

① $\{y_i, x_i\}_{i=1}^m$ tal que:

$$y_i = x_i \beta + e_i$$

$$E(e_i | x_i) = 0$$

$$E(e_i^2 | x_i) = \sigma^2(x_i)$$

$$\tilde{\beta} = \frac{\sum_{i=1}^m h(x_i) y_i}{\sum_{i=1}^m h(x_i) x_i} \quad E[h(x_i) x_i] \neq 0$$

c) $\tilde{\beta} = \left[m^{-1} \left(\sum_{i=1}^m h(x_i) x_i \right) \right]^{-1} \left[m^{-1} \sum_{i=1}^m h(x_i) y_i \right]$

$$\tilde{\beta} = \left[m^{-1} \left(\sum_{i=1}^m h(x_i) x_i \right) \right]^{-1} \left[m^{-1} \sum_{i=1}^m h(x_i) (x_i \beta + e_i) \right]$$

$$\tilde{\beta} = \left[m^{-1} \sum_{i=1}^m h(x_i) x_i \right]^{-1} \left[m^{-1} \beta \sum_{i=1}^m h(x_i) x_i + m^{-1} \sum_{i=1}^m h(x_i) e_i \right]$$

$$\tilde{\beta} = \beta + \left[m^{-1} \sum_{i=1}^m h(x_i) x_i \right]^{-1} \left[m^{-1} \sum_{i=1}^m h(x_i) e_i \right]$$

$$\text{plim } \tilde{\beta} = \beta + [E[h(x_i) x_i]]^{-1} E[h(x_i) e_i]$$

$$'' = \beta + [E[h(x_i) x_i]]^{-1} E(h(x_i)) E(e_i)$$

$$'' = \beta + [E[h(x_i) x_i]]^{-1} E[h(x_i)] E[E(e_i | x_i)]$$

$$'' = \beta + [E[h(x_i) x_i]]^{-1} E[h(x_i)] E(0)$$

plim $\tilde{\beta} = \beta$

$$\tilde{\beta} - \beta = \left[m^{-1} \sum_{i=1}^m h(x_i) x_i \right]^{-1} \left[m^{-1} \sum_{i=1}^m h(x_i) e_i \right]$$

$$\sqrt{m} (\tilde{\beta} - \beta) = \left[m^{-1} \sum_{i=1}^m h(x_i) x_i \right]^{-1} \left[m^{-1/2} \sum_{i=1}^m h(x_i) e_i \right]$$

Se sabe que:

$$m^{-1/2} \sum_{i=1}^m h(x_i) e_i \xrightarrow{d} \text{Normal}(0, \sigma_{(x)}^2 E[h(x_i) x_i])$$

De la demostración de consistencia, se sabe que:

$$\left[n^{-1} \sum_{i=1}^n R(x_i) x_i \right]^{-1} = \left[E[R(x_i) x_i] \right]^{-1} = o_p(1)$$

Por lo tanto:

$$\sqrt{n} (\hat{\beta} - \beta) = \left[E[R(x_i) x_i] \right]^{-1} \left[n^{-1} \sum_{i=1}^n R(x_i) e_i \right] + o_p(1)$$

$$\sqrt{n} (\hat{\beta} - \beta) \xrightarrow{d} \text{Normal} \left(0, \underbrace{\sigma_{\hat{\beta}}^2 \left[E[R(x_i) x_i] \right]^{-1}}_{\text{varianza asintótica}} \right).$$

$$b) \quad R(x_i) = \frac{x_i}{\sigma^2(x_i)}$$

$$\begin{aligned} \sigma_{\hat{\beta}}^2 \left[E[R(x_i) x_i] \right]^{-1} &= \sigma_{\hat{\beta}}^2(x_i) \left[E \left(\frac{x_i}{\sigma^2(x_i)} x_i \right) \right]^{-1} \\ &= \sigma^2(x_i) \left(\frac{x_i^2}{\sigma^2(x_i)} \right)^{-1} \\ &= \frac{\sigma^4(x_i)}{x_i^2} \end{aligned}$$

Entonces:

$$\sqrt{n} (\hat{\beta} - \beta) \xrightarrow{d} \text{Normal} \left(0, \frac{\sigma^4(x_i)}{x_i^2} \right)$$

$$\hat{\beta} - \beta \xrightarrow{d} \text{Normal} \left(0, \frac{\sigma^4(x_i)}{x_i^2 n} \right)$$

$$\hat{\beta} \xrightarrow{d} \text{Normal} \left(\beta, \frac{\sigma^4(x_i)}{x_i^2 n} \right).$$

② $f(y) = \frac{1}{\sqrt{2\pi\theta}} e^{\left[-\frac{(y-\theta)^2}{2\theta}\right]}$, donde $\theta > 0$

$$L(y; \theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\theta}} e^{\left[-\frac{(y_i-\theta)^2}{2\theta}\right]}$$

$$L(y; \theta) = \left(\frac{1}{\sqrt{2\pi\theta}}\right)^n e^{\left[-\frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2\right]} \Rightarrow \text{función de verosimilitud}$$

$$\ln[L(y; \theta)] = \ln\left(\frac{1}{\sqrt{2\pi\theta}}\right)^n + \left[-\frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2\right] \ln e$$

$$\ln[L(y; \theta)] = n \ln\left(\frac{1}{\sqrt{2\pi\theta}}\right) - \frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2 \cdot 1$$

$$\ln[L(y; \theta)] = n \ln 1 - n \ln \sqrt{2\pi\theta} - \frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2$$

$$\ln[L(y; \theta)] = n \cdot 0 - \frac{n}{2} \ln 2\pi\theta - \frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2$$

$$\ln[L(y; \theta)] = -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \theta - \frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta)^2$$

\Rightarrow logaritmo de la función de verosimilitud

CPO:

$$\frac{\partial \ln[L(y; \theta)]}{\partial \theta} = 0$$

$$-\frac{n}{2\theta} - \frac{1}{2\theta} \sum_{i=1}^n (y_i - \theta) (-1) = 0$$

$$-\frac{n}{2\theta} + \frac{1}{\theta} \sum_{i=1}^n (y_i - \theta) = 0$$

$$\frac{1}{\theta} \left[\sum_{i=1}^n y_i - \sum_{i=1}^n \theta \right] = \frac{n}{2\theta}$$

$$\frac{2\theta}{\theta} \left[\sum_{i=1}^n y_i - n\theta \right] = n$$

$$2 \left(\sum_{i=1}^n y_i - n\theta \right) = n$$

$$\sum_{i=1}^n y_i - n\theta = \frac{n}{2}$$

$$n\theta = \sum_{i=1}^n y_i - \frac{n}{2}$$

$$\theta = \frac{\sum_{i=1}^n y_i}{n} - \frac{n}{2n}$$

$$\hat{\theta}_{MLE} = \bar{y} - \frac{1}{2}$$

\Rightarrow este valor de máxima verosimilitud de θ .

CS0:

$$\frac{\partial^2 \ln [L(y; \theta)]}{\partial^2 \theta} = \frac{n}{2\theta^2} - \frac{1}{\theta^2} \sum_{i=1}^n (y_i - \theta) (-1)$$

$$= \frac{n}{2\theta^2} + \frac{1}{\theta^2} \sum_{i=1}^n (y_i - \theta)$$

$$= \frac{n + 2 \sum_{i=1}^n (y_i - \theta)}{2\theta^2}$$

$$= \frac{n + 2 \sum_{i=1}^n y_i - 2n\theta}{2\theta^2}$$

$$= \frac{n + 2 \sum_{i=1}^n y_i - 2n\left(\bar{y} - \frac{1}{2}\right)}{2\theta^2} \rightarrow \text{evaluando en } \hat{\theta}_{MLE}$$

$$2\left(\bar{y} - \frac{1}{2}\right)^2$$

$$= \frac{n + 2 \sum_{i=1}^n y_i - 2 \sum_{i=1}^n y_i + n}{2\left(\frac{\sum_{i=1}^n y_i}{n} - \frac{1}{2}\right)^2}$$

$$= \frac{n}{\left(\frac{\sum_{i=1}^n y_i}{n} - \frac{1}{2}\right)^2}$$

< 0 (debe ser pero debo haber fallado en alguna cuenta)

③ $y_i = \alpha_i + \beta_i x_i + \varepsilon_i$

$(y_i, x_i)'$ $i=1, \dots, m$ iid g $E(\varepsilon_i) = E(z_i \varepsilon_i) = 0$

$m=3$

$$\begin{bmatrix} y_1 & x_1 & z_1 \\ y_2 & x_2 & z_2 \\ y_3 & x_3 & z_3 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 1 \\ 4 & 0 & 0 \\ 1 & 1 & -2 \end{bmatrix}$$

a)

$\sqrt{m}(\hat{\beta} - \beta) \xrightarrow{d} \text{Normal} \left(0, \sigma_{(x_i)}^2 \{ E(x'z) [E(z'z)]^{-1} E(z'x) \}^{-1} \right)$

$$\begin{aligned} x'z(z'z)^{-1}z'x &= (-1 \ 0 \ 1) \begin{pmatrix} 1 \\ 0 \\ -2 \end{pmatrix} \left[(1 \ 0 \ -2) \begin{pmatrix} 1 \\ 0 \\ -2 \end{pmatrix} \right]^{-1} (1 \ 0 \ -2) \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix} \\ &= -3 \cdot 5^{-1} \cdot (-3) \\ &= \frac{9}{5} \end{aligned}$$

Entonces, el intervalo del 95% de confianza es:

$$I_{95\%} = \left[-z_{0.975} \cdot \sqrt{\frac{9}{5} \sigma_{(x_i)}^2} + \hat{\beta}_{v1} ; z_{0.025} \sqrt{\frac{9}{5} \sigma_{(x_i)}^2} + \hat{\beta}_{v1} \right]$$

$$\hat{\beta}_{v1} = (E'X)^{-1}E'y = (-3)^{-1} (1 \ 0 \ -2) \begin{pmatrix} 1 \\ 4 \\ 1 \end{pmatrix} = \frac{-1}{3} (-1) = \frac{1}{3}$$

Por lo tanto, se tiene:

$$I_{95\%} = \left[-z_{0.975} \sqrt{\frac{9}{5} \sigma_{(x_i)}^2} + \frac{1}{3} ; z_{0.025} \sqrt{\frac{9}{5} \sigma_{(x_i)}^2} + \frac{1}{3} \right]$$

$$y_i = \alpha + \beta x_i + \delta e_i + \varepsilon_i$$

$$\hat{\beta} = \frac{\text{Cov}(y, x)}{\text{Var}(x)}$$

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

$$- \bar{x} = 0$$

$$- \bar{y} = 2$$

$$\hat{\beta} = \frac{\sum_{i=1}^n x_i (y_i - 2)}{\sum_{i=1}^n x_i^2}$$

$$\hat{\beta} = \frac{\sum_{i=1}^n x_i y_i - 2 \sum_{i=1}^n x_i}{\sum_{i=1}^n x_i^2}$$

$$\hat{\beta} = \sum_{i=1}^n x_i y_i - 2$$

$$\hat{\beta} = -1.1 + 0.4 + 1.1 - 2$$

$$\hat{\beta} = -1 + 0 + 1 - 2$$

$$\hat{\beta} = -2$$

Esta estimación compuesta con la de variables instrumentales debería arrojar las mismas estimaciones debido a que fueron incorporados los residuos de x sobre z , los cuales son los componentes de la endogeneidad en la ecuación $y_i = \alpha + \beta x_i + \varepsilon_i$, debido a estos correlacionados con ε_i , es decir, $\text{Cov}(\varepsilon_i, \varepsilon_i) \neq 0$, por lo cual al incorporar ε_i ya no tenemos esa fuente de endogeneidad en la estimación.