

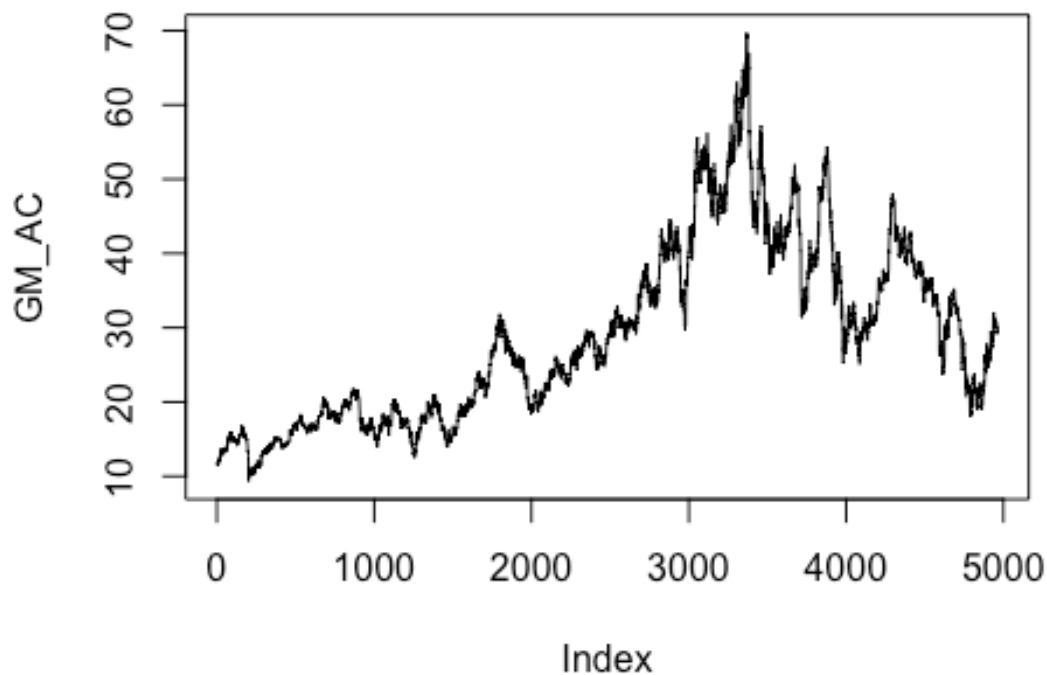
XiangyunLiao_631_HW01

Having a brief idea about how the data look like.

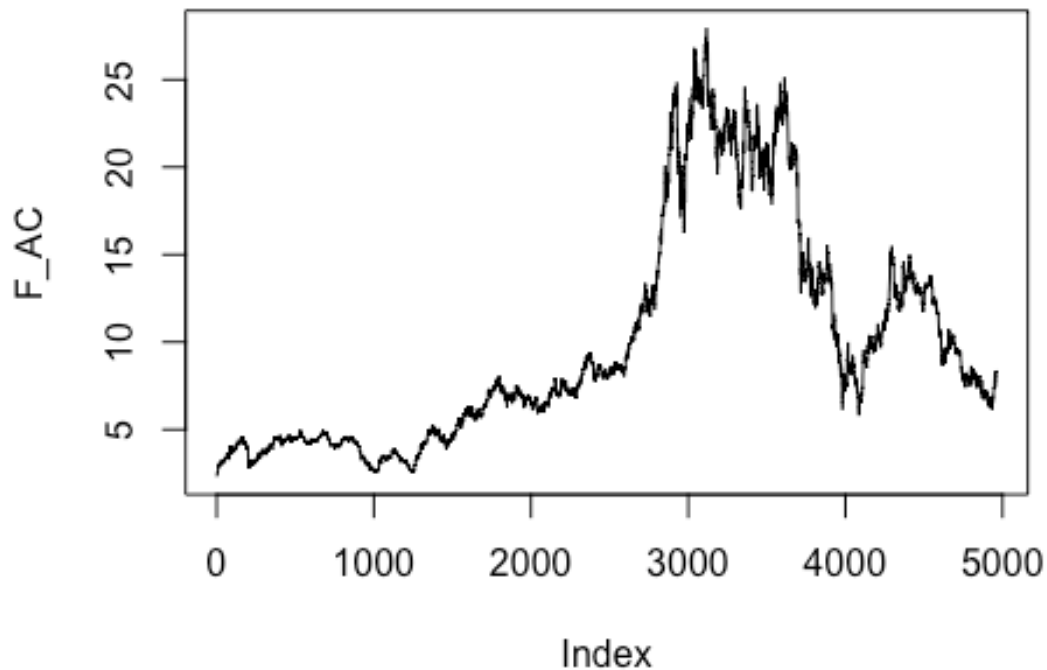
```
dat = read.csv("~/Desktop/631STAT in Fin/datasets/Stock_bond.csv", header =
TRUE)
head(names(dat),n=20)

## [1] "Date"      "GM_Volume"  "GM_AC"      "F_Volume"   "F_AC"
## [6] "UTX_Volume" "UTX_AC"     "CAT_Volume" "CAT_AC"     "MRK_Volume"
## [11] "MRK_AC"     "PFE_Volume" "PFE_AC"     "IBM_Volume" "IBM_AC"
## [16] "MSFT_Volume" "MSFT_AC"    "C_Volume"   "C_AC"       "XOM_Volume"

attach(dat)
plot(GM_AC,type = "l")
```



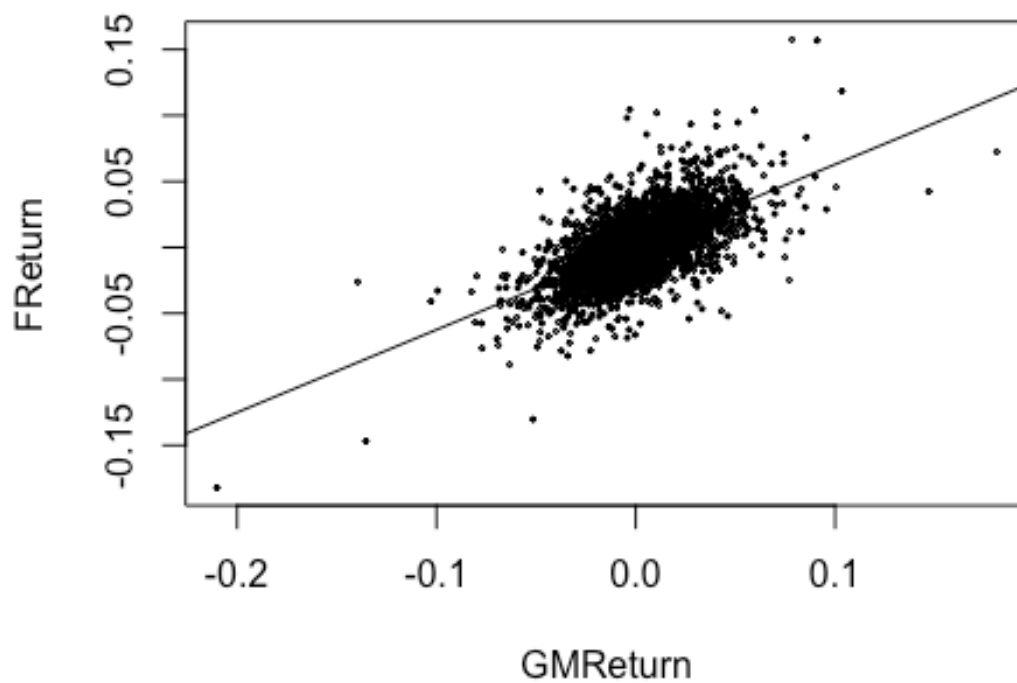
```
plot(F_AC, type = "l")
```



Problem 1:

GM and Ford returns show positively correlated. "Yes", there are several outlying returns, and both of them having outlying number simultaneously in either positive returns or negative ones.

```
n = dim(dat)[1]
GMReturn = GM_AC[2:n]/GM_AC[1:(n-1)] - 1
FReturn = F_AC[2:n]/F_AC[1:(n-1)] - 1
par(mfrow = c(1, 1))
plot(GMReturn, FReturn, type = "p", cex=0.25)
abline(lm(FReturn~GMReturn))
```



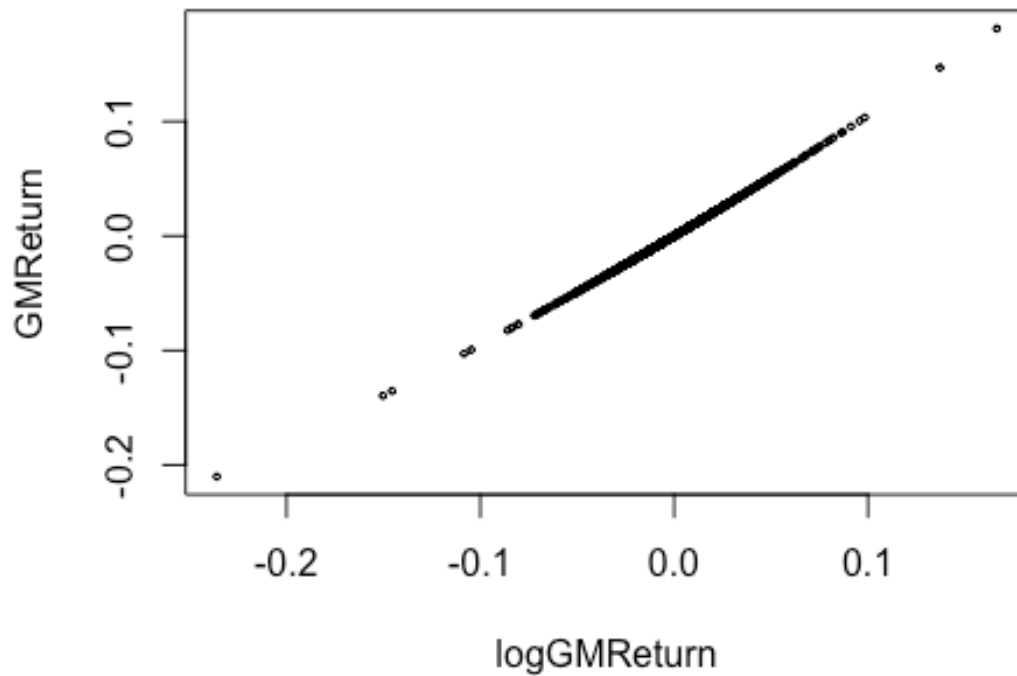
```
cor(FReturn,GMReturn)
```

```
## [1] 0.6139335
```

Problem 2:

The correlation between the return of GM and the log return of GM is 0.9995408, really close to 1, which means taking log does not change the relationship of the data.

```
logGMReturn<- log(GMReturn+1)  
plot(logGMReturn,GMReturn,type = "p",cex=0.35)
```



```
cor(logGMReturn,GMReturn)
```

```
## [1] 0.9995408
```

Problem 3:

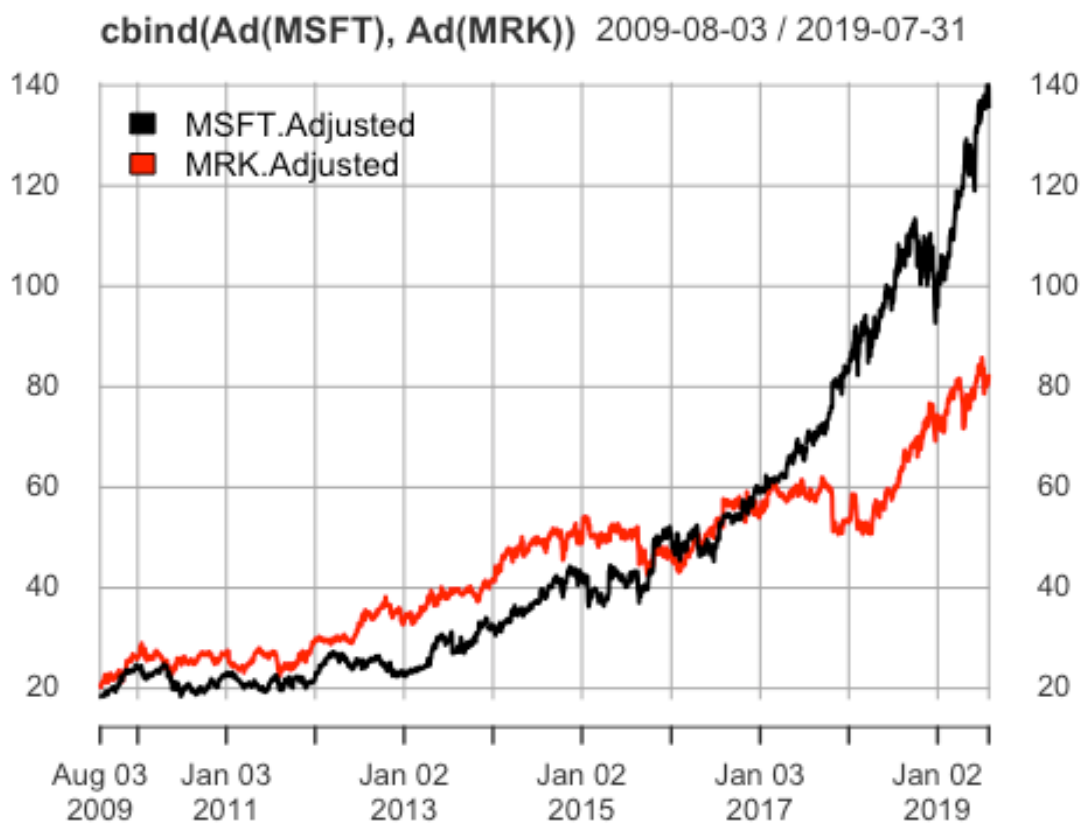
```
getSymbols("MSFT",from = "2009-08-01", to = "2019-08-01")
```

```
## [1] "MSFT"
```

```
getSymbols("MRK",from = "2009-08-01", to = "2019-08-01")
```

```
## [1] "MRK"
```

```
plot(cbind(Ad(MSFT),Ad(MRK)), legend.loc = "topleft")
```



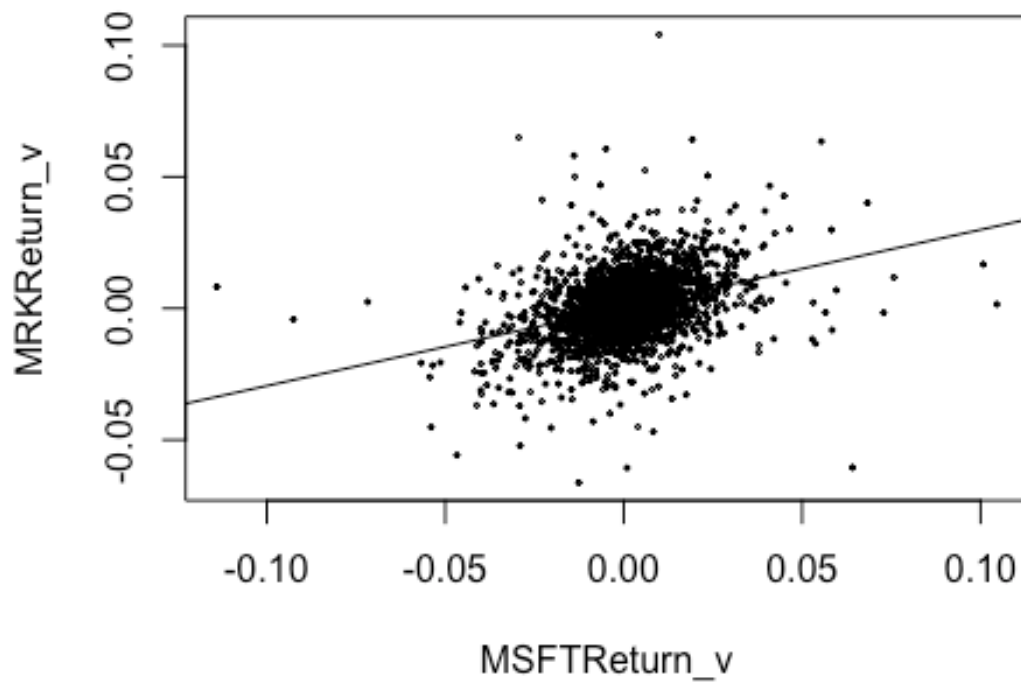
```
MSFTReturn<-dailyReturn(MSFT,type = "arithmetic")
MRKReturn<-dailyReturn(MRK,type = "arithmetic")
MSFTReturn_v <- c(t(MSFTReturn[1:nrow(MSFTReturn),1]))
MRKReturn_v <- c(t(MRKReturn[1:nrow(MRKReturn),1]))
log.MSFTReturn<- log(MSFTReturn_v+1)
log.MRKReturn<- log(MRKReturn_v+1)
```

Stock Microsoft and Merck dose not have strong positive correlation and they almost don't have simultaneously outlying returens.They still have positive correlation but not high.

```
plot(MSFTReturn_v,MRKReturn_v,cex=0.25)
cor(MSFTReturn_v,MRKReturn_v)

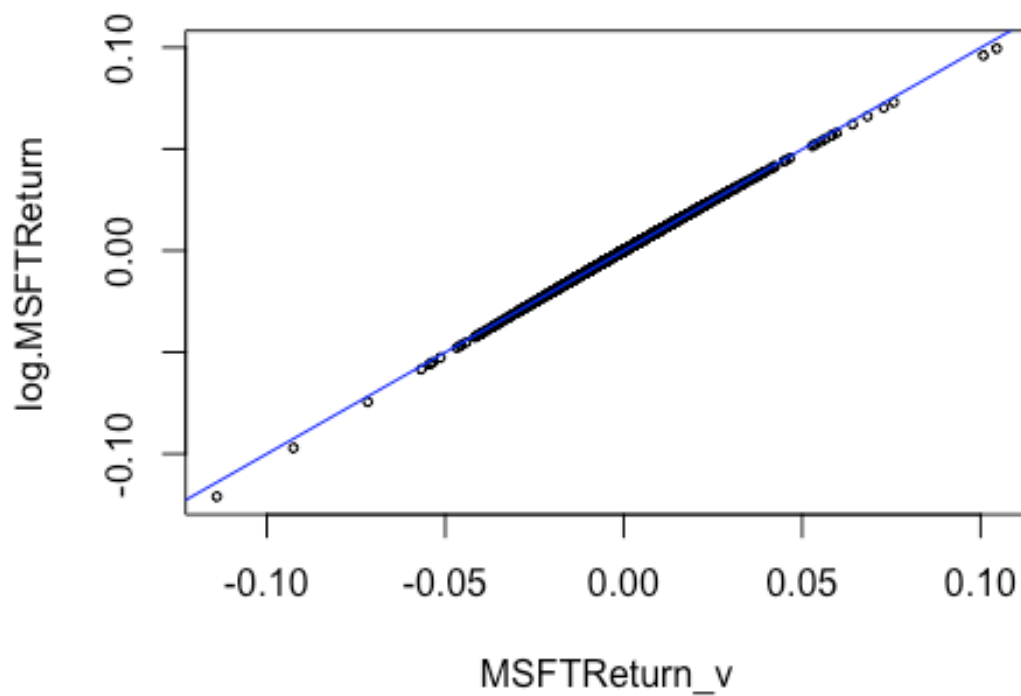
## [1] 0.3467596

abline(lm(MRKReturn_v~MSFTReturn_v))
```



Following is the returns for MSFT versus its log return with their correlation

```
plot(MSFTReturn_v, log.MSFTReturn, cex=0.5)  
abline(lm(log.MSFTReturn~MSFTReturn_v), col="blue")
```

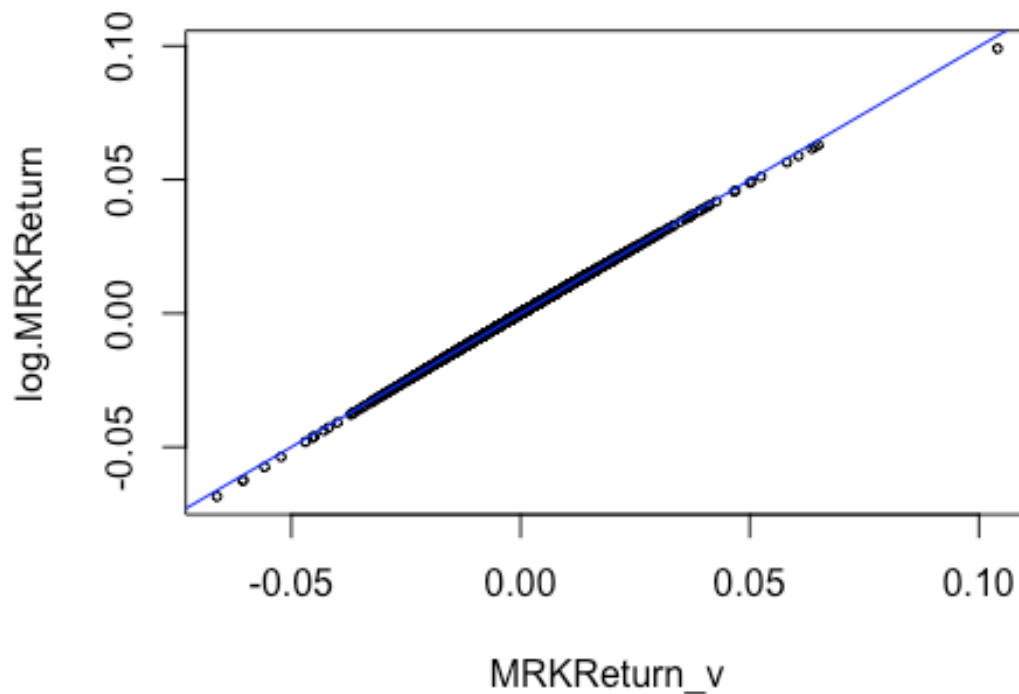


```
cor(MSFTReturn_v, log.MSFTReturn)
```

```
## [1] 0.9997859
```

Following is the returns for MRK versus its log return with their correlation

```
plot(MRKReturn_v, log.MRKReturn, cex=0.5)  
abline(lm(log.MRKReturn~MRKReturn_v), col="blue")
```



```
cor(MRKReturn_v, log.MRKReturn)
```

```
## [1] 0.9998734
```

Problem 4:

The probability that the value of the stock will be below \$950,000 at the close of at least one of the next 45 trading days: 50.99%

```
niter = 1e5 # number of iterations
below = rep(0, niter) # set up storage
set.seed(2009)
for (i in 1:niter)
{
  r = rnorm(45, mean = 0.05/253,
           sd = 0.23/sqrt(253)) # generate random numbers
  logPrice = log(1e6) + cumsum(r)
  minlogP = min(logPrice) # minimum price over next 45 days
  below[i] = as.numeric(minlogP < log(950000))
}
mean(below)

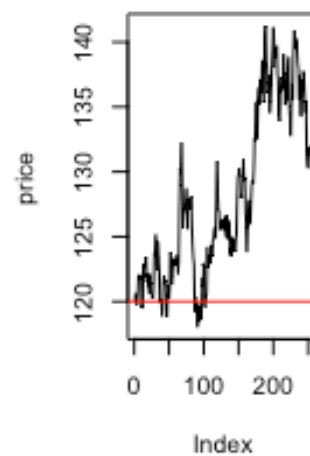
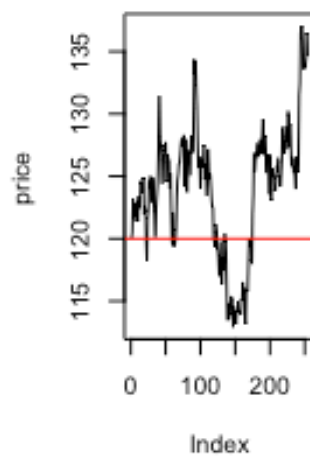
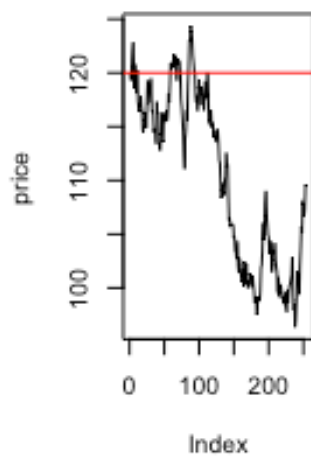
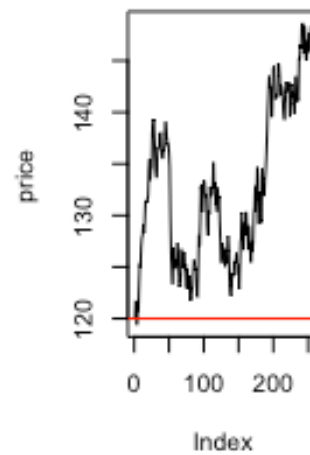
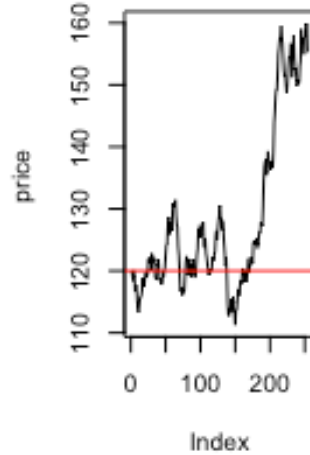
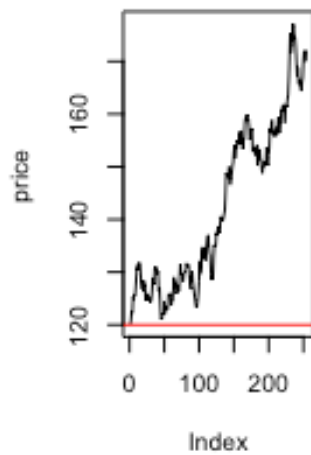
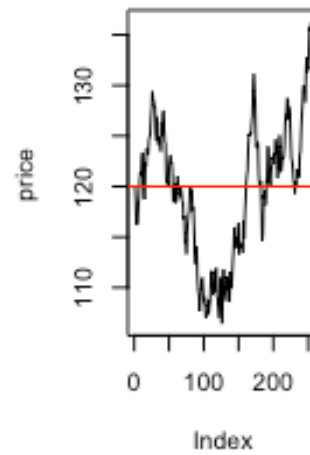
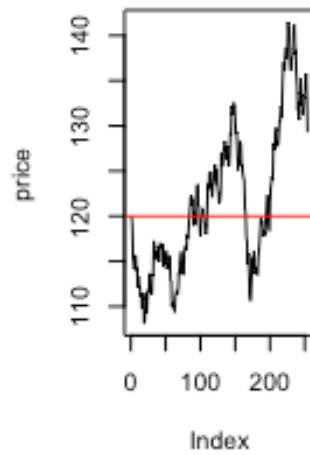
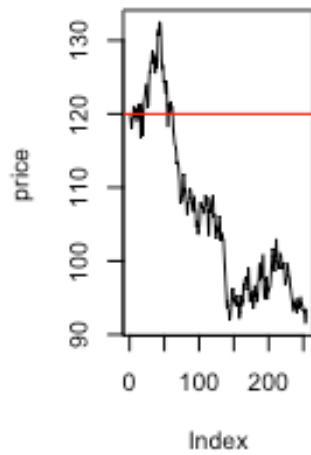
## [1] 0.50988
```


Problem 9:

In this simulation, the mean of the log-returns for 1 year is 0.09601128 and standard deviation of the log-returns for 1 year is 0.1890347

```
set.seed(2012)
n=253
par(mfrow=c(3,3))
for (i in (1:9))
{
  logr = rnorm(n, 0.05 / 253, 0.2 / sqrt(253))
  price = c(120, 120 * exp(cumsum(logr)))
  plot(price, type = "l")
  abline(h=120,col="red")
}
```

这个题目从图像里面有正有负，很难看出趋势。但是根据定义式， μ 是正直，所以我们知道此时应存在一个positive trend



```
mean(logr)*253;sd(logr)*sqrt(253)
## [1] 0.09601128
## [1] 0.1890347
```

Problem 10:

Base on the figures from Problem 9 ,we can see the price series shows short-term momentum which short-run serial correlations are not zero. But because of the i.i.d. normal assumption,we know the next period price should be non-forecastable,which means the appearance of momentum is an illusion.

Problem 11:

code:(price<-c(120, 120 * exp(cumsum(logr)))) This code equals the random walk model:

$$S_t = S_0 + \sum_{s=1}^t Z_s$$

$S_0 = 120$ and $120 * \exp(\text{cumsum}(\text{logr}))$ is cumulated after each cycle

Problem 12:

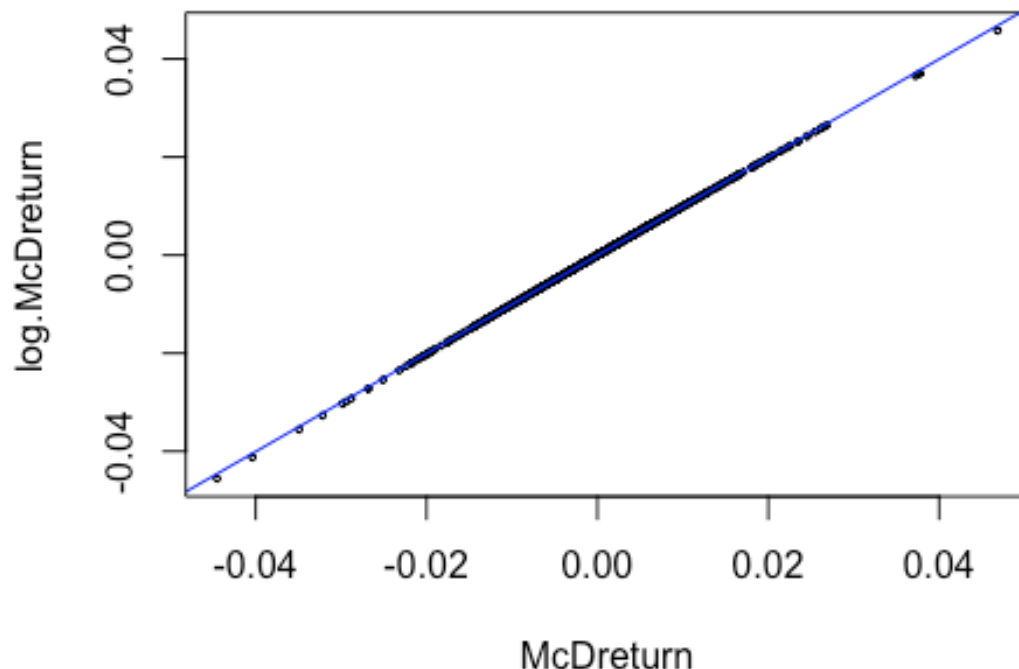
```
data = read.csv("~/Desktop/631STAT in Fin/datasets/MCD_PriceDaily.csv")
head(data)
```

```
##      Date  Open  High  Low Close  Volume Adj.Close
## 1  1/4/2010 62.63 63.07 62.31 62.78  5839300    53.99
## 2  1/5/2010 62.66 62.75 62.19 62.30  7099000    53.58
## 3  1/6/2010 62.20 62.41 61.06 61.45 10551300    52.85
## 4  1/7/2010 61.25 62.34 61.11 61.90  7517700    53.24
## 5  1/8/2010 62.27 62.41 61.60 61.84  6107300    53.19
## 6  1/11/2010 62.02 62.43 61.85 62.32  6081300    53.60
```

```
adjPrice = data[, 7]
```

For the plot shows the linear relationship between the returns and log returns approximately equal because we are computing both of them by short time period, which is $\text{daily } r_t = \log(1 + R_t) \approx R_t$ for small $|t|$ by Taylor expansion.

```
n <- length(adjPrice)
McDreturn <- rep(0,n)
for (i in (1:n))
{McDreturn[i] <- (adjPrice[i+1]/adjPrice[i]-1)}
log.McDreturn <- log(McDreturn+1)
plot(McDreturn,log.McDreturn,cex=0.35)
abline(lm(log.McDreturn~McDreturn),col="blue")
```



Problem 13:

Compare the first moment of the return and its log-return, the two results very close to each other. And the second moment of these two type of daily seems have approximately equal result, perform very constant. It is reasonable to have them same, at short term run have kept the inner relation after taking log on it.

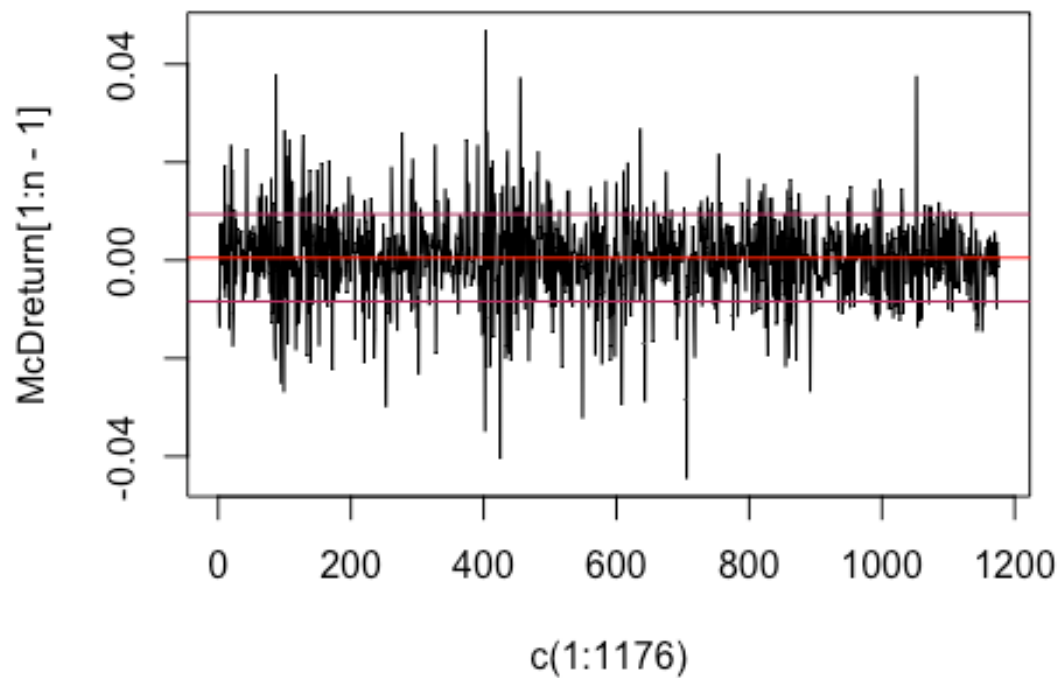
```
mean(McDreturn[1:n-1]);mean(log.McDreturn[1:n-1])

## [1] 0.0005027479
## [1] 0.0004630553

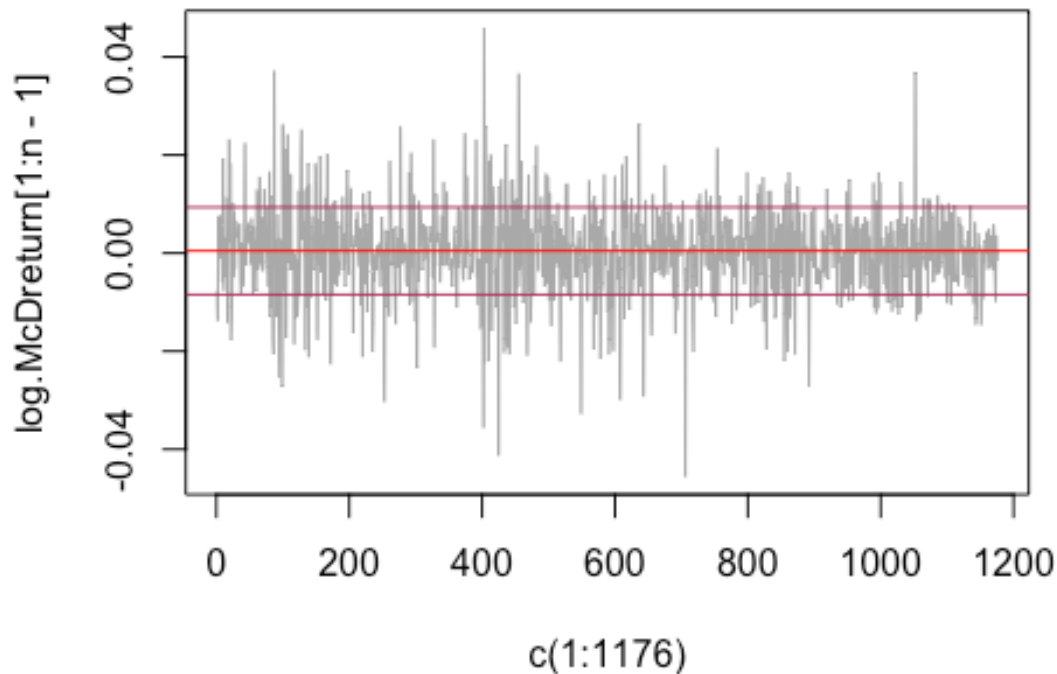
sd(McDreturn[1:n-1]);sd(log.McDreturn[1:n-1])

## [1] 0.008900319
## [1] 0.008901467

plot(c(1:1176),McDreturn[1:n-1],type = "l")
abline(h=mean(McDreturn[1:n-1]),col="red")
abline(h=mean(McDreturn[1:n-1])+sd(McDreturn[1:n-1]),col="maroon")
abline(h=mean(McDreturn[1:n-1])-sd(McDreturn[1:n-1]),col="maroon")
```



```
plot(c(1:1176),log.McDreturn[1:n-1],type = "l",col="darkgray")
abline(h=mean(log.McDreturn[1:n-1]),col="red")
abline(h=mean(log.McDreturn[1:n-1])+sd(log.McDreturn[1:n-1]),col="maroon")
abline(h=mean(log.McDreturn[1:n-1])-sd(log.McDreturn[1:n-1]),col="maroon")
```



Problem 14:

t-test to compare the means of the returns and the log returns is paired-samples t-test. Null hypothesis: true difference in means is equal to 0 and the p-value of this test is 0.9139, which means we failed to reject the null hypothesis. I think they are met in this example.

```
t.test(McDreturn[1:n-1], log.McDreturn[1:n-1], conf.level = 0.95)

##
##  Welch Two Sample t-test
##
## data:  McDreturn[1:n - 1] and log.McDreturn[1:n - 1]
## t = 0.10813, df = 2350, p-value = 0.9139
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.0006801156  0.0007595007
## sample estimates:
##    mean of x    mean of y
## 0.0005027479 0.0004630553
```

Problem 15:

After looking at return and log return data for McDonald's by plot and hypothesis test, we can say log returns and returns are interchangeable at small values.

Problem 17:

I will not make this bet, because of the low probability of the occur make the expect return is negative.

```
n = 1e5
below = rep(0, n)
set.seed(2015)
for (i in 1:n)
{
  r = rnorm(20, mean = 0.0004630553,
            sd = 0.008901467)
  logPrice = log(93.7) + cumsum(r)
  minlogP = min(logPrice)
  below[i] = as.numeric(minlogP < log(84.5))
}
mean(below)

## [1] 0.00354

profit <- mean(below)*125+(1-mean(below))*(-1)
print(profit)

## [1] -0.55396
```

Exercises Questions 1(a):

The probability that after one trading day your investment is worth less than \$990 is 23.066%

$$\log P_t = \log P_0 + r$$

$r \sim \text{Normal}(0.001, 0.000225)$

$$r = \log P_t - \log P_0$$

```
pnorm((log(990)-log(1000)),0.001,0.015)

## [1] 0.2306557
```

Following is using simulation to generate result:

```
n <- 1e5
r <- rep(0,n)
below <- rep(0,n)
for (i in 1:n)
```

```

{
  r[i]= rnorm(1, mean = 0.001,sd = 0.015)
  logPrice[i] = log(1000) + r[i]
  below[i] = as.numeric(logPrice[i] < log(990))
}
prob<- sum(below)/n
print(prob)

## [1] 0.23097

```

Exercises Questions 1(b):

After 5 days is the sum of five i.i.d daily log return, which follow the normal distribution $N(0.005, 0.001125)$ The probability that after five trading days your investment is worth less than \$990 is 32.682%

```

pnorm((log(990)-log(1000)),0.005,sqrt(0.001125))

## [1] 0.3268189

```

Exercises Questions 4:

$$r_t(k) = \log[1 + R_t(k)] = r_t + \dots + r_{t-k+1}$$

$P_1 = 95, P_2 = 103$, and $P_3 = 98$

$$r_3(2) = r_3 + r_2 = \log(P_3/P_2) + \log(P_2/P_1) = 0.03109101$$