Q_z^{-1} \otimes I_d) \\ Q_{\tilde{z}}^{-1} & \end{pmatrix} \text{cov}) \\ &= N(0, (\Sigma_{11} \Sigma_{12} \Sigma_{21} \Sigma_{22})^{-1}) = N(0, \Sigma) \end{aligned}$$

Something really cool that we can do is to test  $H_0: \gamma = \gamma_0$  using the equation  $\pi \gamma = \pi$  and our derived distribution.

Under  $H_0$  we have  $\pi \gamma_0 = \pi$ . Therefore,

$$\begin{aligned} \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi}) &= \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi} - \pi \gamma_0 + \pi) \\ &= \sqrt{n} ((\hat{\pi} - \pi) \gamma_0 - (\hat{\pi} - \pi)) \\ &\stackrel{*}{=} \text{vec}(\pi \gamma) = (\gamma \otimes I_d) \text{vec}(\pi) \\ &= \sqrt{n} ((\gamma_0' \otimes I_d) \text{vec}(\hat{\pi} - \pi) - (\hat{\pi} - \pi)) \\ &= [-I_d \quad (\gamma_0' \otimes I_d)] \sqrt{n} \begin{pmatrix} \hat{\pi} - \pi \\ \text{vec}(\hat{\pi} - \pi) \end{pmatrix} \\ &\xrightarrow{d} N(0, (-I_d \quad (\gamma_0' \otimes I_d)) \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \begin{pmatrix} -I_d \\ (\gamma_0' \otimes I_d) \end{pmatrix}) \\ &= N(0, \underbrace{\Sigma_{11} - (\gamma_0' \otimes I_d) \Sigma_{21} - \Sigma_{12} (\gamma_0 \otimes I_d) + (\gamma_0' \otimes I_d) \Sigma_{22} (\gamma_0 \otimes I_d)}_{\tilde{\Omega}}) \end{aligned}$$

We can get the following consistent estimator for  $\hat{\Omega}$

$$\hat{\Omega} = \hat{\Sigma}_n - (\gamma_0' \otimes I_d) \hat{\Sigma}_{21} - \hat{\Sigma}_{12} (\gamma_0 \otimes I_d) + (\gamma_0' \otimes I_d) \hat{\Sigma}_{22} (\gamma_0 \otimes I_d)$$

And we can construct the following Wald test using the fact that

$$-\hat{\Omega}^{-\frac{1}{2}} \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi}) \xrightarrow{d} N(0, I_d)$$

$$\begin{aligned} \Rightarrow W(\gamma_0) &= n (\hat{\pi} \gamma_0 - \hat{\pi})' \hat{\Omega}^{-1} (\hat{\pi} \gamma_0 - \hat{\pi}) \\ &= \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi})' \hat{\Omega}^{-\frac{1}{2}} \hat{\Omega}^{-\frac{1}{2}} \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi}) \\ &= [\hat{\Omega}^{-\frac{1}{2}} \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi})]' [\hat{\Omega}^{-\frac{1}{2}} \sqrt{n} (\hat{\pi} \gamma_0 - \hat{\pi})] \\ &\xrightarrow{d} \chi^2_d \quad \text{so we reject when } W(\gamma_0) > \chi^2_{d, 1-\alpha}. \end{aligned}$$

Notice what happens to the asymptotic distribution under local alternatives

$$\gamma = \gamma_0 + \frac{d}{\sqrt{n}}$$

$$\begin{aligned} \sqrt{n} (\hat{\pi} \gamma - \hat{\pi}) &= \sqrt{n} ((\hat{\pi} - \pi) \gamma_0 - (\hat{\pi} - \pi) d) - \pi d \\ &\xrightarrow{d} N(-\pi d, \hat{\Omega}) \end{aligned}$$

$$\text{Hence } W(\gamma_0) \xrightarrow{d} \chi^2_d (d' \pi' \pi d).$$

Finally, if  $d \in N(\pi)$  then the test will have trivial power.

$$\Pr_{d \in N(\pi)} (W(\gamma_0) > \chi^2_{d, 1-\alpha}) \rightarrow \alpha, \text{ as } n \rightarrow \infty.$$