## 3．2．2 Random Effect Model（ランダム効果モデル）

Model：

$$
y_{i t}=X_{i t} \beta+v_{i}+u_{i t}, \quad i=1,2, \cdots, n, \quad t=1,2, \cdots, T
$$

where $i$ indicates individual and $t$ denotes time．
The assumptions on the error terms $v_{i}$ and $u_{i t}$ are：

$$
\begin{aligned}
& \mathrm{E}\left(v_{i} \mid X\right)=\mathrm{E}\left(u_{i t} \mid X\right)=0 \text { for all } i, \\
& \mathrm{~V}\left(v_{i} \mid X\right)=\sigma_{v}^{2} \text { for all } i, \quad \mathrm{~V}\left(u_{i t} \mid X\right)=\sigma_{u}^{2} \text { for all } i \text { and } t, \\
& \operatorname{Cov}\left(v_{i}, v_{j} \mid X\right)=0 \text { for } i \neq j, \quad \operatorname{Cov}\left(u_{i t}, u_{j s} \mid X\right)=0 \text { for } i \neq j \text { and } t \neq s, \\
& \operatorname{Cov}\left(v_{i}, u_{j t} \mid X\right)=0 \text { for all } i, j \text { and } t .
\end{aligned}
$$

Note that $X$ includes $X_{i t}$ for $i=1,2, \cdots, n$ and $t=1,2, \cdots, T$ ．

In a matrix form with respect to $t=1,2, \cdots, T$, we have the following:

$$
y_{i}=X_{i} \beta+v_{i} 1_{T}+u_{i}, \quad i=1,2, \cdots, n,
$$

where $y_{i}=\left(\begin{array}{c}y_{i 1} \\ y_{i 2} \\ \vdots \\ y_{i T}\end{array}\right), X_{i}=\left(\begin{array}{c}X_{i 1} \\ X_{i 2} \\ \vdots \\ X_{i T}\end{array}\right)$ and $u_{i}=\left(\begin{array}{c}u_{i 1} \\ u_{i 2} \\ \vdots \\ u_{i T}\end{array}\right)$ are $T \times 1, T \times k$ and $T \times 1$, respectively.

$$
u_{i} \sim N\left(0, \sigma_{u}^{2} I_{T}\right) \text { and } v_{i} 1_{T} \sim N\left(0, \sigma_{v}^{2}\right) \Longrightarrow v_{i} 1_{T}+u_{i} \sim N\left(0, \sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right) .
$$

Again, in a matrix form with respect to $i$, we have the following:

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

where $y=\left(\begin{array}{c}y_{1} \\ y_{2} \\ \vdots \\ y_{n}\end{array}\right), X=\left(\begin{array}{c}X_{1} \\ X_{2} \\ \vdots \\ X_{n}\end{array}\right), v=\left(\begin{array}{c}v_{1} 1_{T} \\ v_{2} 1_{T} \\ \vdots \\ v_{n} 1_{T}\end{array}\right)$ and $u=\left(\begin{array}{c}u_{1} \\ u_{2} \\ \vdots \\ u_{n}\end{array}\right)$ are $n T \times 1, n T \times k, n T \times 1$ and
$n T \times 1$, respectively.

The distribution of $u+v$ is given by:

$$
v+u \sim N\left(0, I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right)
$$

The likelihood function is given by:

$$
\begin{aligned}
L\left(\beta, \sigma_{v}^{2}, \sigma_{u}^{2}\right) & =(2 \pi)^{-n T / 2}\left|I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right|^{-1 / 2} \\
& \times \exp \left(-\frac{1}{2}(y-X \beta)^{\prime}\left(I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right)^{-1}(y-X \beta)\right)
\end{aligned}
$$

Remember that $f(x)=(2 \pi)^{-k / 2}|\Sigma|^{-1 / 2} \exp \left(-\frac{1}{2}(x-\mu)^{\prime} \Sigma^{-1}(x-\mu)\right)$ when $X \sim N(\mu, \Sigma)$, where $X$ denotes a $k$-variate random variable.

The estimators of $\beta, \sigma_{v}^{2}$ and $\sigma_{u}^{2}$ are given by maximizing the following log-likelihood function:

$$
\begin{aligned}
\log L\left(\beta, \sigma_{v}^{2}, \sigma_{u}^{2}\right)= & -\frac{n T}{2} \log (2 \pi)-\frac{1}{2} \log \left|I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right| \\
& -\frac{1}{2}(y-X \beta)^{\prime}\left(I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right)^{-1}(y-X \beta) .
\end{aligned}
$$

MLE of $\beta$, denoted by $\tilde{\beta}$, is given by:

$$
\begin{aligned}
\tilde{\beta} & =\left(X^{\prime}\left(I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right)^{-1} X\right)^{-1} X^{\prime}\left(I_{n} \otimes\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)\right)^{-1} y \\
& =\left(\sum_{i=1}^{n} X_{i}^{\prime}\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)^{-1} X_{i}\right)^{-1}\left(\sum_{i=1}^{n} X_{i}^{\prime}\left(\sigma_{v}^{2} 1_{T} 1_{T}^{\prime}+\sigma_{u}^{2} I_{T}\right)^{-1} y_{i}\right),
\end{aligned}
$$

which is equivalent to GLS.
Note that $\tilde{\beta}$ is not operational, because $\hat{\beta}$ depends on $\sigma_{v}^{2}$ and $\sigma_{u}^{2}$.

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

Regression model：

$$
y=X \beta+u, \quad y: n \times 1, \quad X: n \times k, \quad \beta: k \times 1, \quad u: n \times 1 .
$$

Suppose that $X$ is stochastic．
If $\mathrm{E}(u \mid X)=0$ ，OLSE $\hat{\beta}$ is unbiased because of $\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y=\beta+\left(X^{\prime} X\right)^{-1} X^{\prime} u$ and $\mathrm{E}\left(\left(X^{\prime} X\right)^{-1} X^{\prime} u\right)=0$ ．

However，If $\mathrm{E}(u \mid X) \neq 0$ ，OLSE $\hat{\beta}$ is biased and inconsistent．

Therefore，we need to check if $X$ is correlated with $u$ or not．
$\Longrightarrow$ Hausman＇s Specification Error Test

The null and alternative hypotheses are:

- $H_{0}: X$ and $u$ are independent, i.e., $\operatorname{Cov}(X, u)=0$,
- $H_{1}: X$ and $u$ are not independent.

Suppose that we have two estimators $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$, which have the following properties:

- $\hat{\beta}_{0}$ is consistent and efficient under $H_{0}$, but is not consistent under $H_{1}$,
- $\hat{\beta}_{1}$ is consistent under both $H_{0}$ and $H_{1}$, but is not efficient under $H_{0}$.

Under the conditions above, we have the following test statistic:

$$
\left(\hat{\beta}_{1}-\hat{\beta}_{0}\right)^{\prime}\left(\mathrm{V}\left(\hat{\beta}_{1}\right)-\mathrm{V}\left(\hat{\beta}_{0}\right)\right)^{-1}\left(\hat{\beta}_{1}-\hat{\beta}_{0}\right) \longrightarrow \chi^{2}(k) .
$$

Example: $\hat{\beta}_{0}$ is OLS, while $\hat{\beta}_{1}$ is IV such as 2SLS.
Hausman, J.A. (1978) "Specification Tests in Econometrics," Econometrica, Vol.46, No.6, pp.1251-1271.

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

### 3.4. $\quad$ The Case where $X$ is Correlated with $u$ - Review

The standard regression model is given by:

$$
y=X \beta+u, \quad u \sim N\left(0, \sigma^{2} I_{n}\right)
$$

OLS is:

$$
\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y=\beta+\left(X^{\prime} X\right)^{-1} X^{\prime} u .
$$

If $X$ is not correlated with $u$, i.e., $\mathrm{E}\left(X^{\prime} u\right)=0$, we have the result: $\mathrm{E}(\hat{\beta})=\beta$.
However, if $X$ is correlated with $u$, i.e., $\mathrm{E}\left(X^{\prime} u\right) \neq 0$, we have the result: $\mathrm{E}(\hat{\beta}) \neq \beta$.
$\Longrightarrow \hat{\beta}$ is biased.

Assume that in the limit we have the followings:

$$
\begin{aligned}
& \left(\frac{1}{n} X^{\prime} X\right)^{-1} \longrightarrow M_{x x}^{-1} \\
& \frac{1}{n} X^{\prime} u \longrightarrow M_{x u} \neq 0 \text { when } X \text { is correlated with } u .
\end{aligned}
$$

Therefore, even in the limit,

$$
\operatorname{plim} \hat{\beta}=\beta+M_{x x}^{-1} M_{x u} \neq \beta,
$$

which implies that $\hat{\beta}$ is not a consistent estimator of $\beta$.
Thus, in the case where $X$ is correlated with $u$, OLSE $\hat{\beta}$ is neither unbiased nor consistent.

### 3.4.2 Fixed Effect Model or Random Effect Model

Usually, in the random effect model, we can consider that $v_{i}$ is correlated with $X_{i t}$.

## [Reason:]

$v_{i}$ includes the unobserved variables in the $i$ th individual, i.e., ability, intelligence, and so on.
$X_{i t}$ represents the observed variables in the $i$ th individual, i.e., income, assets, and so
on.
The unobserved variables $v_{i}$ are related to the observed variables $X_{i t}$.
Therefore, we consider that $v_{i}$ is correlated with $X_{i t}$.
Thus, in the case of the random effect model, usually we cannot use OLS or GLS.
In order to use the random effect model, we need to test whether $v_{i}$ is uncorrelated with $X_{i t}$.

Apply Hausman's test.

- $H_{0}: X_{i t}$ and $e_{i t}$ are independent $(\longrightarrow$ Use the random effect model),
- $H_{1}: X_{i t}$ and $e_{i t}$ are not independent $(\longrightarrow$ Use the fixed effect model $)$,
where $e_{i t}=v_{i}+u_{i t}$.

Note that:

- We can use the random effect model under $H_{0}$, but not under $H_{1}$.
- We can use the fixed effect model under both $H_{0}$ and $H_{1}$.
- The random effect model is more efficient than the fixed effect model under $H_{0}$.

Therefore, under $H_{0}$ we should use the random effect model, rather than the fixed effect model.

