

$$y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$$

a) $H_0: \beta_2 = 0$

$$t = \frac{\hat{\beta}_2 - 0}{se(\hat{\beta}_2)} \underset{H_0}{\sim} t_{n-k} \quad \begin{array}{l} \# \text{ of est.} \\ \text{coefficient} \end{array}$$

b) $H_0: \beta_2 = 1$

$$t = \frac{\hat{\beta}_2 - 1}{se(\hat{\beta}_2)} \underset{H_0}{\sim} t_{n-3}$$

c) $H_0: \beta_2 = \beta_3 = 0$

F-test for goodness of fit

$$F = \frac{ESS / k-1}{RSS / n-k} \sim F(k-1, n-k)$$

$$= \frac{R^2 / 2}{(1-R^2) / n-3}$$

R: $y_i = \beta_1 + \varepsilon_i$

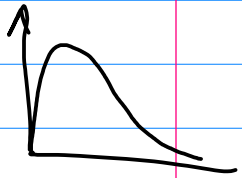
UR: $y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$

$$H_0: \beta_2 = \beta_3$$

$$UR: y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i$$

$$R: y_i = \beta_1 + \beta_2 (X_{2i} + X_{3i}) + \varepsilon_i$$

||
 z_i



$$F = \frac{(RSS_R - RSS_{UR}) / q}{RSS_{UR} / n - k} \sim F(q, n - k)$$

$$F = \frac{(1 - R^2_R - 1 + R^2_{UR}) / q}{(1 - R^2_{UR}) / n - k} =$$

$$= \frac{(R^2_{UR} - R^2_R) / q}{(1 - R^2_{UR}) / n - k} \sim F(q, n - k)$$

$$H_0: \beta_2 + \beta_3 = 1$$

$$UR: y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon_i$$

$$R: y_i = \beta_1 + \beta_2 x_{2i} + (1 - \beta_2) x_{3i} + \varepsilon_i$$

$$\underbrace{y_i - x_{3i}}_{z_i} = \beta_1 + \beta_2 \underbrace{(x_{2i} - x_{3i})}_{h_i} + \varepsilon_i$$

$TSS_R \neq TSS_{UR} \Rightarrow$ F stat should be calculated using RSS (not R^2 !)

$$c) \quad H_0: \beta_2 + \beta_3 = 1 \quad \Theta = \beta_2 + \beta_3 = 1$$

$$H_a: \beta_2 + \beta_3 < 1$$

$$y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon_i$$

$$y_i = \beta_1 + \beta_2 x_{2i} + (1 - \Theta) x_{3i} + \varepsilon_i$$

$$y_i - x_{3i} = \beta_1 + \beta_2 x_{2i} - \Theta x_{3i} + \varepsilon_i$$

$$H_0: \Theta = 1$$

$$H_a: \Theta < 1$$

Prediction error:

$$y_{n+1} = \beta_1 + \beta_2 x_{n+1} + \varepsilon_{n+1}$$

$$\hat{y}_{n+1} = \hat{\beta}_1 + \hat{\beta}_2 x_{n+1}$$

$$E(\hat{y}_{n+1}) = E(\hat{\beta}_1 + \hat{\beta}_2 x_{n+1}) = E(\hat{\beta}_1) + E(\hat{\beta}_2) \cdot x_{n+1}$$

$$= \beta_1 + \beta_2 \cdot x_{n+1}$$

$$E(y_{n+1}) = E(\beta_1 + \beta_2 x_{n+1} + \varepsilon_{n+1}) =$$

$$\beta_1 + \beta_2 x_{n+1} + \underbrace{E(\varepsilon_{n+1})}_0$$

$$E(y_{n+1}) = E(\hat{y}_{n+1})$$

$$\text{Var}(\hat{y}_{n+1} - y_{n+1}) = E(\hat{y}_{n+1} - y_{n+1})^2 =$$

$$= E(\hat{\beta}_1 + \hat{\beta}_2 x_{n+1} - \beta_1 - \beta_2 x_{n+1} - \varepsilon_{n+1})^2 =$$

$$= E((\hat{\beta}_1 - \beta_1) + (\hat{\beta}_2 - \beta_2) x_{n+1} - \varepsilon_{n+1})^2 =$$

$$= E(\hat{\beta}_1 - \beta_1)^2 + x_{n+1}^2 E(\hat{\beta}_2 - \beta_2)^2 + E(\varepsilon_{n+1}^2) +$$

$$+ 2 x_{n+1} E((\hat{\beta}_1 - \beta_1)(\hat{\beta}_2 - \beta_2)) - 2 E((\hat{\beta}_1 - \beta_1) \varepsilon_{n+1}) +$$

$$- 2 x_{n+1} E((\hat{\beta}_2 - \beta_2) \varepsilon_{n+1}) = \text{Var}(\hat{\beta}_1) + x_{n+1}^2 \cdot \text{Var}(\hat{\beta}_2) +$$

$$\sigma^2 + 2 x_{n+1} \cdot \text{Cov}(\hat{\beta}_1, \hat{\beta}_2) - 0 - 0 =$$

$$= \frac{\sigma^2 \sum x_i^2}{\sum (x_i - \bar{x})^2} + x_{n+1}^2 \frac{\sigma^2}{\sum (x_i - \bar{x})^2} + \sigma^2 +$$

$$2x_{n+1} \cdot \frac{-\bar{x} \cdot \sigma^2}{\sum (x_i - \bar{x})^2} = \sigma^2 \left(1 + \frac{1}{n} + \frac{(x_{n+1} - \bar{x})^2}{\sum (x_i - \bar{x})^2} \right) = \sigma^2$$

$$y_{n+1} : \left\{ \hat{y}_{n+1} \pm t_{\alpha/2, n-2} \cdot \sigma \right\} \quad \begin{matrix} \uparrow \\ \text{S}^2 \end{matrix}$$

$$\sigma^2(\hat{\beta}) = \sigma^2(X'X)^{-1} = \begin{bmatrix} \frac{\sigma^2 \sum x_i^2}{n \sum (x_i - \bar{x})^2} & \frac{-\bar{x} \sigma^2}{\sum (x_i - \bar{x})^2} \\ \frac{-\bar{x} \sigma^2}{\sum (x_i - \bar{x})^2} & \frac{\sigma^2}{\sum (x_i - \bar{x})^2} \end{bmatrix}$$

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} \quad X = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}$$

$$X'X = \begin{bmatrix} n & \sum x_i \\ \sum x_i & \sum x_i^2 \end{bmatrix}$$

Multicollinearity

Perfect multicollinearity:

one of regressors is a lin. comb
from other regressors

$$\text{rank}(X) < k \quad \hat{\beta} = (X'X)^{-1}X'y$$

$(X'X)^{-1}$ - is not invertible

\Rightarrow can't obtain $\hat{\beta}$

Perfect MC example: dummy-variable trap

$$\begin{pmatrix} 1 & 1 & 0 & x_1 \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & 1 & 0 & \vdots \\ \vdots & 0 & 1 & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & x_n \end{pmatrix}$$

$\bar{1} = m_i + d_i$

$$\beta_0 + \beta_1 d_i$$

$$\beta_m \cdot m_i + \beta_d d_i$$

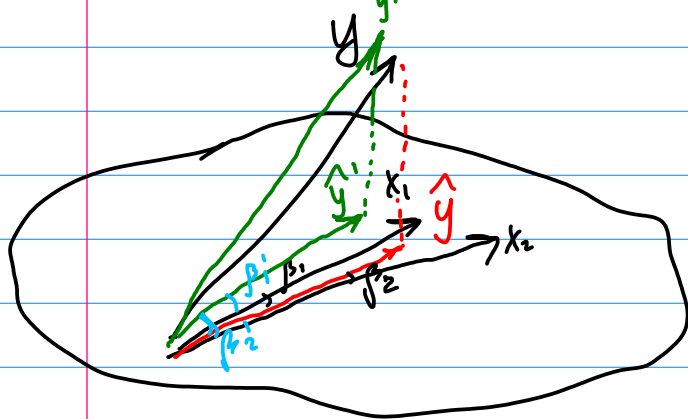
Multi collinearity

- $\hat{\beta}$ - unbiased, not effective
- $se(\hat{\beta})$ are inflated
- t -statistics are smaller
- instability of estimates,

i.e. switching sign

(add new variable /

add new regressor)



Testing for multicollinearity

$$y_i = \beta_0 + \beta_1 \cdot X_{1i} + \dots + \beta_k X_{ki} + \varepsilon_i$$

VIF (variance inflation factor)

$$X_i | X_{-i} \quad (X_i | X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_k)$$

$$\hookrightarrow R_i^2$$

$$VIF(X_i) = \frac{1}{1 - R_i^2} > 10 \Rightarrow \text{multicollinearity}$$