

Generalized Method of Moments

Suppose we have l moment conditions

$$E g(w_i, \theta_0) = 0, \text{ where } w_i := (y_i, x_i', z_i')^T$$

$l \times 1$ $l \times l$

is the data.

Recall the criterion function

$$\mathcal{Q}(\theta) = [E g(w_i, \theta)]' A' A [E g(w_i, \theta)]$$

$\underbrace{\quad}_{\text{pos def}}$
and symmetric

the true parameter θ_0 minimizes $\mathcal{Q}(\theta)$ for any choice of norm $A'A$. However, if $E g(w_i, \theta_0) \neq 0$, then different choices of $A'A$ yield a different minimizer. We refer to such value as the pseudo-tree value.

GMM focuses on the sample version of the criterion function

$$\hat{\theta}_{GMM}(A_n) := \underset{\theta}{\operatorname{argmin}} \left[\frac{1}{n} \sum_{i=1}^n g(w_i, \theta)' \right] A_n' A_n \left[\frac{1}{n} \sum_{i=1}^n g(w_i, \theta) \right]$$

$\underbrace{\qquad\qquad\qquad}_{\mathcal{Q}_n(\theta)}$

In the linear IV model we assume

$$y_i = x_i' \beta + u_i$$

$n \times 1$

$$E \sum_{i=1}^l u_i = 0, \quad l > n.$$

Identification

Assume $E X_i X_i'$ has full column rank K . To see the implications, let

$$X_{i\cdot} = \begin{pmatrix} X_{1i}' & X_{2i}' \end{pmatrix}, \text{ and let } Z_{i\cdot} = \begin{pmatrix} Z_{1i}' & X_{2i}' \end{pmatrix}.$$

$\underbrace{X_{1i}'}_{K \times K_1}$ $\underbrace{X_{2i}'}_{K \times K_2}$
 included endogenous included exogenous

$\underbrace{Z_{1i}'}_{K \times L_1}$ $\underbrace{X_{2i}'}_{L_1 \times K_2}$
 excluded exogenous included exogenous

Let $X_{1i} = \Pi_1 Z_{1i} + \Pi_2 X_{2i}$, which is a linear projection of the element of X_{1i} onto (Z_{1i}', X_{2i}') . Then

$$\begin{aligned} E Z_{i\cdot} X_{i\cdot}' &= E \begin{pmatrix} Z_{1i} \\ X_{2i} \end{pmatrix} (X_{1i}' X_{2i}') \\ &= \begin{pmatrix} E Z_{1i} Z_{1i}' \Pi_1' + E Z_{1i} X_{2i}' \Pi_2' & E Z_{1i} X_{2i}' \\ E X_{2i} Z_{1i}' \Pi_1' + E X_{2i} X_{2i}' \Pi_2' & E X_{2i} X_{2i}' \end{pmatrix}. \end{aligned}$$

Suppose there's a $\theta \neq 0$ such that $E Z_{i\cdot} X_{i\cdot}' \theta = 0$. Then

$$E Z_{i\cdot} X_{i\cdot}' \theta = \begin{pmatrix} E Z_{1i} Z_{1i}' \Pi_1' \theta_1 + E Z_{1i} X_{2i}' \Pi_2' \theta_2 + E Z_{1i} X_{2i}' \theta_2 \\ E X_{2i} Z_{1i}' \Pi_1' \theta_1 + E X_{2i} X_{2i}' \Pi_2' \theta_1 + E X_{2i} X_{2i}' \theta_2 \end{pmatrix}$$

$$= \begin{pmatrix} E Z_{1i} Z_{1i}' & E Z_{1i} X_{2i}' \\ E X_{2i} Z_{1i}' & E X_{2i} X_{2i}' \end{pmatrix} \begin{pmatrix} \Pi_1' \theta_1 \\ \Pi_2' \theta_1 + \theta_2 \end{pmatrix} = 0$$

this second moment

matrix is p.d. iff

the exogenous variables

are all linearly indep

(this requires that Z_{1i} does not form part of X_{2i} , i.e. instruments are not in the outcome model).

Then this must

\Rightarrow be 0.

Then

$$\begin{aligned} \Pi_2' \theta_1 + \theta_2 &= 0 \\ \Pi_2' \theta_1 &= 0 \end{aligned}$$

Notice that if either θ_j is 0, the other must be zero as well, but this would contradict the fact that $\theta \neq 0$.

Hence, suppose $\exists \theta_1 \neq 0$ such that $\Pi_2' \theta_1 = 0$. This means that the matrix Π_2' is rank deficient.

Therefore, we showed that

$$\text{rank}(Ez_i x_i') = k \Leftrightarrow \text{rank}(\Pi_2) = k_2.$$

so that the rank condition is equivalent to another rank condition in terms of the first stage parameters (i.e sufficiently strong linear relationship between $z_{i,:}'$ and $x_{i,:}'$).

From the moment condition we obtain

$$Ez_i y_i = E z_i x_i' \beta$$

$$A E z_i y_i = A E z_i x_i' \underbrace{\beta}_{\text{lex}} \quad \underbrace{\beta}_{\text{lex}}$$

$$\text{rank} \leq \min(\text{rank}(A), \text{rank}(Ez_i x_i')) = k$$

$$\text{rank} \geq \text{rank}(A) + \text{rank}(Ez_i x_i') - l = k$$

therefore, the Gram matrix is invertible.

$$E x_i z_i' A' A E z_i y_i = E x_i z_i' A' A E z_i x_i' \beta$$

$$\Rightarrow \boxed{\beta(A) = (E x_i z_i' A' A E z_i x_i')^{-1} E x_i z_i' A' A E z_i y_i}$$

Consistency

Assume

- (i) $A_n \xrightarrow{P} A$, where A is a finite matrix.
- (ii) $E z_i z_i'$ has rank k
- (iii) $E |x_{ij}|^2 < \infty$, $j = 1, \dots, k$
 $E |z_{ij}|^2 < \infty$, $j = 1, \dots, k$

Then $\hat{\beta}_n(A_n) \xrightarrow{P} \hat{\beta}$, where $\hat{\beta}_n(A_n)$ is defined as follows.

$$\hat{\beta}_n(A_n) = \left(\frac{1}{n} \sum_{i=1}^n x_i z_i' A_n' A_n - \frac{1}{n} \sum_{i=1}^n z_i z_i' \right)^{-1} \frac{1}{n} \sum_{i=1}^n x_i z_i' A_n' A_n - \frac{1}{n} \sum_{i=1}^n x_i y_i$$

Notice that $E z_i z_i' = O(1)$ because

$$\begin{aligned} E \|x_i z_i'\| &\leq (E \|x_i\|^2 E \|z_i\|^2)^{1/2} \\ &= O(1) \text{ by (iii).} \end{aligned}$$

Notice that by (ii) we have that $E x_i z_i' A' A E x_i z_i'$ is p.d.

To see this

$$A E x_i z_i' v \stackrel{\text{exc}}{\ll} \stackrel{\text{exc}}{\ll} \stackrel{k \times k}{\ll} \neq 0 \text{ iff } v \neq 0 \text{ by rank cond.}$$

Hence $v' E x_i' z_i' A' A E x_i z_i' v > 0$.

The implication of this is that $(E x_i z_i' A' A E x_i z_i')^{-1} = O(1)$ because the matrix is bounded away from zero.

Write

$$\begin{aligned}\hat{\beta}_n(A_n) &= \beta + \left(\frac{1}{n} \sum_{i=1}^n z_i x_i' A_n' A_n - \frac{1}{n} \sum_{i=1}^n z_i x_i' \right)^{-1} \frac{1}{n} \sum_{i=1}^n z_i x_i' A_n' A_n - \frac{1}{n} \sum_{i=1}^n z_i u_i \\&= \beta + \left\{ [Ez_i z_i' + o_p(1)] [A'A + o_p(1)] [Ez_i x_i' + o_p(1)] \right\}^{-1} [Ez_i x_i' + o_p(1)] [A'A + o_p(1)] o_p(1) \\&= \beta + \left\{ Ez_i z_i' A'A Ez_i x_i' + o_p(1) O(1) \right\}^{-1} [Ez_i x_i' A'A o_p(1) + o_p(1) O(1)] \\&= \beta + \{ (Ez_i z_i' A'A Ez_i x_i')^{-1} + o_p(1) \} [Ez_i x_i' A'A o_p(1) + o_p(1)] \\&= \beta + \{ O(1) + o_p(1) \} [O(1) o_p(1) + o_p(1)] \\&= \beta + o_p(1).\end{aligned}$$

Asymptotic Normality

Assume, in addition, the following

$$(iv) \quad E Z_{ij}^4 < \infty \quad \text{for all } j=1, \dots, \ell.$$

$$E u_i^4 < \infty$$

$$(v) \quad E u_i^2 Z_i Z_i' \text{ is positive definite.}$$

Notice that (iv) implies that $E u_i^2 Z_i Z_i'$ is $O(t)$. To see this

$$\begin{aligned} E \|u_i^2 Z_i Z_i'\| &\leq (E \|u_i^2\|^2 E \|Z_i Z_i'\|^2)^{1/2} \\ &= (E u_i^4 E \|Z_i\|^4)^{1/2} \\ &= O(t). \end{aligned}$$

Therefore, by the CLT

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i \xrightarrow{d} N(0, \underbrace{E u_i^2 Z_i Z_i'}_{\Sigma})$$

Write

$$\begin{aligned} \sqrt{n} (\hat{\beta}_n(A_n) - \beta_0) &= \left(\frac{1}{n} \sum_{i=1}^n Z_i X_i' A_n' A_n - \frac{1}{n} \sum_{i=1}^n Z_i X_i' \right)^{-1} \frac{1}{n} \sum_{i=1}^n Z_i X_i' A_n' A_n \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i \\ &= [(\alpha' A' A \alpha)^{-1} \alpha' A' A + o_p(1)] \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i \\ &= (\alpha' A' A \alpha)^{-1} \alpha' A' A \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i + o_p(1) O_p(1) \\ &= (\alpha' A' A \alpha)^{-1} \alpha' A' A \frac{1}{\sqrt{n}} \sum_{i=1}^n Z_i u_i + o_p(1) \\ &\xrightarrow{d} N(0, (\alpha' A' A \alpha)^{-1} \alpha' A' A \sqrt{n} A' A \alpha (\alpha' A' A \alpha)^{-1}). \end{aligned}$$

Efficient GMM

The lower bound on the asymptotic variance is given by

$$(\alpha' \Sigma^{-1} \alpha)^{-1}.$$

To see why this is true we need to show that

$$\begin{aligned} \text{Asy Var}(A) - (\alpha' \Sigma^{-1} \alpha)^{-1} & \text{ is p.s.d.} \\ \Leftrightarrow \alpha' \Sigma^{-1} \alpha - (\text{Asy Var}(A))^{-1} & \text{ is p.s.d.} \end{aligned}$$

Write

$$\begin{aligned} \alpha' \Sigma^{-1} \alpha &= \alpha' A' A \alpha \left(\alpha' A' A \Sigma A' A \alpha \right)^{-1} \alpha' A' A \alpha \\ &= \alpha' \Sigma^{1/2} \left[I - \underbrace{\Sigma^{1/2} A' A \alpha \left(\alpha' A' A \Sigma A' A \alpha \right)^{-1} \alpha' A' A \Sigma^{1/2}}_H \right] \Sigma^{1/2} \alpha \\ &= \alpha' \Sigma^{1/2} \left[I - H (H' H)^{-1} H' \right] \Sigma^{1/2} \alpha. \end{aligned}$$

projection matrix = positive semi definite

The efficient choice of $A = \Sigma^{1/2}$.

Suppose we use a matrix $B_{n \times K}$ that has rank K to linearly transform x_i into a vector of K instruments $W_i := \underbrace{B}_{K \times 1} \underbrace{x_i}_{K \times 1}$. We then run IV with W_i .

$$\tilde{\beta}_n(B) = \left(\sum_{i=1}^n w_i x_i' \right)^{-1} \sum_{i=1}^n w_i y_i = (w' x)^{-1} w' y$$

$$\textcircled{*} \quad W = \begin{pmatrix} w_1' \\ \vdots \\ w_n' \end{pmatrix} = \begin{pmatrix} z_1' \\ \vdots \\ z_n' \end{pmatrix} B' = Z B'$$

$$\tilde{\beta}_n(B) - \beta = \frac{(w' x)^{-1} w' u}{n}$$

$$\sqrt{n} (\tilde{\beta}_n(B) - \beta) = \frac{(w' x)^{-1}}{n} \frac{w' u}{\sqrt{n}} = \left(B \frac{z' x}{n} \right)^{-1} B \frac{z' u}{\sqrt{n}}$$

$$\bullet \quad \frac{z' u}{\sqrt{n}} = \frac{1}{\sqrt{n}} \sum_{i=1}^n w_i z_i \xrightarrow{D} N(0, E w_i^2 z_i z_i')$$

$$\bullet \quad \frac{z' x}{n} \xrightarrow{P} E z_i x_i' := Q$$

$$\text{by Slutsky's theorem } \left(B \frac{z' x}{n} \right)^{-1} \xrightarrow{P} (B Q)^{-1}$$

Then

$$\begin{aligned} \sqrt{n} (\tilde{\beta}_n(B) - \beta) &\xrightarrow{D} N(0, (B Q)^{-1} B \Sigma B' (Q' B')^{-1}) \\ &= N(0, (Q' B' (B \Sigma B')^{-1} B Q)^{-1}) \end{aligned}$$

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

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

Therefore, it is p.s.d.

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

$$\underbrace{Q' B' (B' R B')^{-1} B Q}_{\substack{\text{we want this to} \\ \text{cancel each} \\ \text{other}}} = Q' R^{-1} Q$$

$\Rightarrow \boxed{B^* = Q' R^{-1}}$

and plug it to confirm :

$$\cancel{Q' R' Q} (Q' R^{-1} R^{-1} Q)^{-1} Q' R^{-1} Q = V^* \text{ as desired.}$$

We can estimate it as

$$B_n^* = \frac{X' Z}{n} \hat{R}_n^{-1} = \sum_{i=1}^n \frac{x_i z_i'}{n} \hat{R}_n^{-1}$$

where $\hat{R}_n = \frac{1}{n} \sum_{i=1}^n (y_i - x_i' \hat{\beta}_n)^2 z_i z_i'$

↳ some consistent estimator of R

Finally, we can write

$$\begin{aligned} \hat{\beta}_n (B_n^*) &= \left(B_n \sum_{i=1}^n z_i z_i' \right)^{-1} B_n^* \sum_{i=1}^n x_i y_i \\ &= \left(\sum_{i=1}^n x_i z_i' \hat{R}_n^{-1} \sum_{i=1}^n z_i z_i' \right)^{-1} \sum_{i=1}^n x_i z_i' \hat{R}_n^{-1} \sum_{i=1}^n z_i y_i = \hat{\beta}^{2\text{step}}. \end{aligned}$$

Hypothesis Testing

We consider the test

$$H_0: \beta = \beta_0$$

$$H_1: \beta = \beta_0 + \delta, \quad \delta \in \mathbb{R}^K \text{ such that } \delta \neq 0.$$

The proposed statistic is

$$\begin{aligned} W_n &= n (\hat{\beta}_n - \beta_0)' \hat{V}_n^{-1}(A_n) (\hat{\beta}_n - \beta_0) \\ &= \sqrt{n} (\hat{\beta}_n - \beta_0)' \hat{V}_n^{-1}(A_n) \sqrt{n} (\hat{\beta}_n - \beta_0) \\ &= [\hat{V}_n^{-1/2}(A_n) \sqrt{n} (\hat{\beta}_n - \beta_0)]' [\hat{V}_n^{-1/2}(A_n) \sqrt{n} (\hat{\beta}_n - \beta_0)] \end{aligned}$$

Under H_0

$$W_n \xrightarrow{d} \chi_{\kappa}^2 \quad \text{and we reject if } W_n(\beta_0) > \chi_{1-\alpha, \kappa}^2.$$

Under H_1 $\hat{\beta}_n - \beta_0 = \delta + o_p(1)$, then

$$\begin{aligned} \Pr_{H_1} (W_n > \chi_{1-\alpha, \kappa}^2) &= \Pr_{H_1} \left(\frac{W_n}{n} > \frac{\chi_{1-\alpha, \kappa}^2}{n} \right) \\ &= \Pr_{H_1} (\delta' (V(A))^{-1} \delta + o_p(1) > o(1)) \\ &= \Pr_{H_1} (\delta' (V(A))^{-1} \delta + o_p(1) > 0) \end{aligned}$$

Notice that $\delta' (V(A))^{-1} \delta > 0$ because $V(A)$ is pos def and bounded.

Hence by taking limits

$$\lim_{n \rightarrow \infty} \Pr_{H_1} (\delta' (V(A))^{-1} \delta + o_p(1) > 0) = 1.$$

In other words, in the limit the test always rejects if H_0 is not true.

Under local alternatives $\beta = \beta_0 + \delta/\sqrt{n}$ we have that

$$\begin{aligned}\sqrt{n}(\hat{\beta}_n - \beta_0) &= \delta + (\mathbf{Q}' \mathbf{A}' \mathbf{A} \mathbf{Q})^{-1} (\mathbf{Q}' \mathbf{A}' \mathbf{A} \frac{1}{\sqrt{n}} \sum_{i=1}^n z_i u_i + o_p(1)) \\ &\xrightarrow{d} \mathcal{N}(\delta, V(A))\end{aligned}$$

Therefore

$$W_n(\beta_0) \xrightarrow{d} Z_f' Z_f \sim \chi^2_k(\delta' V^{-1}(A) \delta)$$

The power function indexed by δ is given by

$$\alpha \leftarrow \Pr(\chi^2_k(\delta' V(A)^{-1} \delta) > \chi^2_{1-\alpha, k}) \leftarrow 1 - \underbrace{\pi(\delta' V(A)^{-1} \delta)}_{\| \delta \| \rightarrow 0} \quad \underbrace{\Pr}_{\| \delta \| \rightarrow \infty}$$

Overid Test

Suppose we want to test $E \hat{z}_i \hat{u}_i = 0$.

We may use the criterion function

$$\begin{aligned}
 J_n &= n \left(\frac{1}{n} \sum_{i=1}^n \hat{z}_i \hat{u}_i \right)' \hat{\Omega}_n^{-1} \left(\frac{1}{n} \sum_{i=1}^n \hat{z}_i \hat{u}_i \right) \\
 &= \left(\Omega^{-1/2} \frac{1}{\sqrt{n}} \sum_{i=1}^n z_i u_i \right)' \Omega^{1/2} \hat{\Omega}_n^{-1} \Omega^{1/2} \left(\Omega^{-1/2} \frac{1}{\sqrt{n}} \sum_{i=1}^n z_i u_i \right) \\
 &\quad \underbrace{\qquad \qquad \qquad}_{g_n(\beta_n^*)}
 \end{aligned}$$

④ we need \hat{u}_i
so we'll lose
degrees of
freedom

where

$$\begin{aligned}
 g_n(\beta) &= \Omega^{-1/2} \frac{z' u}{\sqrt{n}} - \Omega^{-1/2} z' X \hat{\Omega}_n (\beta_n^* - \beta) \\
 &= \Omega^{-1/2} \frac{z' u}{\sqrt{n}} - \Omega^{-1/2} Q (Q' \Omega^{-1} Q)^{-1} Q' \Omega^{-1} \frac{z' u}{\sqrt{n}} + o_p(1), \\
 &= \left\{ I_n - \Omega^{-1/2} Q (Q' \Omega^{-1} Q)^{-1} Q' \Omega^{-1} \Omega^{-1/2} \right\} \Omega^{-1/2} \frac{z' u}{\sqrt{n}} + o_p(1). \\
 &= \left\{ I_n - \underbrace{\Omega^{-1/2} Q}_{R} \underbrace{(Q' \Omega^{-1/2} \Omega^{-1/2} Q)^{-1}}_{R'} \underbrace{Q' \Omega^{-1/2}}_{R'} \right\} \Omega^{-1/2} \frac{z' u}{\sqrt{n}} + o_p(1). \\
 &= \underbrace{\left\{ I_n - R (R' R)^{-1} R' \right\}}_{\text{idempotent and symmetric}} \Omega^{-1/2} \frac{z' u}{\sqrt{n}} + o_p(1).
 \end{aligned}$$

projection

Write

$$\begin{aligned}
 J_n &= Z' [I_{e-K}(R'R)^{-1}R'] [J_{\ell + \text{op}(1)}] [I_{e-K}(R'R)^{-1}R'] Z \\
 &= Z' [I_{e-K}(R'R)^{-1}R'] Z + \text{op}(1) \\
 &= Z' (I_{e-K}(R'R)^{-1}R') Z + \text{op}(1) \\
 &= Z' (H \Delta H') Z + \text{op}(1) \\
 &\quad \xrightarrow{\text{orthonormal, i.e. pure rotation (normality is preserved)}} \\
 &= \tilde{Z}' \Delta \tilde{Z} + \text{op}(1) \\
 &\quad \xrightarrow{\text{diagonal of 0 and 1s.}} \text{Tr}(I_{e-K}(R'R)^{-1}R') = e - K \\
 &= \sum_{j=1}^{e-n} \tilde{Z}_j + \text{op}(1) \\
 &\xrightarrow{d} \chi^2_{e-K}.
 \end{aligned}$$

Under local alternative we get normals around $\approx \sqrt{n} \delta$.
Hence the non-centrality parameter is

$$\begin{aligned}
 \delta' \sqrt{n}^{-1/2} (I_{e-K}(R'R)^{-1}R') \sqrt{n}^{-1/2} \delta \\
 = \delta' (\sqrt{n}^{-1} - \sqrt{n}^{-1} \sqrt{n}^{-1/2} (\sqrt{n}^{-1/2} \sqrt{n}^{-1} \sqrt{n}^{-1/2})^{-1} \sqrt{n}^{-1/2} \sqrt{n}^{-1}) \delta
 \end{aligned}$$

If $\delta = \sqrt{n}^{-1/2} \pi$ then the non-centrality parameter collapses to zero (trivial power),