

Prep. 2

Q1

$$\text{Var}(y_t) = \text{Var}(\hat{y}_t) + \text{Var}(\hat{u}_t) \quad (*)$$

$$y_t = \alpha + \beta X_t + u_t$$

$$\text{TSS} = \text{ESS} + \text{RSS}$$

$$\text{Var}(y_t) = \underbrace{\text{Var}(\hat{y}_t)}_{\text{Explained var}} + \underbrace{\text{Var}(\hat{u}_t)}_{\text{Unexplained var}} \cdot T$$

Total
var

Explained
var

Unexplained
var

$$R^2 = \frac{\text{ESS}}{\text{TSS}} = \frac{\text{Var}(\hat{y}_t) \cdot T}{\text{Var}(y_t) \cdot T}$$

$$\text{Var}(y_t) = \frac{\sum (y_t - \bar{y})^2}{T}$$

- explained share
of variance

$$\text{TSS} = \sum (y_t - \bar{y})^2$$

$$R^2 = \frac{\text{TSS} - \text{RSS}}{\text{TSS}} = 1 - \frac{\text{RSS}}{\text{TSS}} =$$

$$= 1 - \frac{\text{Var}(\hat{u}_t) \cdot T}{\text{Var}(y_t) \cdot T}$$

ESS = 0 \Rightarrow $R^2 = 0$
(e.g. naive model
on a constant)

RSS = 0 \Rightarrow $R^2 = 1$

$$\Rightarrow R^2 \in [0; 1]$$

$$y_t = \hat{y}_t + \hat{u}_t$$

$$\text{Var}(y_t) = \text{Var}(\hat{y}_t + \hat{u}_t) =$$

$$= \text{Var}(\hat{y}_t) + \text{Var}(\hat{u}_t) + 2 \underbrace{\text{Cov}(\hat{y}_t, \hat{u}_t)}_{?=0}$$

$$\text{Cov}(\hat{y}_t, \hat{u}_t) = \text{Cov}(\hat{\beta}_0 + \hat{\beta}_1 \cdot X_t, \hat{u}_t) =$$

$$= \underbrace{\text{Cov}(\hat{\beta}_0, \hat{u}_t)}_{\text{const}} + \underbrace{\text{Cov}(\hat{\beta}_1 \cdot X_t, \hat{u}_t)}_{\text{const}} =$$

$$= 0 + \hat{\beta}_1 \text{Cov}(X_t, \hat{u}_t) = 0$$

"

0

(from normal
equations)

(Q2)

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

$$\text{Var}(\hat{\beta}_2) = \frac{\sigma_\varepsilon^2}{\sum (X_{2i} - \bar{X}_2)^2} \cdot \frac{1}{1 - r_{X_2, X_3}^2}$$

(a) Which 4 factor allows obtain more precise estimators for $\hat{\beta}_2$?

1) $\sigma_\varepsilon^2 \downarrow$

$\text{TSS}_i \uparrow$

$$\text{TSS}_i = N \cdot \text{Var}(X_i)$$

$$\text{Var}(\hat{\beta}_i) = \frac{\sigma_\varepsilon^2}{\text{TSS}_i \cdot (1 - R_i^2)}$$

R_i^2 - aux. regression
 $X_i \mid X_{-i}$

2) $N \uparrow$

3) $\text{Var}(X_i) \uparrow$

4) $(1 - R_i^2) \uparrow \Rightarrow R_i^2 \downarrow$

\Rightarrow no multicollinearity

(b) $\beta_3 = 0$ - true value

\Rightarrow Estimated reg.

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

has
irrelevant
var.

How it affect on
unbiasedness and precision of $\hat{\beta}_2$

Omitted variable bias (X_3) $\nearrow \beta_3 \neq 0$
 $\searrow r_{X_2, X_3} \neq 0$

if $r_{X_2, X_3} = 0 \Rightarrow$ no bias

if $\beta_3 = 0 \Rightarrow$ no bias

Precision : if $r_{X_2, X_3} \neq 0 \Rightarrow$

$$\text{Var}(\hat{\beta}_2^{\text{est}}) = \frac{\sigma_\varepsilon^2}{\sum (X_{2i} - \bar{X}_2)^2} \cdot \underbrace{\frac{1}{1 - r_{X_2, X_3}^2}}_{\geq 1} \geq \text{Var}(\hat{\beta}_2^{\text{true}}) = \frac{\sigma_\varepsilon^2}{\sum (X_{2i} - \bar{X}_2)^2}$$

(c) Multicollinearity ?

Q3

$$y_i = \beta x_i + \varepsilon_i$$

$$\{(y_i, x_i)\} \text{ i.i.d.}$$

Stoch no AC

$$E(\varepsilon_i) = 0$$

$$\uparrow \\ E(\varepsilon_i | X) = 0$$

$$\text{Cov}(x_i, \varepsilon_i) = \textcircled{E} \left\{ \begin{array}{l} E(\varepsilon_i) = 0 \\ + \\ \text{Cov}(x_i, \varepsilon_i) = 0 \end{array} \right.$$

$$E(x_i \varepsilon_i) - E(x_i)E(\varepsilon_i) = E(x_i \varepsilon_i) = 0$$

$$\text{Var}(\varepsilon_i) = \sigma^2$$

$$\left[\int x_i \varepsilon_i = 0 \right]$$

a) Convergence in probability:

$$\text{plim}_{n \rightarrow \infty} X_n = X, \quad X_n \xrightarrow{P} X$$

$$\forall \varepsilon \quad \lim_{n \rightarrow \infty} P(|X_n - X| > \varepsilon) = 0$$

b) Convergence in distribution

$$X_n \xrightarrow{d} X$$

$$\lim_{n \rightarrow \infty} F_n(x) = F(x)$$

$$c) \quad \text{plim } \hat{\beta} = \text{plim } \frac{\sum x_i y_i}{\sum x_i^2} =$$

$$\text{plim} \frac{\sum X_i (\beta X_i + \varepsilon_i)}{\sum X_i^2} =$$

$$\text{plim} \left(\beta + \frac{\sum X_i \varepsilon_i}{\sum X_i^2} \right) =$$

$$= \beta + \text{plim} \frac{\sum X_i \varepsilon_i}{\sum X_i^2} =$$

$$\text{plim} \bar{X} \rightarrow E(X)$$

$$\text{plim} \frac{\sum X}{n} \rightarrow \mu$$

$$= \beta + \frac{\text{plim} \sum X_i \varepsilon_i / n}{\text{plim} \sum X_i^2 / n} =$$

$$= \beta + \frac{E(X_i \varepsilon_i) = 0}{E(X_i^2)} = \beta$$

Q4

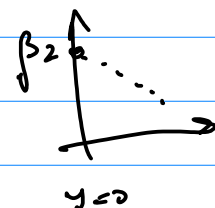
$$W_i = \beta_0 + \beta_1 E_i + \beta_2 Y_i + \beta_3 Y_i^2 + u_i$$

wages educ. years of exp.

$$\frac{dy/y}{dx/x} 1\%, \beta\% \quad \{ (W_i, E_i, Y_i) \}, i.i.d. \quad \frac{dW}{dY} = \beta_2 + \beta_3 \cdot 2Y$$

$$\frac{dy}{100 \cdot dx/x} = \beta \cdot \frac{1}{100}$$

$$E(u_i) = 0 \quad \text{Var}(u_i) = \sigma^2$$



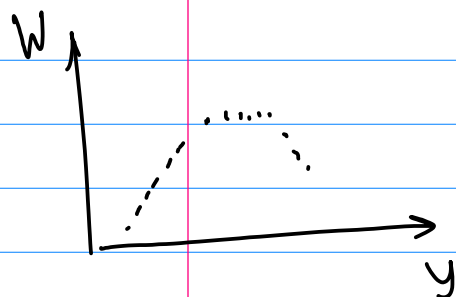
$$u_i \perp E_i, \quad u_i \perp Y_i$$

$$\frac{100 dy/y}{dx/x} \uparrow \uparrow, \frac{1}{100} \beta Y.$$

"beta * 100"

a) Rationale of both Y and Y^2 ?

Signs of β_2 and β_3 ?



Assumes diminishing return of Y on W

$$\Rightarrow \beta_3 < 0$$

$$\beta_2 > 0$$



b) Test that Y affects W

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

$$H_a: \beta_2 \neq 0 \quad \text{or} \quad \beta_3 \neq 0$$

$$F = \frac{(RSS_R - RSS_{UR}) / 2}{RSS_{UR} / (n - 4)} \stackrel{H_0}{\sim} F_{2, n-4}$$

