

Time Series HW3

40/40

B082040005 高念慈

2023-03-10

1. 

Consider the daily stock returns of Apple from January 2020 to February 2023. The price data can be obtained by using R package quantmod.

```
# from 正常 · to 少一天  
getSymbols("AAPL", from="2020-01-01", to='2023-03-01')
```

```
## [1] "AAPL"
```

```
head(AAPL)
```

```
##           AAPL.Open AAPL.High AAPL.Low AAPL.Close AAPL.Volume AAPL.Adjusted  
## 2020-01-02    74.0600    75.1500    73.7975    75.0875    135480400    73.44940  
## 2020-01-03    74.2875    75.1450    74.1250    74.3575    146322800    72.73533  
## 2020-01-06    73.4475    74.9900    73.1875    74.9500    118387200    73.31488  
## 2020-01-07    74.9600    75.2250    74.3700    74.5975    108872000    72.97008  
## 2020-01-08    74.2900    76.1100    74.2900    75.7975    132079200    74.14390  
## 2020-01-09    76.8100    77.6075    76.5500    77.4075    170108400    75.71877
```

取出 adjust price

```
AAPL_adjust = AAPL$AAPL.Adjusted
```

- a. Compute the sample mean, standard deviation, skewness and excess kurtosis of the log returns r_t .

- $r_t = \ln(R_t + 1)$
- $r_t = \ln(P_t) - \ln(P_{t-1})$

Log Return : $r_t = \ln(P_t) - \ln(P_{t-1})$

```
AAPL_log_return = diff(log(AAPL_adjust))  
head(AAPL_log_return)
```

```
##           AAPL.Adjusted  
## 2020-01-02             NA  
## 2020-01-03    -0.009769539  
## 2020-01-06     0.007936367  
## 2020-01-07    -0.004714027  
## 2020-01-08     0.015958210  
## 2020-01-09     0.021018349
```

- sample mean
- standard deviation
- skewness
- excess kurtosis

```
basicStats(AAPL_log_return)
```

```
##          AAPL.Adjusted
## nobs          795.000000
## NAs            1.000000
## Minimum       -0.137708
## Maximum        0.113158
## 1. Quartile   -0.010684
## 3. Quartile    0.014041
## Mean          0.000877
## Median        0.000746
## Sum           0.696621
## SE Mean       0.000815
## LCL Mean      -0.000722
## UCL Mean      0.002477
## Variance      0.000527
## Stdev         0.022961
## Skewness      -0.126218
## Kurtosis      4.122750
```

```
mean(AAPL_log_return,na.rm=T)      # 0.0008773567
```

```
## [1] 0.0008773565
```

```
sqrt(var(AAPL_log_return,na.rm=T)) # 0.02296092
```

```
##          AAPL.Adjusted
## AAPL.Adjusted  0.02296093
```

```
skewness(AAPL_log_return,na.rm=T)  # -0.1262185
```

```
## [1] -0.1262181
## attr(,"method")
## [1] "moment"
```

```
kurtosis(AAPL_log_return,na.rm=T)  # 4.122718
```

```
## [1] 4.12275
## attr(,"method")
## [1] "excess"
```

- b. Estimate the mean and standard deviation of the simple return R_t by assuming the log returns r_t follow a normal distribution $r_t \sim N(\mu, \sigma^2)$.

- $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$
- $R_t = e^{r_t} - 1$
- $r_t \sim N(\mu_{r_t}, \sigma_{r_t}^2)$ · then $e^{r_t} \sim \text{lognormal}(\mu_{r_t}, \sigma_{r_t}^2)$
- $E(e^{r_t}) = e^{\mu_{r_t} + \frac{\sigma_{r_t}^2}{2}}$
- $E(e^{r_t} - 1) = E(R_t) = e^{\mu_{r_t} + \frac{\sigma_{r_t}^2}{2}} - 1$
- $\text{Var}(e^{r_t}) = e^{2\mu + \sigma^2}[e^{\sigma^2} - 1]$
- $\text{Var}(e^{r_t}) = \text{Var}(e^{r_t} - 1) = \text{Var}(R_t)$

```
mu = mean(AAPL_log_return, na.rm=T) # 0.0008773567
va = var(AAPL_log_return, na.rm=T) # 0.000527204

# mean of the simple return
mean_R_t = exp(mu+va/2) - 1
mean_R_t # 0.00114161
```

```
## AAPL.Adjusted
## AAPL.Adjusted 0.00114161
```

```
# standard deviation of the simple return
sd_R_t = sqrt(exp(2*mu+va)*(exp(va)-1))
sd_R_t # 0.02299017
```

```
## AAPL.Adjusted
## AAPL.Adjusted 0.02299017
```

c. Compute the sample mean and the sample standard deviation of the simple return R_t . Compare the results of (b) and (c).

- $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$
- $R_t = e^{r_t} - 1$

simple return

```
AAPL_simple_return = exp(AAPL_log_return) - 1
head(AAPL_simple_return)
```

```
## AAPL.Adjusted
## 2020-01-02 NA
## 2020-01-03 -0.009721972
## 2020-01-06 0.007967944
## 2020-01-07 -0.004702933
## 2020-01-08 0.016086222
## 2020-01-09 0.021240790
```

```
AAPL_simple_return2 = diff(AAPL_adjust)/lag(AAPL_adjust) # lag 幫助往前除一天
head(AAPL_simple_return2)
```

```
##           AAPL.Adjusted
## 2020-01-02           NA
## 2020-01-03  -0.009721972
## 2020-01-06   0.007967944
## 2020-01-07  -0.004702933
## 2020-01-08   0.016086222
## 2020-01-09   0.021240790
```

the sample mean and the sample standard deviation

```
mean(AAPL_simple_return, na.rm = T)      # 0.00114107
```

```
## [1] 0.00114107
```

```
sqrt(var(AAPL_simple_return, na.rm = T)) # 0.02297127
```

```
##           AAPL.Adjusted
## AAPL.Adjusted   0.02297128
```

Estimate

- $\text{mean_R_t} = 0.00114161$
- $\text{sd_R_t} = 0.02299017$

Compute

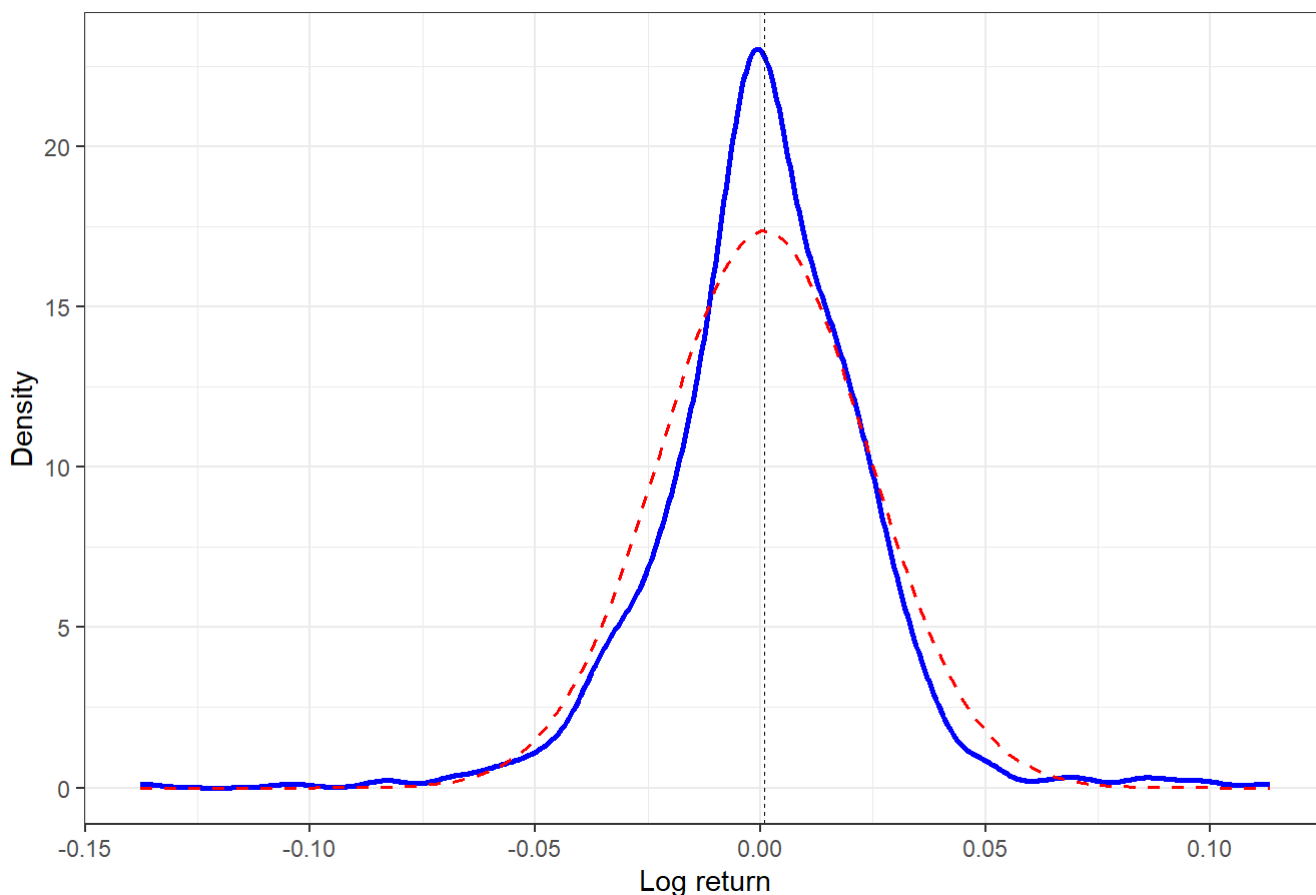
- $\text{mean} = 0.00114107$
- $\text{sd} = 0.02297127$
- 兩者結果幾乎一樣， r_t 可能真的符合常態假設

- d. Find the kernel density estimator and normal density estimator for the log return r_t and the simple return R_t respectively. Compare the empirical kernel density and normal density for r_t and R_t . Plot the two estimated densities on the same graph. (see Page 21 Figure 1.4 in the textbook)

the log return

```
ggplot(na.omit(AAPL_log_return),aes(x=AAPL.Adjusted)) +  
  geom_density(color = "blue",linewidth=1) +  
  geom_vline(aes(xintercept = mu),color="black",linetype="dashed",linewidth=0.1) +  
  theme_bw() +  
  labs(title="log return of Apple",x="Log return",y="Density")+  
  stat_function(fun = dnorm, args = list(mu, sqrt(va)),  
              colour = "red",linewidth=0.6,linetype="dashed")
```

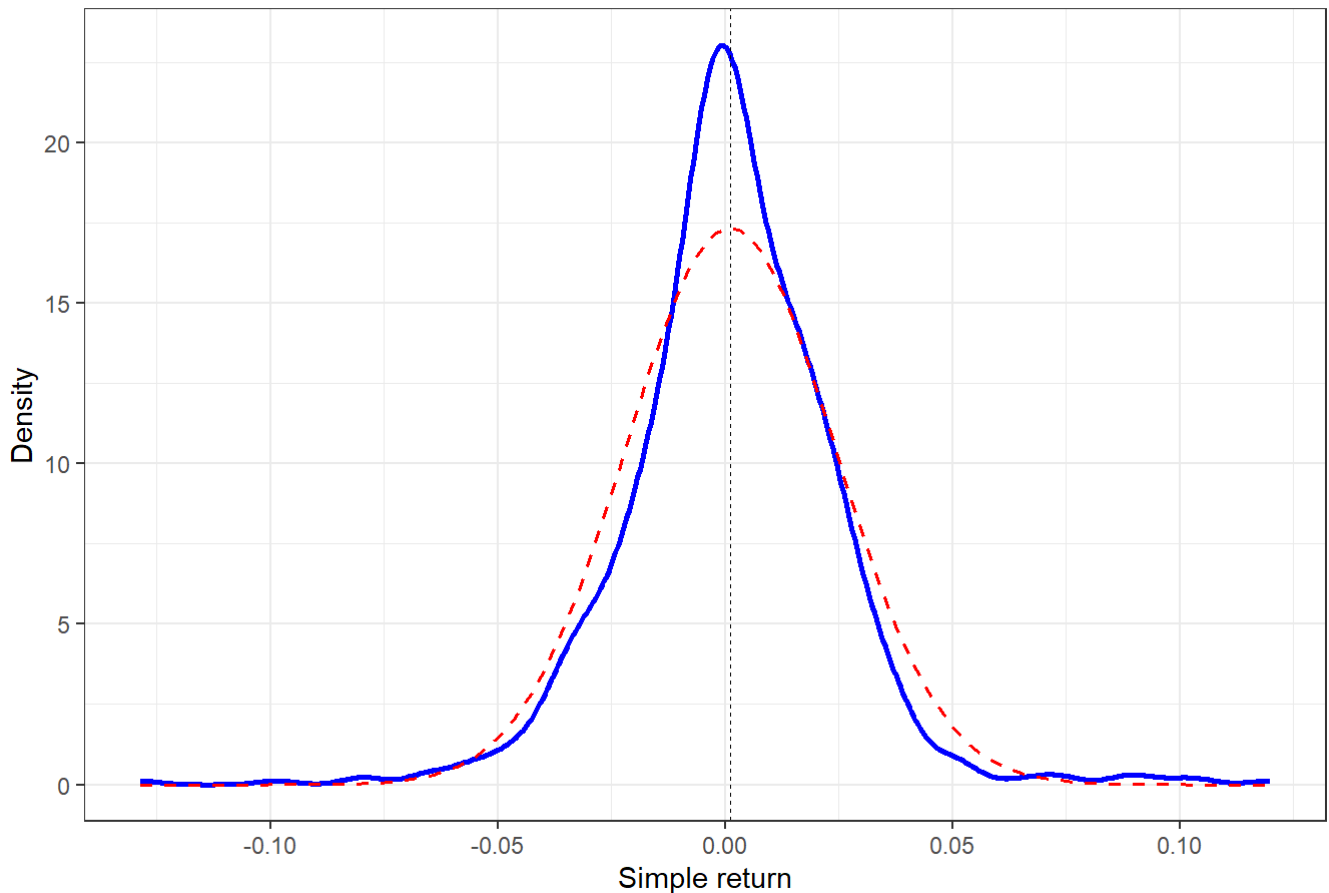
log return of Apple



the simple return

```
ggplot(na.omit(AAPL_simple_return),aes(x=AAPL.Adjusted)) +  
  geom_density(color = "blue",linewidth=1) +  
  geom_vline(aes(xintercept = mean_R_t),color="black",linetype="dashed",linewidth=0.1) +  
  theme_bw() +  
  labs(title="Simple return of Apple",x="Simple return",y="Density")+  
  stat_function(fun = dnorm, args = list(mean_R_t, sd_R_t),  
              colour = "red",linewidth=0.6,linetype="dashed")
```

Simple return of Apple



Compare the empirical kernel density and normal density for r_t and R_t

常態假設對 APPLE 股票的日回報是有問題的。
經驗密度函數在其均值附近有一個更高的峰值，
但尾部比相應的正態分佈更厚。

- In other words, the empirical density function is taller and skinnier
- but with a wider support than the corresponding normal density

2.

Consider the daily stock returns of Taiwan Semiconductor Manufacturing from January 2020 to February 2023.
The price data can be obtained by using R package quantmod.

```
# from 正常 · to 少一天  
getSymbols("TSM", from="2020-01-01", to='2023-03-01')
```

```
## [1] "TSM"
```

```
head(TSM)
```

##	TSM.Open	TSM.High	TSM.Low	TSM.Close	TSM.Volume	TSM.Adjusted
## 2020-01-02	59.60	60.12	59.60	60.04	8432600	56.35028
## 2020-01-03	58.97	58.98	58.04	58.06	10546400	54.49196
## 2020-01-06	57.60	57.69	57.13	57.39	8897200	53.86313
## 2020-01-07	57.45	58.60	56.74	58.32	7444300	54.73599
## 2020-01-08	58.19	58.98	58.11	58.75	5381500	55.13955
## 2020-01-09	59.69	59.71	58.70	59.23	5112700	55.59006

取出 adjust price

```
TSM_adjust = TSM$TSM.Adjusted
```

- a. Compute the sample mean, standard deviation, skewness and excess kurtosis of the log returns r_t .

- $r_t = \ln(R_t + 1)$
- $r_t = \ln(P_t) - \ln(P_{t-1})$

Log Return : $r_t = \ln(P_t) - \ln(P_{t-1})$

```
TSM_log_return = diff(log(TSM_adjust))
head(TSM_log_return)
```

##	TSM.Adjusted
## 2020-01-02	NA
## 2020-01-03	-0.033534023
## 2020-01-06	-0.011606968
## 2020-01-07	0.016075191
## 2020-01-08	0.007345872
## 2020-01-09	0.008137055

- sample mean
- standard deviation
- skewness
- excess kurtosis

```
basicStats(TSM_log_return)
```

```
##          TSM.Adjusted
## nobs      795.000000
## NAs       1.000000
## Minimum   -0.151219
## Maximum    0.119135
## 1. Quartile -0.014314
## 3. Quartile  0.014292
## Mean       0.000548
## Median     -0.000179
## Sum        0.435125
## SE Mean    0.000889
## LCL Mean   -0.001197
## UCL Mean    0.002293
## Variance    0.000628
## Stdev      0.025053
## Skewness    0.058385
## Kurtosis    2.890400
```

```
mean(TSM_log_return,na.rm=T)      # 0.0005480166
```

```
## [1] 0.0005480166
```

```
sqrt(var(TSM_log_return,na.rm=T)) # 0.02505303
```

```
##          TSM.Adjusted
## TSM.Adjusted 0.02505303
```

```
skewness(TSM_log_return,na.rm=T)  # 0.05838448
```

```
## [1] 0.05838536
## attr(,"method")
## [1] "moment"
```

```
kurtosis(TSM_log_return,na.rm=T)  # 2.890411
```

```
## [1] 2.8904
## attr(,"method")
## [1] "excess"
```

b. Estimate the mean and standard deviation of the simple return R_t by assuming the log returns r_t follow a normal distribution $r_t \sim N(\mu, \sigma^2)$.

- $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$
- $R_t = e^{r_t} - 1$
- $r_t \sim N(\mu_{r_t}, \sigma_{r_t}^2)$ · then $e^{r_t} \sim \text{lognormal}(\mu_{r_t}, \sigma_{r_t}^2)$
- $E(e^{r_t}) = e^{\mu_{r_t} + \frac{\sigma_{r_t}^2}{2}}$

- $E(e^{r_t} - 1) = E(R_t) = e^{\mu_t + \frac{\sigma_t^2}{2}} - 1$
- $Var(e^{r_t}) = e^{2\mu + \sigma^2}[e^{\sigma^2} - 1]$
- $Var(e^{r_t}) = Var(e^{r_t} - 1) = Var(R_t)$

```
mu2 = mean(TSM_log_return,na.rm=T) # 0.0005480166
va2 = var(TSM_log_return,na.rm=T) # 0.0006276544

# mean of the simple return
mean_R_t2 = exp(mu2+va2/2) - 1
mean_R_t2 # 0.0008622153
```

```
##          TSM.Adjusted
## TSM.Adjusted 0.0008622152
```

```
# standard deviation of the simple return
sd_R_t2 = sqrt(exp(2*mu2+va2)*(exp(va2)-1))
sd_R_t2 # 0.02507857
```

```
##          TSM.Adjusted
## TSM.Adjusted 0.02507857
```

c. Compute the sample mean and the sample standard deviation of the simple return R_t . Compare the results of (b) and (c).

- $R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$
- $R_t = e^{r_t} - 1$

simple return

```
TSM_simple_return = exp(TSM_log_return) - 1
head(TSM_simple_return)
```

```
##          TSM.Adjusted
## 2020-01-02          NA
## 2020-01-03 -0.032977990
## 2020-01-06 -0.011539867
## 2020-01-07 0.016205092
## 2020-01-08 0.007372919
## 2020-01-09 0.008170251
```

```
TSM_simple_return2 = diff(TSM_adjust)/lag(TSM_adjust) # Lag 幫助往前除一天
head(TSM_simple_return2)
```

```
##           TSM.Adjusted
## 2020-01-02           NA
## 2020-01-03 -0.032977990
## 2020-01-06 -0.011539867
## 2020-01-07  0.016205092
## 2020-01-08  0.007372919
## 2020-01-09  0.008170251
```

the sample mean and the sample standard deviation

```
mean(TSM_simple_return, na.rm = T)      # 0.00086202
```

```
## [1] 0.00086202
```

```
sqrt(var(TSM_simple_return, na.rm = T)) # 0.02510999
```

```
##           TSM.Adjusted
## TSM.Adjusted  0.02510999
```

Estimate

- $\text{mean_R_t2} = 0.0008622153$
- $\text{sd_R_t2} = 0.02507857$

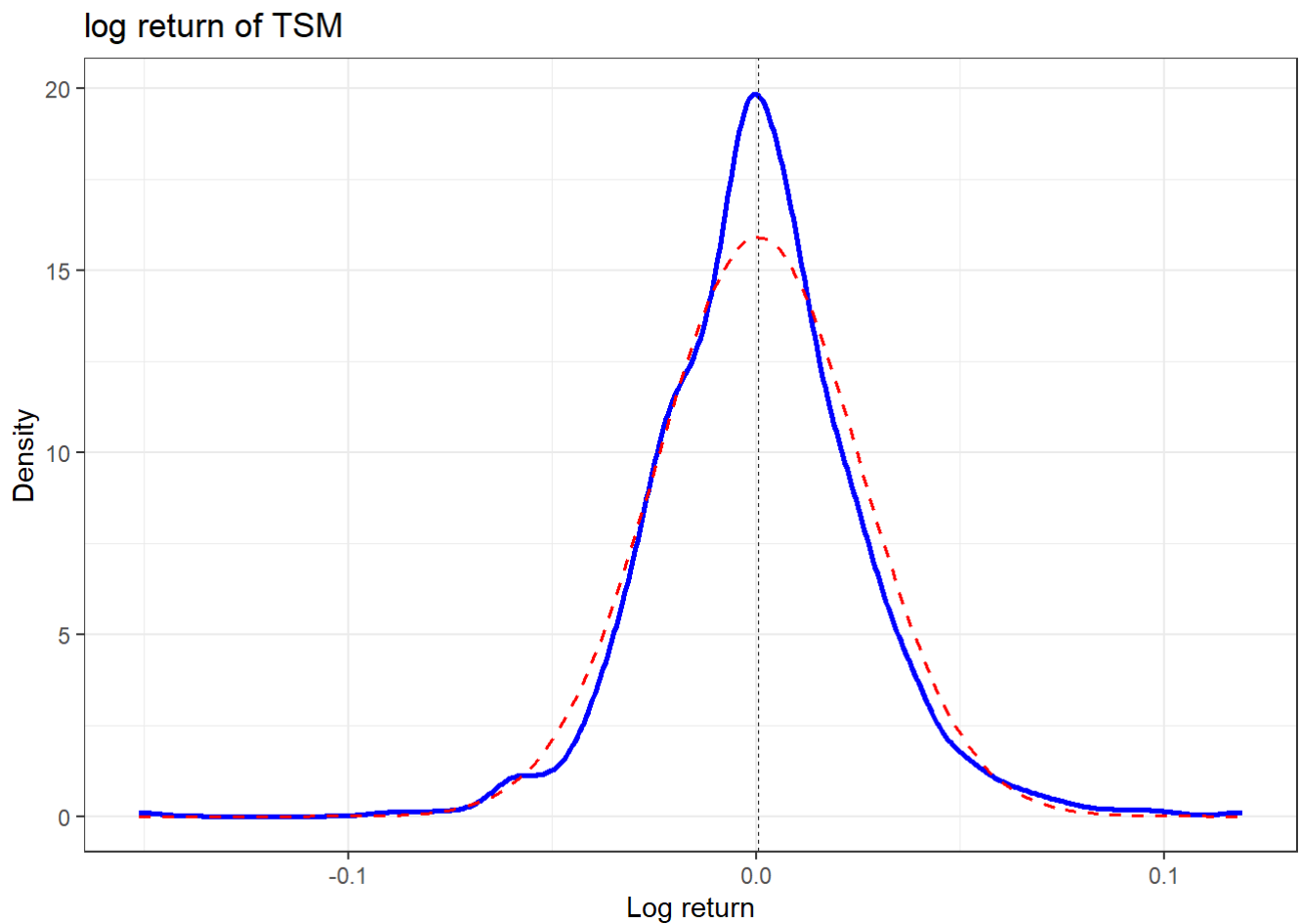
Compute

- $\text{mean} = 0.00086202$
- $\text{sd} = 0.02510999$
- 兩者結果幾乎一樣， r_t 可能真的符合常態假設

- Find the kernel density estimator and normal density estimator for the log return r_t and the simple return R_t respectively. Compare the empirical kernel density and normal density for r_t and R_t . Plot the two estimated densities on the same graph. (see Page 21 Figure 1.4 in the textbook)

the log return

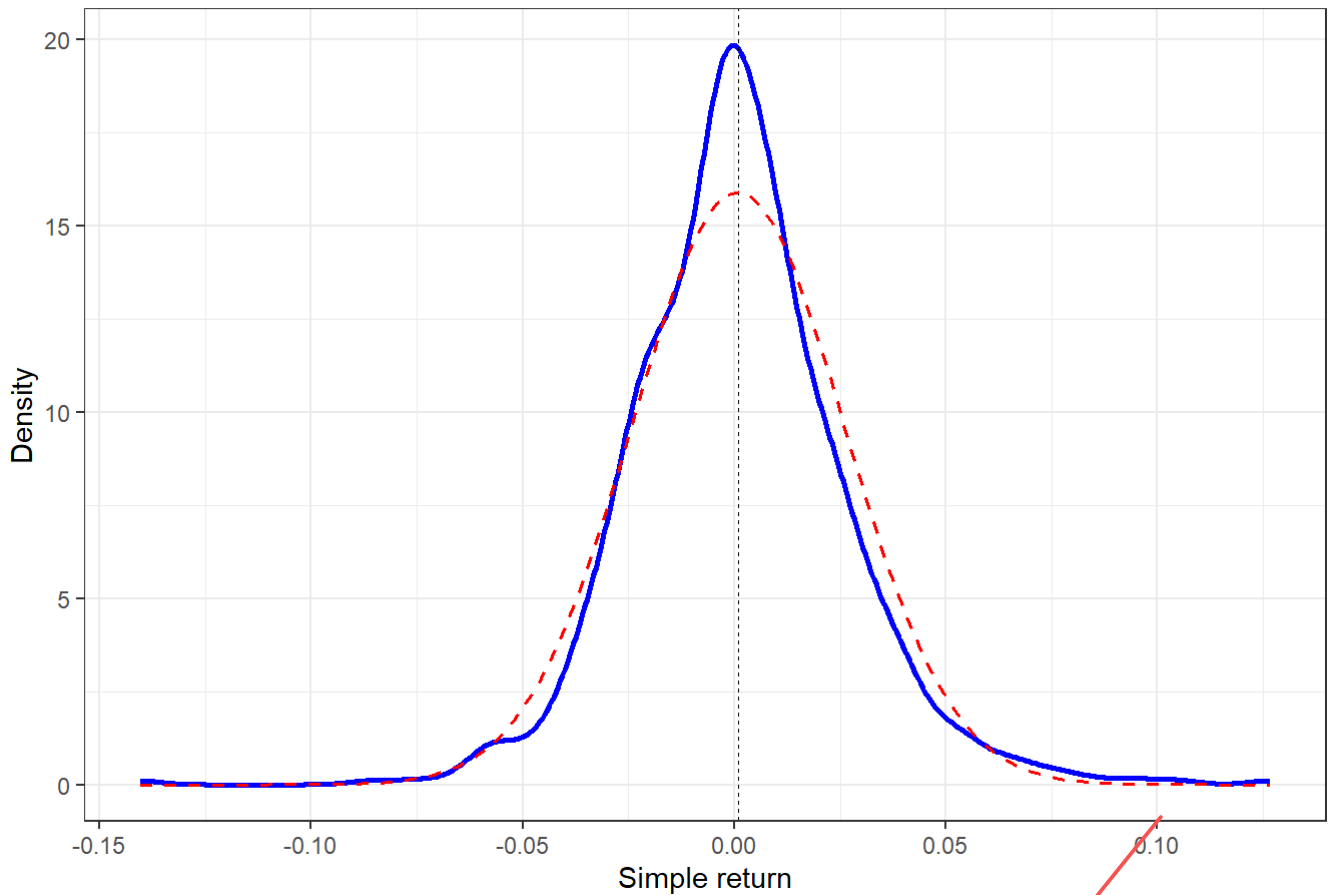
```
ggplot(na.omit(TSM_log_return), aes(x=TSM.Adjusted)) +
  geom_density(color = "blue", linewidth=1) +
  geom_vline(aes(xintercept = mu2), color="black", linetype="dashed", linewidth=0.1) +
  theme_bw() +
  labs(title="log return of TSM", x="Log return", y="Density")+
  stat_function(fun = dnorm, args = list(mu2, sqrt(va2)),
               colour = "red", linewidth=0.6, linetype="dashed")
```



the simple return

```
ggplot(na.omit(TSM_simple_return), aes(x=TSM.Adjusted)) +  
  geom_density(color = "blue", linewidth=1) +  
  geom_vline(aes(xintercept = mean_R_t2), color="black", linetype="dashed", linewidth=0.1) +  
  theme_bw() +  
  labs(title="Simple return of TSM", x="Simple return", y="Density")+  
  stat_function(fun = dnorm, args = list(mean_R_t2, sd_R_t2),  
               colour = "red", linewidth=0.6, linetype="dashed")
```

Simple return of TSM



Compare the empirical kernel density and normal density for r_t and R_t

常態假設對 TSM 股票的日回報是有問題的。
經驗密度函數在其均值附近有一個更高的峰值，
但尾部比相應的正態分佈更厚。

- In other words, the empirical density function is taller and skinnier
- but with a wider support than the corresponding normal density