Introductory Econometrics

Lecture 18: The asymptotic variance of OLS and heteroskedasticity

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Asymptotic normality

- In the previous lecture, we showed that when the data are iid and the regressors are exogenous:

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 X_i + U_i, \\ \mathrm{E}[U_i] &= \mathrm{E}[X_i U_i] = 0, \end{aligned}$$

  the OLS estimator of β_1 is asymptotically normal:

$$\sqrt{n}\left(\hat{\beta}_{1,n} - \beta_1\right) \to_d \mathrm{N}(0, V),$$
$$V = \frac{\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2\right]}{(\mathrm{Var}[X_i])^2}.$$

- For the purpose of hypothesis testing, we need to obtain a consistent estimator of the asymptotic variance V:

$$\hat{V}_n \to_p V.$$

Homoskedastic errors

- Let's assume that the errors are homoskedastic:

$$\mathrm{E}\left[U_i^2 \mid X_i\right] = \sigma^2 \text{ for all } X_i\text{'s.}$$

- In this case, the asymptotic variance can be simplified using the Law of Iterated Expectation:

$$\begin{aligned}
\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2\right] &= \mathrm{E}\left[\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2 \mid X_i\right]\right] \\
&= \mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 \mathrm{E}\left[U_i^2 \mid X_i\right]\right] \\
&= \mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 \sigma^2\right] \\
&= \sigma^2 \mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2\right] = \sigma^2 \mathrm{Var}[X_i].
\end{aligned}$$

- Thus, when the errors are homoskedastic with $\mathrm{E}\left[U_i^2\right] = \sigma^2$,

$$V = \frac{\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2\right]}{(\mathrm{Var}[X_i])^2} = \frac{\sigma^2 \mathrm{Var}[X_i]}{(\mathrm{Var}[X_i])^2} = \frac{\sigma^2}{\mathrm{Var}[X_i]}.$$

- Let $\hat{U}_i = Y_i - \hat{\beta}_{0,n} - \hat{\beta}_{1,n} X_i$, where $\hat{\beta}_{0,n}$ and $\hat{\beta}_{1,n}$ are the OLS estimators of β_0 and β_1.
- A consistent estimator for the asymptotic variance can be constructed by using the Method of Moments.

$$\hat{\sigma}_n^2 = \frac{1}{n} \sum_{i=1}^{n} \hat{U}_i^2,$$

$$\widehat{\mathrm{Var}}[X_i] = \frac{1}{n} \sum_{i=1}^{n} \left(X_i - \bar{X}_n\right)^2, \text{ and}$$

$$\hat{V}_n = \frac{\hat{\sigma}_n^2}{\frac{1}{n} \sum_{i=1}^{n} \left(X_i - \bar{X}_n\right)^2}.$$

$$\hat{V}_n = \frac{\hat{\sigma}_n^2}{\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2}, \qquad \hat{\sigma}_n^2 = \frac{1}{n}\sum_{i=1}^n \hat{U}_i^2, \qquad \hat{U}_i = Y_i - \hat{\beta}_{0,n} - \hat{\beta}_{1,n} X_i.$$

- When proving the consistency of OLS, we showed that

$$\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2 \to_p \operatorname{Var}\left[X_i\right],$$

  and to establish $\hat{V}_n \to_p V$, we need to show that $\hat{\sigma}_n^2 \to_p \sigma^2$.
- Note that the LLN cannot be applied directly to

$$\frac{1}{n}\sum_{i=1}^n \hat{U}_i^2$$

  because $\hat{U}_i$'s are not iid: they are dependent through $\hat{\beta}_{0,n}$ and $\hat{\beta}_{1,n}$.

Proof of $\hat{\sigma}_n^2 \to_p \sigma^2$

- First, write

$$
\begin{aligned}
\hat{U}_i &= Y_i - \hat{\beta}_{0,n} - \hat{\beta}_{1,n} X_i \\
&= (\beta_0 + \beta_1 X_i + U_i) - \hat{\beta}_{0,n} - \hat{\beta}_{1,n} X_i \\
&= U_i - \left(\hat{\beta}_{0,n} - \beta_0\right) - \left(\hat{\beta}_{1,n} - \beta_1\right) X_i
\end{aligned}
$$

- Now,

$$
\hat{\sigma}_n^2 = \frac{1}{n} \sum_{i=1}^{n} \hat{U}_i^2 = \frac{1}{n} \sum_{i=1}^{n} \left(U_i - \left(\hat{\beta}_{0,n} - \beta_0\right) - \left(\hat{\beta}_{1,n} - \beta_1\right) X_i\right)^2 .
$$

- We have

$$\begin{aligned} \hat{\sigma}_n^2 &= \frac{1}{n}\sum_{i=1}^{n}\left(U_i - \left(\hat{\beta}_{0,n} - \beta_0\right) - \left(\hat{\beta}_{1,n} - \beta_1\right) X_i\right)^2 \\ &= \frac{1}{n}\sum_{i=1}^{n} U_i^2 + \left(\hat{\beta}_{0,n} - \beta_0\right)^2 + \left(\hat{\beta}_{1,n} - \beta_1\right)^2 \frac{1}{n}\sum_{i=1}^{n} X_i^2 \\ &\quad -2\left(\hat{\beta}_{0,n} - \beta_0\right)\frac{1}{n}\sum_{i=1}^{n} U_i - 2\left(\hat{\beta}_{1,n} - \beta_1\right)\frac{1}{n}\sum_{i=1}^{n} U_i X_i \\ &\quad +2\left(\hat{\beta}_{0,n} - \beta_0\right)\left(\hat{\beta}_{1,n} - \beta_1\right)\frac{1}{n}\sum_{i=1}^{n} X_i. \end{aligned}$$

- By the LLN,

$$\frac{1}{n}\sum_{i=1}^{n} U_i^2 \to_p \mathrm{E}\left[U_i^2\right] = \sigma^2.$$

- Because $\hat{\beta}_{0,n}$ and $\hat{\beta}_{1,n}$ are consistent,

$$\hat{\beta}_{0,n} - \beta_0 \to_p 0 \text{ and } \hat{\beta}_{1,n} - \beta_1 \to_p 0.$$

Homoskedastic errors

- Thus, when the errors are homoskedastic,

$$\hat{V}_n = \frac{\hat{\sigma}_n^2}{\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2}, \text{ with } \hat{\sigma}_n^2 = \frac{1}{n}\sum_{i=1}^n \hat{U}_i^2,$$

  is a consistent estimator of $V = \frac{\sigma^2}{\text{Var}[X_i]}$.
- Note that

$$s^2 = \frac{1}{n-2}\sum_{i=1}^n \hat{U}_i^2 \to_p \sigma^2,$$

  and therefore

$$\hat{V}_n = \frac{s^2}{\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2}$$

  is also a consistent estimator of $V = \frac{\sigma^2}{\text{Var}[X_i]}$.
- This version has an advantage over the one with $\hat{\sigma}_n^2$: in addition to being consistent, s^2 is also an unbiased estimator of σ^2 if the regressors are strongly exogenous.

Homoskedastic errors: Asymptotic approximation

- Recall that $\sqrt{n}\left(\hat{\beta}_{1,n} - \beta_1\right) \to_d \mathrm{N}(0, V)$ is used as the following approximation:
$$\hat{\beta}_{1,n} \overset{a}{\sim} \mathrm{N}\left(\beta_1, \frac{V}{n}\right),$$
where $\overset{a}{\sim}$ denotes approximately in large samples. Thus, the variance of $\hat{\beta}_{1,n}$ can be taken as approximately V/n.
- Note that, with $\hat{V}_n = \frac{s^2}{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2}$ we have
$$\frac{\hat{V}_n}{n} = \frac{s^2}{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2}\frac{1}{n} = \frac{s^2}{\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2}.$$

$$\frac{\hat{V}_n}{n} = \frac{s^2}{\sum_{i=1}^{n} \left(X_i - \bar{X}_n\right)^2}$$

- Thus, in the case of homoskedastic errors we have the following asymptotic approximation:

$$\hat{\beta}_{1,n} \overset{a}{\sim} \mathrm{N}\left(\beta_1, \frac{s^2}{\sum_{i=1}^{n} \left(X_i - \bar{X}_n\right)^2}\right).$$

- In finite samples, we have the same result exactly, when the regressors are strongly exogenous and the errors are normal.

Asymptotic T-test

- Consider testing $\mathrm{H}_0 : \beta_1 = \beta_{1,0}$ vs $\mathrm{H}_1 : \beta_1 \neq \beta_{1,0}$.
- Consider the behavior of T statistic under $\mathrm{H}_0 : \beta_1 = \beta_{1,0}$. Since

$$\sqrt{n}\left(\hat{\beta}_{1,n} - \beta_1\right) \to_d \mathrm{N}(0, V) \text{ and } \hat{V}_n \to_p V,$$

we have that

$$\begin{aligned} T = \frac{\left(\hat{\beta}_{1,n} - \beta_{1,0}\right)}{\sqrt{\hat{V}_n / n}} &= \frac{\sqrt{n}\left(\hat{\beta}_{1,n} - \beta_{1,0}\right)}{\sqrt{\hat{V}_n}} \\ &\overset{\mathrm{H}_0}{=} \frac{\sqrt{n}\left(\hat{\beta}_{1,n} - \beta_1\right)}{\sqrt{\hat{V}_n}} \\ &\to_d \frac{\mathrm{N}(0, V)}{\sqrt{V}} =_d \mathrm{N}(0, 1). \end{aligned}$$

- We have that under $\mathrm{H}_0 : \beta_1 = \beta_{1,0}$,

$$T = \frac{\left(\hat{\beta}_{1,n} - \beta_{1,0}\right)}{\sqrt{\hat{V}_n / n}} \to_d \mathrm{N}(0,1),$$

  provided that $\hat{V}_n \to_p V$ (the asymptotic variance of $\hat{\beta}_{1,n}$).
- An asymptotic size α test rejects $\mathrm{H}_0 : \beta_1 = \beta_{1,0}$ against $\mathrm{H}_1 : \beta_1 \neq \beta_{1,0}$ when

$$|T| > z_{1-\alpha/2},$$

  where $z_{1-\alpha/2}$ is a standard normal critical value.
- Asymptotically, the variance of the OLS estimator is known - we behave as if the variance was known.

Heteroskedastic errors

- In general, the errors are heteroskedastic: $\mathrm{E}\left[U_i^2 \mid X_i\right]$ is not constant and changes with X_i.
- In this case, $\hat{V}_n = \frac{s^2}{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2}$ is not a consistent estimator of the asymptotic variance $V = \frac{\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2\right]}{(\mathrm{Var}[X_i])^2}$:

$$
\begin{aligned}
\frac{s^2}{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2} \to_p \frac{\mathrm{E}\left[U_i^2\right]}{\mathrm{Var}\left[X_i\right]} \quad &= \quad \frac{\left(\mathrm{E}\left[(X_i - \mathrm{E}\left[X_i\right])^2\right]\right)\left(\mathrm{E}\left[U_i^2\right]\right)}{\left(\mathrm{Var}\left[X_i\right]\right)^2} \\
&\neq \quad \frac{\mathrm{E}\left[(X_i - \mathrm{E}\left[X_i\right])^2 U_i^2\right]}{\left(\mathrm{Var}\left[X_i\right]\right)^2}.
\end{aligned}
$$

A heteroskedasticity consistent (HC) estimator of the asymptotic variance of OLS

- In the case of heteroskedastic errors, a consistent estimator of $V = \frac{\mathrm{E}\left[(X_i - \mathrm{E}[X_i])^2 U_i^2\right]}{(\mathrm{Var}[X_i])^2}$ can be constructed as follows:

$$\hat{V}_n^{HC} = \frac{\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2 \hat{U}_i^2}{\left(\frac{1}{n}\sum_{i=1}^n \left(X_i - \bar{X}_n\right)^2\right)^2}.$$

- One can show that $\hat{V}_n^{HC} \to_p V$ when the errors are heteroskedastic or homoskedastic.
- We have the following asymptotic approximation:

$$\hat{\beta}_{1,n} \overset{a}{\sim} \mathrm{N}\left(\beta_1, \frac{\hat{V}_n^{HC}}{n}\right),$$

  and the standard errors can be computed as $SE\left(\hat{\beta}_{1,n}\right) = \sqrt{\hat{V}_n^{HC}/n}$.

HC variance estimation in Stata

- In Stata, the HC estimator of standard errors can be obtained by adding the option `robust` to the regression command:

```
. regress liver alcohol, robust
```

liver	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
alcohol	3.586388	.550515	6.51	0.000	2.434147	4.73863
_cons	10.85482	2.119993	5.12	0.000	6.417625	15.29202

- Compare with the non-HC standard errors based on $\hat{V}_n$:

```
. regress liver alcohol
```

liver	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
alcohol	3.586388	.7541228	4.76	0.000	2.007991	5.164786
_cons	10.85482	2.802408	3.87	0.001	4.989313	16.72033