

2.1 Consider the following five observations. You are to do all the parts of this exercise using only a calculator.

$$\bar{x} = 1 \quad \bar{y} = 2$$

$x$	$y$	$x - \bar{x}$	$(x - \bar{x})^2$	$y - \bar{y}$	$(x - \bar{x})(y - \bar{y})$
3	4	$3 - 1 = 2$	4	$4 - 2 = 2$	4
2	2	$2 - 1 = 1$	1	$2 - 2 = 0$	0
1	3	$1 - 1 = 0$	0	$3 - 2 = 1$	0
-1	1	$-1 - 1 = -2$	4	$1 - 2 = -1$	2
0	0	$0 - 1 = -1$	1	$0 - 2 = -2$	2
$\sum x_i = 5$		$\sum y_i = 10$		$\sum (x_i - \bar{x}) = 0$	$\sum (y_i - \bar{y}) = 0$
$\sum (x_i - \bar{x})^2 = 10$		$\sum (y_i - \bar{y})^2 = 10$		$\sum (x_i - \bar{x})(y_i - \bar{y}) = 8$	

a. Complete the entries in the table. Put the sums in the last row. What are the sample means  $\bar{x}$  and  $\bar{y}$ ?

b. Calculate  $b_1$  and  $b_2$  using (2.7) and (2.8) and state their interpretation.

c. Compute  $\sum_{i=1}^5 x_i^2$ ,  $\sum_{i=1}^5 x_i y_i$ . Using these numerical values, show that  $\sum (x_i - \bar{x})^2 = \sum x_i^2 - N\bar{x}^2$  and  $\sum (x_i - \bar{x})(y_i - \bar{y}) = \sum x_i y_i - N\bar{x}\bar{y}$ .

d. Use the least squares estimates from part (b) to compute the fitted values of  $y$ , and complete the remainder of the table below. Put the sums in the last row.  
Calculate the sample variance of  $y$ ,  $s_y^2 = \sum_{i=1}^N (y_i - \bar{y})^2 / (N - 1)$ , the sample variance of  $x$ ,  $s_x^2 = \sum_{i=1}^N (x_i - \bar{x})^2 / (N - 1)$ , the sample covariance between  $x$  and  $y$ ,  $s_{xy} = \sum_{i=1}^N (y_i - \bar{y})(x_i - \bar{x}) / (N - 1)$ , the sample correlation between  $x$  and  $y$ ,  $r_{xy} = s_{xy} / (s_x s_y)$  and the coefficient of variation of  $x$ ,  $CV_x = 100(s_x / \bar{x})$ . What is the median, 50th percentile, of  $x$ ?

$$y = 1.2 + 0.8x \quad \hat{e}_i = y_i - \hat{y}_i$$

$x_i$	$y_i$	$\hat{y}_i$	$\hat{e}_i$	$\hat{e}_i^2$	$x_i \hat{e}_i$
3	4	3.6	0.4	0.16	1.2
2	2	2.8	-0.8	0.64	-1.6
1	3	2	1	1	1
-1	1	0.4	0.6	0.36	-0.6
0	0	1.2	-1.2	1.44	0
$\sum x_i = 5$		$\sum y_i = 10$		$\sum \hat{e}_i = 0$	$\sum \hat{e}_i^2 = 6$
$\sum (x_i - \bar{x}) = 0$		$\sum (y_i - \bar{y}) = 0$		$\sum (x_i - \bar{x})(y_i - \bar{y}) = 8$	$\sum x_i \hat{e}_i = 0$

e. On graph paper, plot the data points and sketch the fitted regression line  $\hat{y}_i = b_1 + b_2 x_i$ .

f. On the sketch in part (e), locate the point of the means  $(\bar{x}, \bar{y})$ . Does your fitted line pass through that point? If not, go back to the drawing board, literally.

g. Show that for these numerical values  $\bar{y} = b_1 + b_2 \bar{x}$ .

h. Show that for these numerical values  $\bar{\hat{y}} = \bar{y}$ , where  $\bar{\hat{y}} = \sum \hat{y}_i / N$ .

i. Compute  $\hat{\sigma}^2$ .

j. Compute  $\widehat{\text{var}}(b_2 | x)$  and  $\text{se}(b_2)$ .

(a)

$$\bar{x} = \frac{\sum x_i}{5} = 1 \quad \bar{y} = \frac{\sum y_i}{5} = 2$$

(b)

$$b_2 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} = \frac{8}{10} = 0.8$$

$$b_1 = \bar{y} - b_2 \bar{x} = 2 - 0.8 \times 1 = 1.2$$

$$\Rightarrow y = 1.2 + 0.8x$$

當  $x=0$ ,  $y=1.2$  ; 當  $x$  增加 1 單位,  $y$  增加 0.8 單位

(C).

$$\sum_{i=1}^5 x_i^2 = 3^2 + 2^2 + 1^2 + (-1)^2 + 0^2 = 15$$

$$\sum_{i=1}^5 x_i y_i = 3 \times 4 + 2 \times 2 + 1 \times 3 + (-1) \times 1 + 0 = 18$$

$$\begin{aligned}\textcircled{1} \quad \sum_{i=1}^N (x_i - \bar{x})^2 &= \sum_{i=1}^N (x_i^2 - 2x_i \bar{x} + \bar{x}^2) = \sum_{i=1}^N x_i^2 - 2\bar{x} \sum_{i=1}^N x_i + \sum_{i=1}^N \bar{x}^2 \\ &= \sum_{i=1}^N x_i^2 - 2 \cdot \bar{x} \cdot N \bar{x} + N \cdot \bar{x}^2 = \sum_{i=1}^N x_i^2 - N \bar{x}^2\end{aligned}$$

$$\text{得 } \sum_{i=1}^N (x_i - \bar{x})^2 = 10 = \sum_{i=1}^N x_i^2 - N \bar{x}^2 = 15 - 5 \cdot 1^2 = 10$$

$$\begin{aligned}\textcircled{2} \quad \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y}) &= \sum_{i=1}^N (x_i y_i - x_i \bar{y} - \bar{x} y_i + \bar{x} \bar{y}) \\ &= \sum_{i=1}^N x_i y_i - \bar{y} \sum_{i=1}^N x_i - \bar{x} \sum_{i=1}^N y_i + \sum_{i=1}^N \bar{x} \bar{y} \\ &= \sum_{i=1}^N x_i y_i - \bar{y} \cdot N \cdot \bar{x} - \cancel{\bar{x} \cdot N \cdot \bar{y}} + \cancel{N \cdot \bar{x} \bar{y}} = \sum_{i=1}^N x_i y_i - N \cdot \bar{x} \bar{y}\end{aligned}$$

$$\text{得 } \sum_{i=1}^5 (x_i - \bar{x})(y_i - \bar{y}) = 8 = \sum_{i=1}^5 x_i y_i - N \cdot \bar{x} \cdot \bar{y} = 18 - 5 \cdot 1 \cdot 2 = 8$$

$$(d) S_y^2 = \frac{\sum_{i=1}^N (y_i - \bar{y})^2}{N-1} = \frac{(4-2)^2 + (2-2)^2 + (3-2)^2 + (1-2)^2 + (0-2)^2}{5-1} = \frac{10}{4} = 2.5$$

$$S_x^2 = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1} = \frac{(3-1)^2 + (2-1)^2 + (1-1)^2 + (-1-1)^2 + (0-1)^2}{5-1} = \frac{10}{4} = 2.5$$

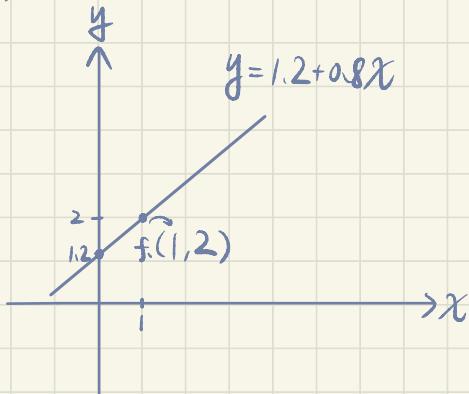
$$S_{xy} = \frac{\sum_{i=1}^N (y_i - \bar{y})(x_i - \bar{x})}{N-1} = \frac{8}{5-1} = 2$$

$$r_{xy} = \frac{S_{xy}}{S_x S_y} = \frac{2}{\sqrt{2.5} \sqrt{2.5}} = 0.8$$

$$CV = 100 \cdot \frac{S_x}{\bar{x}} = 100 \times \frac{\sqrt{2.5}}{1} = 100\sqrt{2.5} \approx 158.1139$$

median of  $x = 1$  (排序  $x: -1, 0, 1, 2, 3$ )

(e)



$$(f) \bar{x} = 1, \bar{y} = 2 \stackrel{\text{代入}}{\Rightarrow} y = 2 = 1.2 + 0.8 \times 1 \#$$

$$(g) \bar{y} = b_1 + b_2 \bar{x} = 2 = 1.2 + 0.8 \times 1 \#$$

$$(h). \quad \hat{\bar{y}} = \frac{\sum \hat{y}_i}{N} = \frac{10}{5} = 2 = \bar{y} \#$$

$$(i). \quad \hat{\sigma}^2 = \frac{\sum_{i=1}^5 \hat{e}_i^2}{N-2} = \frac{\sum_{i=1}^5 (y_i - \hat{y}_i)^2}{5-2}$$

$$= \frac{(0.4)^2 + (-0.8)^2 + (1)^2 + (0.6)^2 + (-1.2)^2}{5-2} = \frac{3.6}{3} = 1.2 \#$$

$$(j). \quad \widehat{\text{Var}}(b_2 | \chi) = \frac{\hat{\sigma}^2}{\sum_{i=1}^5 (\chi_i - \bar{\chi})^2} = \frac{1.2}{10} = 0.12 \#$$

$$se(b_2) = \sqrt{\text{Var}(b_2 | \chi)} = \sqrt{0.12} \approx 0.3464 \#$$

2.14

Consider the regression model  $WAGE = \beta_1 + \beta_2 EDUC + e$ , where  $WAGE$  is hourly wage rate in U.S. 2013 dollars and  $EDUC$  is years of education, or schooling. The regression model is estimated twice using the least squares estimator, once using individuals from an urban area, and again for individuals in a rural area.

$$\text{Urban} \quad \widehat{WAGE} = -10.76 + 2.46 EDUC, \quad N = 986 \\ (\text{se}) \quad (2.27) (0.16) \\ b_1 \quad b_2$$

$$\checkmark \text{Rural} \quad \widehat{WAGE} = -4.88 + 1.80 EDUC, \quad N = 214 \\ (\text{se}) \quad (3.29) (0.24) \\ b_1 \quad b_2$$

- a. Using the estimated **rural regression**, compute the **elasticity of wages** with respect to education at the "point of the means." The sample mean of  $WAGE$  is \$19.74.
- b. The sample mean of  $EDUC$  in the urban area is 13.68 years. Using the estimated **urban regression**, compute the **standard error of the elasticity of wages** with respect to education at the "point of the means." Assume that the mean values are **"givens"** and not random.
- c. What is the predicted wage for an individual with 12 years of education in each area? With 16 years of education?

(a) **Rural**

$$\widehat{WAGE} = -4.88 + 1.80 EDUC = 19.74$$

$$\Rightarrow EDUC = \frac{19.74 + 4.88}{1.8} = 13.6778$$

$$\text{Elasticity of wage} = \frac{\Delta WAGE}{\Delta EDUC} \times \frac{\overline{EDUC}}{\overline{WAGE}} = 1.8 \times \frac{13.6778}{19.74} \\ \approx 1.2472 \#$$

(b) **Urban**

$$\widehat{WAGE} = -10.76 + 2.46 \times 13.68 = 22.8928$$

$$\text{the standard error of the elasticity of wages} = b_2 \times \frac{\overline{EDUC}}{\overline{WAGE}} \\ = 0.16 \times \frac{13.68}{22.8928} = 0.0956 \#$$

(c).

**Urban**

$$EDUC = 12, \widehat{WAGE} = -10.76 + 2.46 \times 12 = 18.76$$

$$EDUC = 16, \widehat{WAGE} = -10.76 + 2.46 \times 16 = 28.60$$

$$EDUC = 12, \widehat{WAGE} = -4.88 + 1.8 \times 12 = 16.72$$

**Rural**

$$EDUC = 16, \widehat{WAGE} = -4.88 + 1.8 \times 16 = 23.92$$

## POEHW0224

Ch2.16

(a)

$rj - rf = \alpha j + \beta j(rm - rf) + ej$  為簡單線性回歸模型

依變數  $rj - rf$ ，自變數  $rm - rf$ 。

根據 CAPM 理論， $\alpha j = 0$ ； $ej$  是為誤差項。

該模型滿足  $y = \beta_0 + \beta_1 x + e$  的形式，故為一個簡單回歸模型。

(b)

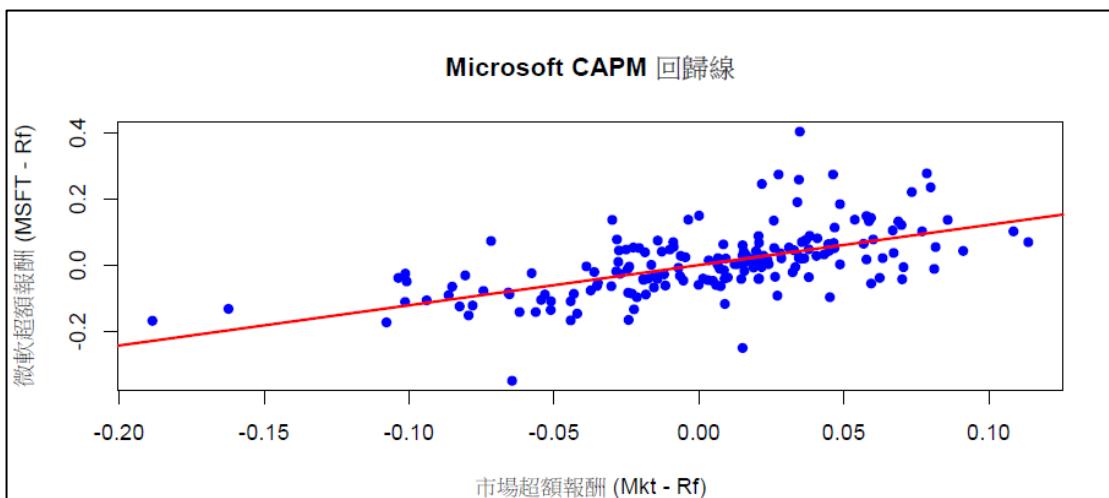
Ford  $\beta$  值為  $1.66 > 1$ ，是為 aggressive stock；

Exxon-Mobil 的  $\beta$  值為  $0.46 < 1$ ，是為 defensive stock。

	Company	Alpha	Beta	P_Value_Alpha	P_Value_Beta
(Intercept)	ge	-0.0036916942	1.1535496	0.4063037	3.316175e-27
(Intercept)1	ibm	0.0037247457	0.9820323	0.4433496	5.111456e-19
(Intercept)2	ford	-0.0001287859	1.6609865	0.9900193	1.617334e-13
(Intercept)3	msft	0.0003690433	1.2112741	0.9513861	1.021569e-18
(Intercept)4	dis	-0.0013317654	1.0109677	0.7775221	9.830474e-21
(Intercept)5	xom	0.0041912103	0.4597585	0.2388874	1.251880e-09
		T_Value_Alpha	T_Value_Beta	R_Squared	
(Intercept)		-0.83239086	12.865157	0.4818235	
(Intercept)1		0.76826190	10.018799	0.3605778	
(Intercept)2		-0.01252689	7.991316	0.2640405	
(Intercept)3		0.06105219	9.911595	0.3556321	
(Intercept)4		-0.28297853	10.625278	0.3880986	
(Intercept)5		1.18173455	6.411911	0.1876323	

(c)

呈上圖， $\alpha$  的 p 值和 t 值皆不顯著，故不能拒絕  $\alpha j = 0$  的假設。



(d)

比較 CAPM 原始模型(有截距  $\alpha$ )和假設  $\alpha = 0$  時的模型， $\beta$  值的差異。

結果如下圖，可以發現  $\alpha = 0$  時  $\beta$  值的變化不大。

Company	Beta_Original	Beta_No_Intercept	Difference
mkt	ge	1.1535496	1.1454280 -0.0081215451
mkt1	ibm	0.9820323	0.9902265 0.0081942569
mkt2	ford	1.6609865	1.6607032 -0.0002833226
mkt3	msft	1.2112741	1.2120860 0.0008118771
mkt4	dis	1.0109677	1.0080379 -0.0029298182
mkt5	xom	0.4597585	0.4689790 0.0092204559

Ch2.16 code

(a)(b)

```
# 設定工作目錄
```

```
setwd("C:/Users/bella/Desktop/NYCU/計量經濟/POEdata")
```

```
# 確認檔案是否存在
```

```
list.files()
```

```
# 載入 capm5.rdata
```

```
load("capm5.rdata")
```

```
# 檢查數據格式
```

```
head(capm5)
```

```
# 公司名稱
```

```
companies <- c("ge", "ibm", "ford", "msft", "dis", "xom")
```

```
# 建立空的 data frame 來存放結果
```

```
results <- data.frame(
```

```
    Company = character(),
```

```
    Alpha = numeric(),
```

```
    Beta = numeric(),
```

```
    P_Value_Alpha = numeric(),
```

```
    P_Value_Beta = numeric(),
```

```
    T_Value_Alpha = numeric(),
```

```
    T_Value_Beta = numeric(),
```

```
    R_Squared = numeric(),
```

```
    stringsAsFactors = FALSE
```

```

)

# 估計 CAPM 模型
for (company in companies){
  formula <- as.formula(paste0(company, " - riskfree ~ mkt - riskfree"))
  model <- lm(formula, data = capm5)
  summary_model <- summary(model)

  # 提取回歸結果
  alpha <- coef(model)[1]  # 截距
  beta <- coef(model)[2]   # β 值

  p_value_alpha <- coef(summary_model)[1, 4]  # 截距的 p 值
  p_value_beta <- coef(summary_model)[2, 4]   # β 的 p 值

  t_value_alpha <- coef(summary_model)[1, 3]  # 截距的 t 值
  t_value_beta <- coef(summary_model)[2, 3]   # β 的 t 值

  r_squared <- summary_model$r.squared  # R2

  # 將結果存入 data frame
  results <- rbind(results, data.frame(
    Company = company,
    Alpha = alpha,
    Beta = beta,
    P_Value_Alpha = p_value_alpha,
    P_Value_Beta = p_value_beta,
    T_Value_Alpha = t_value_alpha,
    T_Value_Beta = t_value_beta,
    R_Squared = r_squared
  ))
}

# 顯示結果
print(results)

```

**(c)**  
# 微軟 (MSFT) 的回歸模型

```

msft_model <- capm_models[["msft"]]

# 顯示回歸結果
summary(msft_model)

# 繪製微軟的回歸線
plot(capm5$mkt - capm5$riskfree,
      capm5$msft - capm5$riskfree,
      main = "Microsoft CAPM 回歸線",
      xlab = "市場超額報酬 (Mkt - Rf)",
      ylab = "微軟超額報酬 (MSFT - Rf)",
      pch = 16, col = "blue")

# 加入回歸線
abline(msft_model, col = "red", lwd = 2)

# 檢查截距值 alpha
alpha_value <- coef(msft_model)[1]
cat("微軟的截距 (alpha):", alpha_value, "\n")

# 如果 alpha 接近 0，輸出結論
if (abs(alpha_value) < 0.05) {
  cat("截距接近 0，符合 CAPM 理論。\\n")
} else {
  cat("截距不為 0，可能表示市場無效率或模型假設不完全。\\n")
}

```

#### (d)

```

# 公司名稱
companies <- c("ge", "ibm", "ford", "msft", "dis", "xom")

# 建立空的 data frame 來存放結果
results_no_intercept <- data.frame(
  Company = character(),
  Beta_Original = numeric(),
  Beta_No_Intercept = numeric(),
  Difference = numeric(),
  stringsAsFactors = FALSE
)

```

```

)

for (company in companies) {
  # 原本的 CAPM 回歸 (有截距)
  formula1 <- as.formula(paste0(company, " - riskfree ~ mkt - riskfree"))
  model1 <- lm(formula1, data = capm5)
  beta_original <- coef(model1)[2] # 原始  $\beta$ 

  # 假設  $\alpha = 0$  的 CAPM 回歸 (無截距)
  formula2 <- as.formula(paste0(company, " - riskfree ~ mkt - riskfree - 1"))
  model2 <- lm(formula2, data = capm5)
  beta_no_intercept <- coef(model2)[1] # 無截距時的  $\beta$ 

  # 計算  $\beta$  的變化
  difference <- beta_no_intercept - beta_original

  # 存入 data frame
  results_no_intercept <- rbind(results_no_intercept, data.frame(
    Company = company,
    Beta_Original = beta_original,
    Beta_No_Intercept = beta_no_intercept,
    Difference = difference
  ))
}

# 顯示結果
print(results_no_intercept)

```

## POEHW0224

Ch2.16

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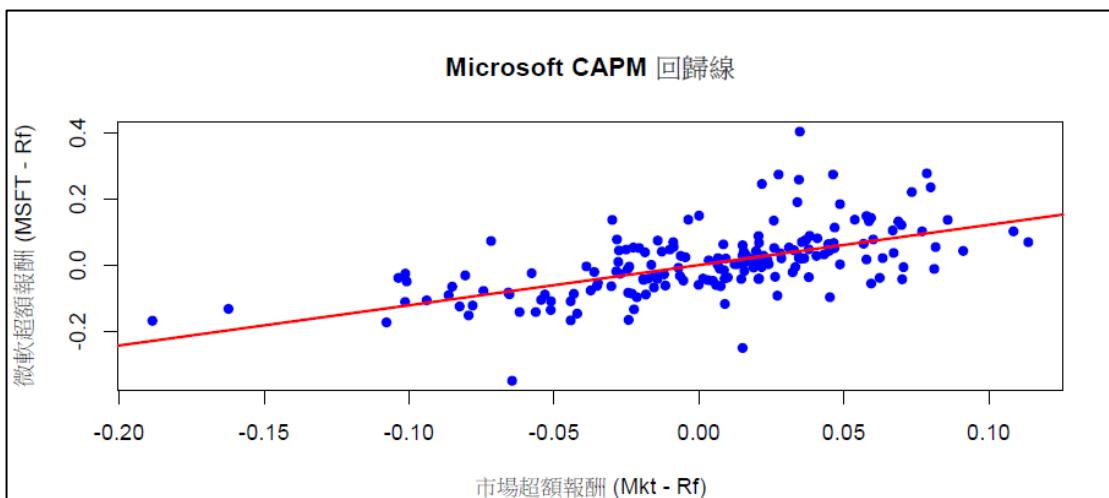
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  beta <- coef(model)[2]   # β 值

  p_value_alpha <- coef(summary_model)[1, 4]  # 截距的 p 值
  p_value_beta <- coef(summary_model)[2, 4]   # β 的 p 值

  t_value_alpha <- coef(summary_model)[1, 3]  # 截距的 t 值
  t_value_beta <- coef(summary_model)[2, 3]   # β 的 t 值

  r_squared <- summary_model$r.squared  # R2

  # 將結果存入 data frame
  results <- rbind(results, data.frame(
    Company = company,
    Alpha = alpha,
    Beta = beta,
    P_Value_Alpha = p_value_alpha,
    P_Value_Beta = p_value_beta,
    T_Value_Alpha = t_value_alpha,
    T_Value_Beta = t_value_beta,
    R_Squared = r_squared
  ))
}

# 顯示結果
print(results)

```

**(c)**  
# 微軟 (MSFT) 的回歸模型

```

msft_model <- capm_models[["msft"]]

# 顯示回歸結果
summary(msft_model)

# 繪製微軟的回歸線
plot(capm5$mkt - capm5$riskfree,
      capm5$msft - capm5$riskfree,
      main = "Microsoft CAPM 回歸線",
      xlab = "市場超額報酬 (Mkt - Rf)",
      ylab = "微軟超額報酬 (MSFT - Rf)",
      pch = 16, col = "blue")

# 加入回歸線
abline(msft_model, col = "red", lwd = 2)

# 檢查截距值 alpha
alpha_value <- coef(msft_model)[1]
cat("微軟的截距 (alpha):", alpha_value, "\n")

# 如果 alpha 接近 0，輸出結論
if (abs(alpha_value) < 0.05) {
  cat("截距接近 0，符合 CAPM 理論。\\n")
} else {
  cat("截距不為 0，可能表示市場無效率或模型假設不完全。\\n")
}

```

#### (d)

```

# 公司名稱
companies <- c("ge", "ibm", "ford", "msft", "dis", "xom")

# 建立空的 data frame 來存放結果
results_no_intercept <- data.frame(
  Company = character(),
  Beta_Original = numeric(),
  Beta_No_Intercept = numeric(),
  Difference = numeric(),
  stringsAsFactors = FALSE
)

```

```

)

for (company in companies) {
  # 原本的 CAPM 回歸 (有截距)
  formula1 <- as.formula(paste0(company, " - riskfree ~ mkt - riskfree"))
  model1 <- lm(formula1, data = capm5)
  beta_original <- coef(model1)[2] # 原始  $\beta$ 

  # 假設  $\alpha = 0$  的 CAPM 回歸 (無截距)
  formula2 <- as.formula(paste0(company, " - riskfree ~ mkt - riskfree - 1"))
  model2 <- lm(formula2, data = capm5)
  beta_no_intercept <- coef(model2)[1] # 無截距時的  $\beta$ 

  # 計算  $\beta$  的變化
  difference <- beta_no_intercept - beta_original

  # 存入 data frame
  results_no_intercept <- rbind(results_no_intercept, data.frame(
    Company = company,
    Beta_Original = beta_original,
    Beta_No_Intercept = beta_no_intercept,
    Difference = difference
  ))
}

# 顯示結果
print(results_no_intercept)

```