

1. Reduced form equations:

(a)  $y_i = \mathbf{z}'_i \mathbf{\Pi} \boldsymbol{\beta} + v_i$

(b)  $v_i = \mathbf{u}'_i \boldsymbol{\beta} + e_i$

(c) Let  $\mathbf{w}_i = \mathbf{\Pi}' \mathbf{z}_i$  so that  $y_i = \mathbf{w}'_i \boldsymbol{\beta} + v_i$ . Since  $E(\mathbf{w}_i v_i) = 0$  a simple answer is

$$\begin{aligned} \boldsymbol{\beta} &= (E \mathbf{w}_i \mathbf{w}'_i)^{-1} (E(\mathbf{w}_i y_i)) \\ &= (\mathbf{\Pi}' E(\mathbf{z}_i \mathbf{z}'_i) \mathbf{\Pi})^{-1} (\mathbf{\Pi}' E(\mathbf{z}_i y_i)) \end{aligned}$$

More generally, since  $E(\mathbf{z}_i v_i) = 0$  the equation is overidentified. So for any weight matrix  $\mathbf{W}$  we can also write the coefficient as

$$\begin{aligned} \boldsymbol{\beta} &= (E(\mathbf{w}_i \mathbf{z}'_i) \mathbf{W} E(\mathbf{z}_i \mathbf{w}'_i))^{-1} (E(\mathbf{w}_i \mathbf{z}'_i) \mathbf{W} E(\mathbf{z}_i y_i)) \\ &= (\mathbf{\Pi}' E(\mathbf{z}_i \mathbf{z}'_i) \mathbf{W} E(\mathbf{z}_i \mathbf{z}'_i) \mathbf{\Pi})^{-1} (\mathbf{\Pi}' E(\mathbf{z}_i \mathbf{z}'_i) \mathbf{W} E(\mathbf{z}_i y_i)) \end{aligned}$$

(d)  $\mathbf{\Pi} = E(\mathbf{z}_i \mathbf{z}'_i)^{-1} E(\mathbf{z}_i \mathbf{x}'_i)$

(e) The identification condition is  $\text{rank}(\mathbf{\Pi}) = k$

2. Estimation of  $\mathbf{Q}$

(a)  $\tilde{\mathbf{Q}} = \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i$

(b)  $\hat{\mathbf{Q}} = \frac{1}{J} \sum_{j=1}^J \mathbf{z}_j \mathbf{z}'_j$

(c) As  $n \rightarrow \infty$ ,  $\tilde{\mathbf{Q}} \rightarrow_p E(\mathbf{z}_i \mathbf{z}'_i) = \mathbf{Q}$

As  $J \rightarrow \infty$ ,  $\hat{\mathbf{Q}} \rightarrow_p E(\mathbf{z}_j \mathbf{z}'_j) = \mathbf{Q}$

(d) Yes, these two limits are the same, because the distributions in the two samples are identical.

(e)  $\tilde{\mathbf{Q}}$  is more efficient if  $n > J$ .

$\hat{\mathbf{Q}}$  is more efficient if  $n < J$ .

They are equally efficient if  $n = J$

3. Estimation of  $\boldsymbol{\beta}$  given  $\mathbf{\Pi}$

(a) A simple estimator is

$$\tilde{\boldsymbol{\beta}}_1 = \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i \right) \mathbf{\Pi} \right)^{-1} \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i y_i \right) \right) \tag{1}$$

A GMM estimator is

$$\tilde{\boldsymbol{\beta}} = \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i \right) \mathbf{W} \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i \right) \mathbf{\Pi} \right)^{-1} \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i \right) \mathbf{W} \left( \sum_{i=1}^n \mathbf{z}_i y_i \right) \right)$$

The efficient GMM estimator sets  $\mathbf{W} = \hat{\boldsymbol{\Omega}}^{-1}$  where  $\hat{\boldsymbol{\Omega}}$  is an estimate of  $\boldsymbol{\Omega} = E(\mathbf{z}_i \mathbf{z}'_i v_i^2)$ . Notice that the error is  $v_i$  from the reduced form, not  $e_i$  from the structural form. This is because we are estimating  $y_i = \mathbf{z}'_i \mathbf{\Pi} \boldsymbol{\beta} + v_i$  not  $y_i = \mathbf{x}'_i \boldsymbol{\beta} + e_i$ . Using the preliminary estimate (1) we construct  $\hat{v}_i = y_i - \mathbf{z}'_i \mathbf{\Pi} \tilde{\boldsymbol{\beta}}$  and

$$\hat{\boldsymbol{\Omega}} = \frac{1}{n-k} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}'_i \hat{v}_i^2$$

Then the efficient estimator is

$$\tilde{\beta}_2 = \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \mathbf{\Pi} \right)^{-1} \left( \mathbf{\Pi}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \sum_{i=1}^n \mathbf{z}_i y_i \right) \right)$$

(b) Sample 1

(c) As  $n \rightarrow \infty$ ,

$$\tilde{\beta}_1 = \left( \mathbf{\Pi}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \mathbf{\Pi} \right)^{-1} \left( \mathbf{\Pi}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i y_i \right) \right) \xrightarrow{p} (\mathbf{\Pi}' \mathbf{Q} \mathbf{\Pi})^{-1} \mathbf{\Pi}' E(\mathbf{z}_i y_i) = \beta$$

as defined in 1(c). The asymptotic approximation is as  $n$  goes to infinity. Also,

$$\begin{aligned} \tilde{\beta}_2 &= \left( \mathbf{\Pi}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \mathbf{\Pi} \right)^{-1} \left( \mathbf{\Pi}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i y_i \right) \right) \\ &\xrightarrow{p} (\mathbf{\Pi}' \mathbf{Q} \mathbf{\Omega}^{-1} \mathbf{Q} \mathbf{\Pi})^{-1} \mathbf{\Pi}' \mathbf{Q} \mathbf{\Omega}^{-1} E(\mathbf{z}_i y_i) = \beta \end{aligned}$$

#### 4. Estimation of $\mathbf{\Pi}$

(a)  $\hat{\mathbf{\Pi}} = \left( \sum_{j=1}^J \mathbf{z}_j \mathbf{z}_j' \right)^{-1} \left( \sum_{j=1}^J \mathbf{z}_j \mathbf{x}_j' \right)$

(b) Sample 2

(c) As  $J \rightarrow \infty$ ,

$$\hat{\mathbf{\Pi}} = \left( \frac{1}{J} \sum_{j=1}^J \mathbf{z}_j \mathbf{z}_j' \right)^{-1} \left( \frac{1}{J} \sum_{j=1}^J \mathbf{z}_j \mathbf{x}_j' \right) \xrightarrow{p} E(\mathbf{z}_j \mathbf{z}_j')^{-1} E(\mathbf{z}_j \mathbf{x}_j') = \mathbf{\Pi}$$

as defined in 1(d). The asymptotics is as  $J$  goes to infinity.

#### 5. Estimation of $\beta$ . when $\mathbf{\Pi}$ unknown

(a)  $\hat{\beta}_1 = \left( \hat{\mathbf{\Pi}}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Pi}} \right)^{-1} \left( \hat{\mathbf{\Pi}}' \left( \sum_{i=1}^n \mathbf{z}_i y_i \right) \right)$  or

$$\tilde{\beta}_2 = \left( \hat{\mathbf{\Pi}}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Pi}} \right)^{-1} \left( \hat{\mathbf{\Pi}}' \left( \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \sum_{i=1}^n \mathbf{z}_i y_i \right) \right)$$

This is just the answer in 3(a), replacing the known  $\mathbf{\Pi}$  with the estimate  $\hat{\mathbf{\Pi}}$

(b) As  $\min(n, J) \rightarrow \infty$

$$\hat{\beta}_1 = \left( \hat{\mathbf{\Pi}}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Pi}} \right)^{-1} \left( \hat{\mathbf{\Pi}}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i y_i \right) \right) \xrightarrow{p} (\mathbf{\Pi}' \mathbf{Q} \mathbf{\Pi})^{-1} \mathbf{\Pi}' E(\mathbf{z}_i y_i) = \beta$$

$$\begin{aligned} \tilde{\beta}_2 &= \left( \hat{\mathbf{\Pi}}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Pi}} \right)^{-1} \left( \hat{\mathbf{\Pi}}' \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i \mathbf{z}_i' \right) \hat{\mathbf{\Omega}}^{-1} \left( \frac{1}{n} \sum_{i=1}^n \mathbf{z}_i y_i \right) \right) \\ &\xrightarrow{p} (\mathbf{\Pi}' \mathbf{Q} \mathbf{\Omega}^{-1} \mathbf{Q} \mathbf{\Pi})^{-1} \mathbf{\Pi}' \mathbf{Q} \mathbf{\Omega}^{-1} E(\mathbf{z}_i y_i) = \beta \end{aligned}$$