# Econometrics II TA Session \#13* 

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## Contents

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## 1 Solutions to Excercise 2-Question 1

## Question 1

(1)

At first, consider the stacked regression model:

$$
y=X \beta+u,
$$

where $y=\left(y_{1}, y_{2}, \cdots, y_{n}\right)^{\prime}, u=\left(u_{1}, u_{2}, \cdots, u_{n}\right)^{\prime}$ and the data matrix $X$ is

$$
X=\left(\begin{array}{c}
X_{1} \\
X_{2} \\
\vdots \\
X_{n}
\end{array}\right)
$$

The OLS estimator of the above model is

$$
\begin{align*}
\hat{\beta} & =b+\left(X^{\prime} X\right)^{-1} X^{\prime} u \\
& =b+\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} X_{i}\right)^{-1}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} u_{i}\right) . \tag{1}
\end{align*}
$$

By taking the probability limit on both sides, we have

$$
\begin{align*}
\operatorname{plim}_{n \rightarrow \infty} \hat{\beta} & =\operatorname{plim}_{n \rightarrow \infty}\left[b+\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} X_{i}\right)^{-1}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} u_{i}\right)\right] \\
& =b+\operatorname{plim}_{n \rightarrow \infty}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} X_{i}\right)^{-1} \operatorname{plim}_{n \rightarrow \infty}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} u_{i}\right) . \tag{2}
\end{align*}
$$

Here, suppose that $\mathbb{E}\left[X_{i}^{\prime} X_{i}\right]<\infty$. By the WLLN, we have

$$
\begin{aligned}
\operatorname{plim}_{n \rightarrow \infty}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} X_{i}\right) & \rightarrow \mathbb{E}\left[X_{i}^{\prime} X_{i}\right]<\infty \\
\operatorname{plim}_{n \rightarrow \infty}\left(\frac{1}{n} \sum_{i=1}^{n} X_{i}^{\prime} u_{i}\right) & \rightarrow \mathbb{E}\left[X_{i}^{\prime} u_{i}\right] \neq 0
\end{aligned}
$$

In the Eq. (2), the orthogonality condition is violated, so we can say

$$
\operatorname{plim}_{n \rightarrow \infty} \hat{\beta} \nrightarrow b
$$

Because this model is over identified, we have to estimate the regressor by GMM. The estimator satisfies the following relationship:

$$
\begin{equation*}
\hat{\beta}_{G M M}=\underset{\beta}{\arg \min }\left[\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)\right)^{\prime} W\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)\right)\right] . \tag{3}
\end{equation*}
$$

In practice, we solve the following minimization problem to derive the GMM estimator of Eq. (1):

$$
\begin{equation*}
\min _{\beta}\left(Z^{\prime}(y-X \beta)\right)^{\prime} W\left(Z^{\prime}(y-X \beta)\right) . \tag{4}
\end{equation*}
$$

The weight matrix $W$ is a random, symmetric, $L \times L$ positive definite matrix. We use the estimator of $W, \hat{W}$, instead of the weight matrix. Assume that $\hat{W} \xrightarrow{p} W$. When we estimate $W$, we regard the inverse matrix of the variance-covariance matrix of $Z^{\prime} u$ as $W$. Suppose that $\operatorname{Var}(u)=\sigma^{2} \Omega$. Then, $\operatorname{Var}\left(Z^{\prime} u\right)=\mathbb{E}\left(Z^{\prime} u\left(Z^{\prime} u\right)^{\prime}\right)=\sigma^{2} Z^{\prime} \Omega Z=W^{-1}$. The GMM estimator is

$$
\begin{equation*}
\hat{\beta}_{G M M}=\left(X^{\prime} Z \hat{W} Z^{\prime} X\right)^{-1}\left(X^{\prime} Z \hat{W} Z^{\prime} y\right) . \tag{5}
\end{equation*}
$$

The solution of Eq. (3) is obtained as

$$
\begin{equation*}
\hat{\beta}_{G M M}=\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y . \tag{6}
\end{equation*}
$$

We begin with the proof of the consistency.

$$
\begin{align*}
\hat{\beta}_{G M M} & =\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime}(X \beta+u) \\
& =\beta+\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} u \\
& =\beta+\left[\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{n} Z^{\prime} X\right)\right]^{-1} \\
& \times\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{n} Z^{\prime} u\right) . \tag{7}
\end{align*}
$$

Assume that $\frac{1}{n} X^{\prime} Z \xrightarrow{p} M_{x z}$ and $\frac{1}{n} Z^{\prime} \Omega Z \xrightarrow{p} M_{z \Omega z}$. From the orthogonality condition, we can prove that the GMM estimator has consistency.

Next, we show that the GMM estimator has the asymptotic normality. Then, from the CLT, we have

$$
\frac{1}{\sqrt{n}} Z^{\prime} u \xrightarrow{d} N\left(0, \sigma^{2} M_{z \Omega z}\right) .
$$

By rewriting the Eq. (7), we can establish the following relationship:

$$
\begin{aligned}
\sqrt{n}\left(\hat{\beta}_{G M M}-\beta\right) & =\left[\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{n} Z^{\prime} X\right)\right]^{-1} \\
& \times\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{\sqrt{n}} Z^{\prime} u\right)
\end{aligned}
$$

By using this result, $\hat{\beta}_{G M M}$ is asymptotically distributed as:

$$
\begin{equation*}
\sqrt{n}\left(\hat{\beta}_{G M M}-\beta\right) \xrightarrow{d} N\left(0, \sigma^{2}\left(M_{x z} M_{z \Omega z}{ }^{-1} M_{x z}^{\prime}\right)^{-1}\right) . \tag{8}
\end{equation*}
$$

## 2 Solutions to Excercise 2-Question 2

## Question 2

(12)

Under $H_{0}, \hat{\beta}$ is consistent and efficient. Thus we should use $\hat{\beta}$. Note that $\tilde{\beta}$ is also consistent and not efficient.

Under $H_{1}$, only $\tilde{\beta}$ is consistent. Thus we should use $\tilde{\beta}$.


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