Homework 5

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1) Stock used Is APPLE

Fit model:

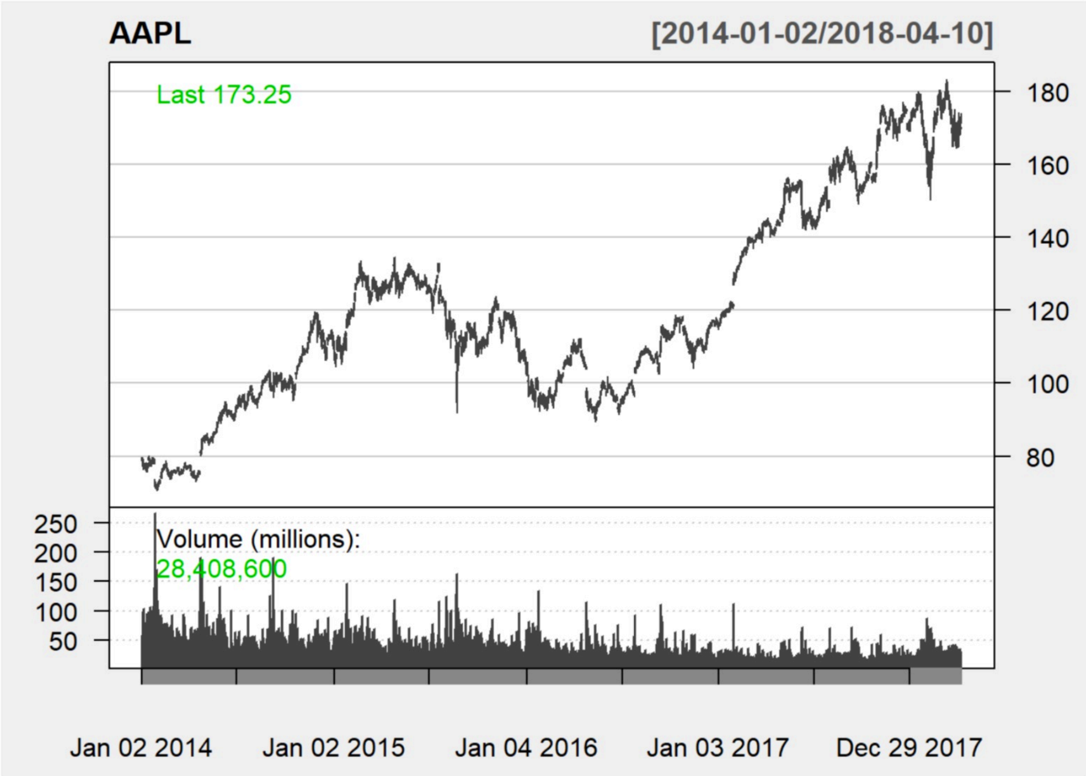
```
appleclose<-as.xts(data.frame(SPYClose = AAPL$"AAPL.Close"))
#daily log returns of the stock
appleclose.log<- log(dailyReturn(appleclose)+1)
#To find any serial correlations in the log returns, lets perform the Box test
Box.test(appleclose.log, lag=10, type ='Ljung')
```

```
##
##  Box-Ljung test
##
## data:  appleclose.log
## X-squared = 9.3513, df = 10, p-value = 0.4991
```

The p value is high. Therefore we can not reject the null hypothesis (serial correlation) and say that there is no serial correlation in the log returns.

Fit the GARCH(1,1) model using a Skewed Student-t distribution for the innovations. Use the fitted model to produce 1-step to 5-step ahead volatility forecasts.

```
ms.log.m1 <- garchFit(~garch(1, 1), data = appleclose.log, trace = F,cond.dist = "std",
                      include.mean = F)
# Note: standardDeviation value is volatility forecast
ms.log.m1.predict <- predict(ms.log.m1, n.ahead = 5)
ms.log.m1.predict
```



Predict:

```
##   meanForecast  meanError standardDeviation
## 1            0 0.01703075        0.01703075
## 2            0 0.01696786        0.01696786
## 3            0 0.01690949        0.01690949
## 4            0 0.01685534        0.01685534
## 5            0 0.01680512        0.01680512
```

Fit an IGARCH(1,1) model with Gaussian innovations to the return series. Write down the fitted model. Use the fitted IGARCH(1,1) model to predict the volatility for the next five trading days.

2)

```
> m2=Igarch(log_return,volcnt=F)
Maximized log-likehood:  -3121.829

Coefficient(s):
       Estimate  Std. Error   t value Pr(>|t|)
mu   0.000740288 0.000385037   1.92264 0.054525 .
beta 0.976004639 0.003297053 296.02333  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


> last_return=log_return[length(log_return)]
> last_vol=m2$volatility[length(log_return)]
```

```
> beta=m2$par[2]
> step1=sqrt((1-beta)*last_return*last_return+beta*last_vol*last_vol)
> step5=sqrt(5)*step1
> step1
      beta
0.01107464
> step5
      beta
0.02476364
```

The volatility for next five trading days is 0.025

3)

Fit model:

```
> m3 = garchFit(~aparch(1,1), data = daily_log_return, trace = F, delta = 2, include.delta = F, cond.dist = "std")
> summary(m3)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~aparch(1, 1), data = daily_log_return, delta = 2,
    cond.dist = "std", include.delta = F, trace = F)

Mean and Variance Equation:
 data ~ aparch(1, 1)
<environment: 0x000000002c23fa80>
 [data = daily_log_return]

Conditional Distribution:
 std

Coefficient(s):
        mu       omega      alpha1      gamma1       beta1       shape
5.4177e-04  6.7811e-05  1.5677e-01  1.9605e-01  8.0251e-01  3.8652e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     5.418e-04   7.554e-04    0.717  0.47327
omega  6.781e-05   3.476e-05    1.951  0.05108 .
alpha1 1.568e-01   4.786e-02    3.275  0.00106 **
gamma1 1.961e-01   9.128e-02    2.148  0.03173 *
beta1  8.025e-01   5.532e-02   14.506  < 2e-16 ***
shape  3.865e+00   4.958e-01    7.796 6.44e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:
 2146.521    normalized:  2.1316

Description:
 Sun Apr 22 17:17:41 2018 by user: SY


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  3183.054  0
 Shapiro-Wilk Test  R    W      0.9259069 0
 Ljung-Box Test     R    Q(10)  9.127148  0.5200808
 Ljung-Box Test     R    Q(15)  15.02346  0.4497287
 Ljung-Box Test     R    Q(20)  17.14892  0.6432834
 Ljung-Box Test     R^2  Q(10)  3.470468  0.9680916
 Ljung-Box Test     R^2  Q(15)  5.201968  0.9902739
 Ljung-Box Test     R^2  Q(20)  5.973236  0.9989332
 LM Arch Test       R    TR^2   4.66591   0.9682177

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-4.251283 -4.222000 -4.251354 -4.240157
```

Model:

$$r_t = 5.418*10^{-4} + a_t, \quad \varepsilon_t \sim t_{3.87}$$

$$\sigma_t^2 = 6.781*10^{-5} + 0.1568(|a_{t-1}| - 0.1961*a_{t-1})^2 + 0.8025*\sigma_{t-1}^2$$

4)

2、

3、

```
GE=read.csv("./GE.csv",header=T)
> GE.prices=GE$Adj.Close[length(GE$Adj.Close):1]
> GE.returns=returns(GE.prices)[-1]
> model=Igarch(GE.returns,volcnt=F)
Maximized log-likehood:  -4156.492

Coefficient(s):
       Estimate  Std. Error  t value Pr(>|t|)
mu   0.00047908  0.00033439   1.4327  0.15194
beta 0.93598715  0.00695296 134.6171  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> last_return=GE.returns[length(GE.returns)]
> last_vol=model$volatility[length(GE.returns)]
> beta=model$par[2]
> step1=sqrt((1-beta)*last_return*last_return+beta*last_vol*last_
vol)
> VaR1=model$par[1]-step1*1.65> VaR1
         mu
-0.01671023
 > VaR1=model$par[1]-step1*2.34
> VaR1
         mu
-0.02389849
> step5=sqrt(5)*step1
> VaR5=model$par[1]-step5*1.65
> VaR5
         mu
-0.03795738
> VaR5=model$par[1]-step5*2.34
> VaR5
          mu
-0.05403082
```

When p=0.05, one-day VaR=-0.0167, five-day VaR=-0.0380

When p=0.01, one-day VaR=-0.0239, five-day VaR=-0.0540

4、

Yes, r_t^0 is serially correlated because miu is not zero.

$\rho(1) = cov(r_t^0, r_{t-1}^0) / sqrt(var(r_t^0)*var(r_{t-1}^0))$

$= (-0.05^2*0.4)/(1.5^2+(2*0.4*0.05^2)/(1-0.4))$

$= -0.000443787$

$\rho(2) = (-0.05^2*0.4^2)/(1.5^2+(2*0.4*0.05^2)/(1-0.4))$

$= -0.0001775148$

$\rho(3) = (-0.05^2*0.4^3)/(1.5^2+(2*0.4*0.05^2)/(1-0.4))$

$= -7.100592e-05$

5、

(a)

```
> m2=garchFit(~arma(0,0)+garch(1,1),data=GE.returns,trace=F)
> step1=sqrt(m2@fit$params$params[2]+m2@fit$params$params[3]*m2@h.
t[length(m2@h.t)]+m2@fit$params$params[5]*GE.returns[length(GE.re
turns)]^2)
> VaR1=m2@fit$params$params[1]-step1*1.65
> VaR1
          mu
-0.005540696
> VaR1=m2@fit$params$params[1]-step1*2.34
> VaR1
          mu
-0.008041823
> step5=step1*sqrt(5)
> VaR5=m2@fit$params$params[1]-step5*1.65
> VaR5
         mu
-0.01293357
> VaR5=m2@fit$params$params[1]-step5*2.34
> VaR5
         mu
-0.01852626
```

When p=0.05, one-day VaR=-0.00554, five-day VaR=-0.0129

When p=0.01, one-day VaR=-0.00804, five-day VaR=-0.0185

(b)

```
> m3=garchFit(~arma(0,0)+garch(1,1),data=GE.returns,trace=F,cond.
dist = "std")
> step1=sqrt(m2@fit$params$params[2]+m2@fit$params$params[3]*m2@h.
t[length(m2@h.t)]+m2@fit$params$params[5]*GE.returns[length(GE.re
turns)]^2)
> VaR1=m3@fit$params$params[1]-step1*1.65
> VaR1
          mu
-0.005636639
```

```
> VaR1=m3@fit$params$params[1]-step1*2.34
> VaR1
         mu
-0.008137766
> step5=step1*sqrt(5)
> VaR5=m3@fit$params$params[1]-step5*1.65
> VaR5
        mu
-0.01302951
> VaR5=m3@fit$params$params[1]-step5*2.34
> VaR5
       mu
-0.0186222
```

When p=0.05, one-day VaR=-0.00564, five-day VaR=-0.0130

When p=0.01, one-day VaR=-0.00814, five-day VaR=-0.0186

6、

(a)

```
> IBM=read.csv("./IBM.csv",header=T)
> SP500=IBM$sprtrn
> IBM=IBM$RET
> M=rep(0,length(IBM))
> S=rep(0,length(IBM))
> for (i in 1:length(IBM)){
+   if (IBM[i]>0){M[i]=1}
+   if (SP500[i]>0){S[i]=1}
+ }
> Mt=M[3:length(M)]
> Mt_1=M[2:(length(M)-1)]
> Mt_2=M[1:(length(M)-2)]
> St_1=S[2:(length(M)-1)]
> St_2=S[1:(length(M)-2)]
> model=glm(Mt~Mt_1+Mt_2+St_1+St_2,family=binomial)
> summary(model)
Call:
glm(formula = Mt ~ Mt_1 + Mt_2 + St_1 + St_2, family = binomial)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4265  -1.2354   0.9898   1.0604   1.2426

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.13546    0.15688   0.863   0.3879
```

```
Mt_1         0.43339    0.16902   2.564   0.0103 *
Mt_2        -0.13747    0.16970  -0.810   0.4179
St_1        -0.11002    0.17043  -0.646   0.5186
St_2        -0.03988    0.17046  -0.234   0.8150
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1004.07  on 729  degrees of freedom
Residual deviance:  996.36  on 725  degrees of freedom
AIC: 1006.4

Number of Fisher Scoring iterations: 4
```

It is not useful. From the summary of this model, all coefficients are insignificant.

(b)

```
> train_M=M[1:(length(M)-50)]
> train_S=S[1:(length(M)-50)]
> test_M=M[(length(M)-49):length(M)]
> test_S=S[(length(M)-49):length(M)]
> train_Mt=train_M[3:length(train_M)]
> train_Mt_1=train_M[2:(length(train_M)-1)]
> train_Mt_2=train_M[1:(length(train_M)-2)]
> train_St_1=train_S[2:(length(train_M)-1)
> train_St_2=train_S[1:(length(train_M)-2)]
> model_new=glm(train_Mt~train_Mt_1+train_Mt_2+train_St_1+train_S
t_2,family=binomial)
> summary(model_new)
Call:
glm(formula = train_Mt ~ train_Mt_1 + train_Mt_2 + train_St_1 +
    train_St_2, family = binomial)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3979  -1.2124   0.9959   1.0711   1.2494

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.082010   0.161896   0.507   0.6125
train_Mt_1   0.422840   0.175088   2.415   0.0157 *
train_Mt_2  -0.183643   0.175633  -1.046   0.2957
train_St_1  -0.061563   0.177114  -0.348   0.7281
train_St_2  -0.004386   0.177014  -0.025   0.9802
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 937.73  on 679  degrees of freedom
Residual deviance: 930.22  on 675  degrees of freedom
AIC: 940.22

Number of Fisher Scoring iterations: 4
> M_estimate=rep(0,50)
> count=0
> for (i in 1:50){
+   if (exp(0.082+0.423*M[length(M)-51+i]-0.184*S[length(M)-51+i]
+          -0.062*M[length(M)-52+i]-0.004*S[length(M)-51+i])
+     /(1+exp(0.082+0.423*M[length(M)-51+i]-0.184*S[length(M)-51+
i]
+            -0.062*M[length(M)-52+i])-0.004*S[length(M)-51+i])>0.
5){
+     M_estimate[i]=1
+   }
+   if (M_estimate[i]!=M[length(M)-50+i]){
+     count=count+1
+   }
+ }
> count
[1] 15
```

There are 15 errors in prediction.

7、

(a)

```
> CAT=read.csv("./CAT.csv",header=T
> returns=c()
> start=CAT$PRICE[1]
> end=CAT$PRICE[1]
> time=CAT$min[1]
> count=35> for (i in 2:length(CAT$min)){
+   if (((CAT$hour[i]==9) & (CAT$min[i]>=30))|((CAT$hour[i]==16) &
(CAT$min[i]<=30))|
+      ((CAT$hour[i]>9) & (CAT$hour[i]<16))){
+   if (CAT$min[i-1]>CAT$min[i]){
+     returns=c(returns,log(end/start))
+     start=CAT$PRICE[i]
+     end=CAT$PRICE[i]
```

```
+     temp=CAT$min[i]+60
+     while (count<temp){
+       count=count+5
+       returns=c(returns,0)
+     }
+     count=count%%60
+   }
+   else{
+     if (CAT$min[i]<count){
+       end=CAT$PRICE[i]
+     }else{
+       returns=c(returns,log(end/start))
+       start=CAT$PRICE[i]
+       end=CAT$PRICE[i]
+       count=count+5
+     }
+   }
+   }
+ }
> Box.test (returns, lag = 10, type = "Ljung")
        Box-Ljung test

data:  returns
X-squared = 19.107, df = 10, p-value = 0.03892
```

According to the box-test, the p_value is smaller than 0.05, which means there exists se rial correlation.

(b)

```
> length(returns)
[1] 453
> returns
[1]  1.110086e-04  5.704917e-03 -3.448871e-04  1.378597e-03  1.5483
87e-03  1.545994e-03
  [7]  0.000000e+00  2.228891e-03  2.053038e-03 -1.883499e-03 -3.42
4658e-04  1.712475e-04
 [13]  1.209886e-03 -5.491502e-04  0.000000e+00  1.710279e-03  5.12
4263e-04  1.364955e-03
 [19]  1.022147e-03  0.000000e+00  2.890421e-03  0.000000e+00 -9.78
5717e-04  4.248720e-05
 [25]  5.946061e-04  1.154578e-03  4.548031e-04  3.978504e-03 -3.04
5688e-03 -1.017467e-03
 [31]  1.186944e-03 -1.694772e-04  0.000000e+00  3.388682e-04  0.00
0000e+00 -8.472423e-04
```

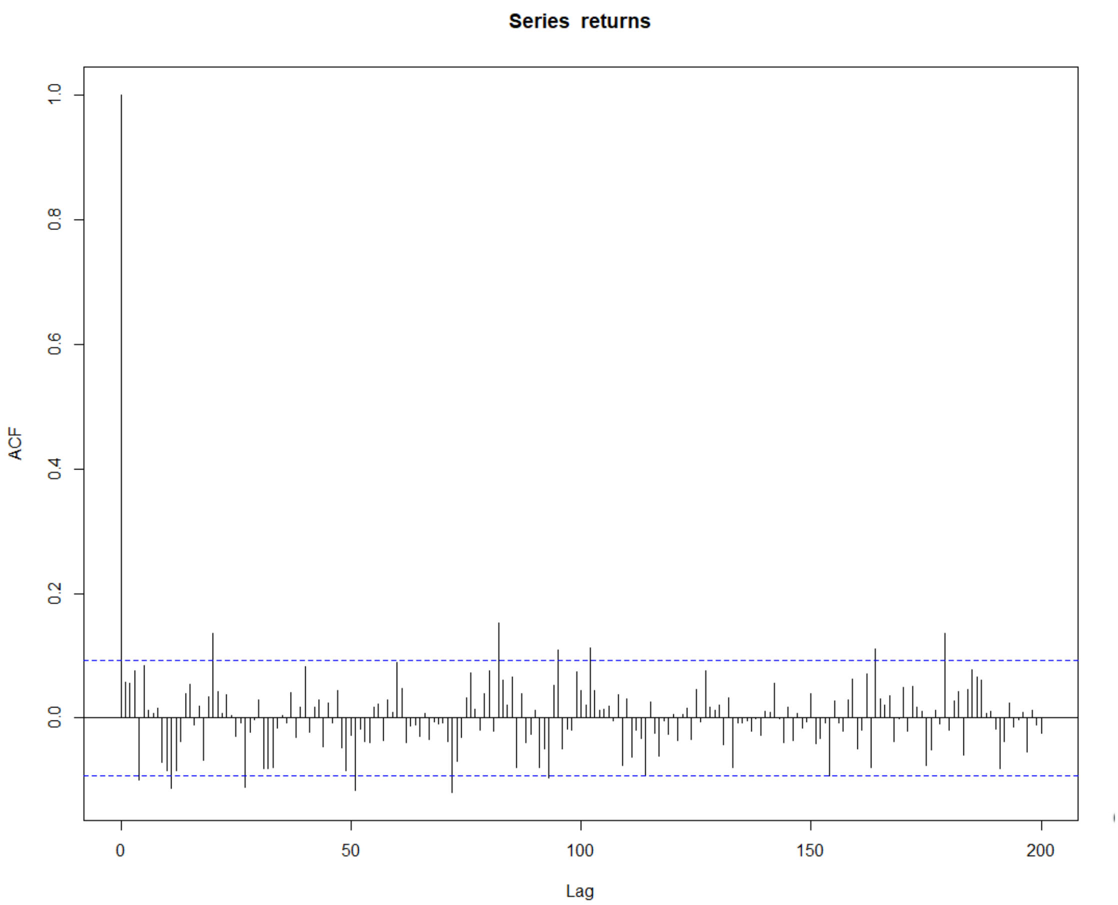
```
 [37] -1.866147e-03  3.395009e-04 -6.604476e-04 -5.096407e-04  3.05
8052e-04  0.000000e+00
 [43]  0.000000e+00 -1.019888e-03  8.669857e-04  0.000000e+00 -5.09
9873e-04  6.800408e-04
 [49] -8.501522e-04 -3.402518e-04  1.182078e-03  4.249352e-04 -6.80
0408e-04 -1.700825e-04
 [55]  1.274914e-03  1.698514e-04 -2.209946e-03 -1.701693e-04  0.00
0000e+00 -8.937122e-04
 [61]  4.921289e-04 -4.256859e-05  8.509915e-04 -1.701693e-04  1.70
1693e-04  1.701693e-04
 [67] -1.701693e-04  8.508828e-05 -6.805036e-04 -8.512812e-04 -1.1
75959e-03  0.000000e+00
 [73]  4.944464e-05  8.520065e-04 -1.703432e-04 -6.817795e-04 -1.02
3367e-03 -1.706630e-04
 [79] -5.120765e-04  8.536429e-05 -3.415301e-04  3.414717e-04 -1.53
7279e-03  7.178125e-04
 [85]  0.000000e+00  3.057683e-04  9.799621e-04  0.000000e+00  0.00
0000e+00  0.000000e+00
 [91]  0.000000e+00 -2.051633e-03 -1.397002e-03 -3.428767e-04 -4.3
56230e-04  4.622109e-03
 [97] -6.834102e-04  0.000000e+00  1.709548e-04 -8.546643e-05  2.90
0778e-03  1.191794e-03
[103]  3.905260e-03  3.214621e-03 -3.378949e-04  6.756757e-04  6.75
3335e-04  5.906999e-05
[109]  1.687762e-06  1.180737e-03  0.000000e+00 -1.685914e-04 -2.53
2288e-03 -1.607105e-03
[115]  5.500434e-04 -1.015572e-03  1.015744e-03 -2.032521e-03  3.39
0405e-04  3.389256e-04
[121] -3.373450e-04 -5.086901e-04 -3.901688e-05  0.000000e+00  1.0
45322e-03  1.779134e-03
[127]  7.613891e-04 -1.353867e-03  4.215520e-04 -2.522326e-04 -1.7
78147e-04  8.469911e-05
[133]  6.773921e-04  1.226657e-03  5.072280e-04  1.098483e-03  0.00
0000e+00  3.394694e-04
[139] -3.377808e-04  1.687479e-03 -8.429216e-05 -1.686198e-04  1.6
83518e-03 -6.737410e-04
[145] -3.370408e-04  1.515535e-03 -1.768645e-03 -1.096538e-03 -7.1
76478e-04  0.000000e+00
[151]  2.348447e-04 -3.045688e-03 -2.541834e-04  5.421524e-04 -1.1
86340e-03 -6.803524e-04
[157] -1.697218e-06  9.330337e-04 -5.105593e-04  1.657658e-03  5.91
0491e-04  1.522457e-03
[163]  0.000000e+00 -1.690188e-04 -7.083800e-04  9.873071e-04  6.75
7899e-04 -1.689332e-04
```

```
[169] -1.098669e-03  2.027713e-03  8.441312e-05  4.219587e-04  3.37
4958e-04 -1.154902e-03
[175] -1.689332e-04  0.000000e+00 -1.521684e-03  0.000000e+00  0.00
0000e+00  0.000000e+00
[181]  5.834865e-03  0.000000e+00  3.656669e-03 -1.196787e-03  0.00
0000e+00  2.792051e-03
[187]  8.390073e-04 -3.361910e-04  0.000000e+00  3.860685e-03  1.17
2235e-03  1.630674e-03
[193]  1.670983e-04 -1.504640e-03  1.638495e-03 -1.670568e-03  0.00
0000e+00  1.354730e-03
[199] -2.342313e-03  1.004689e-03  1.337793e-03  0.000000e+00 -1.00
3009e-03 -6.525067e-04
[205] -6.713550e-04  9.374425e-04  2.506058e-03 -2.171916e-03 -4.9
86188e-04  1.170862e-03
[211]  2.089733e-04  5.029664e-04 -4.528634e-04 -8.361904e-04  0.00
0000e+00  5.614673e-04
[217] -1.479544e-03 -3.682013e-03 -8.388558e-04 -3.458134e-04 -1.3
40949e-03 -1.681379e-04
[223] -3.346228e-04  7.400207e-05  1.176767e-03  1.679402e-04  5.87
6674e-04  0.000000e+00
[229]  1.844555e-03  0.000000e+00  3.451182e-04  0.000000e+00  0.00
0000e+00 -5.027231e-04
[235]  9.214660e-04 -1.674621e-04  8.371704e-04  1.673500e-04 -1.38
9971e-03  1.675744e-04
[241]  0.000000e+00  0.000000e+00 -3.350645e-04 -5.028074e-04  6.37
1360e-05  5.866823e-04
[247] -8.381528e-04  1.676586e-04  8.381878e-05 -5.029760e-04 -1.6
93638e-04  3.354016e-04
[253] -1.492426e-04  0.000000e+00 -1.677149e-04 -1.397964e-03 -1.6
79402e-04 -6.720430e-04
[259] -1.682086e-03  1.177559e-03 -5.045833e-04  5.044985e-04 -6.7
27212e-04 -2.610198e-03
[265]  1.347709e-03  1.683360e-04  0.000000e+00  4.293078e-03  0.00
0000e+00  3.033369e-03
[271]  0.000000e+00  0.000000e+00  0.000000e+00  1.684920e-03 -3.36
5870e-04  2.856425e-03
[277] -2.856425e-03 -5.909684e-03 -5.946836e-03  0.000000e+00  1.9
58031e-03  1.189970e-03
[283]  2.036661e-03 -1.357082e-03  1.696066e-03  1.694342e-06  0.00
0000e+00  1.354555e-03
[289]  3.125398e-03  2.358492e-03  4.036463e-04 -3.364172e-04  0.00
0000e+00  1.682510e-04
[295] -2.168880e-03  1.852632e-03 -3.365870e-04 -1.178948e-03 -8.4
29571e-04 -5.058596e-04
```

```
[301] -5.061156e-04  1.854819e-03 -8.846762e-04  1.179345e-03  1.64
8750e-03  0.000000e+00
[307] -3.363040e-04  9.244087e-04  0.000000e+00  3.854861e-03 -9.20
3096e-04  1.171058e-03
[313]  1.002506e-03 -1.420633e-03 -6.691201e-04 -1.423130e-03  1.8
42716e-04 -1.021895e-04
[319]  0.000000e+00 -1.005868e-03 -1.845042e-03  1.225933e-03  1.67
7993e-04 -2.015452e-03
[325]  3.361345e-04  4.200092e-04 -4.199052e-05  1.343184e-03  3.35
5142e-04  0.000000e+00
[331]  7.546505e-05  0.000000e+00  1.844539e-04 -1.760704e-04 -7.80
0280e-04  1.006374e-03
[337] -1.341067e-04 -4.191993e-04  1.592023e-03  1.673081e-03 -1.6
71821e-04  7.420679e-04
[343]  0.000000e+00 -9.193866e-04  0.000000e+00 -4.609655e-03 -1.3
27420e-04  1.680249e-04
[349] -4.201151e-04  1.679262e-03 -8.389614e-05  1.676446e-03  8.37
1704e-04 -6.696803e-04
[355] -1.706362e-03 -6.712536e-04  1.176077e-03  0.000000e+00  5.02
8916e-04  0.000000e+00
[361] -4.030232e-03  0.000000e+00  0.000000e+00  0.000000e+00  3.70
1216e-03 -1.344086e-03
[367] -1.766413e-03  3.363043e-03  3.357958e-04  1.342282e-03  0.00
0000e+00 -6.708033e-04
[373] -5.033135e-04 -1.679544e-03  8.402656e-04  6.883873e-04  1.67
8556e-04  1.442300e-03
[379] -5.027231e-04 -5.028916e-04 -1.174398e-03  1.719258e-03  1.5
07159e-03  0.000000e+00
[385] -1.338778e-04  2.674245e-03  0.000000e+00  1.034385e-03 -3.33
5557e-04  1.667918e-04
[391] -1.667639e-04 -3.319984e-04  4.437157e-04 -1.667639e-04  0.0
00000e+00 -5.005423e-04
[397]  0.000000e+00  0.000000e+00 -5.007093e-04  1.669310e-04 -4.67
2398e-05  1.652064e-04
[403]  2.318910e-04 -3.335001e-04  1.667639e-04  5.001250e-04 -4.16
8230e-04  3.334445e-04
[409] -3.335001e-04  0.000000e+00 -3.336113e-04  1.095496e-03  1.66
7361e-04 -1.167932e-03
[415]  6.674454e-04 -1.001335e-03  1.668614e-03 -1.667361e-04 -1.6
68892e-03  1.001502e-03
[421] -1.335559e-03 -1.001002e-03  0.000000e+00  1.671821e-04 -6.4
22393e-04  6.873088e-04
[427] -1.605432e-04  3.696824e-04 -1.171450e-03  6.863016e-04 -8.3
65751e-05 -7.198038e-04
```

```
[433] -5.024705e-04  5.444000e-04  1.171450e-03  0.000000e+00 -7.52
8546e-04  6.692321e-04
[439]  1.504137e-03 -1.670425e-04  5.009602e-04  1.871370e-03 -1.08
3559e-03  2.249158e-03
[445]  1.081216e-03  1.412136e-03  1.327250e-03  3.315650e-04  0.00
0000e+00  0.000000e+00
[451]  0.000000e+00 -1.657138e-04  0.000000e+00
```

(c)



There is no auto-correlation between intrday 5-minute log return series.