

Advanced Econometric Methods

EMET3011/8014

Lecture 12

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Announcements/Reminders

- Please get a fresh copy of the course notes PDF
- No more changes to course notes
- No computer lab today
- Today's lab time is extra office hours
- After today you can meet me/Varang by appointment

Today's Lecture

- Large Sample OLS

Large Sample OLS

We now return to the linear regression problem

Introduce more reasonable assumptions

Establish consistency and asymptotic normality

Assumptions

We retain the linear model assumption

$$y_t = \mathbf{x}_t' \boldsymbol{\beta} + u_t \quad (t = 1, \dots, T)$$

- Notation: t (resp., T) instead of n (resp., N)

The other OLS assumptions are adjusted as follows:

Assumption. (Ergodic Regressors): The sequence $\{\mathbf{x}_t\}$ is

1. identically distributed
2. satisfies $\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \xrightarrow{p} \mathbb{E} [\mathbf{x}_t \mathbf{x}_t'] =: \boldsymbol{\Sigma}_{xx}$ as $T \rightarrow \infty$
3. $\boldsymbol{\Sigma}_{xx}$ is positive definite

Note: Independence is not required

Example: Markov process with

- Unique, globally stable stationary distribution π_∞
- $\mathbf{x}_1 \sim \pi_\infty$
- $\mathbb{E} [\mathbf{x}_t \mathbf{x}_t']$ positive definite

Assumption. (Weak Exogeneity):

1. $\{u_t\}$ is IID with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t^2] = \sigma^2$
2. u_t and $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_t$ independent for all t

Note: Current shocks permitted to affect future regressors

Example: AR(1) model with IID shocks (see last lecture)

- $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_t =$ lagged state variables y_0, \dots, y_{t-1}
- These are functions of u_0, \dots, u_{t-1}
- Hence independent of u_t

Estimators

Expression for estimator of β is unchanged:

$$\hat{\beta}_T := (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

We require as before that \mathbf{X} is full column rank

To estimate σ^2 we use

$$\hat{\sigma}_T^2 := \frac{\text{SSR}}{T}$$

(Not $T - K$ because the difference will be insignificant)

Recall that

$$\hat{\beta}_T - \beta = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{u}$$

Multiplying and dividing by T ,

$$\hat{\beta}_T - \beta = \left[\frac{1}{T} \mathbf{X}'\mathbf{X} \right]^{-1} \cdot \frac{1}{T} \mathbf{X}'\mathbf{u}$$

Expanding out the matrix products (exercise), we obtain

$$\hat{\beta}_T - \beta = \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right]^{-1} \cdot \frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t$$

What happens to these two sample means as $T \rightarrow \infty$?

Lemma. If ER and WE hold, then

$$\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t \xrightarrow{p} \mathbf{0}$$

and

$$T^{-1/2} \sum_{t=1}^T \mathbf{x}_t u_t \xrightarrow{d} \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \mathbf{\Sigma}_{xx})$$

Proof: Suffices to show that, for any vector $\mathbf{a} \in \mathbb{R}^K$,

$$\mathbf{a}' \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t \right] \xrightarrow{p} \mathbf{a}' \mathbf{0} \quad \text{and} \quad \mathbf{a}' \left[T^{-1/2} \sum_{t=1}^T \mathbf{x}_t u_t \right] \xrightarrow{d} \mathbf{a}' \mathbf{z}$$

Equivalent: Suffices to show that

$$\frac{1}{T} \sum_{t=1}^T m_t \xrightarrow{p} 0 \quad \text{and} \quad T^{-1/2} \sum_{t=1}^T m_t \xrightarrow{d} \mathcal{N}(0, \sigma^2 \mathbf{a}' \boldsymbol{\Sigma}_{\mathbf{x}\mathbf{x}} \mathbf{a})$$

where

$$m_t := \mathbf{a}' \mathbf{x}_t u_t$$

Strategy:

- Show that $\{m_t\}$ is an MDS
- Apply MDS LLN/CLT

Let $\mathcal{F}_t := \{\mathbf{x}_1, \dots, \mathbf{x}_t, \mathbf{x}_{t+1}, u_1, \dots, u_t\}$

Claim: If ER and WE hold, then $m_t := \mathbf{a}'\mathbf{x}_t u_t$ is

1. a MDS with respect to $\{\mathcal{F}_t\}$
2. identically distributed with $\mathbb{E}[m_t^2] = \sigma^2 \mathbf{a}'\Sigma_{xx}\mathbf{a}$
3. satisfies $\frac{1}{T} \sum_{t=1}^T \mathbb{E}[m_t^2 | \mathcal{F}_{t-1}] \xrightarrow{p} \sigma^2 \mathbf{a}'\Sigma_{xx}\mathbf{a}$

The MDS LLN/CLT now yields claim on previous slide:

$$\frac{1}{T} \sum_{t=1}^T m_t \xrightarrow{p} 0 \quad \text{and} \quad T^{-1/2} \sum_{t=1}^T m_t \xrightarrow{d} \mathcal{N}(0, \sigma^2 \mathbf{a}'\Sigma_{xx}\mathbf{a})$$

▷ Proof that $m_t = \mathbf{a}'\mathbf{x}_t u_t$ is a MDS with respect to

$$\mathcal{F}_t := \{\mathbf{x}_1, \dots, \mathbf{x}_t, \mathbf{x}_{t+1}, u_1, \dots, u_t\}$$

Clearly $\{m_t\}$ is adapted to $\{\mathcal{F}_t\}$

Moreover,

$$\begin{aligned}\mathbb{E}[m_{t+1} \mid \mathcal{F}_t] &= \mathbb{E}[u_{t+1} \mathbf{a}'\mathbf{x}_{t+1} \mid \mathcal{F}_t] \\ &= \mathbf{a}'\mathbf{x}_{t+1} \mathbb{E}[u_{t+1} \mid \mathcal{F}_t] && (\because \mathbf{x}_{t+1} \in \mathcal{F}_t) \\ &= \mathbf{a}'\mathbf{x}_{t+1} \mathbb{E}[u_{t+1}] \\ &= \mathbf{a}'\mathbf{x}_{t+1} 0 \\ &= 0\end{aligned}$$

▷ Proof that $\mathbb{E} [m_t^2] = \sigma^2 \mathbf{a}' \boldsymbol{\Sigma}_{xx} \mathbf{a}$

$$\mathbb{E} [m_t^2] = \mathbb{E} [u_t^2 (\mathbf{a}' \mathbf{x}_t)^2] = \mathbb{E} [u_t^2] \mathbb{E} [(\mathbf{a}' \mathbf{x}_t)^2] = \sigma^2 \mathbb{E} [(\mathbf{a}' \mathbf{x}_t)^2]$$

$$(\mathbf{a}' \mathbf{x}_t)^2 = \mathbf{a}' \mathbf{x}_t \mathbf{a}' \mathbf{x}_t = \mathbf{a}' \mathbf{x}_t \mathbf{x}_t' \mathbf{a} \text{ by symmetry of inner product}$$

$$\therefore \mathbb{E} [(\mathbf{a}' \mathbf{x}_t)^2] = \mathbf{a}' \mathbb{E} [\mathbf{x}_t \mathbf{x}_t'] \mathbf{a} = \mathbf{a}' \boldsymbol{\Sigma}_{xx} \mathbf{a}$$

$$\therefore \mathbb{E} [m_t^2] = \sigma^2 \mathbf{a}' \boldsymbol{\Sigma}_{xx} \mathbf{a}$$

▷ Proof that $\frac{1}{T} \sum_{t=1}^T \mathbb{E} [m_t^2 | \mathcal{F}_{t-1}] \xrightarrow{p} \sigma^2 \mathbf{a}' \boldsymbol{\Sigma}_{xx} \mathbf{a}$

Since $\mathbf{x}_t \in \mathcal{F}_{t-1}$, we have

$$\mathbb{E} [m_t^2 | \mathcal{F}_{t-1}] = \mathbb{E} [u_t^2 (\mathbf{a}' \mathbf{x}_t)^2 | \mathcal{F}_{t-1}] = \sigma^2 (\mathbf{a}' \mathbf{x}_t)^2 = \sigma^2 \mathbf{a}' \mathbf{x}_t \mathbf{x}_t' \mathbf{a}$$

$$\therefore \frac{1}{T} \sum_{t=1}^T \mathbb{E} [m_t^2 | \mathcal{F}_{t-1}] = \frac{1}{T} \sum_{t=1}^T (\sigma^2 \mathbf{a}' \mathbf{x}_t \mathbf{x}_t' \mathbf{a}) = \sigma^2 \mathbf{a}' \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right] \mathbf{a}$$

Applying ER, we get $\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \xrightarrow{p} \boldsymbol{\Sigma}_{xx}$

$$\therefore \frac{1}{T} \sum_{t=1}^T \mathbb{E} [m_t^2 | \mathcal{F}_{t-1}] \xrightarrow{p} \sigma^2 \mathbf{a}' \boldsymbol{\Sigma}_{xx} \mathbf{a}$$

That was a lot of work. . .

But we can now easily prove:

- Consistency of $\hat{\beta}_T$
- Consistency of $\hat{\sigma}_T^2$
- Asymptotic normality of $\hat{\beta}_T$

In the next three slides we assume ER and WE hold

Theorem. $\hat{\beta}_T \xrightarrow{p} \beta$ as $T \rightarrow \infty$

Proof: Recall that

$$\hat{\beta}_T - \beta = \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right]^{-1} \cdot \frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t$$

$$\left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right]^{-1} \xrightarrow{p} \Sigma_{\mathbf{xx}}^{-1} \quad \text{and} \quad \frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t \xrightarrow{p} \mathbf{0}$$

$$\therefore \hat{\beta}_T - \beta \xrightarrow{p} \Sigma_{\mathbf{xx}}^{-1} \mathbf{0} = \mathbf{0}$$

$$\therefore \hat{\beta}_T \xrightarrow{p} \beta$$

Theorem. $\hat{\sigma}_T^2 := \frac{SSR}{T} \xrightarrow{p} \sigma^2$

Proof: Using $y_t = \mathbf{x}_t' \boldsymbol{\beta} + u_t$ and $\boldsymbol{\gamma}_T := \boldsymbol{\beta} - \hat{\boldsymbol{\beta}}_T$, we have

$$\hat{\sigma}_T^2 = \frac{1}{T} \sum_{t=1}^T (y_t - \mathbf{x}_t' \hat{\boldsymbol{\beta}}_T)^2 = \frac{1}{T} \sum_{t=1}^T (u_t + \mathbf{x}_t' \boldsymbol{\gamma}_T)^2$$

Expanding out the square,

$$\begin{aligned} \hat{\sigma}_T^2 &= \frac{1}{T} \sum_{t=1}^T u_t^2 + 2\boldsymbol{\gamma}_T' \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t u_t \right] + \boldsymbol{\gamma}_T' \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right] \boldsymbol{\gamma}_T \\ &\xrightarrow{p} \sigma^2 + 0 + 0 \end{aligned}$$

- Check details
- Check same true if $\hat{\sigma}_T^2 := \frac{SSR}{T-K}$

Asymptotic Normality

Theorem. $\sqrt{T}(\hat{\beta}_T - \beta) \xrightarrow{d} \mathcal{N}(\mathbf{0}, \sigma^2 \Sigma_{\mathbf{xx}}^{-1})$

Proof: Observe that

$$\sqrt{T}(\hat{\beta}_T - \beta) = \left[\frac{1}{T} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \right]^{-1} \cdot \left[T^{-1/2} \sum_{t=1}^T \mathbf{x}_t u_t \right]$$

$$T^{-1/2} \sum_{t=1}^T u_t \mathbf{x}_t \xrightarrow{d} \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \Sigma_{\mathbf{xx}})$$

$$\therefore \sqrt{T}(\hat{\beta}_T - \beta) \xrightarrow{d} \Sigma_{\mathbf{xx}}^{-1} \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \Sigma_{\mathbf{xx}}^{-1} \text{var}[\mathbf{z}] \Sigma_{\mathbf{xx}}^{-1})$$

Result follows because $\Sigma_{\mathbf{xx}}^{-1} \text{var}[\mathbf{z}] \Sigma_{\mathbf{xx}}^{-1} = \Sigma_{\mathbf{xx}}^{-1} \sigma^2 \Sigma_{\mathbf{xx}} \Sigma_{\mathbf{xx}}^{-1} = \sigma^2 \Sigma_{\mathbf{xx}}^{-1}$

Finally:

- Keep checking course home page — practice questions coming
- Review the lecture slides — check the details!

Exam:

- Will cover the whole course with emph on latter half
- No R questions, just analytical exercises