

## OLS Estimates

- The OLS estimates for  $\beta$  minimize

$$S(\beta) = \sum_{i=1}^n \epsilon_i^2 = \epsilon' \epsilon.$$

- From Lecture 6:

$$\hat{\beta} = (\mathbf{x}'\mathbf{x})^{-1} \mathbf{x}'\mathbf{y}$$

provided  $(\mathbf{x}'\mathbf{x})^{-1}$  exists.

- $(\mathbf{x}'\mathbf{x})^{-1}$  will exist if  $\mathbf{x}$  has full column rank (i.e., each of the columns of the matrix are linearly independent).
- The fitted values can be written as

$$\hat{\mathbf{y}} = \mathbf{x}\hat{\beta}.$$

- The residuals are

$$\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}}.$$

viewed as the predicted values of unknown random errors  $\epsilon$ .

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- The estimated Variance-Covariance matrix for  $\beta$  given by

$$\widehat{Var}(\hat{\beta}) = \hat{\sigma}^2 (\mathbf{x}'\mathbf{x})^{-1} = \hat{\sigma}^2 \mathbf{C}.$$

- The standard errors can be found by looking at the diagonal elements of this matrix.

$$se(\hat{\beta}_j) = \hat{\sigma} \sqrt{c_{jj}}$$

for  $j = 0, 1, \dots, p$ .

- The  $100(1 - \alpha)\%$  confidence intervals for individual regression coefficients are given by

$$\hat{\beta}_j \pm t_{(n-(p+1);\alpha/2)} se(\hat{\beta}_j) \quad j = 0, 1, \dots, p.$$