# Econometrics 2 （2018）TA session $7^{*}$ 

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22 November 2018

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## 3．1 Panel model：Basics

Consider a dataset with time and individual specified structure．Then the model is described as follows：

$$
\begin{align*}
& y_{i t}=X_{i t} \beta+v_{i}+u_{i t}  \tag{1}\\
& i \text { : individual }(i=1,2, \cdots, n)  \tag{2}\\
& t: \text { time }(t=1,2, \cdots, T) \tag{3}
\end{align*}
$$

－The error term $u_{i t}$ assume that
$-E\left[u_{i t}\right]=0, V\left(u_{i t}\right)=\sigma_{u}^{2}$
$-\operatorname{Cov}\left(u_{i t}, u_{j s}\right)=0$ for $i \neq j, t \neq s$.
－The variable $v_{i}=z_{i} \alpha$
－vary across the individual $i$ ．

[^0]- $z_{i}$ may be observable(race, sex ...) or unobservable(skill, preference ...).


### 3.1.1 Difference between fixed effect model and random effect model

- $z_{i}$ is correlated with $X_{i, t}$ and $v_{i}=z_{i} \alpha$ is constant term across $i$.
$\rightarrow$ fixed effect model
- $z_{i}$ is uncorrelated with $X_{i, t}$.
$\rightarrow$ random effect model


### 3.2 Fixed effect model

$y:(n T \times 1), X:$ regressor $(n T \times k), \alpha:$ individual effect $(n \times 1), u:$ error term $(n T \times 1)$

$$
\begin{equation*}
y=X \beta+D \alpha+u \tag{4}
\end{equation*}
$$

where

$$
D=\left(I_{n} \otimes 1_{T}\right)
$$

Multipling $M_{D}=I_{n T}-D\left(D^{\prime} D\right)^{-1} D^{\prime}$ from left side of (6),

$$
\begin{equation*}
M_{D} y=M_{D} X \beta+M_{D} u \tag{5}
\end{equation*}
$$

OLS estimator of $\beta$ in (5) is fixed effect estimator,

$$
\hat{\beta}_{F E}=\left(X^{\prime} M_{D} X\right)^{-1} X^{\prime} M_{D} y
$$

Individual effect can be recovered as below
( $\rightarrow$ least squares dummy variable (LSDV) model)

$$
\begin{aligned}
& y=X \hat{\beta}_{f e}+D \hat{\alpha}+M_{(X, D)} u, \quad \hat{\alpha}, \hat{\beta}_{f e} \text { is OLS estimator } \\
\Longrightarrow & D^{\prime} y=D^{\prime} X \hat{\beta}_{f e}+D^{\prime} D \hat{\alpha} \\
\Longrightarrow & \hat{\alpha}=\left(D^{\prime} D\right)^{-1} D^{\prime}\left(y-X \hat{\beta}_{f e}\right)
\end{aligned}
$$

### 3.3 Random effect model

$$
\begin{equation*}
y_{i}=X_{i} \beta+\epsilon_{i}, \quad \epsilon_{i}=1_{T} v_{i}+u_{i} \sim N(0, \Omega) \tag{6}
\end{equation*}
$$

where

$$
\Omega=\left(\begin{array}{cccc}
\sigma_{u}^{2}+\sigma_{v}^{2} & \sigma_{v}^{2} & \cdots & \sigma_{v}^{2}  \tag{7}\\
\sigma_{v}^{2} & \sigma_{u}^{2}+\sigma_{v}^{2} & \cdots & \vdots \\
\vdots & \cdots & \ddots & \vdots \\
\sigma_{v}^{2} & \cdots & \cdots & \sigma_{u}^{2}+\sigma_{v}^{2}
\end{array}\right)
$$

Conditions of this model are
－$E\left(v_{i} \mid X\right)=E\left(u_{i t} \mid X\right)=0$ for all $i$
－$E\left(v_{i} \mid X\right)=\sigma_{v}^{2}$
－$V\left(u_{i t} \mid X\right)=\sigma_{u}^{2}$
－ $\operatorname{Cov}\left(v_{i}, v_{j} \mid X\right)=0$ for $i \neq j$
－ $\operatorname{Cov}\left(u_{i t}, u_{j s} \mid X\right)=0$ for $i \neq j$ and $t \neq s$
－ $\operatorname{Cov}\left(v_{i}, u_{j t} \mid X\right)=0$ for all $i, j$ and $t$

MLE of this model is

$$
\hat{\beta}_{r e}=\left(X^{\prime} \Omega X\right)^{-1} X^{\prime} \Omega y
$$

This is equivalent to GLS（efficient estimator）．

## 3．4 Hausman＇s Specification Error（特定化誤差）

Now we consider a regression model：

$$
y=X \beta+u
$$

If $E[u \mid X]=0, \operatorname{OLSE}\left(\hat{\beta}=\left(X^{\prime} X\right)^{-1} X y\right)$ have unbiasedness and consistency．
－unbiasedness：

$$
\begin{aligned}
E[\hat{\beta}] & =\beta+E\left[\left(X^{\prime} X\right)^{-1} X^{\prime} u\right] \\
& =\beta+E\left[\left(X^{\prime} X\right)^{-1} X^{\prime} E[u \mid X]\right]
\end{aligned}
$$

－consistency：OLSE can be written as below，

$$
\begin{align*}
\hat{\beta} & =\left(X^{\prime} X\right)^{-1} X^{\prime} y \\
& =\beta+\left(X^{\prime} X\right)^{-1} X^{\prime} u  \tag{8}\\
& =\beta+\left(\frac{1}{n} X^{\prime} X\right)^{-1} \frac{1}{n} X^{\prime} u .
\end{align*}
$$

Suppose that

$$
\begin{align*}
M_{x x} & \equiv \frac{1}{n} \sum_{i=1}^{n} x_{i} x_{i}^{\prime} \\
& \rightarrow Q^{-1} . \tag{10}
\end{align*}
$$

If $E[u \mid X]=0, E\left[X^{\prime} u\right]=E\left[X^{\prime} E[u \mid X]\right]=0$. So

$$
\begin{align*}
M_{u x} & \equiv \frac{1}{n} \sum_{i=1}^{n} \underset{(k \times 1)(1 \times 1)}{x_{i}} u_{i} \\
& \rightarrow E\left[\begin{array}{l}
x \times 1)(1 \times 1) \\
u
\end{array}\right]  \tag{11}\\
& =E[x E[u \mid x]]=0 . \tag{12}
\end{align*}
$$

However, if $E[u \mid X] \neq 0$, OLSE $\hat{\beta}$ is biased and inconsistent. So we should check whether $X$ is correlated with $u$.

## $\rightarrow$ Hausman's Specification Error Test

### 3.4.1 Hausman's Specification Error Test

The null and alternative hypotheses are:
$H_{0}: E\left[X^{\prime} u\right]=0(\operatorname{Cov}(X, u)=0(X$ is not correlated with $u))$
$H_{1}: E\left[X^{\prime} u\right] \neq 0(X$ is correlated with $u)$
If

- " $\hat{\beta}_{0}$ : consistent and efficient, $\hat{\beta}_{1}$ : consistent and not efficient"
$\Longleftrightarrow E\left[X^{\prime} u\right]=0$
- $\hat{\beta}_{0}$ : not consistent, $\hat{\beta}_{1}$ : consistent
$\Longleftrightarrow E\left[X^{\prime} u\right] \neq 0$
are valid, you can rewrite the condition below:
$H_{0}: \hat{\beta}_{0}:$ consistent and efficient, $\hat{\beta}_{1}$ : consistent and not efficient
$H_{1}: \hat{\beta}_{0}$ : not consistent, $\hat{\beta}_{1}$ : consistent
Example
- $\hat{\beta}_{0}$ is OLSE, while $\hat{\beta}_{1}$ is IV estimator such as 2SLS
- $\hat{\beta}_{0}$ is MLE or GLSE $\tilde{\beta}$ in RE model, while $\hat{\beta}_{1}$ is OLSE in FE model.


### 3.5 Choice of Fixed Effect Model or Random Effect Model

Review

- $v_{i}$ isn't correlated with $X \rightarrow$ Random Effect Model

$$
\Longleftrightarrow H_{0}: E\left[X^{\prime}(u+v)\right]=0
$$

- $v_{i}$ is correlated with $X \rightarrow$ Fixed Effect Model
$\Longleftrightarrow H_{1}: E\left[X^{\prime}(u+v)\right] \neq 0$


### 3.5.2 Fixed Effect Model or Random Effect Model

We set $\hat{\beta}_{f e}:$ FE model and $\hat{\beta}_{r e}:$ RE model. Asymptotic properties of them are

$$
\begin{aligned}
& \sqrt{T} \hat{\beta}_{r e} \rightarrow N\left(0, V_{0}\right) \\
& \sqrt{T} \hat{\beta}_{f e} \rightarrow N\left(0, V_{1}\right)
\end{aligned}
$$

where $V_{0}$ is Cramer-Rao bound ( $T$ is sample size).
Under $H_{0}$,

$$
\begin{equation*}
V\left[\hat{\beta}_{f e}-\hat{\beta}_{r e}\right]=V\left[\hat{\beta}_{f e}\right]-V\left[\hat{\beta}_{r e}\right] . \tag{13}
\end{equation*}
$$

Test statistic is

$$
\left(\hat{\beta}_{f e}-\hat{\beta}_{r e}\right)^{\prime}\left[V\left[\hat{\beta}_{f e}\right]-V\left[\hat{\beta}_{r e}\right]\right]^{-1}\left(\hat{\beta}_{f e}-\hat{\beta}_{r e}\right) \rightarrow \chi^{2}(k)
$$

## [Proof of (13)]

We prove that under $H_{0}$,

$$
\begin{equation*}
C^{\prime} \equiv \operatorname{cov}\left(\hat{\beta}_{f e}-\hat{\beta}_{r e}, \hat{\beta}_{r e}\right)=0 \tag{14}
\end{equation*}
$$

Consider a new estimator

$$
\begin{array}{r}
\hat{q} \equiv \hat{\beta}_{f e}-\hat{\beta}_{r e} \\
\hat{\beta}_{2}=\hat{\beta}_{r e}-r C^{\prime} \hat{q}
\end{array}
$$

Variance of $\hat{\beta}_{2}$ is

$$
V\left[\hat{\beta}_{2}\right]=V\left[\hat{\beta}_{r e}\right]-2 r C^{\prime} C+r^{2} C^{\prime} V[\hat{q}] C
$$

Difference between $V\left[\hat{\beta}_{2}\right]$ and $V\left[\hat{\beta}_{r e}\right]$ is

$$
F(r)=V\left[\hat{\beta}_{2}\right]-V\left[\hat{\beta}_{r e}\right]=-2 r C^{\prime} C+r^{2} C^{\prime} V[\hat{q}] C
$$

By taking derivatives with respect to $r$,

$$
F^{\prime}(r)=-2 C^{\prime} C+2 r C^{\prime} V[\hat{q}] C
$$

When $r=0, F(0)=0$ and $F^{\prime}(0)=-2 C^{\prime} C$ (negative semi-definite) From this result, $F(r)$ is negative semi-definite for small $r$. So we can find that $C^{\prime} C=0(C=0)$


[^0]:    ＊All comments welcome！
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