

STA457#3

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```
install.packages("readxl")
```

```
library("readxl")  
IBM = read_excel("C:\\Users\\Jonathan\\Desktop\\IBM457.xlsx")
```

```
IBM
```

```
## # A tibble: 1,006 x 1  
##   Adj_Close  
##   <dbl>  
## 1    110.  
## 2    109.  
## 3    110.  
## 4    108.  
## 5    104.  
## 6    107.  
## 7    109.  
## 8    112.  
## 9    113.  
## 10   112.  
## # ... with 996 more rows
```

```
mean(IBM$Adj_Close)
```

```
## [1] 134.768
```

Question 1

```
length(IBM$Adj_Close)
```

```
## [1] 1006
```

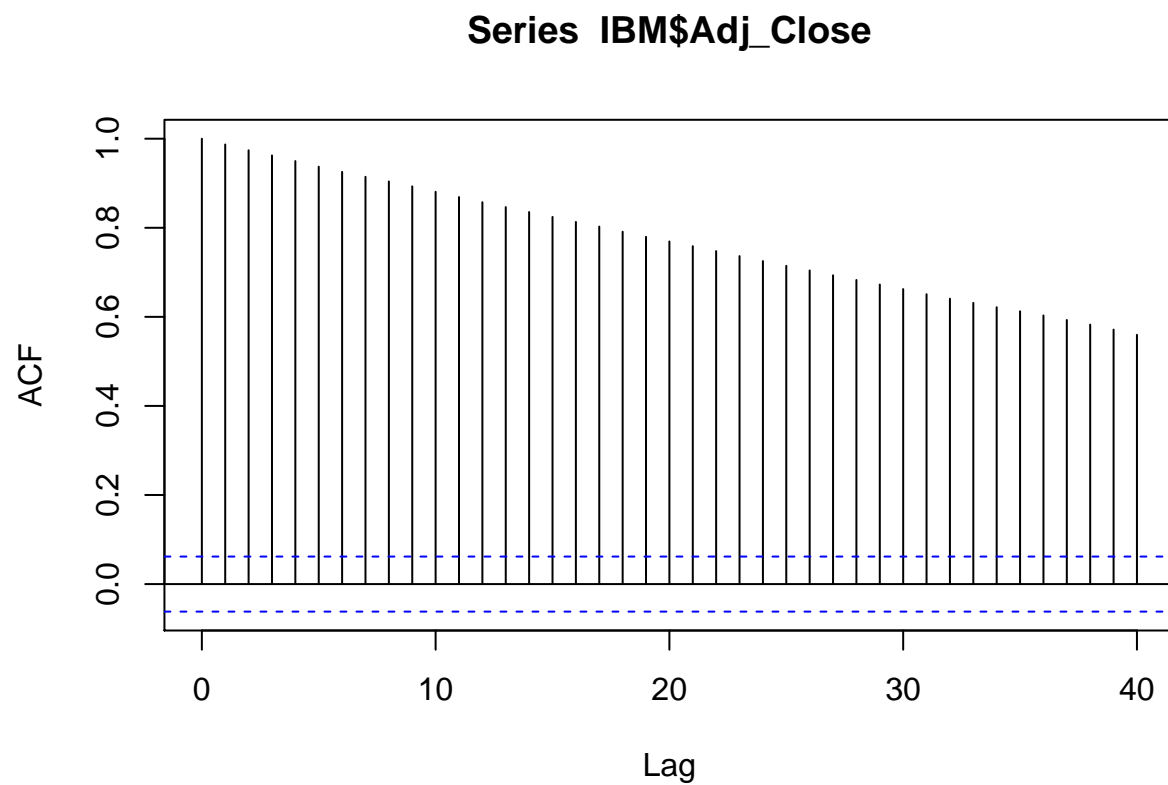
```
head(IBM,30)
```

```
## # A tibble: 30 x 1  
##   Adj_Close  
##   <dbl>  
## 1    110.  
## 2    109.  
## 3    110.  
## 4    108.  
## 5    104.
```

```
## 6      107.  
## 7      109.  
## 8      112.  
## 9      113.  
## 10     112.  
## # ... with 20 more rows
```

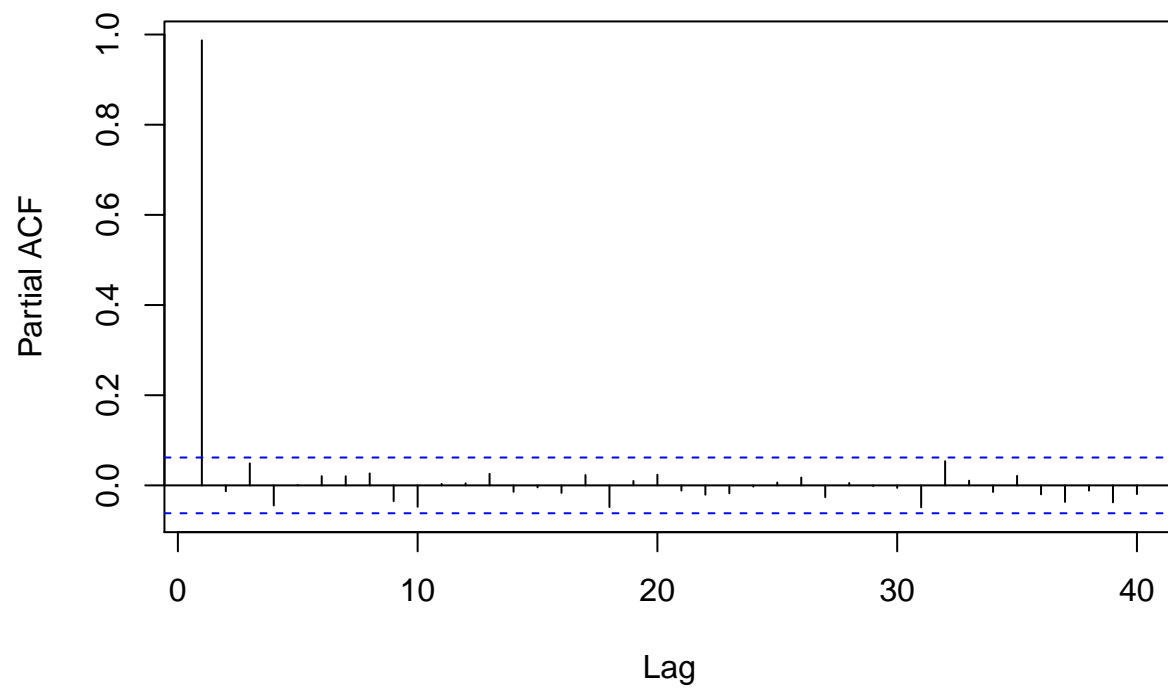
Question 2

```
acf(IBM$Adj_Close, lag.max =40)
```



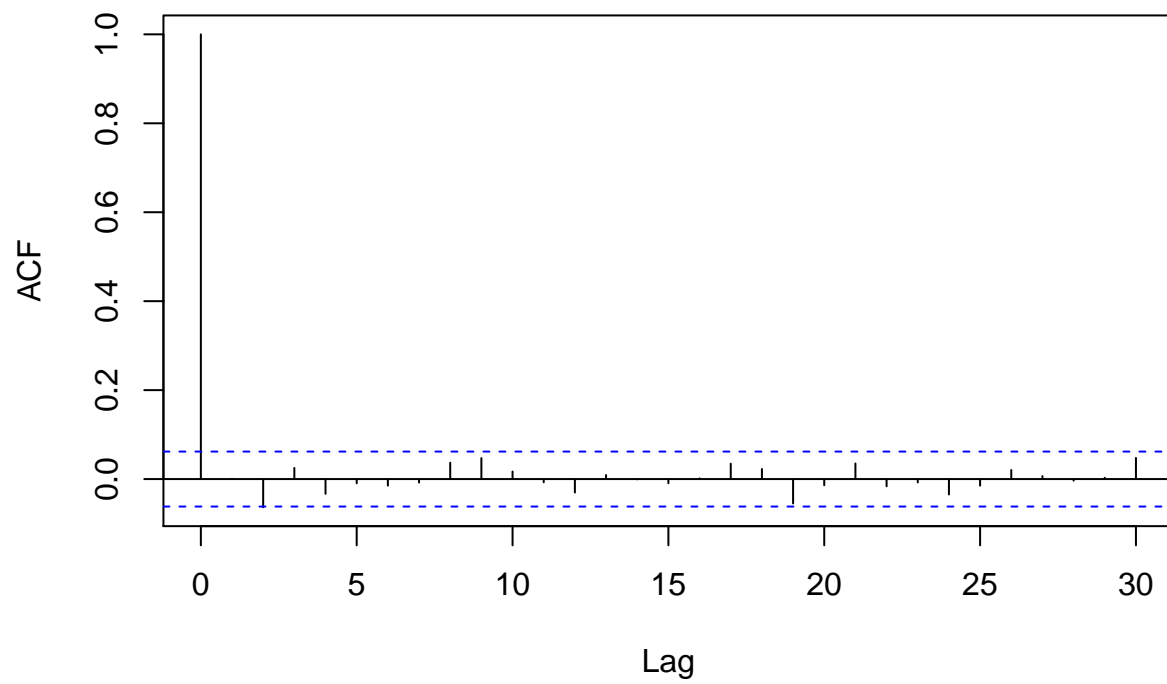
```
pacf(IBM$Adj_Close, lag.max =40)
```

Series IBM\$Adj_Close



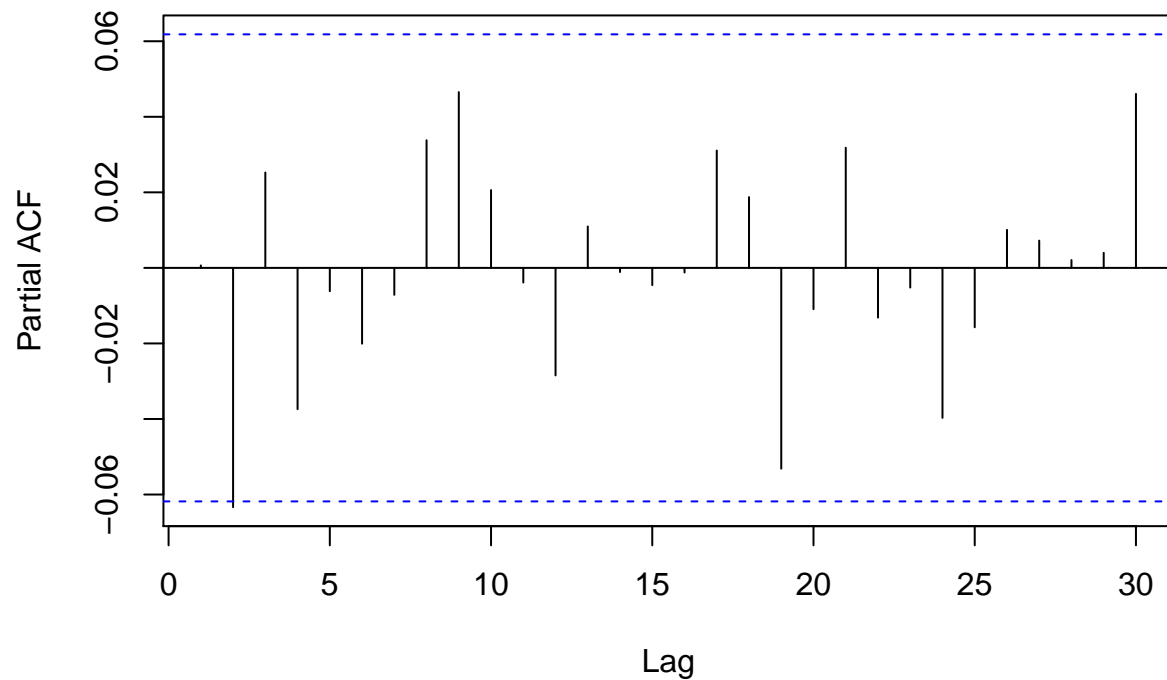
```
acf(diff(IBM$Adj_Close, lag.max =40))
```

Series diff(IBM\$Adj_Close, lag.max = 40)



```
pacf(diff(IBM$Adj_Close, lag.max =40))
```

Series diff(IBM\$Adj_Close, lag.max = 40)



ACF decreases slowly. pacf cuts off at lag 1. we would fit an ar1 model.

Question 3

```
Box.test(IBM$Adj_Close, lag=5, type = "Ljung-Box")
```

```
##  
## Box-Ljung test  
##  
## data: IBM$Adj_Close  
## X-squared = 4680.7, df = 5, p-value < 2.2e-16
```

P value is less than 0.05, we reject the null hypothesis.

Null hypothesis: $p(1) = \dots = p(5) = 0$ for some $K = \{5\}$, i.e white noise hypothesis

Alt hypothesis: one or more of $p(1), \dots, p(5)$ is nonzero

Question 4

```
ar_model=arima(IBM$Adj_Close, order=c(1,0,0))
Box.test(ar_model$resid, lag=5, type="Ljung-Box")
```

```
##
## Box-Ljung test
##
## data: ar_model$resid
## X-squared = 5.5574, df = 5, p-value = 0.3517
```

```
ar_model
```

```
##
## Call:
## arima(x = IBM$Adj_Close, order = c(1, 0, 0))
##
## Coefficients:
##          ar1  intercept
##      0.9905   132.6845
## s.e.  0.0043     5.1762
##
## sigma^2 estimated as 2.915:  log likelihood = -1967.57,  aic = 3941.14
```

Null hypothesis: $p(1) = \dots = p(5) = 0$ for some $K = \{5\}$, i.e white noise hypothesis

Alt hypothesis: one or more of $p(1), \dots, p(5)$ is nonzero

P is greater than 0.05, therefore we fail to reject null hypothesis

Find no evidence that any autocorrelation are 0

AR(1) model with the estimated parameters

$132.6845 - 0.9905y_{t-1} + \text{error } t$

Question 5

```
install.packages("tseries")
```

```
library("tseries")
```

```
## Registered S3 method overwritten by 'xts':  
##   method      from  
##   as.zoo.xts zoo
```

```
## Registered S3 method overwritten by 'quantmod':  
##   method      from  
##   as.zoo.data.frame zoo
```

```
pp.test(IBM$Adj_Close)
```

```
##  
## Phillips-Perron Unit Root Test  
##  
## data: IBM$Adj_Close  
## Dickey-Fuller Z(alpha) = -13.637, Truncation lag parameter = 7,  
## p-value = 0.349  
## alternative hypothesis: stationary
```

Is similar to ADF test

```
adf.test(IBM$Adj_Close)
```

```
##  
## Augmented Dickey-Fuller Test
```

```
##  
## data:  IBM$Adj_Close  
## Dickey-Fuller = -2.9457, Lag order = 10, p-value = 0.178  
## alternative hypothesis: stationary
```

There is a unit root

since the p value is greater than 0.05, fail to reject null hypothesis

the series might contain a unit root

```
kpss.test(IBM$Adj_Close)
```

```
## Warning in kpss.test(IBM$Adj_Close): p-value smaller than printed p-value
```

```
##  
## KPSS Test for Level Stationarity  
##  
## data:  IBM$Adj_Close  
## KPSS Level = 1.9266, Truncation lag parameter = 7, p-value = 0.01
```

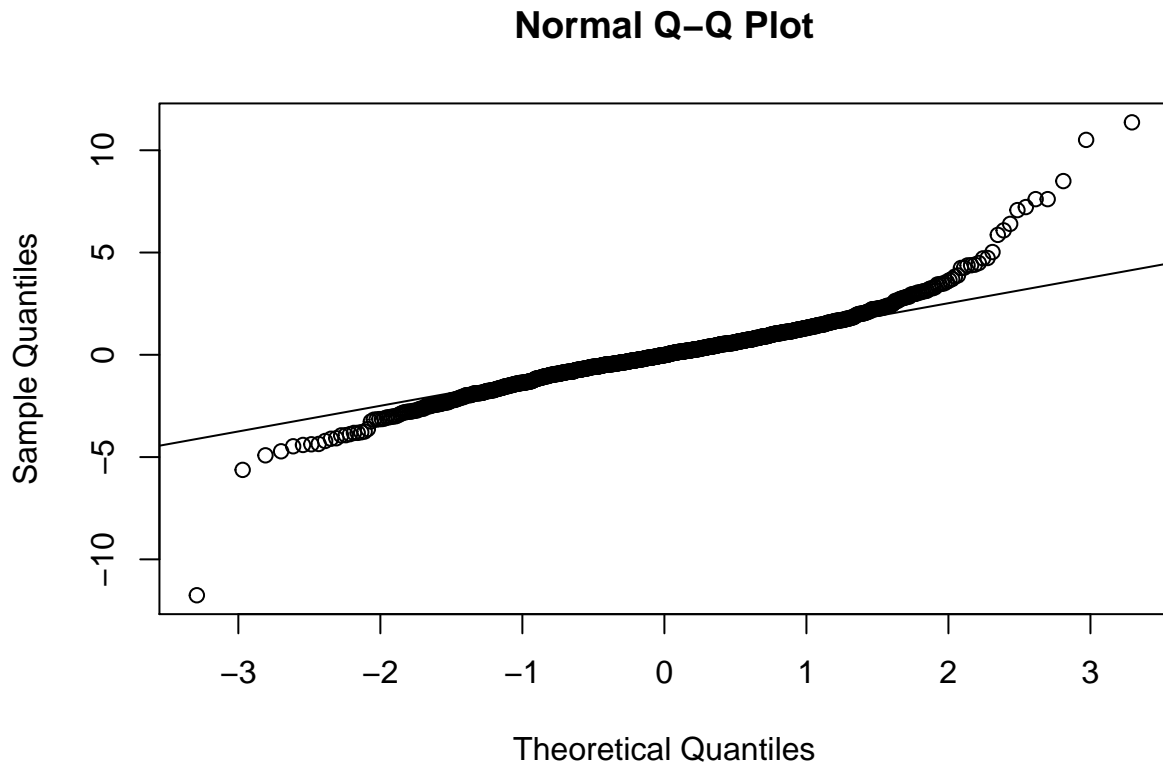
Null hypothesis is that it is stationary

Alternative it is not stationary

p value smaller than 0.05, reject null

Question 6

```
noise=resid(ar_model)  
qqnorm(noise)  
qqline(noise)
```

```
shapiro.test(noise)
```

```
##  
##  Shapiro-Wilk normality test  
##  
## data:  noise  
## W = 0.92283, p-value < 2.2e-16
```

QQ plot shows. Not normally distributed, skewed.

Null hypothesis is that the data is normally distributed

Alternative is that it is not normally distributed

our p value is less than 0.05, we reject the null, therefore data is not normally distributed. Confirmed by qq plot

Question 7

```
install.packages("forecast")
```

```
library(forecast)
```

```
## Registered S3 methods overwritten by 'forecast':  
##   method          from  
##   fitted.fracdiff  fracdiff  
##   residuals.fracdiff fracdiff
```

```
arima_model=auto.arima(IBM$Adj_Close, ic=c("aic"))  
arima_noise=resid(arima_model)
```

```
arima_model
```

```
## Series: IBM$Adj_Close  
## ARIMA(0,1,0)  
##  
## sigma^2 estimated as 2.928:  log likelihood=-1965.86  
## AIC=3933.72   AICc=3933.73   BIC=3938.63
```

AR order 0, MA order 0. D is 1

$Y_t = Y_{t-1} + e_t$

Question 8

```
install.packages("MASS")
```

```
library(MASS)  
fit <- fitdistr(noise, densfun="t")
```

```
## Warning in dt((x - m)/s, df, log = TRUE): NaNs produced  
## Warning in dt((x - m)/s, df, log = TRUE): NaNs produced  
## Warning in dt((x - m)/s, df, log = TRUE): NaNs produced  
## Warning in dt((x - m)/s, df, log = TRUE): NaNs produced
```

```
fit
```

```
##           m           s           df  
##  -0.007168365  1.136027403  3.471574750  
## ( 0.043065636) ( 0.045999682) ( 0.410663801)
```

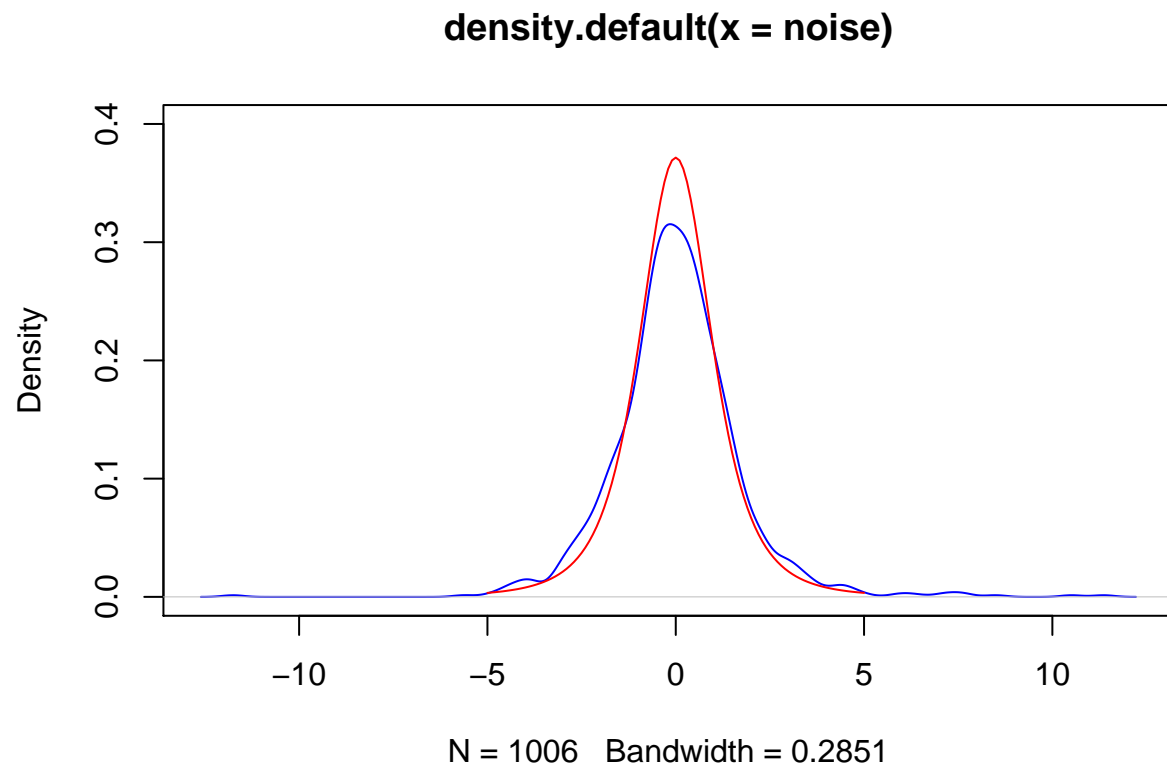
Question 8

```
fit
```

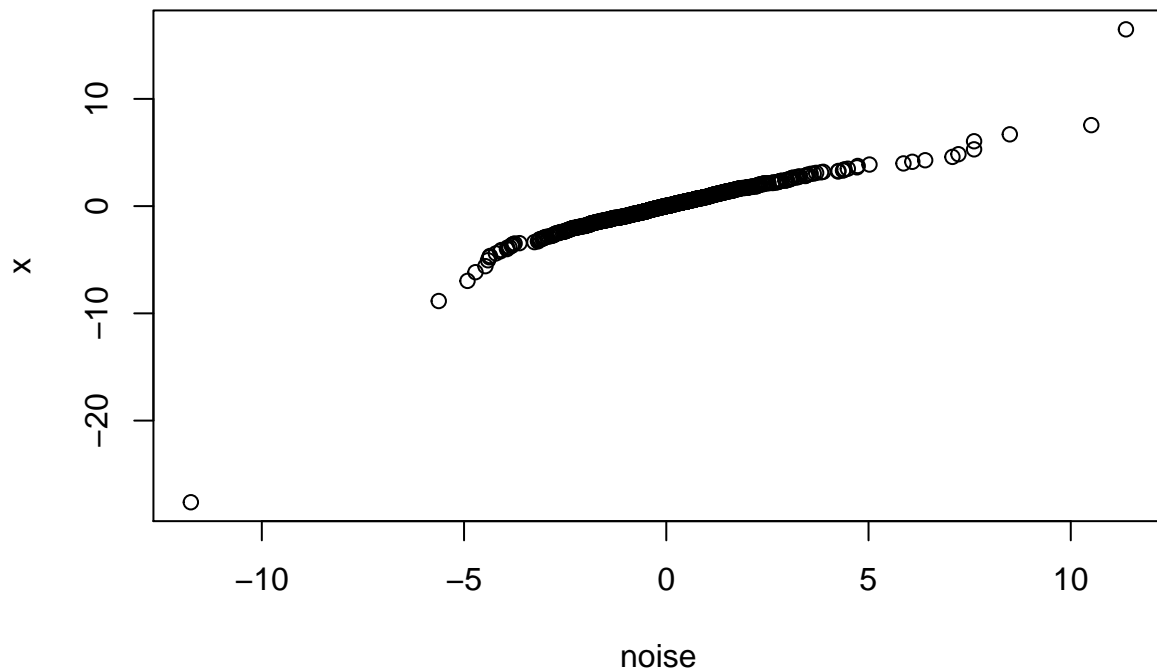
```
##           m           s           df  
##  -0.007168365   1.136027403   3.471574750  
##  ( 0.043065636) ( 0.045999682) ( 0.410663801)
```

Question 9

```
plot(density(noise), ylim = c(0, 0.4), col="blue")  
curve(dt(x, fit$estimate[3]), from = -5, to = 5, add=TRUE, col="red")
```



```
x=rt(10000, fit$estimate[3])  
qqplot(noise, x)
```



Looking at density plot, it shows a reasonable fit

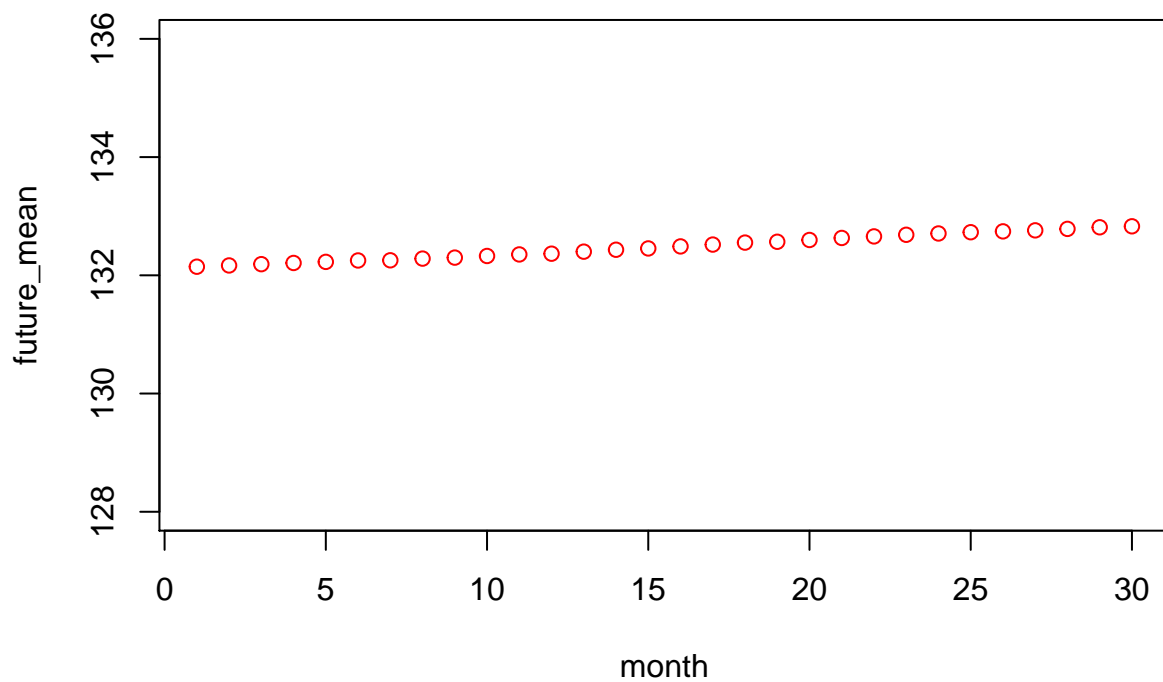
Question 10

```
n=length(IBM$Adj_Close)
niter=50000
n.ahead=30
#Creating an empty matrix for future observations
futureobs=matrix(0,nrow=niter, ncol=n.ahead)
for (i in 1:niter) {
  #Generating errors from ARIMA's residuals
  errors=sample(arima_noise,n.ahead,replace=TRUE)
  for (j in 1:n.ahead) {
    #Assigning values to future observations based on the ARIMA model
    if (j==1){futureobs[i,j]=IBM$Adj_Close[n]+errors[j]}
    else {futureobs[i,j]=futureobs[i,j-1]+errors[j]}
  }
}
#Calculating mean values for each day of the month
future_mean=apply(futureobs,2,mean)
#Calculating the confidence bands
u1=0*(1:n.ahead)
```

```

l1=u1
for (k in 1:n.ahead){
  u1[k]=quantile(futureobs[,k],0.975)
  l1[k]=quantile(futureobs[,k],0.025)
}
month=seq(1:30)
plot(month,future_mean,col="red", ylim=c(128,136))

```



Question 11

```

n=length(IBM$Adj_Close)
n

```

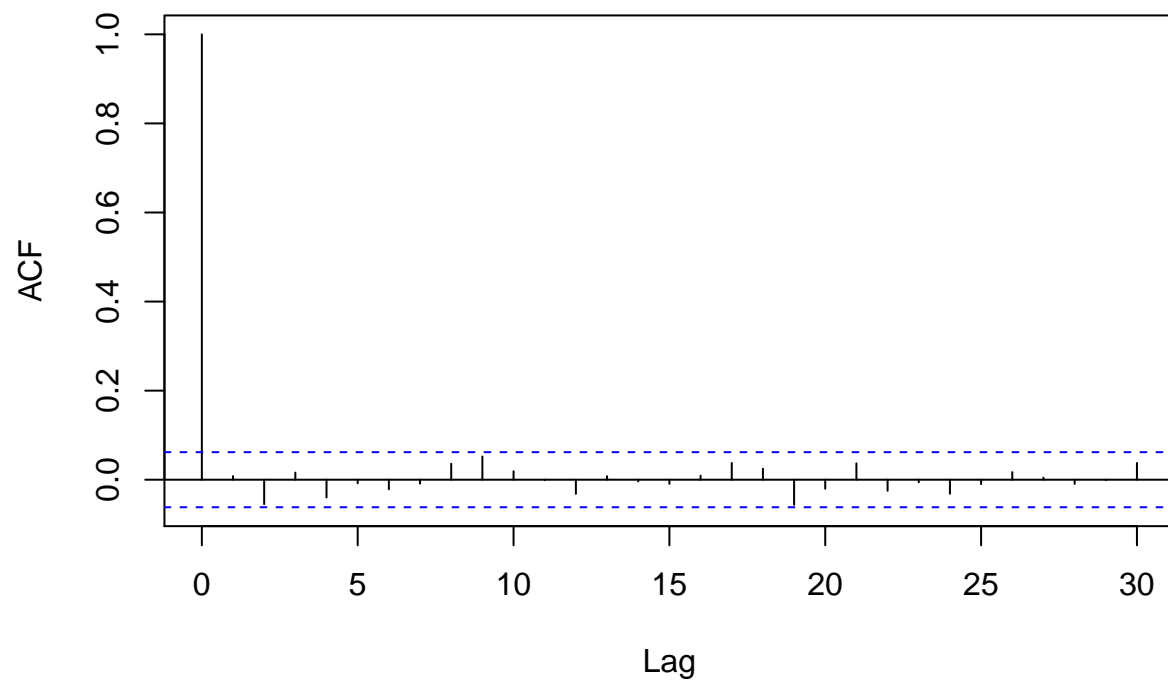
```
## [1] 1006
```

```

lret <- log(IBM$Adj_Close[-1]/IBM$Adj_Close[-n])
acf(lret)

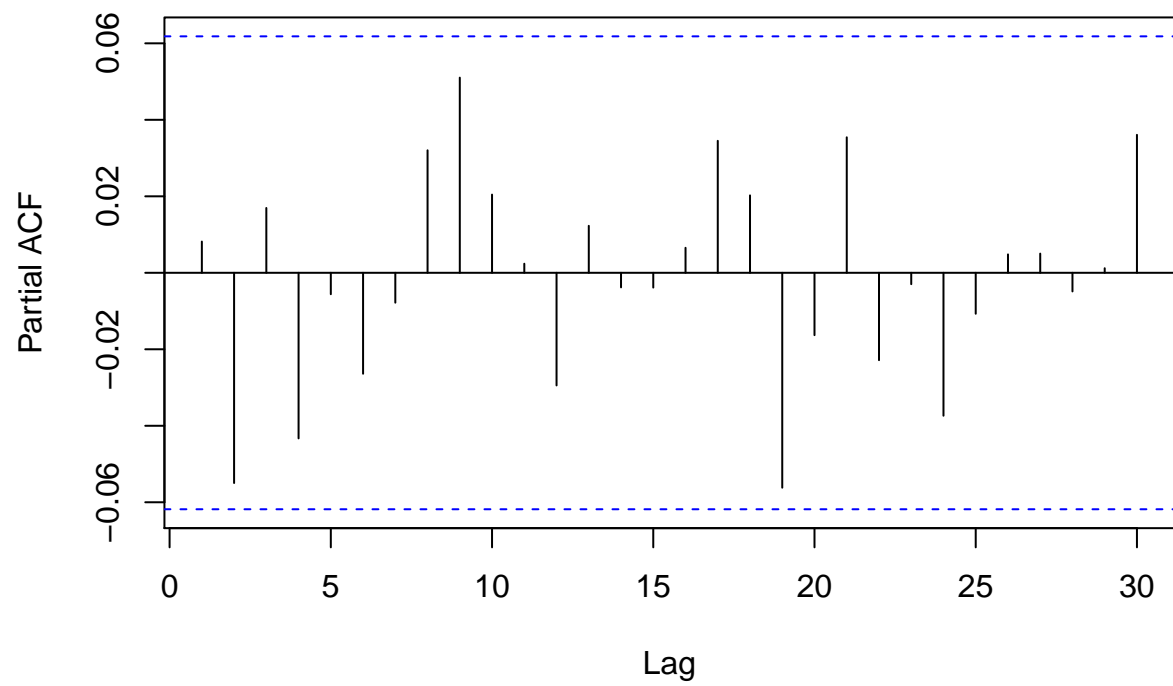
```

Series lret

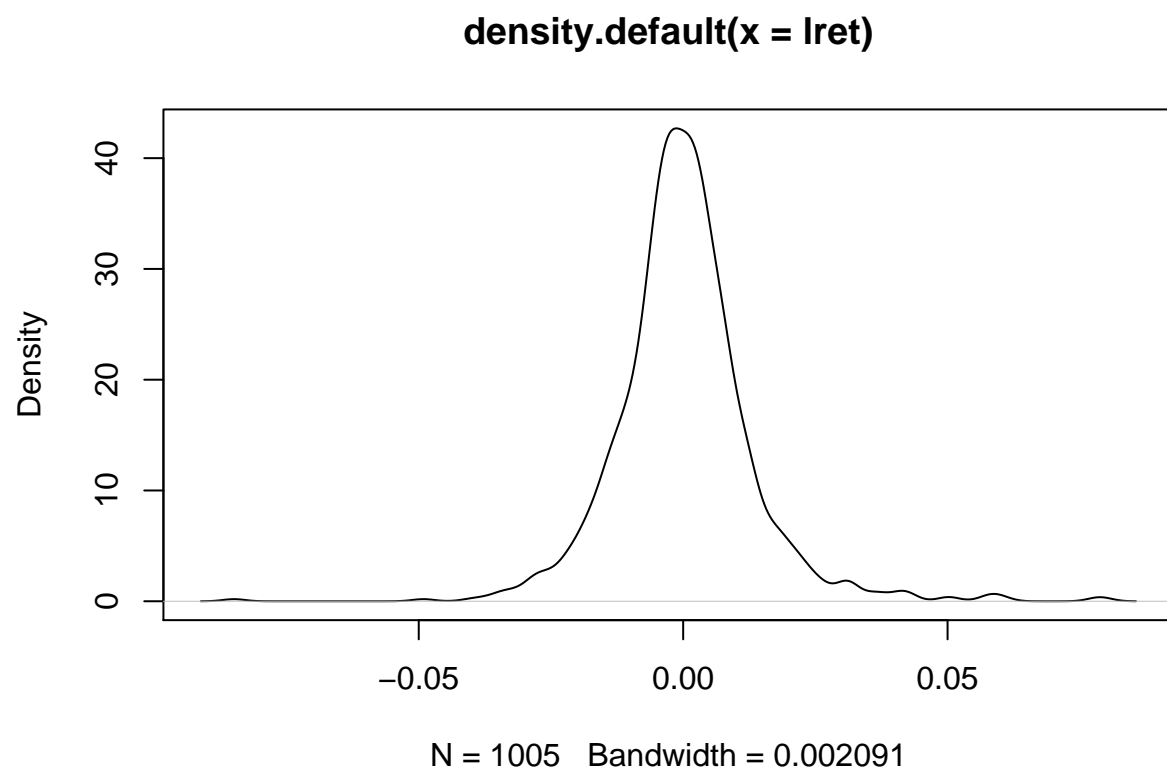


```
pacf(lret)
```

Series lret



```
plot(density(lret))
```



Log returns show more normality