

- When $E(u_i | x_i) \neq 0$ (continued)

Classical Measurement Error is another case we have a definite idea about the direction of inconsistency.

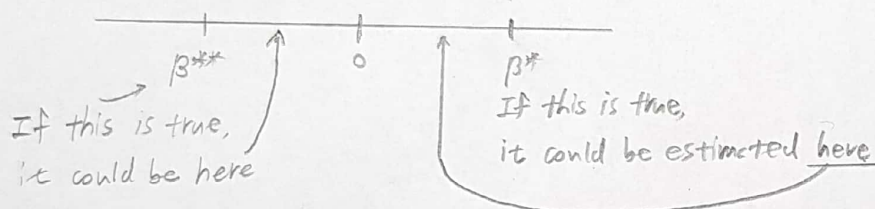
Classical assumption.

① x_i^* & v_i are uncorrelated: $E(x_i^* v_i) = 0$

② v_i & u_i are uncorrelated: $E(v_i u_i) = 0$.

In this case, "bias" or "a direction of consistency" is toward zero.

If the coefficient is positive, it is going to be smaller.
 If " negative, it is going to be bigger



True model $y_i = \alpha + \beta x_i^* + u_i$

But we cannot see x_i^* so that we should use \tilde{x}_i where $\tilde{x}_i = x_i^* + v_i$ (observed)

Then, $y_i = \alpha + \beta(x_i - v_i) + u_i = \alpha + \beta x_i - \beta v_i + u_i$
 x_i, v_i : correlated.

$$\hat{\beta} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\sum_{i=1}^n (x_i - \bar{x}) y_i}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\sum_{i=1}^n (x_i - \bar{x})(\alpha + \beta x_i - \beta v_i + u_i)}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$\sum_{i=1}^n (x_i - \bar{x})(\bar{y}) = -\sum_{i=1}^n x_i \bar{y} + \sum_{i=1}^n \bar{x} \bar{y} = 0$
 $(\because \sum_{i=1}^n x_i = \sum_{i=1}^n \bar{x})$

$$= \frac{\sum_{i=1}^n (x_i - \bar{x}) \alpha + \beta \sum_{i=1}^n (x_i - \bar{x}) x_i - \beta \sum_{i=1}^n (x_i - \bar{x}) (-\beta v_i + u_i)}{\sum_{i=1}^n (x_i - \bar{x})^2} = \beta + \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x}) (u_i - \beta v_i)}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

By $\sum_{i=1}^n (x_i - \bar{x}) \bar{x} = 0$,
 $\sum_{i=1}^n (x_i - \bar{x}) x_i = \sum_{i=1}^n (x_i - \bar{x})^2$

(Note) $\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n} \sum_{i=1}^n x_i^2 - \bar{x}^2 \xrightarrow{P} E(x_i^2) - \{E(x_i)\}^2 = \text{Var}(x_i)$
 $\xrightarrow{P} E(x_i^2)$ by LLN
 $= \text{Var}(x_i^* + v_i)$
 $= \text{Var}(x_i^*) + \text{Var}(v_i)$

(Note) $\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 (u_i - \beta v_i) = \frac{1}{n} \sum_{i=1}^n x_i (u_i - \beta v_i) - \bar{x} \left(\frac{1}{n} \sum_{i=1}^n (u_i - \beta v_i) \right)$

$\downarrow P$ $E\{x_i(u_i - \beta v_i)\}$ $\downarrow P$ $E(u_i - \beta v_i)$

$\xrightarrow{P} E\{x_i(u_i - \beta v_i)\} = E(x_i) \cdot E(u_i - \beta v_i)$

$= E\{x_i^* + v_i\}(u_i - \beta v_i) = E(x_i^* + v_i) E(u_i - \beta v_i)$

$\underbrace{\hspace{10em}}_{=0}$

$= -\beta E(v_i^2) = -\beta \text{Var}(v_i)$

If it is large, it is close to 1.
If not, inconsistency.

$= \beta - \frac{\beta \text{Var}(v_i)}{\text{Var}(x_i^*) + \text{Var}(v_i)} = \beta \left(1 - \frac{\text{Var}(v_i)}{\text{Var}(x_i^*) + \text{Var}(v_i)} \right) = \left(\frac{\text{Var}(x_i^*)}{\text{Var}(x_i^*) + \text{Var}(v_i)} \right) \beta$

* How to deal with $E(u_i | x_i) \neq 0$?

- IV (GMM) / Panel data
- MLE
- Non-parametric method / Semi-parametric method

• Why OLS fails when $E(u_i | x_i) \neq 0$?

F.O.C $\frac{1}{n} \sum_{i=1}^n x_i (y_i - x_i' \hat{\beta}_{OLS}) = 0$

$\underbrace{\hspace{10em}}_{=\hat{u}_i} \rightarrow x_i \text{ and } \hat{u}_i \text{ are orthogonal.}$

We are setting the sample correlation of \hat{u}_i & x_i to be zero.
But when $E(u_i | x_i) \neq 0$, then $E(u_i x_i) \neq 0$.



Find Instrumental Variable, $Z \neq x$

• IV.

What we need to find is a set of K variables $Z_i = \begin{pmatrix} z_{i1} \\ z_{i2} \\ \vdots \\ z_{ik} \end{pmatrix}$ s.t. $E(Z_i u_i) = 0$ (because there are K numbers of unknown β_s).

Then, we can use $\frac{1}{n} \sum_{i=1}^n Z_i (y_i - x_i' \hat{\beta}_{IV}) = 0$, Solve for $\hat{\beta}_{IV}$.

We can call Z_i as instrumental variables.

$$\text{Sol: } \frac{1}{n} \sum_{i=1}^n Z_i y_i = \frac{1}{n} \sum_{i=1}^n Z_i x_i' \hat{\beta}_{IV}$$

$$\begin{pmatrix} z_{i1} \\ z_{i2} \\ \vdots \\ z_{ik} \end{pmatrix} (x_{i1} \ x_{i2} \ \dots \ x_{ik}) = \begin{pmatrix} z_{i1}x_{i1} & z_{i1}x_{i2} & \dots & z_{i1}x_{ik} \\ z_{i2}x_{i1} & z_{i2}x_{i2} & \dots & z_{i2}x_{ik} \\ \vdots & \vdots & \ddots & \vdots \\ z_{ik}x_{i1} & z_{ik}x_{i2} & \dots & z_{ik}x_{ik} \end{pmatrix}$$

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n Z_i x_i' &= \begin{pmatrix} \frac{1}{n} (z_{11}x_{11} + z_{11}x_{21} + \dots + z_{11}x_{n1}) & \dots & \frac{1}{n} (z_{11}x_{1k} + z_{11}x_{2k} + \dots + z_{11}x_{nk}) \\ \vdots & \ddots & \vdots \\ \frac{1}{n} (z_{k1}x_{11} + z_{k1}x_{21} + \dots + z_{k1}x_{n1}) & \dots & \frac{1}{n} (z_{k1}x_{1k} + z_{k1}x_{2k} + \dots + z_{k1}x_{nk}) \end{pmatrix} \\ &= \begin{pmatrix} \frac{1}{n} \sum_{i=1}^n z_{i1}x_{i1} & \frac{1}{n} \sum_{i=1}^n z_{i1}x_{i2} & \dots & \frac{1}{n} \sum_{i=1}^n z_{i1}x_{ik} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{n} \sum_{i=1}^n z_{ik}x_{i1} & \frac{1}{n} \sum_{i=1}^n z_{ik}x_{i2} & \dots & \frac{1}{n} \sum_{i=1}^n z_{ik}x_{ik} \end{pmatrix} \\ &\quad K \times K \text{ matrix.} \end{aligned}$$

Therefore, we need to be able to invert $\frac{1}{n} \sum_{i=1}^n Z_i x_i'$, $K \times K$ matrix.

$E(Z_i x_i')$ invertible.

(If Z_i and x_i are independent,
then $E(Z_i x_i') = E(Z_i) E(x_i')$ \Rightarrow Both of them have rank=1.)
Thus, not suitable for IV.

Therefore, Z_i, X_i should be correlated.

* For IV,

$$\textcircled{1} E(Z_i U_i) = 0 \Leftrightarrow \text{CoV}(Z_i, U_i) = 0$$

$$\textcircled{2} \text{CoV}(Z_i, X_i) \neq 0$$

- If we don't have K IVs, $E(Z_{ij} U_i) = 0 \quad j = 1 \sim J < K$

$$\begin{aligned} \text{then } E(Z_{i1} \cdot (y_i - X_i' \hat{\beta})) &= 0 \\ &\vdots \\ E(Z_{iJ} \cdot (y_i - X_i' \hat{\beta})) &= 0 \end{aligned}$$

↓ Handling $1 \sim J$, $y_i = X_i' \beta + u_i$

$$\begin{pmatrix} E[Z_{i1} (u_i - X_i' (\hat{\beta} - \beta))] \\ E[Z_{iJ} (u_i - X_i' (\hat{\beta} - \beta))] \end{pmatrix} \Rightarrow \begin{aligned} E[Z_{i1} \cdot X_i' (\hat{\beta} - \beta)] &= 0 \\ &\vdots \\ E[Z_{iJ} \cdot X_i' (\hat{\beta} - \beta)] &= 0 \end{aligned}$$

i.e.,

$$\begin{pmatrix} E(Z_{i1} X_i') \\ \vdots \\ E(Z_{iJ} X_i') \end{pmatrix} (\hat{\beta} - \beta) = 0$$

$J \times K$ matrix

가치가 부족하면 일단 이런 상황.

그냥 이것만 가지고 측정하기도 하지만, 실제 이것만 가지고 눈으로는 본질들을...
(Not so much useful...)

- If we have $J > K$, what to do?

⇒ One idea is to find the variables of Z_{i1}, \dots, Z_{iJ} , that has best correlation w/ X_i

Regress X_{i1} on Z_i and find the fitted value $\hat{X}_{i1} = Z_i' \hat{\pi}_1$

Regress X_{i2} on Z_i and " $\hat{X}_{i2} = Z_i' \hat{\pi}_2$

⋮

Regress X_{iK} on Z_i and " $\hat{X}_{iK} = Z_i' \hat{\pi}_K$

2 Stage
least squares.

- IV and 2SLS estimator. $\begin{cases} Z_i: k \times 1 \text{ vector} \\ Z'X: k \times k \text{ matrix} \end{cases}$

Def < IV >

Under $E(u_i | X_i) \neq 0$, assume $E(Z_i u_i) = 0 \Leftrightarrow E(Z' u) = 0$.

$Y = X\beta + u$. By $E(Z_i u_i) = 0$, $\frac{1}{n} \sum_{i=1}^n Z_i (y_i - X_i' \hat{\beta}_{IV}) = 0$

$$\frac{1}{n} Z' (Y - X \hat{\beta}_{IV}) = 0 \quad (\because \hat{u}_{IV} \text{ is orthogonal to } Z)$$

i.e., $Z'(Y - X \hat{\beta}_{IV}) = 0$

$$\Rightarrow \hat{\beta}_{IV} = (Z'X)^{-1} Z'Y = \left(\sum_{i=1}^n Z_i X_i' \right)^{-1} \left(\sum_{i=1}^n Z_i y_i \right)$$

Def < 2SLS >

Regress X_i on Z_i : $\hat{\pi}_i = (Z'Z)^{-1} Z'X_i$

the fitted value \hat{X}_i : $\hat{X}_i = Z \hat{\pi}_i = Z(Z'Z)^{-1} Z'X_i = P_Z X_i$

$$\hat{X}_K = Z \hat{\pi}_K = Z(Z'Z)^{-1} Z'X_K = P_Z X_K$$

Using $\hat{X}_1 \sim \hat{X}_K$ as IV,

IV matrix is $[P_Z X_1 : \dots : P_Z X_K] = P_Z [X_1 : \dots : X_K] = P_Z X$

IV estimating these as IV: $\hat{\beta}_{IV} = (X' P_Z X)^{-1} X' P_Z Y$

$$= (X' P_Z P_Z' X)^{-1} X' P_Z Y$$

(In fact, $P_Z' X$ is OLS estimator)

* Z_{ij} : when $J < K$, useless

when $J > K$, use them for 2SLS.