- However, $\beta_{M M}$ is inconsistent when $\mathrm{E}\left(x^{\prime} u\right) \neq 0$, i.e.,

$$
\beta_{M M}=\left(X^{\prime} X\right)^{-1} X^{\prime} y=\beta+\left(X^{\prime} X\right)^{-1} X^{\prime} u=\beta+\left(\frac{1}{n} X^{\prime} X\right)^{-1}\left(\frac{1}{n} X^{\prime} u\right) \nrightarrow \beta
$$

Note as follows:

$$
\frac{1}{n} X^{\prime} u=\frac{1}{n} \sum_{i=1}^{n} x_{i}^{\prime} u_{i} \longrightarrow \mathrm{E}\left(x^{\prime} u\right) \neq 0
$$

In order to obtain a consistent estimator of $\beta$, we find the instrumental variable $z$ which satisfies $\mathrm{E}\left(z^{\prime} u\right)=0$.

Let $z_{i}$ be the $i$ th realization of $z$, where $z_{i}$ is a $1 \times k$ vector.
Then, we have the following:

$$
\frac{1}{n} Z^{\prime} u=\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} u_{i} \longrightarrow \mathrm{E}\left(z^{\prime} u\right)=0
$$

The $\beta$ which satisfies $\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} u_{i}=0$ is denoted by $\beta_{I V}$, i.e., $\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta_{I V}\right)=0$.

Thus, $\beta_{I V}$ is obtained as:

$$
\beta_{I V}=\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} x_{i}\right)^{-1}\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} y_{i}\right)=\left(Z^{\prime} X\right)^{-1} Z^{\prime} y
$$

Note that $Z^{\prime} X$ is a $k \times k$ square matrix, where we assume that the inverse matrix of $Z^{\prime} X$ exists.

Assume that as $n$ goes to infinity there exist the following moment matrices:

$$
\begin{aligned}
& \frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} x_{i}=\frac{1}{n} Z^{\prime} X \longrightarrow M_{z x}, \\
& \frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} z_{i}=\frac{1}{n} Z^{\prime} Z \longrightarrow M_{z z} \\
& \frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} u_{i}=\frac{1}{n} Z^{\prime} u \longrightarrow 0 .
\end{aligned}
$$

As $n$ goes to infinity, $\beta_{I V}$ is rewritten as:

$$
\begin{aligned}
\beta_{I V} & =\left(Z^{\prime} X\right)^{-1} Z^{\prime} y=\left(Z^{\prime} X\right)^{-1} Z^{\prime}(X \beta+u)=\beta+\left(Z^{\prime} X\right)^{-1} Z^{\prime} u \\
& =\beta+\left(\frac{1}{n} Z^{\prime} X\right)^{-1}\left(\frac{1}{n} Z^{\prime} u\right) \longrightarrow \beta+M_{z x} \times 0=\beta,
\end{aligned}
$$

Thus, $\beta_{I V}$ is a consistent estimator of $\beta$.

- We consider the asymptotic distribution of $\beta_{I V}$.

By the central limit theorem,

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

Note that $\mathrm{V}\left(\frac{1}{\sqrt{n}} Z^{\prime} u\right)=\frac{1}{n} \mathrm{~V}\left(Z^{\prime} u\right)=\frac{1}{n} \mathrm{E}\left(Z^{\prime} u u^{\prime} Z\right)=\frac{1}{n} \mathrm{E}\left(\mathrm{E}\left(Z^{\prime} u u^{\prime} Z \mid Z\right)\right)$
$=\frac{1}{n} \mathrm{E}\left(Z^{\prime} \mathrm{E}\left(u u^{\prime} \mid Z\right) Z\right)=\frac{1}{n} \mathrm{E}\left(\sigma^{2} Z^{\prime} Z\right)=\mathrm{E}\left(\sigma^{2} \frac{1}{n} Z^{\prime} Z\right) \longrightarrow \mathrm{E}\left(\sigma^{2} M_{z z}\right)=\sigma^{2} M_{z z}$.

We obtain the following asymmptotic distribution：

$$
\sqrt{n}\left(\beta_{I V}-\beta\right)=\left(\frac{1}{n} Z^{\prime} X\right)^{-1}\left(\frac{1}{\sqrt{n}} Z^{\prime} u\right) \longrightarrow N\left(0, \sigma^{2} M_{z x}^{-1} M_{z z} M_{z x}^{-1 \prime}\right)
$$

Practically，for large $n$ we use the following distribution：

$$
\beta_{I V} \sim N\left(\beta, s^{2}\left(Z^{\prime} X\right)^{-1} Z^{\prime} Z\left(Z^{\prime} X\right)^{-1 \prime}\right)
$$

where $s^{2}=\frac{1}{n-k}\left(y-X \beta_{I V}\right)^{\prime}\left(y-X \beta_{I V}\right)$ ．
－In the case where $z_{i}$ is a $1 \times r$ vector for $r>k, Z^{\prime} X$ is a $r \times k$ matrix，which is not a square matrix．$\quad \Longrightarrow$ Generalized Method of Moments（GMM，一般化積率法）

## 4．2 Generalized Method of Moments（GMM，一般化積率法）

In order to obtain a consistent estimator of $\beta$ ，we have to find the instrumental variable $z$ which satisfies $\mathrm{E}\left(z^{\prime} u\right)=0$ ．

For now，however，suppose that we have $z$ with $\mathrm{E}\left(z^{\prime} u\right)=0$ ．

Let $z_{i}$ be the $i$ th realization（i．e．，the $i$ th data）of $z$ ，where $z_{i}$ is a $1 \times r$ vector and $r>k$ ．

Then，using the law of large number，we have the following：

$$
\frac{1}{n} Z^{\prime} u=\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime} u_{i}=\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right) \longrightarrow \mathrm{E}\left(z^{\prime} u\right)=0
$$

The number of equations（i．e．，$r$ ）is larger than the number of parameters（i．e．，$k$ ）．

Let us define $W$ as a $r \times r$ weight matrix, which is symmetric.

We solve the following minimization problem:

$$
\min _{\beta}\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)\right)^{\prime} W\left(\frac{1}{n} \sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)\right),
$$

which is equivalent to:

$$
\min _{\beta}\left(Z^{\prime}(y-X \beta)\right)^{\prime} W\left(Z^{\prime}(y-X \beta)\right)
$$

i.e.,

$$
\min _{\beta}(y-X \beta)^{\prime} Z W Z^{\prime}(y-X \beta) .
$$

Note that $\sum_{i=1}^{n} z_{i}^{\prime}\left(y_{i}-x_{i} \beta\right)=Z^{\prime}(y-X \beta)$.
$W$ should be the inverse matrix of the variance-covariance matrix of $Z^{\prime}(y-X \beta)=Z^{\prime} u$.
Suppose that $\mathrm{V}(u)=\sigma^{2} \Omega$.

Then, $\mathrm{V}\left(Z^{\prime} u\right)=\mathrm{E}\left(Z^{\prime} u\left(Z^{\prime} u\right)^{\prime}\right)=\mathrm{E}\left(Z^{\prime} u u^{\prime} Z\right)=Z^{\prime} \mathrm{E}\left(u u^{\prime}\right) Z=\sigma^{2} Z^{\prime} \Omega Z=W^{-1}$.
The following minimization problem should be solved.

$$
\min _{\beta}(y-X \beta)^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime}(y-X \beta) .
$$

The solution of $\beta$ is given by the GMM estimator, denoted by $\beta_{G M M}$.

Remark: For the model: $y=X \beta+u$ and $u \sim\left(0, \sigma^{2} \Omega\right)$, solving the following minimization problem:

$$
\min _{\beta}(y-X \beta)^{\prime} \Omega^{-1}(y-X \beta),
$$

GLS is given by:

$$
b=\left(X^{\prime} \Omega^{-1} X\right)^{-1} X^{\prime} \Omega^{-1} y .
$$

Note that $b$ is the best linear unbiased estimator.

Remark: The solution of the above minimization problem is equivalent to the GLE estimator of $\beta$ in the following regression model:

$$
Z^{\prime} y=Z^{\prime} X \beta+Z^{\prime} u
$$

where $Z, y, X, \beta$ and $u$ are $n \times r, n \times 1, n \times k, k \times 1$ and $n \times 1$ matrices or vectors.
Note that $r>k$.
$y^{*}=Z^{\prime} y, X^{*}=Z^{\prime} X$ and $u^{*}=Z^{\prime} u$ denote $r \times 1, r \times k$ and $r \times 1$ matrices or vectors, where $r>k$.

Rewrite as follows:

$$
y^{*}=X^{*} \beta+u^{*},
$$

$\Longrightarrow r$ is taken as the sample size.
$u^{*}$ is a $r \times 1$ vector.

The elements of $u^{*}$ are correlated with each other, beacuse each element of $u^{*}$ is a function of $u_{1}, u_{2}, \cdots, u_{n}$.

The variance of $u^{*}$ is:

$$
\mathrm{V}\left(u^{*}\right)=\mathrm{V}\left(Z^{\prime} u\right)=\sigma^{2} Z^{\prime} \Omega Z .
$$

## Go back to GMM:

$$
\begin{aligned}
& (y-X \beta)^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime}(y-X \beta) \\
& =y^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y-\beta^{\prime} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y-y^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta+\beta^{\prime} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta \\
& =y^{\prime} Z W Z^{\prime} y-2 y^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta+\beta^{\prime} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta
\end{aligned}
$$

Note that $\beta^{\prime} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y=y^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta$ because both sides are scalars.
Remember that $\frac{\partial A x}{x}=A^{\prime}$ and $\frac{\partial x^{\prime} A x}{x}=\left(A+A^{\prime}\right) x$.

Then, we obtain the following derivation:

$$
\begin{aligned}
& \frac{\partial(y-X \beta)^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime}(y-X \beta)}{\partial \beta} \\
& \quad=-2\left(y^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{\prime}+\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X+\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{\prime}\right) \beta \\
& \quad=-2 X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y+2 X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X \beta=0
\end{aligned}
$$

The solution of $\beta$ is denoted by $\beta_{G M M}$, which is:

$$
\beta_{G M M}=\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} y
$$

The mean of $\beta_{G M M}$ is asymptotically obtained.

$$
\begin{aligned}
\beta_{G M M} & =\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime}(X \beta+u) \\
& =\beta+\left(X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} \Omega Z\right)^{-1} Z^{\prime} u \\
& =\beta+\left(\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{n} Z^{\prime} X\right)\right)^{-1}\left(\frac{1}{n} X^{\prime} Z\right)\left(\frac{1}{n} Z^{\prime} \Omega Z\right)^{-1}\left(\frac{1}{n} Z^{\prime} u\right)
\end{aligned}
$$

