

Technical Exercise 1

① Let $y = \log_b x$. Then $b^y = x$. Taking logarithms ^(base a) of both sides, we have $\log_a b^y = \log_a x$. From the properties of logarithms, we have $y \log_a b = \log_a x$. Solving for y gives $y = \frac{\log_a x}{\log_a b}$. Therefore, $\log_b x = \frac{\log_a x}{\log_a b}$.

② Consider the following mappings:

$b \leftarrow e$, $a \leftarrow 10$, $x \leftarrow \text{Net Sales}$, $y \leftarrow \text{Total Comp}$

$X_1 \leftarrow \log_a x$, $Y \leftarrow \log_a y$, $W \leftarrow \log_b x$, $Z \leftarrow \log_b y$

Because of ①, we have $W_t = \frac{1}{\log_a b} X_{1t}$ & $Z_t = \frac{1}{\log_a b} Y_t$.

From Technical Exercise 2 of Ex Set 03, we know that

slope of regression of Z on $W = \frac{1/\log_a b}{1/\log_a b} * \text{slope of regression of } Y \text{ on } X_1$.

Therefore, the regression slopes are the same.

Technical Exercise 2

$$\begin{aligned} \textcircled{1} \quad p = \log x_2 - \log x_1 &\Leftrightarrow p = \log \left(\frac{x_2}{x_1} \right) \\ &\Leftrightarrow e^p = \frac{x_2}{x_1} \\ &\Leftrightarrow e^p - 1 = \frac{x_2 - x_1}{x_1} \\ &\Leftrightarrow (e^p - 1) * 100\% = \left(\frac{x_2 - x_1}{x_1} \right) * 100\% \end{aligned}$$

p	$e^p - 1$	p	$e^p - 1$	p	$e^p - 1$
0	0	0.4	≈ 0.492	0.9	≈ 1.46
0.01	≈ 0.01	0.5	≈ 0.649	1	≈ 1.718
0.1	≈ 0.105	0.6	≈ 0.822		
0.2	≈ 0.221	0.7	≈ 1.014		
0.3	≈ 0.350	0.8	≈ 1.226		

The approximation is quite severe as soon as $p > 0.3$, the error starts from about 5 percentage points to 72 percentage points!

Technical Exercise 3

Case 1. Regression with only an intercept

Here $X_t = 1$. Thus,

$$\begin{aligned}\hat{\beta} &= \left(\frac{1}{n} \sum_{t=1}^n X_t X_t' \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n X_t Y_t \right) = \left(\frac{1}{n} \sum_{t=1}^n 1 \cdot 1 \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n 1 \cdot Y_t \right) \\ &= \left(\frac{1}{n} \cdot n \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n Y_t \right) = \bar{Y}.\end{aligned}$$

Case 2. Simple linear regression

Here $X_t = (1, X_{1t})'$. Thus,

$$\begin{aligned}\hat{\beta} &= \left(\frac{1}{n} \sum_{t=1}^n X_t X_t' \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n X_t Y_t \right) = \left(\frac{1}{n} \sum_{t=1}^n \begin{pmatrix} 1 \\ X_{1t} \end{pmatrix} (1 \ X_{1t}) \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n \begin{pmatrix} 1 \\ X_{1t} \end{pmatrix} Y_t \right) \\ &= \left(\frac{1}{n} \sum_{t=1}^n \begin{pmatrix} 1 & X_{1t} \\ X_{1t} & X_{1t}^2 \end{pmatrix} \right)^{-1} \left(\frac{1}{n} \sum_{t=1}^n \begin{pmatrix} Y_t \\ X_{1t} Y_t \end{pmatrix} \right) \\ &= \begin{pmatrix} \frac{1}{n} \sum_{t=1}^n 1 & \frac{1}{n} \sum_{t=1}^n X_{1t} \\ \frac{1}{n} \sum_{t=1}^n X_{1t} & \frac{1}{n} \sum_{t=1}^n X_{1t}^2 \end{pmatrix}^{-1} \begin{pmatrix} \frac{1}{n} \sum_{t=1}^n Y_t \\ \frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \end{pmatrix}\end{aligned}$$

$$\begin{aligned}
&= \begin{pmatrix} 1 & \bar{X}_1 \\ \bar{X}_1 & \frac{1}{n} \sum_{t=1}^n X_{1t}^2 \end{pmatrix}^{-1} \begin{pmatrix} \bar{Y} \\ \frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \end{pmatrix} \\
&= \frac{1}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \begin{pmatrix} \frac{1}{n} \sum_{t=1}^n X_{1t}^2 & -\bar{X}_1 \\ -\bar{X}_1 & 1 \end{pmatrix} \begin{pmatrix} \bar{Y} \\ \frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \end{pmatrix} \\
&= \frac{1}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \begin{pmatrix} \left(\frac{1}{n} \sum_{t=1}^n X_{1t}^2 \right) \bar{Y} - \bar{X}_1 \left(\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \right) \\ -\bar{X}_1 \bar{Y} + \frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \end{pmatrix} \\
&= \begin{pmatrix} \frac{\left(\frac{1}{n} \sum_{t=1}^n X_{1t}^2 \right) \bar{Y} - \bar{X}_1 \left(\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \right)}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \\ \frac{\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t - \bar{X}_1 \bar{Y}}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \end{pmatrix}
\end{aligned}$$

From past exercises,

$$\begin{aligned}
\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t - \bar{X}_1 \bar{Y} &= \\
\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2 &=
\end{aligned}$$

Therefore,

$$\frac{\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t - \bar{X}_1 \bar{Y}}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} = \frac{\frac{1}{n} \sum_{t=1}^n (X_{1t} - \bar{X}_1)(Y_t - \bar{Y})}{\frac{1}{n} \sum_{t=1}^n (X_{1t} - \bar{X}_1)^2} = \hat{\beta}_1.$$

$$\begin{aligned} \frac{\left(\frac{1}{n} \sum_{t=1}^n X_{1t}^2 \right) \bar{Y} - \bar{X}_1 \left(\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \right)}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} &= \frac{\left(\frac{1}{n} \sum_{t=1}^n X_{1t}^2 \right) \bar{Y} - (\bar{X}_1)^2 \bar{Y} + (\bar{X}_1)^2 \bar{Y} - \bar{X}_1 \left(\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t \right)}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \\ &= \frac{\bar{Y} \left(\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2 \right) - \bar{X}_1 \left[\frac{1}{n} \sum_{t=1}^n X_{1t} Y_t - \bar{X}_1 \bar{Y} \right]}{\frac{1}{n} \sum_{t=1}^n X_{1t}^2 - (\bar{X}_1)^2} \\ &= \bar{Y} - \bar{X}_1 \cdot \hat{\beta}_1 = \hat{\beta}_0 \end{aligned}$$

Technical Exercise 4

$$\begin{aligned} \textcircled{1} \quad & \frac{\partial}{\partial \hat{\beta}_0} \sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})^2 \\ &= \sum_{t=1}^n \frac{\partial}{\partial \hat{\beta}_0} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})^2 \\ &= \sum_{t=1}^n 2(Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})(-1) \end{aligned}$$

$$\begin{aligned} & \frac{\partial}{\partial \hat{\beta}_1} \sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})^2 \\ &= \sum_{t=1}^n \frac{\partial}{\partial \hat{\beta}_1} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})^2 \\ &= \sum_{t=1}^n 2(Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})(-X_{1t}) \end{aligned}$$

The first order conditions are

$$\begin{cases} \sum_{t=1}^n (-2)(Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \\ \sum_{t=1}^n (-2X_{1t})(Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \end{cases}$$

properties of
summation
 \Rightarrow

$$\begin{cases} -2 \sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \\ -2 \sum_{t=1}^n X_{1t} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \end{cases}$$

Divide both
sides by (-2)
 \Rightarrow

$$\begin{cases} \sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \\ \sum_{t=1}^n X_{1t} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \end{cases}$$

$$\textcircled{2} \quad \sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \Rightarrow \sum_{t=1}^n Y_t - n\hat{\beta}_0 - \hat{\beta}_1 \sum_{t=1}^n X_{1t} = 0$$

$$\Rightarrow \sum_{t=1}^n Y_t = n\hat{\beta}_0 + \hat{\beta}_1 \sum_{t=1}^n X_{1t}$$

$$\sum_{t=1}^n X_{1t} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0 \Rightarrow \sum_{t=1}^n X_{1t} Y_t - \hat{\beta}_0 \sum_{t=1}^n X_{1t} - \hat{\beta}_1 \sum_{t=1}^n X_{1t}^2 = 0$$

$$\Rightarrow \sum_{t=1}^n X_{1t} Y_t = \hat{\beta}_0 \sum_{t=1}^n X_{1t} + \hat{\beta}_1 \sum_{t=1}^n X_{1t}^2$$

$$\textcircled{3} \quad \begin{pmatrix} n & \sum_{t=1}^n X_{1t} \\ \sum_{t=1}^n X_{1t} & \sum_{t=1}^n X_{1t}^2 \end{pmatrix} \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix} = \begin{pmatrix} \sum_{t=1}^n Y_t \\ \sum_{t=1}^n X_{1t} Y_t \end{pmatrix}$$

$$\textcircled{4} \quad \text{(a)} \quad \sum_{t=1}^n \underbrace{(Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})}_{e_t} = 0 \Rightarrow \sum_{t=1}^n e_t = 0$$

this is the residual for the t th observation. Optimal $(\hat{\beta}_0, \hat{\beta}_1)$ have to satisfy first-order conditions!

Start from:

(b) correlation coefficient between X_1 and residuals

$$= \frac{\frac{1}{n} \sum_{t=1}^n (X_{1t} - \bar{X}_1)(e_t - \bar{e})}{\sqrt{\frac{1}{n} \sum_{t=1}^n (X_{1t} - \bar{X}_1)^2} \sqrt{\frac{1}{n} \sum_{t=1}^n (e_t - \bar{e})^2}}$$

Tech Ex 2, Ex Set 02

Note that

$$\frac{1}{n} \sum_{t=1}^n (X_{1t} - \bar{X}_1)(e_t - \bar{e}) \stackrel{!}{=} \frac{1}{n} \sum_{t=1}^n X_{1t} e_t - \bar{X}_1 \bar{e}$$

$\bar{e} = 0$ from (a)

$$= \frac{1}{n} \sum_{t=1}^n X_{1t} e_t$$

definition of residual \downarrow

$$= \frac{1}{n} \sum_{t=1}^n X_{1t} (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t})$$

FOC $\downarrow = 0$

Therefore, correlation coefficient between X_1 and residuals is zero.

(c) From $\sum_{t=1}^n (Y_t - \hat{\beta}_0 - \hat{\beta}_1 X_{1t}) = 0$, we have $\sum_{t=1}^n Y_t = \sum_{t=1}^n (\hat{\beta}_0 + \hat{\beta}_1 X_{1t})$

But $\hat{Y}_t = \hat{\beta}_0 + \hat{\beta}_1 X_{1t}$, so $\sum_{t=1}^n Y_t = \sum_{t=1}^n \hat{Y}_t$. Therefore $\frac{1}{n} \sum_{t=1}^n Y_t = \frac{1}{n} \sum_{t=1}^n \hat{Y}_t$.