

# linear IV model

$$y_i = x_{1i}' \delta + x_{2i}' \beta + u_i \quad (1)$$

$1 \times 1$        $1 \times k_1$     $k_1 \times 1$        $1 \times k_2$     $k_2 \times 1$        $1 \times 1$

$$x_{1i}' = z_i' \pi_1' + x_{2i}' \pi_2' + v_i' \quad (2)$$

$1 \times k_1$        $k_1 \times 1$     $k_1 \times k_1$        $1 \times k_2$     $k_2 \times k_1$        $1 \times k_1$

where

$$\begin{aligned} E z_i u_i &= 0 \\ E z_i v_i' &= 0 \\ E x_{2i} u_i &= 0 \\ E x_{2i} v_i' &= 0 \end{aligned}$$

A) Identification :

$$E \begin{pmatrix} z_i \\ x_{2i} \end{pmatrix} u_i = \begin{pmatrix} 0_{k_1 \times 1} \\ 0_{k_2 \times 1} \end{pmatrix}$$

Replace the structural equation (1)

$$\begin{pmatrix} E z_i (y_i - x_{1i}' \delta - x_{2i}' \beta) \\ E x_{2i} (y_i - x_{1i}' \delta - x_{2i}' \beta) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} E z_i y_i \\ E x_{2i} y_i \end{pmatrix} = \underbrace{\begin{pmatrix} E z_i x_{1i}' & E z_i x_{2i}' \\ E x_{2i} x_{1i}' & E x_{2i} x_{2i}' \end{pmatrix}}_{\text{rank condition!}} \begin{pmatrix} \delta \\ \beta \end{pmatrix}$$

must have full column rank to be able to take a generalized inverse (i.e. rank condition!)

We can replace (2) onto the rank condition.

$$\begin{pmatrix} E Z_i Z_i' \pi_1' + E Z_i X_{2i}' \pi_2' & E Z_i X_{2i}' \\ E X_{2i} Z_i' \pi_1' + E X_{2i} X_{2i}' \pi_2' & E X_{2i} X_{2i}' \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} E Z_i Z_i' \pi_1' a + E Z_i X_{2i}' (\pi_2' a + b) \\ E X_{2i} Z_i' \pi_1' a + E X_{2i} X_{2i}' (\pi_2' a + b) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} E Z_i Z_i' & E Z_i X_{2i}' \\ E X_{2i} Z_i' & E X_{2i} X_{2i}' \end{pmatrix} \begin{pmatrix} \pi_1' a \\ \pi_2' a + b \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

If exogenous variables  
are linearly independent  
this matrix of 2nd  
moments is p.d.

This must be 0.

Then

$$\pi_1' a = 0$$

$$\pi_2' a + b = 0$$

CASE 1:  $a = 0, b \neq 0$

Can't happen due to eq 2.

CASE 2:  $a \neq 0, b = 0$

Both  $\pi_1'$   $\pi_2'$  are rank  
deficient

CASE 3:  $a \neq 0, b \neq 0$

$\pi_1'$  is rank deficient.

The rank condition means that  $\pi_1'$  cannot be rank deficient.

## B) Estimation Approach

### B.1) Fitted Values Approach :

$$y = X_1 \delta + X_2 \beta + u$$

$\begin{matrix} n \times 1 & n \times k_1 & k_1 \times 1 & n \times k_2 & k_2 \times 1 & n \times 1 \end{matrix}$

$$X_1 = Z \pi_1' + X_2 \pi_2' + V$$

$\begin{matrix} n \times k_1 & n \times c & c \times k_1 & n \times k_2 & k_2 \times k_1 & n \times k_1 \end{matrix}$

↙ We can vectorize and estimate (see old tutorial)  
but let's assume  $k_1 = 1$ .

$$X_1 = Z \pi_1 + X_2 \pi_2 + V$$

$n \times 1$        $n \times k_1$   $k_1 \times 1$        $n \times k_2$   $k_2 \times 1$        $n \times 1$

We define  $\tilde{Z}_i = \begin{pmatrix} z_i \\ x_{2i} \end{pmatrix}$  and project  $x_{1i}$  onto the subspace of cols  $\tilde{Z}_i$ .

$(k_1+k_2) \times 1$

$$\hat{X}_1 = Z (\tilde{Z}' \tilde{Z})^{-1} \tilde{Z}' X_1, \quad \hat{V} = X_1 - P_{\tilde{Z}} X_1$$

$$= P_{\tilde{Z}} X_1, \quad = M_{\tilde{Z}} X_1.$$

Next we plug this into the first equation and estimate

$$\hat{\beta} = (X_1' M_{X_2} X_1)^{-1} X_1' M_{X_2} y$$

$$= (X_1' P_{\tilde{Z}} M_{X_2} P_{\tilde{Z}} X_1)^{-1} X_1' P_{\tilde{Z}} M_{X_2} y$$

$$= \underbrace{\int X_1' P_{\tilde{Z}} M_{X_2} X_1}_{\text{hopefully } = O_p(n)} + \underbrace{\frac{X_1' P_{\tilde{Z}} M_{X_2} U}{X_1' P_{\tilde{Z}} M_{X_2} P_{\tilde{Z}} X_1}}_{\text{hopefully } = o_p(1)}$$

Take  $\frac{X_1' P_{\tilde{Z}} M_{X_2} U}{n} = \frac{X_1' P_{\tilde{Z}} U}{n} - \frac{X_1' P_{\tilde{Z}} P_{X_2} U}{n}$

$$\bullet \frac{X_1' (Z \ X_2)}{n} \begin{pmatrix} Z' Z & Z' X_2 \\ X_2' Z & X_2' X_2 \end{pmatrix}^{-1} \begin{pmatrix} Z' \\ X_2' \end{pmatrix} \frac{U}{n}$$

$$\bullet \frac{X_1' Z}{n} = E x_{1i} z_i' + o_p(1) = O(1)$$

$$\bullet \begin{pmatrix} E z_i z_i' & E z_i x_{2i}' \\ E x_{2i} z_i & E x_{2i} x_{2i}' \end{pmatrix}^{-1} \begin{pmatrix} Z' U \\ X_2' U \end{pmatrix} \frac{1}{n} = E z_i u_i + o_p(1) = o_p(1)$$

$$\bullet \frac{X_1' X_2}{n} = E x_{1i} x_{2i}' + o_p(1) = O(1)$$

if no collinearity  
this is bounded

$$\bullet \frac{X_2' U}{n} = E x_{2i} u_i + o_p(1) = o_p(1)$$

if  $z_i, x_{2i}$  have finite 2nd moments.

- Notice that  $P_{x_2} u$  involves  $\frac{x_2' u}{n} = E x_{2i} u_i + o_p(1)$   
 $= o_p(1)$ .

We only need to check the other matrix(es) so that they don't explode.

## B.2) Control Function Approach:

We once again regress  $x_{1i}$  onto  $\tilde{z}_i$  and keep the residue

$$\begin{aligned}\hat{V} &= M_{\tilde{z}} x_1 \\ &= (I - P_{\tilde{z}}) x_1\end{aligned}$$

The second stage controls for this new regressor as well. Notice that

$$\begin{aligned}M_{\hat{V}} &= I - \hat{V} (\hat{V}' \hat{V})^{-1} \hat{V}' \\ &= I - (I - P_{\tilde{z}}) x_1 (x_1' (I - P_{\tilde{z}}) x_1)^{-1} x_1' (I - P_{\tilde{z}})\end{aligned}$$

Now

$$f = (x_1' M_{x_2} M_{\hat{V}} M_{x_2} x_1)^{-1} x_1' M_{x_2} M_{\hat{V}} M_{x_2} y$$

and once again we can define everything in terms of  $P_{x_2}$ ,  $P_{\tilde{z}}$  to analyze. See midterm 2019, which was also covered in a previous tutorial. In that exam the focus is on  $\lambda$ , but we could also focus on  $f$ .

### c) Efficiency

Not using all instruments is always (weakly) inefficient.

$$\tilde{\beta}_n \text{ using } \tilde{W}_n = \begin{pmatrix} \hat{\Omega}_{11}^{-1} & 0 \\ 0 & 0 \end{pmatrix}$$

$$\hat{\beta}_n \text{ using } W_n^* = \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{pmatrix}^{-1}$$

$$\text{Avar}(\tilde{\beta}_n) = (Q' W Q)^{-1} Q' W \Omega W Q (Q' W Q)^{-1}$$

$$\text{Avar}(\hat{\beta}_n) = (Q' \Omega^{-1} Q)^{-1}$$

$$\text{Avar}(\tilde{\beta}_n) - \text{Avar}(\hat{\beta}_n) \text{ is p.s.d.}$$

iff

(from assignment)

$$\text{Avar}(\hat{\beta}_n)^{-1} - \text{Avar}(\tilde{\beta}_n)^{-1} \text{ is p.s.d.}$$

$$\begin{aligned} & Q' \Omega^{-1} Q - Q' W Q (Q' W \Omega W Q)^{-1} Q' W Q \\ &= Q' \Omega^{-1/2} \left( I - \Omega^{1/2} Q' W Q (Q' W \Omega^{1/2} \Omega^{1/2} W Q)^{-1} Q' W Q \Omega^{1/2} \right) \Omega^{-1/2} Q \\ &= \underbrace{X' Q' \Omega^{-1/2} \left( I - H (H' H)^{-1} H' \right) \Omega^{1/2} Q X}_{\text{idempotent and symmetric}} \geq 0 \end{aligned}$$

$$X' X \geq 0$$

## d) Efficient Instruments

What if we have MEAN INDEP instead of uncorrelatedness?

$$E[u_i | z_i] = 0 \quad \text{instead of} \quad E[u_i z_i] = 0$$



$$E[u_i g(z_i)] = 0 \quad \text{for every measurable } g(\cdot).$$

$$\Downarrow \\ g^{-1}(B) \in \mathcal{A} \\ \text{for every } B \in \mathcal{B}(\mathbb{R}).$$

We can do GMM using  $g(z_i)$  instead of  $z_i$ !

$$\text{The efficient } g^*(z) = \frac{E(x_i | z_i)}{E(u_i^2 | z_i)} \rightarrow \begin{array}{l} \text{project endogenous!} \\ \text{project ignored} \\ \text{errors!} \end{array}$$

You can use the same trick as part c) to show this is more efficient by using Law of Iterated Expectations.

e) Asymptotics

$$\hat{\beta}_n(W_n) = \beta_0 + \left( \frac{X'Z}{n} W_n \frac{Z'X}{n} \right)^{-1} \frac{X'Z}{n} W_n \frac{Z'U}{n}$$

$$\Rightarrow \sqrt{n} (\hat{\beta}_n - \beta_0) = \left( \frac{X'Z}{n} W \frac{Z'X}{n} \right)^{-1} \frac{X'Z}{n} W \downarrow \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i$$

$$= \left( \sum_{x,z} W \sum_{z,x} \right)^{-1} \sum_{x,z} W \downarrow \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i$$

$$+ \underbrace{\text{op}(1)}_{\text{op}(1)} \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i$$

if  $\text{Var}(Z_i u_i) = O(1)$   
by CLT

$$= \frac{1}{\sqrt{n}} \sum_{i=1}^n \xi_i + \text{op}(1)$$

ECON 626: This is called asymptotic linear representation of an estimator, and  $\xi_i$  is called an influence function.

where  $\xi_i = \left( \sum_{x,z} W \sum_{z,x} \right)^{-1} \sum_{x,z} W Z_i u_i$

Notice that by CLT

$$\sqrt{n} (\hat{\beta}_n - \beta_0) \xrightarrow{d} \mathcal{N}(0, E \xi_i \xi_i')$$

## f) Inference

Even though we don't know the distribution of  $\hat{\beta}$  because we don't know the joint distribution of the data, we can approximate the distribution of  $\sqrt{n}(\hat{\beta}_n - \beta)$ !

• Consider testing  $\beta = \beta_0$ :

$$W_n = \sqrt{n}(\hat{\beta}_n - \beta)' \widehat{\text{Avar}}(\hat{\beta}_n)^{-1} \sqrt{n}(\hat{\beta}_n - \beta)$$

↑  
Wald  
statistic!

assuming we  
used efficient  
weights.

$$= \left\{ (\alpha' \Omega^{-1} \alpha)^{1/2} \sqrt{n}(\hat{\beta}_n - \beta) \right\}' \left\{ (\alpha' \Omega^{-1} \alpha)^{1/2} \sqrt{n}(\hat{\beta}_n - \beta) \right\}$$

if we plug  $\beta = \beta_0$  this is  $\xrightarrow{d} N(0, \Omega)$

$$\xrightarrow{d} \chi^2_{\alpha}$$

Now consider the alternative hypothesis  $H_1: \beta = \beta_0 + \delta$

$$W_n \underset{H_1}{=} \left\{ (\alpha' \Omega^{-1} \alpha)^{1/2} \sqrt{n} \delta \right\}' \left\{ (\alpha' \Omega^{-1} \alpha)^{1/2} \sqrt{n} \delta \right\} + o_p(1)$$

explodes to infinity!

it's not useful to mimic  
finite sample behavior.



then  $H_1: \beta = \beta_0 + \delta/\sqrt{n}$

$$W_n = \left\{ (Q' \Omega^{-1} Q)^{1/2} (\sqrt{n} (\beta_n^* - \beta_0) + \delta) \right\}' \left\{ (Q' \Omega^{-1} Q)^{1/2} (\sqrt{n} (\beta_n^* - \beta_0) + \delta) \right\}$$

$$\xrightarrow{\delta} \chi^2_k \left( \left( (Q' \Omega^{-1} Q)^{1/2} \delta \right)' \left( (Q' \Omega^{-1} Q)^{1/2} \delta \right) \right)$$

$$= \chi^2_k \left( \delta' \underbrace{(Q' \Omega^{-1} Q)}_{\text{is p.d. because}} \delta \right)$$

is p.d. because  $\text{AVAR}(\hat{\beta})^{-1} = O(1)$ .

So power increases as  $\delta$  increases.

- Now consider testing  $H_0: E[u_i] = 0$ . We'll use the criterion function itself!

$$\begin{aligned} \text{let } \bar{g}_n(b) &= \frac{1}{n} \sum_{i=1}^n z_i (y_i - x_i' b) \\ &= \frac{1}{n} z' (y - Xb) \end{aligned}$$

$$J_n(b) = \sqrt{n} \bar{g}_n(b)' \hat{\Omega}_n^{-1} \sqrt{n} \bar{g}_n(b).$$

Notice that

$$\begin{aligned} C' \sqrt{n} \bar{g}_n(\hat{\beta}_n) &= \Omega^{-1/2} \sqrt{n} \bar{g}_n(\hat{\beta}_n) \\ &= \Omega^{-1/2} \frac{1}{\sqrt{n}} \sum_{i=1}^n z_i (y_i - x_i' \hat{\beta}_n \pm x_i' \beta_0) \end{aligned}$$

$$= \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} - \Omega^{-1/2} Z'X \hat{\alpha}_n(\hat{\beta}_n - \beta_0)$$

$$= \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} - \Omega^{-1/2} Z'X (X'Z \hat{\Sigma}_n^{-1} Z'X)^{-1} X'Z \hat{\Sigma}_n^{-1} \frac{Z'U}{\sqrt{n}}$$

$$= \underbrace{\left\{ I_e - \Omega^{-1/2} Z'X (X'Z \hat{\Sigma}_n^{-1} Z'X)^{-1} X'Z \hat{\Sigma}_n^{-1} \Omega^{1/2} \right\}}_{D_n} \Omega^{-1/2} \frac{Z'U}{\sqrt{n}}$$

where

$$D_n = I_e - \Omega^{-1/2} \frac{Z'X}{n} \left( \frac{X'Z}{n} \hat{\Sigma}_n^{-1} \frac{Z'X}{n} \right)^{-1} \frac{X'Z}{n} \hat{\Sigma}_n^{-1} \Omega^{1/2}$$

$$= I_e - \Omega^{-1/2} E Z_i X_i' (E X_i X_i' \hat{\Sigma}_n^{-1} E Z_i X_i')^{-1} E X_i X_i' \hat{\Sigma}_n^{-1} \Omega^{1/2} + o_p(1)$$

$$= I_e - \Omega^{-1/2} E Z_i X_i' [ (E X_i X_i' \Omega^{-1} E Z_i X_i')^{-1} + o_p(1) ] E X_i X_i' [ \Omega^{1/2} + o_p(1) ] \Omega^{1/2} + o_p(1)$$

$$= I_e - \Omega^{-1/2} E Z_i X_i' (E X_i X_i' \Omega^{-1} E Z_i X_i')^{-1} E X_i X_i' \Omega^{1/2} + o_p(1)$$

provided  
 $\Omega^{-1}$ ,  $E Z_i X_i'$   
 are bounded

(i.e.  $\text{Var}(U_i | X_i)$  is pos def,  $E \|Z_i X_i'\|^2 \leq (E \|Z_i\|^2 E \|X_i\|^2)^{1/2}$  finite second moments)

$$= I_e - \underbrace{\Omega^{-1/2} E Z_i X_i'}_R \underbrace{(E X_i X_i' \Omega^{-1} E Z_i X_i')^{-1}}_{R'} \underbrace{\Omega^{-1/2} E Z_i X_i'}_R \underbrace{E X_i X_i' \Omega^{1/2}}_{R'} + o_p(1)$$

$$= \underbrace{I_e - R(R'R)^{-1}R'}_{\text{A projection matrix!}} + o_p(1)$$

A projection matrix!

Properties:

- Eigenvalues are either 0 or 1
- Has orthonormal eigen decomp.

$$= D + o_p(1)$$

therefore

$$J_n(\hat{\beta}_n) = \left[ \Omega^{-1/2} \sqrt{n} \hat{g}_n(\hat{\beta}_n) \right]' \Omega^{1/2} \hat{\Sigma}_n^{-1} \Omega^{1/2} \left[ \Omega^{-1/2} \sqrt{n} \hat{g}_n(\hat{\beta}_n) \right]$$

$$= \left[ D_n \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} \right]' \left[ I_l + o_p(1) \right] \left[ D_n \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} \right]$$

$$= \left[ D \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} + o_p(1) O_p(1) \right]' \left[ I_l + o_p(1) \right] \left[ D \Omega^{-1/2} \frac{Z'U}{\sqrt{n}} + o_p(1) O_p(1) \right]$$

$$= \left[ N' D' + o_p(1) \right] \left[ I_l + o_p(1) \right] \left[ D N + o_p(1) \right]$$

$$= N' D N + o_p(1) \quad \text{because } DN = O_p(1)$$

$$= N' C \Lambda C' N = \underbrace{\tilde{N}'}_{N(0, I)} \Lambda \underbrace{\tilde{N}}_{N(0, I)} = \sum_{i=1}^{\text{tr}(\Lambda)} \tilde{n}_i' \tilde{n}_i$$

$$\xrightarrow{d} \chi^2_{\text{rank}(D)} = \chi^2_{\text{tr}(D)} = \chi^2_{l-k}$$

For alternative hypothesis is the same idea with non-centered standard normals.

$$J_n(\hat{\beta}_n) \xrightarrow{d, H_1} \chi^2_{l-k} \left( \delta' \Omega^{-1/2} D \Omega^{-1/2} \delta \right)$$

(\*) Notice up top where this noncentrality appears

### 3) Multiple Equations (Extra :)

Suppose  $M$  equations are identified:

$$y_{1i} = X_{1i}' d_1 + u_{1i}$$

$$y_{mi} = X_{mi}' d_m + u_{mi}$$

where

$$E \sum_i u_{ji} = 0$$

$$\text{rank} (E \sum_i X_{ji}' u_{ji}) = k_j$$

In matrix form can be written as

$$y_1 = X_1 d_1 + u_1$$

$$y_m = X_m d_m + u_m$$

where  $X_j = \begin{pmatrix} X_{j1}' \\ \vdots \\ X_{jn}' \end{pmatrix}$ .

$$\Rightarrow y = \begin{pmatrix} X_1 & & 0 \\ & \ddots & \\ 0 & & X_M \end{pmatrix} \begin{pmatrix} d_1 \\ \vdots \\ d_M \end{pmatrix} + u$$

where  $k = k_1 + \dots + k_M$

$$y = X d + u$$

The population moment conditions are

$$E \begin{pmatrix} \sum_i z_i u_{1i} \\ \vdots \\ \sum_i z_i u_{mi} \end{pmatrix} = E (u_i \otimes z_i) = 0$$

The sample moment conditions are

$$\begin{pmatrix} Z_1' u_1 \\ \vdots \\ Z_m' u_m \end{pmatrix} = \begin{pmatrix} Z_1' & & 0 \\ & \ddots & \\ 0 & & Z_m' \end{pmatrix} \begin{pmatrix} u_1 \\ \vdots \\ u_m \end{pmatrix}$$

$$= (I_m \otimes Z') \begin{pmatrix} u_1 \\ \vdots \\ u_m \end{pmatrix}$$

$$= \underbrace{(I_m \otimes Z')}_{m \times mn} u_{mn \times 1}$$

$$= (I_m \otimes Z') (y - Xd)$$

$$= (I_m \otimes Z') (y - Xd)$$

$$= 0_{m \times 1}$$

We can solve the system as with a regular GMM estimator

$$\hat{\beta}_n = \underset{\beta \in \mathbb{R}^k}{\operatorname{argmin}} \quad \| (I_m \otimes Z') (Y - X\beta) \|_{W_n}$$

$$= \underset{\beta \in \mathbb{R}^k}{\operatorname{argmin}} \quad [(I_m \otimes Z') (Y - X\beta)]' W_n [(I_m \otimes Z') (Y - X\beta)]$$

Where we can expand the criterion function.

$$= \begin{pmatrix} Z' (Y_1 - X_1 \beta) \\ \vdots \\ Z' (Y_m - X_m \beta) \end{pmatrix}' \begin{pmatrix} W_{11} & \dots & W_{1m} \\ \vdots & \ddots & \vdots \\ W_{m1} & \dots & W_{mm} \end{pmatrix} \begin{pmatrix} Z' (Y_1 - X_1 \beta) \\ \vdots \\ Z' (Y_m - X_m \beta) \end{pmatrix}$$

$$= \begin{pmatrix} (Y_1 - X_1 \beta)' Z & \dots & (Y_m - X_m \beta)' Z \end{pmatrix} \begin{pmatrix} W_{11} & \dots & W_{1m} \\ \vdots & \ddots & \vdots \\ W_{m1} & \dots & W_{mm} \end{pmatrix} \begin{pmatrix} Z' (Y_1 - X_1 \beta) \\ \vdots \\ Z' (Y_m - X_m \beta) \end{pmatrix}$$

consider this

$$= \begin{pmatrix} U_1' Z W_{11} + \dots + U_m' Z W_{m1} & \dots & U_1' Z W_{1m} + \dots + U_m' Z W_{mm} \end{pmatrix} \begin{pmatrix} Z' (Y_1 - X_1 \beta) \\ \vdots \\ Z' (Y_m - X_m \beta) \end{pmatrix}$$

$$= U_1' Z W_{11} Z' U_1 + \dots + U_m' Z W_{m1} Z' U_1 + \dots + U_1' Z W_{1m} Z' U_m + \dots + U_m' Z W_{mm} Z' U_m$$

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

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

$$\bullet \frac{(I_m \otimes Z)' X}{n} = \frac{1}{n} \begin{pmatrix} Z' \cdot & 0 \\ 0 & Z' \cdot \\ & \dots \\ & 0 \end{pmatrix} \begin{pmatrix} x_1 & \dots & 0 \\ 0 & \dots & x_m \end{pmatrix} = \begin{pmatrix} \frac{Z' x_1}{n} & \dots & 0 \\ 0 & \dots & \frac{Z' x_m}{n} \end{pmatrix}$$

$$\xrightarrow{P} \begin{pmatrix} \theta_1 & \dots & 0 \\ 0 & \dots & \theta_m \end{pmatrix} =: C$$

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

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

$$\bullet \frac{(I_m \otimes Z)' U}{\sqrt{n}} = \frac{1}{\sqrt{n}} \sum_{i=1}^n \underbrace{(u_i \otimes z_i)}_{\xi_i} \xrightarrow{d} N(0, E \xi_i \xi_i')$$

$$= N(0, E[u_i u_i' \otimes z_i z_i'])$$

$$\bullet E[u_i u_i' \otimes z_i z_i'] = E \left[ \begin{pmatrix} u_{i1} u_{i1} & \dots & u_{i1} u_{im} \\ \vdots & \ddots & \vdots \\ u_{im} u_{i1} & \dots & u_{im} u_{im} \end{pmatrix} \otimes z_i z_i' \right]$$

$$= E \left[ \begin{pmatrix} u_{i1}^2 z_i z_i' & \dots & u_{i1} u_{im} z_i z_i' \\ \vdots & \ddots & \vdots \\ u_{im} u_{i1} z_i z_i' & \dots & u_{im}^2 z_i z_i' \end{pmatrix} \right]$$

provided

$$E \| u_{ji} u_{ri} z_i z_i' \| \leq [E \| u_{ji} u_{ri} \|^2 E \| z_i z_i' \|^2]^{1/2}$$

$$\leq [ (E |u_{ji}|^4 E |u_{ri}|^4)^{1/2} E \| z_i \|^4 ]^{1/2}$$

so it suffices to assume fourth moments.

When  $E(U_i U_i' \otimes Z_i Z_i')$  is block diagonal i.e.  $E U_j U_i' Z_i Z_i' = 0$  l x e.  
 then the efficient weighting matrix  $W_n$  is

$$\begin{aligned} \mathcal{Q}^{-1} &= \begin{bmatrix} E U_1^2 Z_1 Z_1' & & 0 \\ & \ddots & \\ 0 & & E U_m^2 Z_m Z_m' \end{bmatrix}^{-1} \\ &= \begin{bmatrix} (E U_1 Z_1 Z_1')^{-1} & & 0 \\ & \ddots & \\ 0 & & (E U_m Z_m Z_m')^{-1} \end{bmatrix} \\ &= \begin{bmatrix} \mathcal{Q}_{11}^{-1} & & 0 \\ & \ddots & \\ 0 & & \mathcal{Q}_{mm}^{-1} \end{bmatrix} \end{aligned}$$

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