

# Definition

objective: estimate the effect of  $X$  on  $Y$

$Y$   
dependent var.  
explained  
regressand

$X$   
independent var.  
explanatory  
regressor

e.g. pollution  
wage

trade  
educ.

# Simple linear regression (SLR) model

$$y = \beta_0 + \beta_1 x + u$$

intercept                      slope                      unobserved  
or error term

$$\Delta y = \beta_1 \Delta x + \Delta u$$

$\beta_1$  :  $\Delta y$  for  $\Delta x = 1$  (all else constant)

Objective : estimate  $\beta_0$  and  $\beta_1$

2 assumptions :

$$E(u) = 0$$

$$E(u|x) = E(u)$$

$$\Rightarrow E(u|x) = 0$$

$$\text{corr.}(x, u) = 0$$

$$E(x \cdot u) = 0$$

## Deriving OLS estimates

Sample analogs : estimates  $\hat{\beta}_0$  and  $\hat{\beta}_1$  such that

$$\frac{1}{n} \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

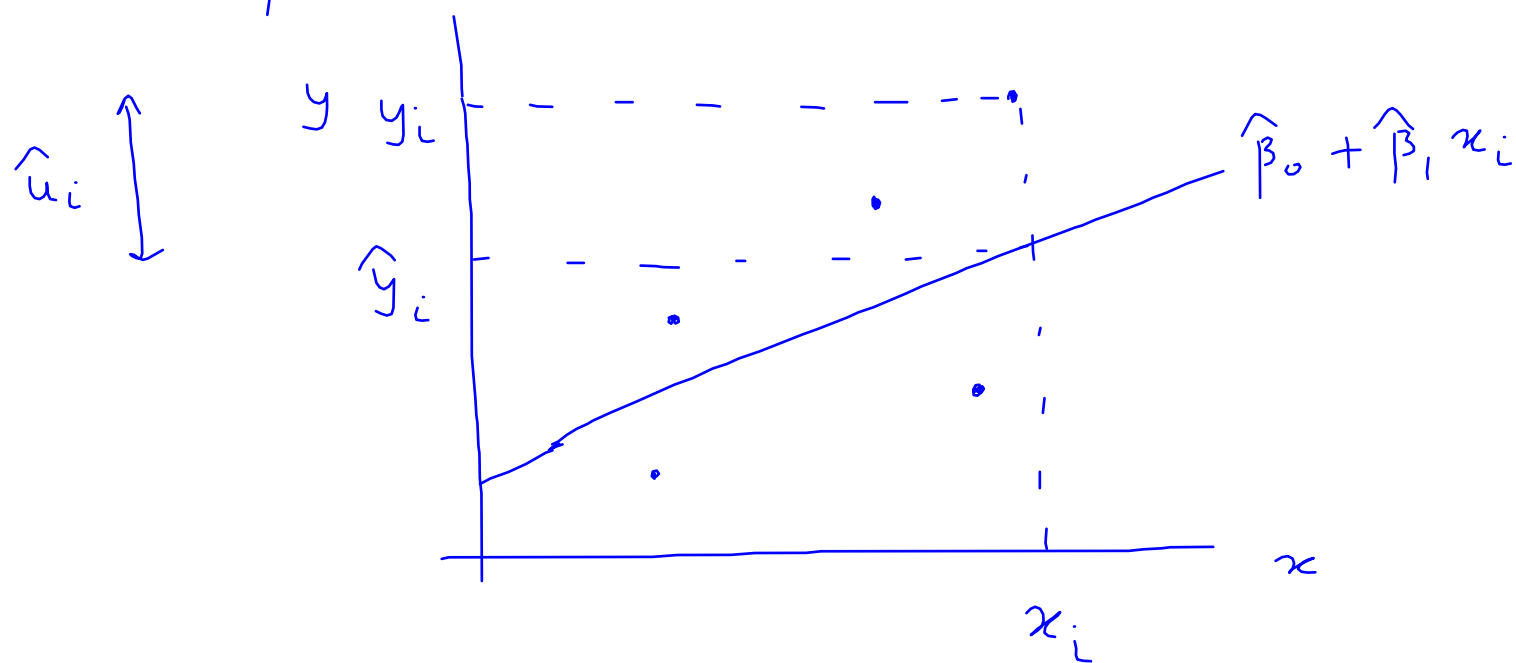
$n$ : sample size

$i$ : obs  $i$   
 $1, 2, \dots, n$

$$\frac{1}{n} \sum_{i=1}^n x_i (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

Estimated regression line:

$$\hat{\beta}_0 + \hat{\beta}_1 x_i = \hat{y}_i$$



For  $i$ th obs.  $y_i$ : dep. var. value

$\hat{y}_i$ : fitted value

$$\hat{u}_i \text{ (residual)} = y_i - \hat{y}_i$$

$\hat{\beta}_0$  and  $\hat{\beta}_1$  also minimize the sum of squared residuals (SSR)  $\rightarrow \sum_{i=1}^n \hat{u}_i^2$

Method  $\rightarrow$  also called ordinary least squares (OLS)

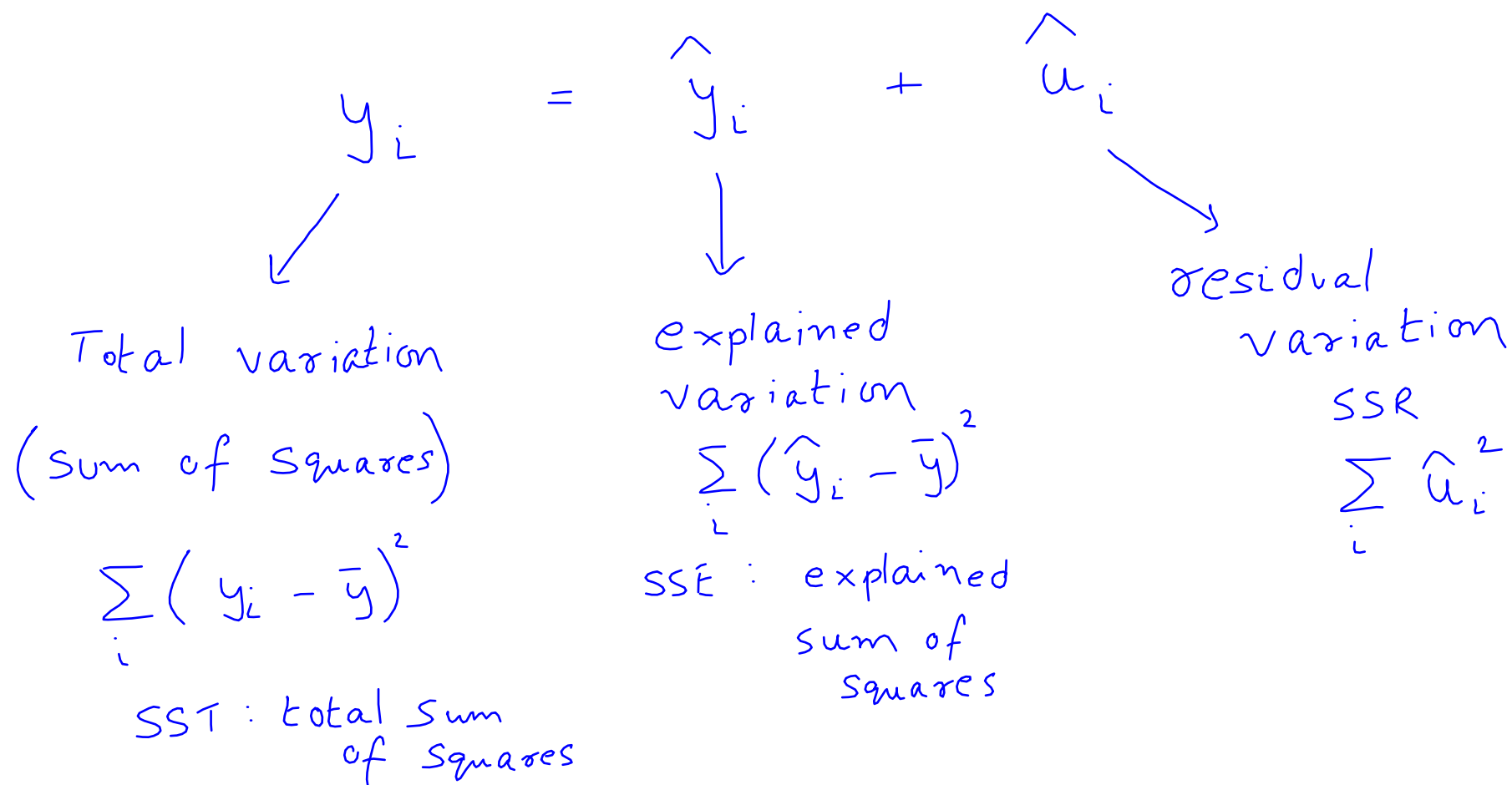
$$\hat{\beta}_1 = \frac{\text{how } x \text{ \& } y \text{ covary}}{\text{how } x \text{ varies}}$$

$$= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

;  $\bar{x}, \bar{y}$  :  
sample  
means

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

For each obs.



$$R^2 = \frac{SSE}{SST} = 1 - \frac{SSR}{SST}$$

$$0 \leq R^2 \leq 1$$

also = square of correl<sup>n</sup> b/w  $y$  and  $\hat{y}$

High  $R^2$ : not the ultimate objective



## Example

$y$ (wage)	$x$ (educ)
3.1	11
3.2	12
3	11
6	8
5.3	12
8.8	16
11	18
5	12
3.6	12
18	17

$$\begin{aligned}\bar{y} - \hat{\beta}_0 - \hat{\beta}_1\bar{x} &= 0 \\ \overline{xy} - \hat{\beta}_0\bar{x} - \hat{\beta}_1\overline{x^2} &= 0\end{aligned}$$

$$\begin{aligned}6.742 - \hat{\beta}_0 - 12.9\hat{\beta}_1 &= 0 \\ 97.234 - 12.9\hat{\beta}_0 - 175.1\hat{\beta}_1 &= 0\end{aligned}$$

$$\begin{aligned}\hat{\beta}_0 &= -8.492 \\ \hat{\beta}_1 &= 1.181\end{aligned}$$

$\bar{x}$ ,  $\bar{y}$ ,  $\overline{xy}$ , and  $\overline{x^2}$  : sample average of  $x$ ,  $y$ ,  $xy$ , and  $x^2$

## Functional form

dep. var. ( $y$ )  $\rightarrow$  price of house (\$1,000)

indep. var. ( $x$ )  $\rightarrow$  size in sq. ft.

$$y = \beta_0 + \beta_1 x + u$$

$$\hat{\beta}_1 = 0.14$$

$$\text{For } \Delta x = 1, \quad \Delta y = 0.14 \quad (\text{i.e. } \hat{\beta}_1)$$

$$\log(y) = \beta_0 + \beta_1 x + u$$

$$\hat{\beta}_1 = 0.0004$$

Approx. effect:  
of  $\Delta x = 1$

$$\begin{aligned} \therefore \Delta y &= 100 \hat{\beta}_1 \\ &= 0.04\% \end{aligned}$$

$$\log(y) = \beta_0 + \beta_1 \log(x) + u$$

$$\hat{\beta}_1 = 0.873$$

For  $\Delta x = 1\%$

$$\Delta y = 0.873\% \quad (\text{i.e. } \hat{\beta}_1) \quad \begin{array}{l} \text{approx.} \\ \text{effect} \end{array}$$

# Expected value of OLS estimators

Under certain assumptions  $\rightarrow$  OLS unbiased

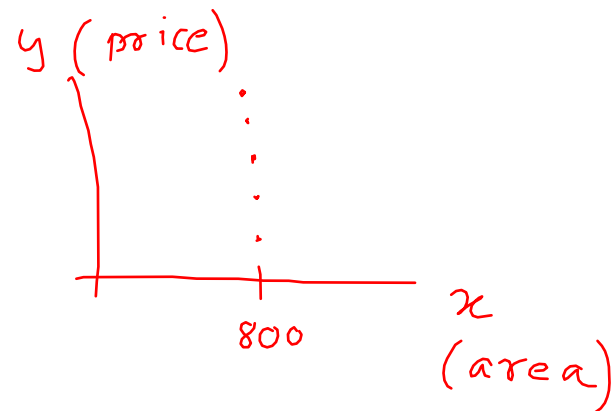
$$E(\hat{\beta}) = \beta$$

Assumptions:

linear model (in parameters)  
i.e.  $\beta$ 's

random sample

variation in  $x$



$$E(u|x) = E(u)$$

$$= 0 \rightarrow x \text{ exogenous}$$

$$E(u|x) \neq 0 \rightarrow x \text{ endogenous}$$

$$y = \beta_0 + \beta_1 x + u$$

$$E(y|x) = \beta_0 + \beta_1 x$$

## Variance of OLS estimators

Variance  $\longrightarrow$  precision

Assumption of homoskedasticity

$$\text{Var}(u|x) = \text{Var}(u) = \sigma^2$$

$$y = \beta_0 + \beta_1 x + u$$

$$\text{Var}(y|x) = \sigma^2$$

$$\text{var}(\hat{\beta}_1) = \frac{\sigma^2}{\text{variation in } x} = \frac{\sigma^2}{\text{SST}_x} = \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\text{sd}(\hat{\beta}_1) = \frac{\sigma}{\sqrt{\text{SST}_x}}$$

$\sigma$  : unknown

unbiased estimator of  $\sigma^2$  :  $\hat{\sigma}^2$

$$\hat{\sigma}^2 = \frac{SSR}{(n-2)} = \frac{\sum_{i=1}^n \hat{u}_i^2}{(n-2)}$$

$\rightarrow$  2  $\beta$ 's estimated

std. error of  $\hat{\beta}_1$  :  $se(\hat{\beta}_1) = \frac{\hat{\sigma}}{\sqrt{SST_x}}$

$\hat{\sigma}$  : standard error  
of regression