

### 4.3 Generalized Method of Moments (GMM, 一般化積率法) II

— Nonlinear Case —

Consider the general case:

$$E(h(\theta; w)) = 0,$$

which is the orthogonality condition.

A  $k \times 1$  vector  $\theta$  denotes a parameter to be estimated.

$h(\theta; w)$  is a  $r \times 1$  vector for  $r \geq k$ .

Let  $w_i = (y_i, x_i)$  be the  $i$ th observed data, i.e., the  $i$ th realization of  $w$ .

Define  $g(\theta; W)$  as:

$$g(\theta; W) = \frac{1}{n} \sum_{i=1}^n h(\theta; w_i),$$

where  $W = \{w_n, w_{n-1}, \dots, w_1\}$ .

$g(\theta; W)$  is a  $r \times 1$  vector for  $r \geq k$ .

Let  $\hat{\theta}$  be the GMM estimator which minimizes:

$$g(\theta; W)'S^{-1}g(\theta; W),$$

with respect to  $\theta$ .

● Solve the following first-order condition:

$$\frac{\partial g(\theta; W)'}{\partial \theta}S^{-1}g(\theta; W) = 0,$$

with respect to  $\theta$ . There are  $r$  equations and  $k$  parameters.

### Computational Procedure:

Linearizing the first-order condition around  $\theta = \hat{\theta}$ ,

$$\begin{aligned} 0 &= \frac{\partial g(\theta; W)'}{\partial \theta}S^{-1}g(\theta; W) \\ &\approx \frac{\partial g(\hat{\theta}; W)'}{\partial \theta}S^{-1}g(\hat{\theta}; W) + \frac{\partial g(\hat{\theta}; W)'}{\partial \theta}S^{-1}\frac{\partial g(\hat{\theta}; W)}{\partial \theta'}(\theta - \hat{\theta}) \\ &= \hat{D}'S^{-1}g(\hat{\theta}; W) + \hat{D}'S^{-1}\hat{D}(\theta - \hat{\theta}), \end{aligned}$$

where  $\hat{D} = \frac{\partial g(\hat{\theta}; W)}{\partial \theta'}$ , which is a  $r \times k$  matrix.

Note that in the second term of the second line the second derivative is ignored and omitted.

Rewriting, we have the following equation:

$$\theta - \hat{\theta} = -(\hat{D}'S^{-1}\hat{D})^{-1}\hat{D}'S^{-1}g(\hat{\theta}; W).$$

Replacing  $\theta$  and  $\hat{\theta}$  by  $\hat{\theta}^{(i+1)}$  and  $\hat{\theta}^{(i)}$ , respectively, we obtain:

$$\hat{\theta}^{(i+1)} = \hat{\theta}^{(i)} - (\hat{D}^{(i)'}S^{-1}\hat{D}^{(i)})^{-1}\hat{D}^{(i)'}S^{-1}g(\hat{\theta}^{(i)}; W),$$

where  $\hat{D}^{(i)} = \frac{\partial g(\hat{\theta}^{(i)}; W)}{\partial \theta'}$ .

Given  $S$ , repeat the iterative procedure for  $i = 1, 2, 3, \dots$ , until  $\hat{\theta}^{(i+1)}$  is equal to  $\hat{\theta}^{(i)}$ .

How do we derive the weight matrix  $S$ ?

- In the case where  $h(\theta; w_i)$ ,  $i = 1, 2, \dots, n$ , are mutually independent,  $S$  is:

$$\begin{aligned}
 S &= V\left(\sqrt{n}g(\theta; W)\right) = nE\left(g(\theta; W)g(\theta; W)'\right) \\
 &= nE\left(\left(\frac{1}{n}\sum_{i=1}^n h(\theta; w_i)\right)\left(\frac{1}{n}\sum_{j=1}^n h(\theta; w_j)\right)'\right) = \frac{1}{n}\sum_{i=1}^n\sum_{j=1}^n E\left(h(\theta; w_i)h(\theta; w_j)'\right) \\
 &= \frac{1}{n}\sum_{i=1}^n E\left(h(\theta; w_i)h(\theta; w_i)'\right),
 \end{aligned}$$

which is a  $r \times r$  matrix.

Note that

- (i)  $E(h(\theta; w_i)) = 0$  for all  $i$  and accordingly  $E(g(\theta; W)) = 0$ ,
- (ii)  $g(\theta; W) = \frac{1}{n}\sum_{i=1}^n h(\theta; w_i) = \frac{1}{n}\sum_{j=1}^n h(\theta; w_j)$ ,
- (iii)  $E(h(\theta; w_i)h(\theta; w_j)') = 0$  for  $i \neq j$ .

The estimator of  $S$ , denoted by  $\hat{S}$  is given by:  $\hat{S} = \frac{1}{n}\sum_{i=1}^n h(\hat{\theta}; w_i)h(\hat{\theta}; w_i)' \rightarrow S$ .

- Taking into account serial correlation of  $h(\theta; w_i)$ ,  $i = 1, 2, \dots, n$ ,  $S$  is given by:

$$\begin{aligned} S &= V\left(\sqrt{n}g(\theta; W)\right) = nE\left(g(\theta; W)g(\theta; W)'\right) \\ &= nE\left(\left(\frac{1}{n}\sum_{i=1}^n h(\theta; w_i)\right)\left(\frac{1}{n}\sum_{j=1}^n h(\theta; w_j)\right)'\right) = \frac{1}{n}\sum_{i=1}^n \sum_{j=1}^n E\left(h(\theta; w_i)h(\theta; w_j)'\right). \end{aligned}$$

Note that  $E\left(\sum_{i=1}^n h(\theta; w_i)\right) = 0$ .

Define  $\Gamma_\tau = E\left(h(\theta; w_i)h(\theta; w_{i-\tau})'\right) < \infty$ , i.e.,  $h(\theta; w_i)$  is stationary.

Stationarity:

- (i)  $E\left(h(\theta; w_i)\right)$  does not depend on  $i$ ,
- (ii)  $E\left(h(\theta; w_i)h(\theta; w_{i-\tau})'\right)$  depends on time difference  $\tau$ .  
 $\implies E\left(h(\theta; w_i)h(\theta; w_{i-\tau})'\right) = \Gamma_\tau$

$$\begin{aligned}
S &= \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}(h(\theta; w_i)h(\theta; w_j)') \\
&= \frac{1}{n} \left( \mathbb{E}(h(\theta; w_1)h(\theta; w_1)') + \mathbb{E}(h(\theta; w_1)h(\theta; w_2)') + \cdots + \mathbb{E}(h(\theta; w_1)h(\theta; w_n)') \right. \\
&\quad \mathbb{E}(h(\theta; w_2)h(\theta; w_1)') + \mathbb{E}(h(\theta; w_2)h(\theta; w_2)') + \cdots + \mathbb{E}(h(\theta; w_2)h(\theta; w_n)') \\
&\quad \vdots \\
&\quad \left. \mathbb{E}(h(\theta; w_n)h(\theta; w_1)') + \mathbb{E}(h(\theta; w_n)h(\theta; w_2)') + \cdots + \mathbb{E}(h(\theta; w_n)h(\theta; w_n)') \right) \\
&= \frac{1}{n} (\Gamma_0 \quad + \Gamma_1' \quad + \Gamma_2' \quad + \cdots + \Gamma_{n-1}' \\
&\quad \Gamma_1 \quad + \Gamma_0 \quad + \Gamma_1' \quad + \cdots + \Gamma_{n-2}' \\
&\quad \vdots \\
&\quad \Gamma_{n-1} + \Gamma_{n-2} + \Gamma_{n-3} + \cdots + \Gamma_0)
\end{aligned}$$

$$\begin{aligned}
&= \frac{1}{n} \left( n\Gamma_0 + (n-1)(\Gamma_1 + \Gamma'_1) + (n-2)(\Gamma_2 + \Gamma'_2) + \cdots + (\Gamma_{n-1} + \Gamma'_{n-1}) \right) \\
&= \Gamma_0 + \sum_{i=1}^{n-1} \frac{n-i}{n} (\Gamma_i + \Gamma'_i) = \Gamma_0 + \sum_{i=1}^{n-1} \left(1 - \frac{i}{n}\right) (\Gamma_i + \Gamma'_i) \\
&= \Gamma_0 + \sum_{i=1}^q \left(1 - \frac{i}{q+1}\right) (\Gamma_i + \Gamma'_i).
\end{aligned}$$

Note that  $\Gamma'_\tau = \mathbb{E}(h(\theta; w_{i-\tau})h(\theta; w_i)') = \Gamma(-\tau)$ , because  $\Gamma_\tau = \mathbb{E}(h(\theta; w_i)h(\theta; w_{i-\tau})')$ .

In the last line,  $n$  is replaced by  $q+1$ , where  $q < n$ .

We need to estimate  $\Gamma_\tau$  as:  $\hat{\Gamma}_\tau = \frac{1}{n} \sum_{i=\tau+1}^n h(\hat{\theta}; w_i)h(\hat{\theta}; w_{i-\tau})'$ .

As  $\tau$  is large,  $\hat{\Gamma}_\tau$  is unstable.

Therefore, we choose the  $q$  which is less than  $n$ .

$S$  is estimated as:

$$\hat{S} = \hat{\Gamma}_0 + \sum_{i=1}^q \left(1 - \frac{i}{q+1}\right) (\hat{\Gamma}_i + \hat{\Gamma}'_i),$$

$\implies$  the Newey-West Estimator

Note that  $\hat{S} \rightarrow S$ , because  $\hat{\Gamma}_\tau \rightarrow \Gamma_\tau$  as  $n \rightarrow \infty$ .

### **Asymptotic Properties of GMM:**

GMM is consistent and asymptotic normal as follows:

$$\sqrt{n}(\hat{\theta} - \theta) \rightarrow N\left(0, (D'S^{-1}D)^{-1}\right),$$

where  $D$  is a  $r \times k$  matrix, and  $\hat{D}$  is an estimator of  $D$ , defined as:

$$D = \frac{\partial g(\theta; W)}{\partial \theta'}, \quad \hat{D} = \frac{\partial g(\hat{\theta}; W)}{\partial \theta'}.$$

## Proof of Asymptotic Normality:

Assumption 1:  $\hat{\theta} \rightarrow \theta$

Assumption 2:  $\sqrt{n}g(\theta; W) \rightarrow N(0, S)$ , i.e.,  $S = \lim_{n \rightarrow \infty} V(\sqrt{n}g(\theta; W))$ .

The first-order condition of GMM is:

$$\frac{\partial g(\theta; W)'}{\partial \theta} S^{-1} g(\theta; W) = 0.$$

The GMM estimator, denote by  $\hat{\theta}$ , satisfies the above equation.

Therefore, we have the following:

$$\frac{\partial g(\hat{\theta}; W)'}{\partial \theta} \hat{S}^{-1} g(\hat{\theta}; W) = 0.$$

Linearize  $g(\hat{\theta}; W)$  around  $\hat{\theta} = \theta$  as follows:

$$g(\hat{\theta}; W) = g(\theta; W) + \frac{\partial g(\bar{\theta}; W)}{\partial \theta'}(\hat{\theta} - \theta) = g(\theta; W) + \bar{D}(\hat{\theta} - \theta),$$

where  $\bar{D} = \frac{\partial g(\bar{\theta}; W)}{\partial \theta'}$ , and  $\bar{\theta}$  is between  $\hat{\theta}$  and  $\theta$ .

⇒ **Theorem of Mean Value** (平均値の定理)

Substituting the linear approximation at  $\hat{\theta} = \theta$ , we obtain:

$$\begin{aligned} 0 &= \hat{D}'\hat{S}^{-1}g(\hat{\theta}; W) \\ &= \hat{D}'\hat{S}^{-1}\left(g(\theta; W) + \bar{D}(\hat{\theta} - \theta)\right) \\ &= \hat{D}'\hat{S}^{-1}g(\theta; W) + \hat{D}'\hat{S}^{-1}\bar{D}(\hat{\theta} - \theta), \end{aligned}$$

which can be rewritten as:

$$\hat{\theta} - \theta = -(\hat{D}'\hat{S}^{-1}\bar{D})^{-1}\hat{D}'\hat{S}^{-1}g(\theta; W).$$

Note that  $\bar{D} = \frac{\partial g(\bar{\theta}; W)}{\partial \theta'}$ , where  $\bar{\theta}$  is between  $\hat{\theta}$  and  $\theta$ .

From Assumption 1,  $\hat{\theta} \rightarrow \theta$  implies  $\bar{\theta} \rightarrow \theta$

Therefore,

$$\sqrt{n}(\hat{\theta} - \theta) = -(\hat{D}'\hat{S}^{-1}\bar{D})^{-1}\hat{D}'S^{-1} \times \sqrt{ng}(\theta; W).$$

Accordingly, the GMM estimator  $\hat{\theta}$  has the following asymptotic distribution:

$$\sqrt{n}(\hat{\theta} - \theta) \rightarrow N(0, (D'S^{-1}D)^{-1}).$$

Note that  $\hat{D} \rightarrow D$ ,  $\bar{D} \rightarrow D$ ,  $\hat{S} \rightarrow S$  and Assumption 2 are utilized.