

Economics 326
Methods of Empirical Research in Economics
Lecture 6: Estimating the variance of errors

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The importance of σ^2

- ▶ The variance of $\hat{\beta}$ depends on unknown $\sigma^2 = EU_i^2$:

$$\text{Var}(\hat{\beta} | X_1, \dots, X_n) = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

- ▶ If U 's were observable, we could estimate σ^2 by $\frac{1}{n} \sum_{i=1}^n U_i^2$.
- ▶ Note that $E\left(\frac{1}{n} \sum_{i=1}^n U_i^2\right) = \frac{1}{n} \sum_{i=1}^n EU_i^2 = \frac{1}{n} \sum_{i=1}^n \sigma^2 = \sigma^2$.
- ▶ However, such an estimator is infeasible.
- ▶ Instead, we have \hat{U} 's:

$$\hat{U}_i = Y_i - \hat{\alpha} - \hat{\beta}X_i.$$

- ▶ A feasible estimator of σ^2 is

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

- ▶ It turns out that $\hat{\sigma}^2$ is biased.

An unbiased estimator of σ^2

- ▶ An unbiased estimator of σ^2 is:

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

- ▶ For the unbiasedness of s^2 , we will use the following assumptions:

1. $Y_i = \alpha + \beta X_i + U_i$,
2. $E(U_i | X_1, \dots, X_n) = 0$ for all i 's,
3. $E(U_i^2 | X_1, \dots, X_n) = \sigma^2$ for all i 's,
4. $E(U_i U_j | X_1, \dots, X_n) = 0$ for all $i \neq j$.

An unbiased estimator of σ^2

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

- ▶ In order to construct \hat{U}_i , first we need to estimate two parameters α and β :

$$\hat{U}_i = Y_i - \hat{\alpha} - \hat{\beta}X_i,$$

and s^2 adjusts for the estimation of α and β by dividing by $n - 2$ instead of n .

- ▶ To show that $Es^2 = \sigma^2$ (unbiasedness), we need to show that

$$E \sum_{i=1}^n \hat{U}_i^2 = (n-2) \sigma^2.$$

- ▶ We need to express \hat{U} 's using U 's, since $EU_i^2 = \sigma^2$.

Expansion of \hat{U}_i

From

$$\begin{aligned}\hat{U}_i &= Y_i - \hat{\alpha} - \hat{\beta}X_i, \text{ and} \\ \hat{\alpha} &= \bar{Y} - \hat{\beta}\bar{X},\end{aligned}$$

we have

$$\begin{aligned}\hat{U}_i &= Y_i - (\bar{Y} - \hat{\beta}\bar{X}) - \hat{\beta}X_i \\ &= (Y_i - \bar{Y}) - \hat{\beta}(X_i - \bar{X}).\end{aligned}\tag{1}$$

Next,

$$\begin{aligned}Y_i &= \alpha + \beta X_i + U_i, \\ \bar{Y} &= \alpha + \beta \bar{X} + \bar{U}, \text{ and} \\ Y_i - \bar{Y} &= \beta(X_i - \bar{X}) + U_i - \bar{U}.\end{aligned}\tag{2}$$

By combining (1) and (2),

$$\hat{U}_i = (U_i - \bar{U}) - (\hat{\beta} - \beta)(X_i - \bar{X}).$$

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

From

$$\hat{U}_i = (U_i - \bar{U}) - (\hat{\beta} - \beta) (X_i - \bar{X}),$$

We have

$$\begin{aligned}\hat{U}_i^2 &= [(U_i - \bar{U}) - (\hat{\beta} - \beta) (X_i - \bar{X})]^2 \\ &= (U_i - \bar{U})^2 + (\hat{\beta} - \beta)^2 (X_i - \bar{X})^2 - \\ &\quad - 2 (\hat{\beta} - \beta) (X_i - \bar{X}) (U_i - \bar{U}).\end{aligned}$$

Thus,

$$\begin{aligned}\sum_{i=1}^n \hat{U}_i^2 &= \sum_{i=1}^n (U_i - \bar{U})^2 + (\hat{\beta} - \beta)^2 \sum_{i=1}^n (X_i - \bar{X})^2 \\ &\quad - 2 (\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X}) (U_i - \bar{U}).\end{aligned}$$

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

$$\begin{aligned}\sum_{i=1}^n \hat{U}_i^2 &= \sum_{i=1}^n (U_i - \bar{U})^2 + (\hat{\beta} - \beta)^2 \sum_{i=1}^n (X_i - \bar{X})^2 \\ &\quad - 2(\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X})(U_i - \bar{U}).\end{aligned}$$

We will show that

- ▶ $E \left[\sum_{i=1}^n (U_i - \bar{U})^2 \right] = (n-1) \sigma^2,$
- ▶ $E \left[(\hat{\beta} - \beta)^2 \sum_{i=1}^n (X_i - \bar{X})^2 \right] = \sigma^2,$
- ▶ $E \left[(\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X})(U_i - \bar{U}) \right] = \sigma^2,$

and therefore,

$$E \sum_{i=1}^n \hat{U}_i^2 = (n-1) \sigma^2 + \sigma^2 - 2\sigma^2 = (n-2) \sigma^2.$$

$$E \sum_{i=1}^n (U_i - \bar{U})^2 = (n-1)\sigma^2$$

First,

$$\begin{aligned} \sum_{i=1}^n (U_i - \bar{U})^2 &= \sum_{i=1}^n (U_i - \bar{U}) U_i \\ &= \sum_{i=1}^n U_i^2 - \bar{U} \sum_{i=1}^n U_i \\ &= \sum_{i=1}^n U_i^2 - \left(\frac{1}{n} \sum_{i=1}^n U_i \right) \sum_{i=1}^n U_i \\ &= \sum_{i=1}^n U_i^2 - \frac{1}{n} \left(\sum_{i=1}^n U_i \right)^2. \end{aligned}$$

$$E \sum_{i=1}^n (U_i - \bar{U})^2 = (n-1)\sigma^2$$

$$\begin{aligned} \sum_{i=1}^n (U_i - \bar{U})^2 &= \sum_{i=1}^n U_i^2 - \frac{1}{n} \left(\sum_{i=1}^n U_i \right)^2 \\ &= \sum_{i=1}^n U_i^2 - \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n U_i U_j \\ &= \sum_{i=1}^n U_i^2 - \frac{1}{n} \left(\sum_{i=1}^n U_i^2 + \sum_{i=1}^n \sum_{j \neq i} U_i U_j \right). \end{aligned}$$

$$\begin{aligned} E \sum_{i=1}^n (U_i - \bar{U})^2 &= \sum_{i=1}^n E U_i^2 - \frac{1}{n} \left(\sum_{i=1}^n E U_i^2 + \sum_{i=1}^n \sum_{j \neq i} E U_i U_j \right) \\ &= \sum_{i=1}^n \sigma^2 - \frac{1}{n} \left(\sum_{i=1}^n \sigma^2 + 0 \right) = n\sigma^2 - \frac{1}{n} n\sigma^2 \\ &= (n-1)\sigma^2. \end{aligned}$$

$$E (\hat{\beta} - \beta)^2 \sum_{i=1}^n (X_i - \bar{X})^2 = \sigma^2$$

- ▶ First, note that since conditionally on X 's,

$$E \hat{\beta} = \beta,$$

we have that conditionally on X 's,

$$\begin{aligned} E (\hat{\beta} - \beta)^2 &= E (\hat{\beta} - E \hat{\beta})^2 \\ &= \text{Var} (\hat{\beta}). \end{aligned}$$

- ▶ The conditional variance of $\hat{\beta}$ given X_1, \dots, X_n is

$$\text{Var} (\hat{\beta}) = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

- ▶ Thus,

$$E (\hat{\beta} - \beta)^2 \sum_{i=1}^n (X_i - \bar{X})^2 = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \sum_{i=1}^n (X_i - \bar{X})^2 = \sigma^2.$$

$$E(\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X})(U_i - \bar{U}) = \sigma^2$$

► First,

$$\sum_{i=1}^n (X_i - \bar{X})(U_i - \bar{U}) = \sum_{i=1}^n (X_i - \bar{X}) U_i.$$

► Next,

$$\hat{\beta} - \beta = \frac{\sum_{i=1}^n (X_i - \bar{X}) U_i}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

► Thus,

$$\begin{aligned} & (\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X})(U_i - \bar{U}) \\ &= \frac{\sum_{i=1}^n (X_i - \bar{X}) U_i}{\sum_{i=1}^n (X_i - \bar{X})^2} \sum_{i=1}^n (X_i - \bar{X}) U_i \\ &= \frac{1}{\sum_{i=1}^n (X_i - \bar{X})^2} \left(\sum_{i=1}^n (X_i - \bar{X}) U_i \right)^2. \end{aligned}$$

$$E (\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X}) (U_i - \bar{U}) = \sigma^2$$

$$\begin{aligned} (\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X}) (U_i - \bar{U}) &= \\ &= \frac{1}{\sum_{i=1}^n (X_i - \bar{X})^2} \left(\sum_{i=1}^n (X_i - \bar{X}) U_i \right)^2. \end{aligned}$$

Conditional on X 's,

$$\begin{aligned} &E \left[(\hat{\beta} - \beta) \sum_{i=1}^n (X_i - \bar{X}) (U_i - \bar{U}) \right] \\ &= \frac{1}{\sum_{i=1}^n (X_i - \bar{X})^2} E \left(\sum_{i=1}^n (X_i - \bar{X}) U_i \right)^2 \\ &= \frac{1}{\sum_{i=1}^n (X_i - \bar{X})^2} \left(\sigma^2 \sum_{i=1}^n (X_i - \bar{X})^2 \right) = \sigma^2. \end{aligned}$$

Estimation of the variance of $\hat{\beta}$

- ▶ The variance of $\hat{\beta}$ (conditional on X 's):

$$\text{Var}(\hat{\beta}) = \frac{\sigma^2}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

It is unknown because σ^2 is unknown.

- ▶ The estimator of σ^2 :

$$s^2 = \frac{1}{n-2} \sum_{i=1}^n \hat{U}_i^2 = \frac{1}{n-2} \sum_{i=1}^n (Y_i - \hat{\alpha} - \hat{\beta}X_i)^2.$$

- ▶ The estimator for the variance of $\hat{\beta}$:

$$\widehat{\text{Var}}(\hat{\beta}) = \frac{s^2}{\sum_{i=1}^n (X_i - \bar{X})^2}.$$

- ▶ The standard error of $\hat{\beta}$:

$$SE(\hat{\beta}) = \sqrt{\widehat{\text{Var}}(\hat{\beta})} = \sqrt{\frac{s^2}{\sum_{i=1}^n (X_i - \bar{X})^2}}.$$