## Computational Procedure:

(1) Compute $\hat{S}^{(i)}=\hat{\Gamma}_{0}+\sum_{i=1}^{q}\left(1-\frac{i}{q+1}\right)\left(\hat{\Gamma}_{i}+\hat{\Gamma}_{i}^{\prime}\right)$, where $\hat{\Gamma}_{\tau}=\frac{1}{n} \sum_{i=\tau+1}^{n} h\left(\hat{\theta} ; w_{i}\right) h\left(\hat{\theta} ; w_{i-\tau}\right)^{\prime}$. $q$ is set by a researcher.
(2) Use the following iterative procedure:

$$
\hat{\theta}^{(i+1)}=\hat{\theta}^{(i)}-\left(\hat{D}^{(i)} \hat{S}^{(i)-1} \hat{D}^{(i)}\right)^{-1} \hat{D}^{(i)} \hat{S}^{(i)-1} g\left(\hat{\theta}^{(i)} ; W\right) .
$$

(3) Repeat (1) and (2) until $\hat{\theta}^{(i+1)}$ is equal to $\hat{\theta}^{(i)}$.

In (2), remember that when $S$ is given we take the following iterative procedure:

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

where $\hat{D}^{(i)}=\frac{\partial g\left(\hat{\theta}^{(i)} ; W\right)}{\partial \theta^{\prime}} . \quad S$ is replaced by $\hat{S}^{(i)}$.

- If the assumption $\mathrm{E}(h(\theta ; w))=0$ is violated, the GMM estimator $\hat{\theta}$ is no longer consistent.

Therefore, we need to check if $\mathrm{E}(h(\theta ; w))=0$.
From Assumption 2, note as follows:

$$
J=(\sqrt{n} g(\hat{\theta} ; W))^{\prime} \hat{S}^{-1}(\sqrt{n} g(\hat{\theta} ; W)) \longrightarrow \chi^{2}(r-k),
$$

which is called Hansen's $J$ test.

Because of $r$ equations and $k$ parameters, the degree of freedom is given by $r-k$.

If $J$ is small enough, we can judge that the specified model is correct.

## Testing Hypothesis:

Remember that the GMM estimator $\hat{\theta}$ has the following asymptotic distribution:

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

Consider testing the following null and alternative hypotheses:

- The null hypothesis: $\quad H_{0}: R(\theta)=0$,
- The alternative hypothesis: $H_{1}: R(\theta) \neq 0$,
where $R(\theta)$ is a $p \times k$ vector function for $p \leq k$.
$p$ denotes the number of restrictions.
$R(\theta)$ is linearized as: $R(\hat{\theta})=R(\theta)+R_{\bar{\theta}}(\hat{\theta}-\theta)$, where $R_{\bar{\theta}}=\frac{\partial R(\bar{\theta})}{\partial \theta^{\prime}}$, which is a $p \times k$ matrix.

Note that $\bar{\theta}$ is bewteen $\hat{\theta}$ and $\theta . \quad$ If $\hat{\theta} \longrightarrow \theta$, then $\bar{\theta} \longrightarrow \theta$ and $R_{\bar{\theta}} \longrightarrow R_{\theta}$.
Under the null hypothesis $R(\theta)=0$, we have $R(\hat{\theta})=R_{\bar{\theta}}(\hat{\theta}-\theta)$, which implies that the distribution of $R(\hat{\theta})$ is equivalent to that of $R_{\bar{\theta}}(\hat{\theta}-\theta)$.

The distribution of $\sqrt{n} R(\hat{\theta})$ is given by:

$$
\sqrt{n} R(\hat{\theta})=\sqrt{n} R_{\bar{\theta}}(\hat{\theta}-\theta) \longrightarrow N\left(0, R_{\theta}\left(D^{\prime} S^{-1} D\right)^{-1} R_{\theta}^{\prime}\right)
$$

Therefore, under the null hypothesis, we have the following distribution:

$$
n R(\hat{\theta})\left(R_{\theta}\left(D^{\prime} S^{-1} D\right)^{-1} R_{\theta}^{\prime}\right)^{-1} R(\hat{\theta})^{\prime} \longrightarrow \chi^{2}(p)
$$

Practically, replacing $\theta$ by $\hat{\theta}$ in $R_{\theta}, D$ and $S$, we use the following test statistic:

$$
n R(\hat{\theta})\left(R_{\hat{\theta}}\left(\hat{D}^{\prime} \hat{S}^{-1} \hat{D}\right)^{-1} R_{\hat{\theta}}^{\prime}\right)^{-1} R(\hat{\theta})^{\prime} \longrightarrow \chi^{2}(p) .
$$

$\Longrightarrow$ Wald type test

Examples of $\boldsymbol{h}(\boldsymbol{\theta} ; \boldsymbol{w})$ ：

1．OLS：
Regression Model：$\quad y_{i}=x_{i} \beta+\epsilon_{i}, \quad \mathrm{E}\left(x_{i}^{\prime} \epsilon_{i}\right)=0$
$h\left(\theta ; w_{i}\right)$ is taken as：

$$
h\left(\theta ; w_{i}\right)=x_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)
$$

2．IV（Instrumental Variable，操作変数法）：
Regression Model：$\quad y_{i}=x_{i} \beta+\epsilon_{i}, \quad \mathrm{E}\left(x_{i}^{\prime} \epsilon_{i}\right) \neq 0, \quad \mathrm{E}\left(z_{i}^{\prime} \epsilon_{i}\right)=0$
$h\left(\theta ; w_{i}\right)$ is taken as：

$$
h\left(\theta ; w_{i}\right)=z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)
$$

where $z_{i}$ is a vector of instrumental variables．

When $z_{i}$ is a $1 \times k$ vector，the GMM of $\beta$ is equivalent to the instrumental variable（IV）estimator．

When $z_{i}$ is a $1 \times r$ vector for $r>k$ ，the GMM of $\beta$ is equivalent to the two－stage least squares（2SLS）estimator．

3．NLS（Nonlinear Least Squares，非線形最小二乗法）：
Regression Model：$\quad f\left(y_{i}, x_{i}, \beta\right)=\epsilon_{i}, \quad \mathrm{E}\left(x_{i}^{\prime} \epsilon_{i}\right) \neq 0, \quad \mathrm{E}\left(z_{i}^{\prime} \epsilon_{i}\right)=0$
$h\left(\theta ; w_{i}\right)$ is taken as：

$$
h\left(\theta ; w_{i}\right)=z_{i}^{\prime} f\left(y_{i}, x_{i}, \beta\right)
$$

where $z_{i}$ is a vector of instrumental variables．

