

Example  $y_i = \beta_1 + \beta_2 x_i + u_i$

$i$	$x_i$	$y_i$	$\bar{x}$	$\bar{y}$	$x_i - \bar{x}$	$y_i - \bar{y}$	$\hat{y}_i$
1	8	1	5	3	8-5=3	1-3=-2	$7 - \frac{4}{5}(8) = 0.6$
2	4	3	5	3	4-5=-1	3-3=0	$7 - \frac{4}{5}(4) = 3.8$
3	6	2	5	3	6-5=1	2-3=-1	$7 - \frac{4}{5}(6) = 2.2$
4	2	6	5	3	2-5=-3	6-3=3	$7 - \frac{4}{5}(2) = 5.4$

OLS by hand

Use the OLS formulas

$$\hat{\beta}_2 = \frac{\sum (y_i - \bar{y})(x_i - \bar{x})}{\sum (x_i - \bar{x})^2} = \frac{-2 \cdot 3 + 0 \cdot (-1) + 1 \cdot (-1) + 3 \cdot (-3)}{3^2 + (-1)^2 + 1^2 + (-3)^2}$$

$$= \frac{-6 - 1 - 9}{9 + 1 + 1 + 9} = -\frac{4}{5}$$

$$\hat{\beta}_1 = \bar{y} - \hat{\beta}_2 \bar{x}$$

$$= 3 - \left(-\frac{4}{5}\right) 5 = 3 + \frac{4}{5} 5 = 3 + 4 = 7$$

$$\hat{y}_i = 7 - \frac{4}{5} x_i$$

estimated regression line

Calculate  $R^2$  based on the regression above.

$$R^2 = \frac{ESS}{TSS} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2}$$

$$\begin{aligned}
 R^2 &= \frac{ESS}{TSS} = \frac{\sum (Y_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} \\
 &= \frac{(0.6-3)^2 + (3.8-3)^2 + (2.2-3)^2 + (5.4-3)^2}{(1-3)^2 + (3-3)^2 + (2-3)^2 + (6-3)^2} \\
 &= \frac{12.8}{14} \\
 &= 0.91
 \end{aligned}$$

The estimated model explains 91% of the variation in  $Y$ .

→ model only includes one explanatory variable ( $X$ )

⇒  $X$  "explains" 91% of the variation in  $Y$ .

### Units of Measurement example

What happens to the slope estimate when we multiply  $Y_i$  by some constant  $\lambda$ ?

Untransformed model:  $Y_i = \beta_1 + \beta_2 X_i + u_i$

→ estimated version:  
 $\hat{Y}_i = \hat{\beta}_1 + \hat{\beta}_2 X_i$

Transformation of  $Y$ :  $Y_i^* = \lambda Y_i$

Transformed model:  $Y_i^* = \beta_1^* + \beta_2^* X_i + u_i$

$$\text{Slope estimator: } \beta_2^* = \frac{\sum (x_i - \bar{x})(Y_i^* - \bar{Y}^*)}{\sum (x_i - \bar{x})^2}$$

$$= \frac{\sum (x_i - \bar{x})(\lambda Y_i - \lambda \bar{Y})}{\sum (x_i - \bar{x})^2}$$

$$= \lambda \hat{\beta}_2$$

---

Units of Measurement Practice problem

---

see slides for set-up.

Solution

Plug the transformed data into the intercept estimator:

$$\hat{\beta}_1 = \bar{Y} - \hat{\beta}_2 \bar{X}$$

$$= \frac{1}{n} \sum \tilde{Y}_i - \hat{\beta}_2 \frac{1}{n} \sum \tilde{X}_i$$

[by definition of the sample mean]

$$= \frac{1}{n} \sum (Y_i - \bar{Y}) - \hat{\beta}_2 \frac{1}{n} \sum (x_i - \bar{x})$$

[plug in the transformed variable]

$$\text{Aside: } \frac{1}{n} \sum (y_i - \bar{y}) = 0.$$

Proof:

$$\frac{1}{n} \sum (y_i - \bar{y}) = \frac{1}{n} \sum y_i - \frac{1}{n} \sum \bar{y}$$

$$= \frac{1}{n} \sum y_i - \frac{1}{n} n \bar{y}$$

$$= \frac{1}{n} \sum y_i - \bar{y}$$

$$= \bar{y} - \bar{y}$$

$$= 0$$

definition of  $\bar{y}$

---

$$\text{Then } \hat{\beta}_1 = (0) - \hat{\beta}_2(0) \\ = 0$$