

# Advanced Econometrics

## Chapter 9: Robust OLS and IV

In Choi

Sogang University

# The model and assumptions

- Model

$$y = X\beta + \varepsilon$$

- Assumptions on the error terms

$$(i) E[\varepsilon|X] = 0$$

$$(ii) E[\varepsilon\varepsilon'|X] = \begin{Bmatrix} \sigma^2\Omega \\ \Sigma \end{Bmatrix} \quad (\Omega, \Sigma > 0).$$

# OLS estimation under heteroskedasticity

- Assume heteroskedasticity. That is,

$$\Sigma = \begin{bmatrix} \sigma_1^2 & & & 0 \\ & \ddots & & \vdots \\ & & \ddots & \\ 0 & & & \sigma_n^2 \\ \vdots & & & & \end{bmatrix}$$

- OLS estimation

The OLS estimator can be written as

$$b = \beta + (X'X)^{-1} X'\varepsilon.$$

# OLS estimation under heteroskedasticity

## 1. Unbiasedness

$$E[b] = E[E[b|X]] = \beta.$$

## 2. Variance–Covariance Matrix

$$\begin{aligned} \text{Var}[b|X] &= E[(b - \beta)(b - \beta)' | X] \\ &= E\left[(X'X)^{-1} X' \varepsilon \varepsilon' X (X'X)^{-1} | X\right] \\ &= (X'X)^{-1} X' \Sigma X (X'X)^{-1}. \end{aligned}$$

The unconditional variance is

$$E[\text{Var}[b|X]].$$

If  $\varepsilon$  is normally distributed,

$$b|X \sim N\left(\beta, (X'X)^{-1} X' \Sigma X (X'X)^{-1}\right).$$

# OLS estimation under heteroskedasticity

## 3. Consistency

Suppose that

$$\frac{X'X}{n} \xrightarrow{p} Q > 0$$

$$\frac{X'\Sigma X}{n} \xrightarrow{p} P > 0.$$

Then

$$\begin{aligned} \text{Var}[b|X] &= \frac{1}{n} \left( \frac{X'X}{n} \right)^{-1} \frac{X'\Sigma X}{n} \left( \frac{X'X}{n} \right)^{-1} \\ &\xrightarrow{p} 0 \end{aligned}$$

and

$$\text{Var}[b] \xrightarrow{p} 0.$$

# OLS estimation under heteroskedasticity

Using this and Chebyshev's inequality, we have for and  $\alpha \in \mathbb{R}^k - \{0\}$  and  $\varepsilon > 0$

$$\begin{aligned} P [ |\alpha' (b - \beta)| > \varepsilon ] &\leq \frac{\alpha' E (b - \beta) (b - \beta)' \alpha}{\varepsilon^2} \\ &= \frac{\alpha' \text{Var} (b) \alpha}{\varepsilon^2} \\ &\rightarrow 0 \text{ as } n \rightarrow \infty \end{aligned}$$

which implies

$$b \xrightarrow{P} \beta.$$

## 4. Asymptotic distribution of $b$

Assume  $(x_i, \varepsilon_i)$  is a sequence of independent observations with

$$\begin{aligned} E(\varepsilon\varepsilon') &= \text{diag}(\sigma_1^2, \dots, \sigma_n^2) \\ &= \Sigma. \end{aligned}$$

In addition, assume for any  $\lambda \in \mathbb{R}^k - \{0\}$  and  $\delta > 0$

$$E|\lambda'x_i\varepsilon_i|^{2+\delta} \leq B \text{ for all } i.$$

Then, we can apply the CLT for a sequence of independent random variables, with gives

$$\frac{\sum_{i=1}^n \lambda'x_i\varepsilon_i}{\sqrt{n}} \xrightarrow{d} N\left(0, \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n E(\lambda'x_i\varepsilon_i^2x_i'\lambda)\right).$$

But

$$\begin{aligned}\frac{1}{n} \sum_{i=1}^n E (\lambda' x_i \varepsilon_i^2 x_i' \lambda) &= \frac{1}{n} \sum_{i=1}^n E E (\lambda' x_i \varepsilon_i^2 x_i' \lambda | X) \\ &= \frac{1}{n} \sum_{i=1}^n \sigma_i^2 \lambda' E (x_i x_i') \lambda \\ &= \frac{1}{n} \lambda' \sum_{i=1}^n \sigma_i^2 E (x_i x_i') \lambda \\ &\rightarrow \text{plim} \frac{1}{n} \lambda' \sum_{i=1}^n \sigma_i^2 x_i x_i' \lambda \\ &= \text{plim} \frac{1}{n} \lambda' (X' \Sigma X) \lambda.\end{aligned}$$



Thus

$$\frac{\sum_{i=1}^n x_i \varepsilon_i}{\sqrt{n}} \xrightarrow{d} N(0, P),$$

where

$$P = \text{plim} \frac{1}{n} X' \Sigma X,$$

and we obtain

$$\sqrt{n}(b - \beta) \xrightarrow{d} N(0, Q^{-1} P Q^{-1}).$$

- IV estimation

The IV estimator is written as

$$b_{IV} = \beta + (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'\epsilon.$$

Assume  $(z_i', \epsilon_i)'$  is a sequence of independent random vectors with

$$E(\epsilon\epsilon'|Z) = \text{diag}(\sigma_1^2, \dots, \sigma_n^2) = \Sigma$$

and  $E|\lambda'z_i\epsilon_i|^{2+\delta} \leq B$  for all  $i$  for any  $\lambda \in \mathbb{R}^k - \{0\}$  and  $\delta > 0$ .

# IV estimation under heteroskedasticity

- In addition, assume

$$\begin{aligned}\frac{Z'Z}{n} &\xrightarrow{p} Q_{ZZ} (> 0) \\ \frac{Z'X}{n} &\xrightarrow{p} Q_{ZX} (\neq 0) \\ \frac{X'X}{n} &\xrightarrow{p} Q_{XX} (> 0) \\ \frac{Z'\Sigma Z}{n} &\xrightarrow{p} Q_{Z\Sigma Z}.\end{aligned}$$

- The CLT gives

$$\frac{\sum_{i=1}^n z_i \varepsilon_i}{\sqrt{n}} \xrightarrow{d} N \left( 0, \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^{\infty} E(z_i \varepsilon_i^2 z_i') \right) = N(0, Q_{Z\Sigma Z})$$

as before.

- Let

$$Q_{XX.Z} = (Q_{XZ} Q_{ZZ}^{-1} Q_{ZX})^{-1} Q_{XZ} Q_{ZZ}^{-1},$$

which is the probability limit of  $\frac{1}{n}(X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}$ .  
Then, we obtain

$$\sqrt{n}(b_{IV} - \beta) \xrightarrow{d} N(0, Q_{XX.Z} Q_{ZZ\Sigma Z} Q'_{XX.Z}).$$

# Robust estimation of asymptotic covariance matrices

- We can still use OLS for inference if its variance–covariance matrix

$$(X'X)^{-1} X'\Sigma X (X'X)^{-1}$$

can be estimated.

- Notice that

$$\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_n^2).$$

Obviously,  $\sigma_1^2, \dots, \sigma_n^2$  cannot be estimated. But what we need is to estimate  $X'\Sigma X$  not  $\Sigma$ .

- We may write

$$\frac{1}{n} X'\Sigma X = \frac{1}{n} \sum_{i=1}^n \sigma_i^2 x_i x_i'.$$

# Robust estimation of asymptotic covariance matrices

- This and

$$\frac{1}{n} \sum_{i=1}^n \varepsilon_i^2 x_i x_i'$$

have the same probability limit by the LLN. We replace  $\varepsilon_i^2$  with  $e_i^2$  (OLS residuals) and, then, have

$$\begin{aligned} & \frac{1}{n} \sum_{i=1}^n e_i^2 x_i x_i' \\ = & \frac{1}{n} \sum_{i=1}^n [\varepsilon_i - x_i' (\hat{\beta} - \beta)]^2 x_i x_i' \\ = & \frac{1}{n} \sum_{i=1}^n \varepsilon_i^2 x_i x_i' + o_p(1). \end{aligned}$$

(See White, 1980, *Econometrica* for details)

# Robust estimation of asymptotic covariance matrices

- Thus  $\frac{1}{n} \sum_{i=1}^n e_i^2 x_i x_i'$  consistently estimate  $\frac{1}{n} X' \Sigma X$ , and the estimated asymptotic variance–covariance matrix  $b$  is

$$\left( \frac{1}{n} X' X \right)^{-1} \left( \frac{1}{n} \sum_{i=1}^n e_i^2 x_i x_i' \right) \left( \frac{1}{n} X' X \right)^{-1} \xrightarrow{p} Q^{-1} P Q^{-1}.$$

- We can use this result for hypothesis testing. Suppose that the null hypothesis is

$$H_0 : R\beta = r.$$

# Robust estimation of asymptotic covariance matrices

- Then, Wald test is defined by

$$W = (Rb - r)' \left[ R (X'X)^{-1} \sum_{i=1}^n e_i^2 x_i x_i' (X'X)^{-1} R' \right]^{-1} (Rb - r),$$

(heteroskedasticity robust Wald test)

and as  $n \rightarrow \infty$

$$W \xrightarrow{d} \chi^2(J), \quad J = \text{rank}(R).$$

- This follows because

$$\begin{aligned} W &= \sqrt{n} (Rb - r)' \left[ R \left( \frac{X'X}{n} \right)^{-1} \left( \frac{1}{n} \sum_{i=1}^n e_i^2 x_i x_i' \right) \left( \frac{X'X}{n} \right)^{-1} R' \right]^{-1} \\ &\quad \times \sqrt{n} (Rb - r) \\ &\xrightarrow{d} N(0, I_J)' N(0, I_J) = \chi^2(J). \end{aligned}$$



# Robust estimation of asymptotic covariance matrices

- If the null hypothesis is  $H_0 : \beta_k = \beta_k^0$ , use the t-ratio

$$t = \frac{b_k - \beta_k^0}{\sqrt{V_{kk}}}$$

where

$$V = (X'X)^{-1} \sum_{i=1}^n e_i^2 x_i x_i' (X'X)^{-1}.$$

As  $n \rightarrow \infty$

$$t \xrightarrow{d} N(0, 1).$$

This is celebrated White's heteroskedasticity robust t-ratio.