

# Advanced Econometrics

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# Normal regression model

- The normal regression model is the linear regression with an independent, homoskedastic normal error

$$Y = X'\beta + e$$
$$e \sim N(0, \sigma^2)$$

- Likelihood is the joint (conditional) probability of the observed sample. It is denoted as  $L()$ .
- For the estimation of the model with fully specified distribution we usually use the ML estimator which maximises likelihood (or equivalently  $\ln L() = \ell()$ )
- In the case of normal regression the loglikelihood is

$$\ell(\beta, \sigma^2) = \ln L(\beta, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - X_i'\beta)^2$$

- The maximisation problem

$$\left(\hat{\beta}_{mle}, \hat{\sigma}_{mle}^2\right) = \underset{\beta \in \mathbb{R}^k, \sigma^2 > 0}{\operatorname{argmax}} \ln L(\beta, \sigma^2)$$

# Normal regression model

- Solving first order conditions we obtain

$$\hat{\beta}_{mle} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y} = \hat{\beta}_{ols}$$

$$\hat{\sigma}_{mle}^2 = \frac{1}{n} \sum_{i=1}^n \hat{e}_i^2 = \hat{\sigma}_{ols}^2$$

- Method of Moments estimators and ML estimators identical! This result is exceptional - in many cases these estimators are different.
- Under assumptions of normal regression model we can prove that

$$\hat{\beta} | \mathbf{X} \sim N(\beta, \sigma^2 (\mathbf{X}'\mathbf{X})^{-1})$$

- Using normality of  $\hat{\beta}$  we prove that statistic  $T$  has t-student distribution

$$T(\beta) = \frac{\hat{\beta}_j - \beta_j}{\sqrt{s^2 (\mathbf{X}'\mathbf{X})_{jj}^{-1}}} = \frac{\hat{\beta}_j - \beta_j}{se(\hat{\beta}_j)} \sim t_{n-k}$$

- Confidence interval

$$\widehat{C} = \left[ \widehat{\beta} - c \times s(\widehat{\beta}), \widehat{\beta} + c \times s(\widehat{\beta}) \right]$$

- Probability  $\alpha$  of  $\widehat{C}$  covering the true value of  $\beta$  is

$$\mathbb{P} \left[ \beta \in \widehat{C} \right] = \mathbb{P} \left[ -c < T(\beta) < c \right] = 2F(c) - 1 = 1 - \alpha$$

where  $F()$  is cdf of  $T(\beta)$  and  $\alpha$  is known as confidence level

# Significance test (t - test)

- Consider null  $H_0$  and alternative hypotheses  $H_1$

$$H_0 : \beta_j = \beta$$

$$H_1 : \beta_j \neq \beta$$

- We reject  $H_0$  (and accept  $H_1$ ) if  $|T| > c$  as large value of  $|T|$  suggests that  $\hat{\beta}$  deviates *significantly* from  $\beta$ .
- We can make two errors
  - reject  $H_0$  which is true (type 1 error)
  - not reject  $H_0$  which is false (type 2 error)
- Probability of type 1 error is equal to

$$\mathbb{P}[|T| > c | H_0 \text{ true}] = \alpha$$

where  $\alpha$  is called significance level

- Probability of type 2 error

$$\mathbb{P}[|T| < c | H_0 \text{ false}] = \beta$$

$1 - \beta$  (probability of rejecting false  $H_0$ ) is known as the power of the test

# Bibliography