Exploratory Data Analysis

Loading libraries

The below code chunk loads the libraries we will be using in our analysis:

Reading and cleaning data

First, we input our stock data.

Our stock data consists of the following indices between 2000 and 2021:

- S&P500
- NASDAQ
- NYSE100

Important: Before running the code below, make sure your Knit directory is 'Document Directory'. This can be done by clicking the drop-down menu next to Knit, going to Knit directory and clicking on Document Directory.

```
setwd("..")
sp<-read.csv("Data/sp500.csv")
ny<-read.csv("Data/nyse.csv")
nas<-read.csv("Data/nasdaq.csv")
```

Now we will change the 'caldt' column to the Date format in order to plot the time series for each index:

```
sp$caldt<-as.Date(sp$caldt, format="%d/%m/%Y")
ny$caldt<-as.Date(ny$caldt, format="%d/%m/%Y")
nas$caldt<-as.Date(nas$caldt, format="%d/%m/%Y")

str(sp)
```

```
## 'data.frame':    5032 obs. of  2 variables:
##  $ caldt : Date, format: "2001-01-02" "2001-01-03" ...
##  $ spindx: num  1283 1348 1333 1298 1296 ...
```

```
str(ny)
```

```
## 'data.frame':    5284 obs. of  2 variables:
##  $ caldt : Date, format: "2000-01-03" "2000-01-04" ...
##  $ spindx: num  1455 1399 1402 1403 1441 ...
```

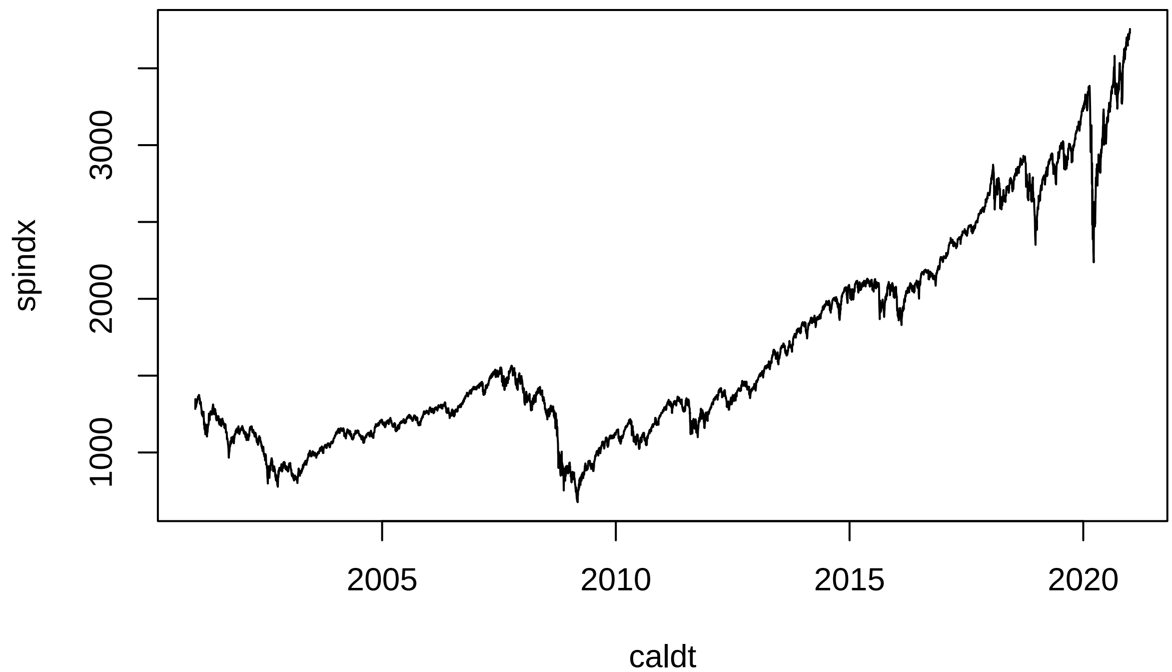
```r
str(nas)
```

```
## 'data.frame':    5284 obs. of  2 variables:
##  $ caldt : Date, format: "2000-01-03" "2000-01-04" ...
##  $ ncindx: num  4131 3902 3878 3727 3883 ...
```

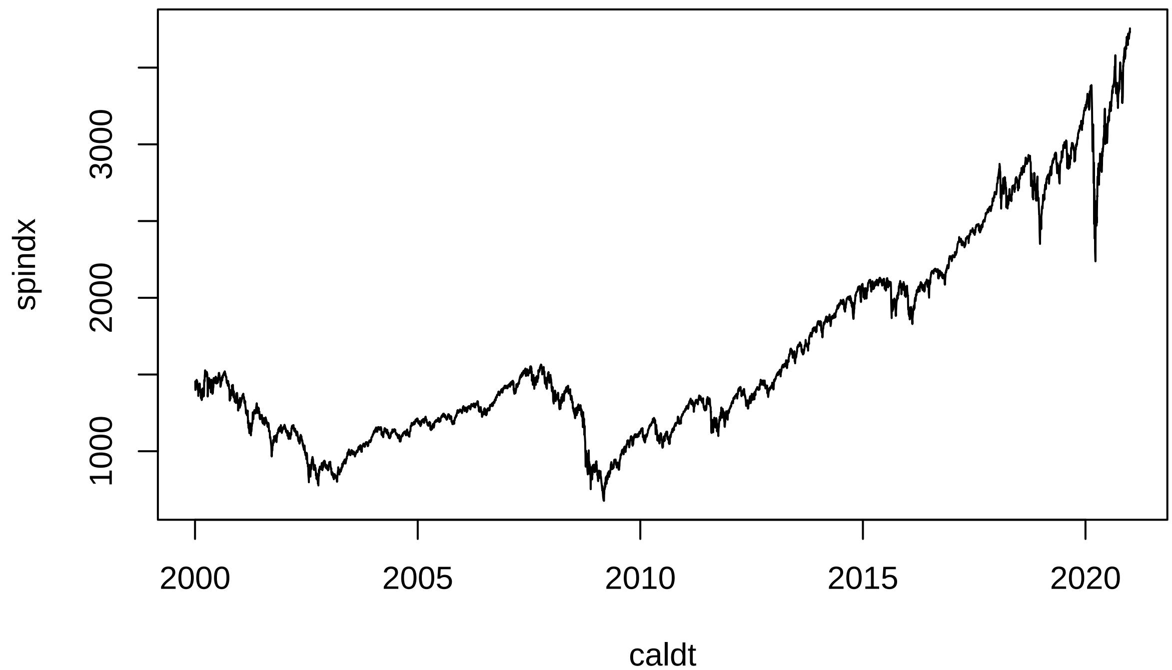
Initial Plots

We will start off by making a basic of stock price against time for each index, to get an idea of what our data looks like:

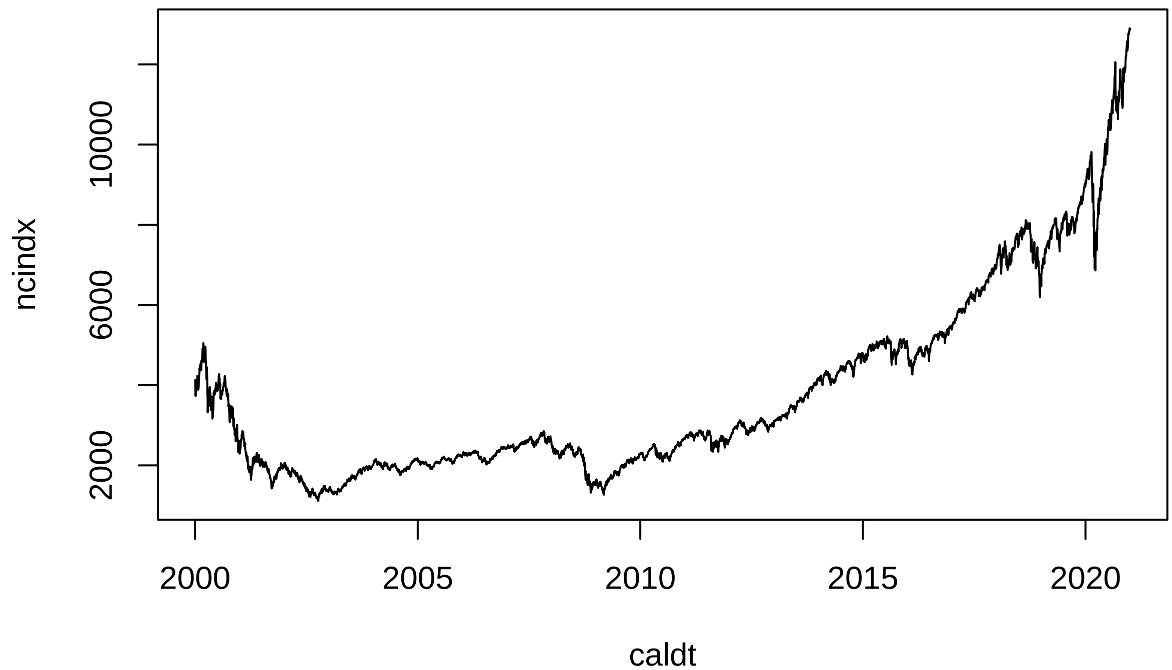
```r
plot(sp, type='l')
```




```r
plot(ny, type='l')
```



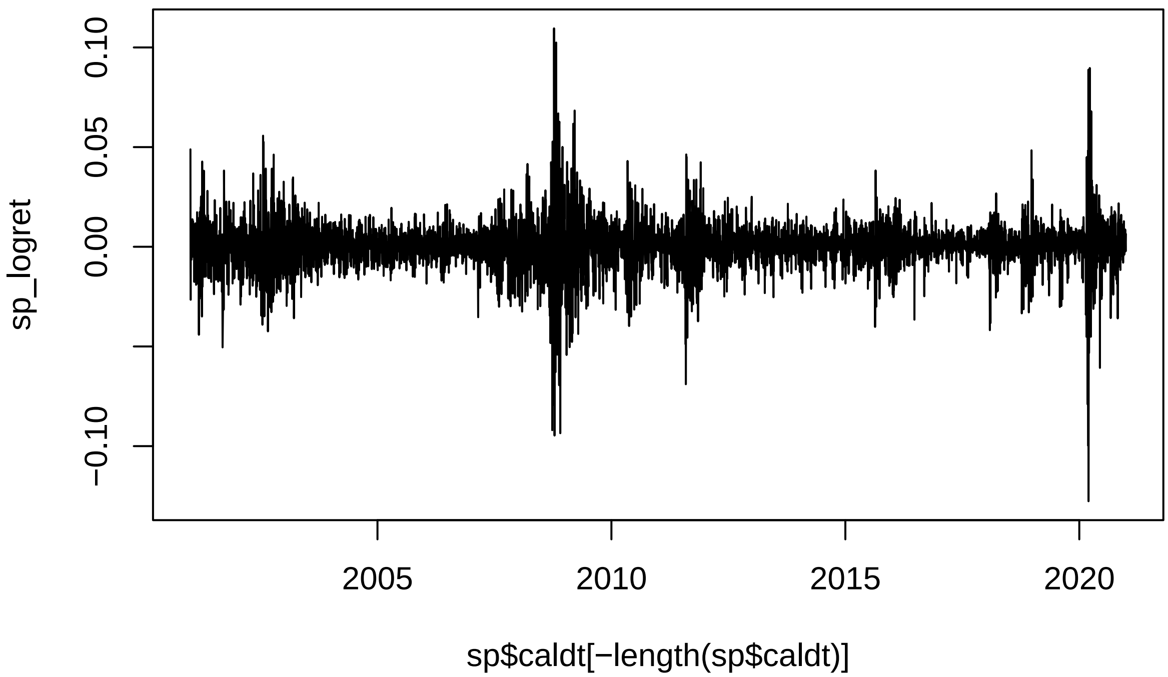

```
plot(nas, type='l')
```



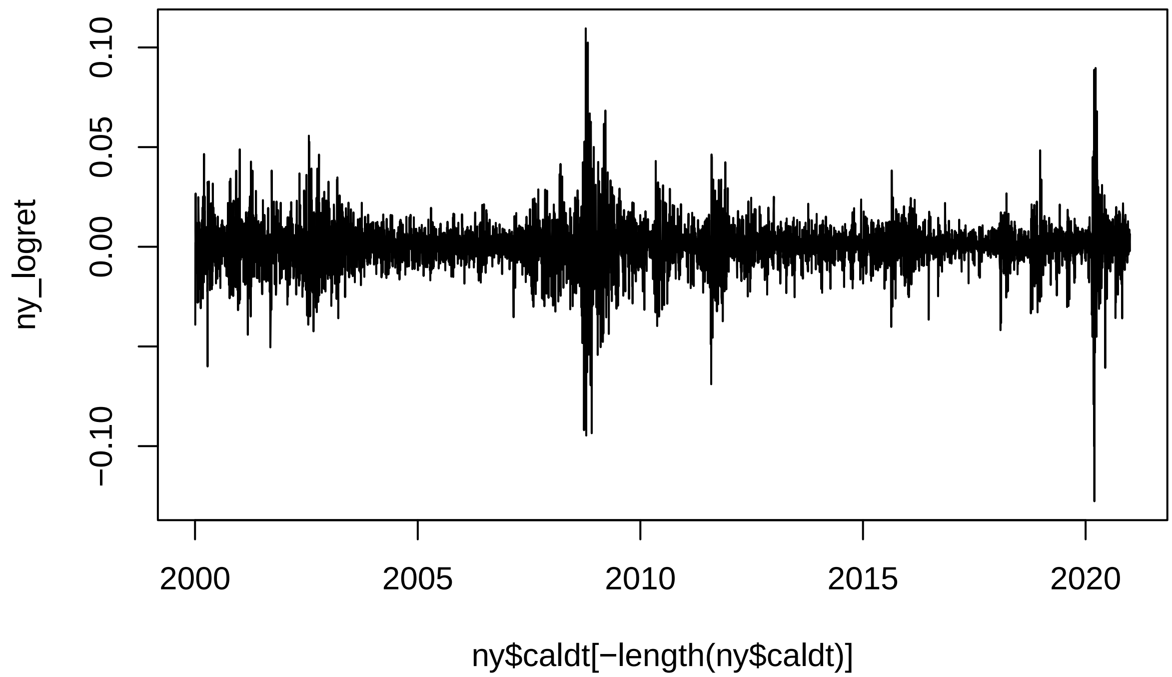
They all follow the same basic pattern, which is what we would expect, with the iconic fall in stock-price during the 2008-2009 period of the 'Great Recession'.

However, the stock price directly does not give us much information. Instead, we will take at the **daily log stock returns**.

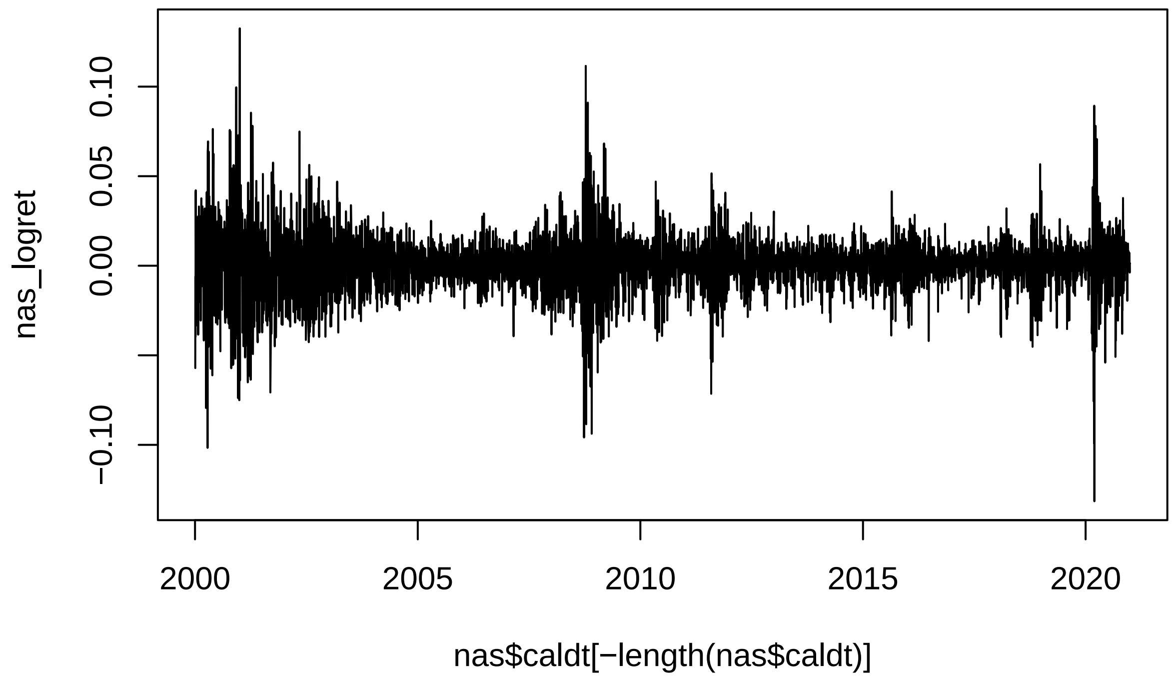
```
sp_logret <- diff(log(sp$spindx))
ny_logret <- diff(log(ny$spindx))
nas_logret <- diff(log(nas$ncindx))

plot(sp$caldt[-length(sp$caldt)],sp_logret,type='l')
```




```
plot(ny$caldt[-length(ny$caldt)],ny_logret, type='l')
```



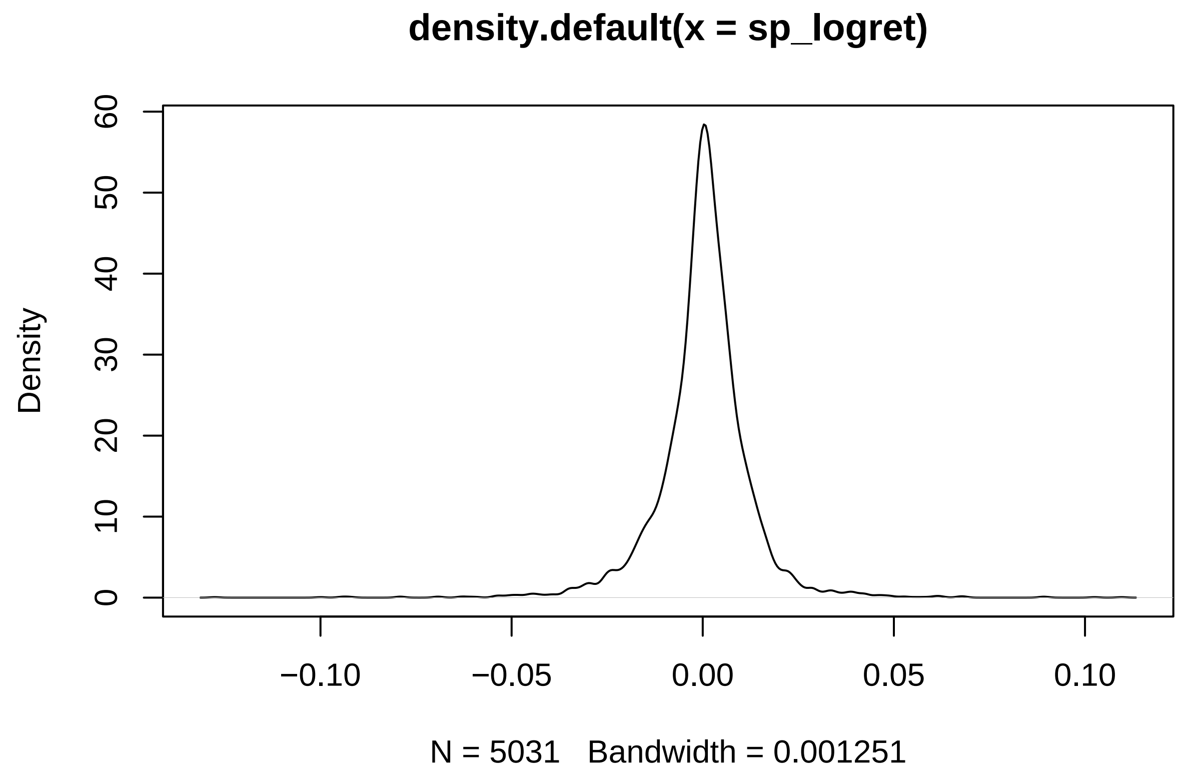

```
plot(nas$caldt[-length(nas$caldt)],nas_logret, type='l')
```



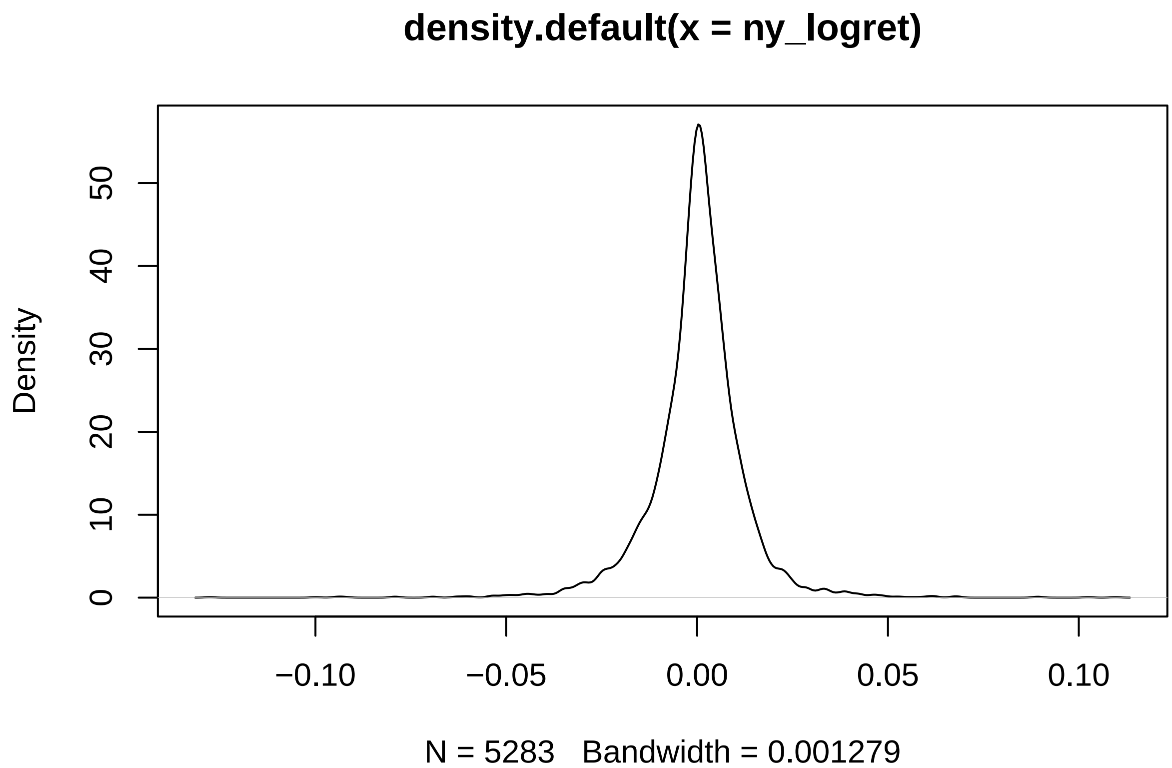
We can see that the returns average around 0% with very high variability during 2008-2009 (caused by the Great Recession) and during 2020 (caused by COVID-19).

Let us now plot the density of the returns to try to understand the distribution which will be helpful when we try to model the returns later one:

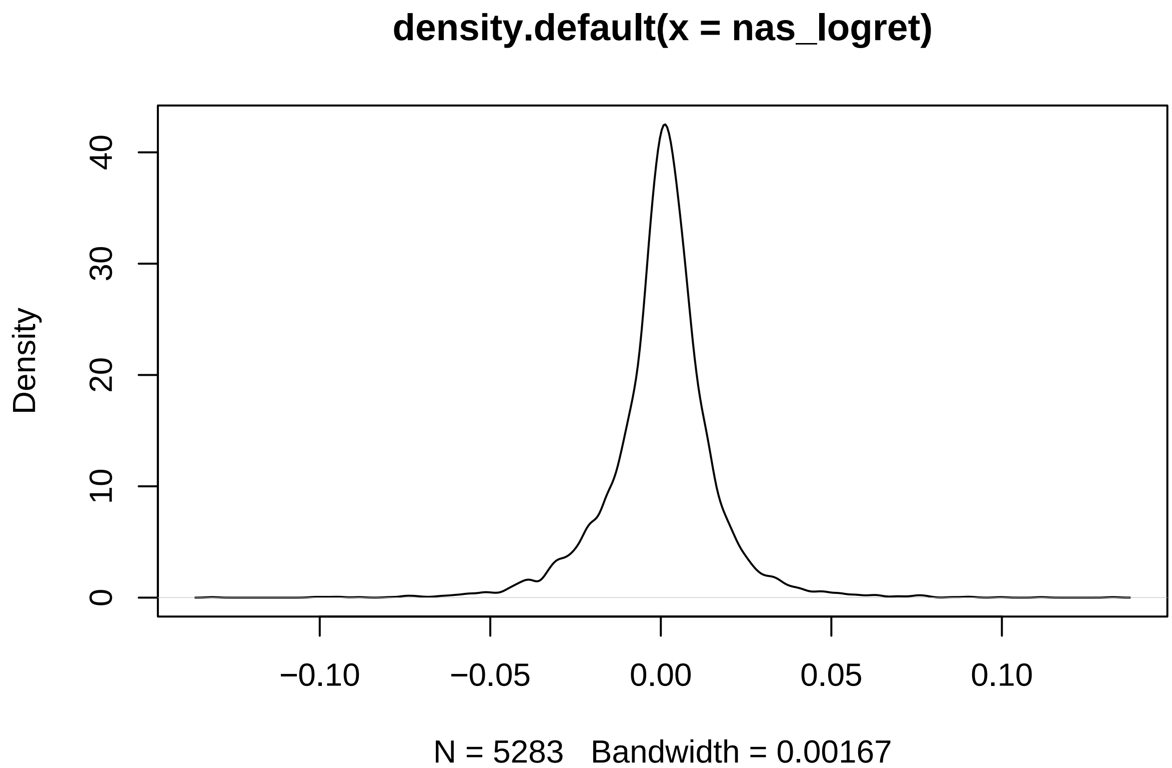
```
plot(density(sp_logret))
```




```
plot(density(ny_logret))
```

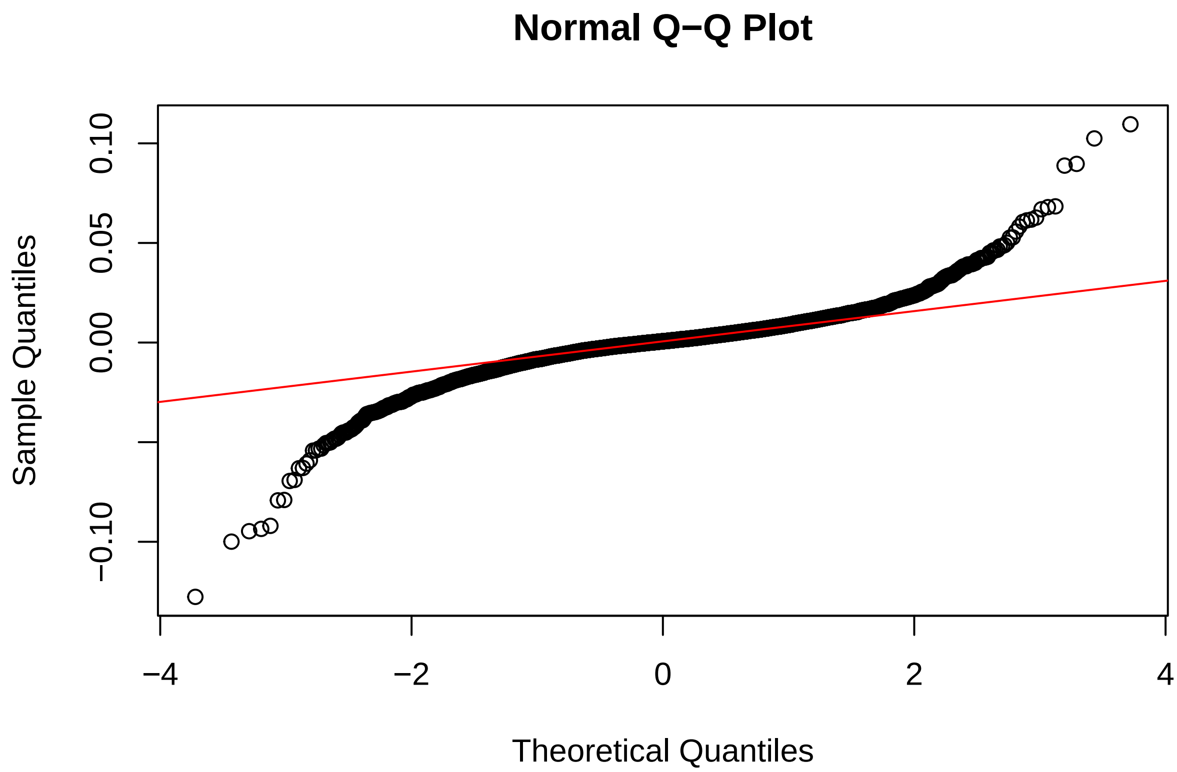



```
plot(density(nas_logret))
```

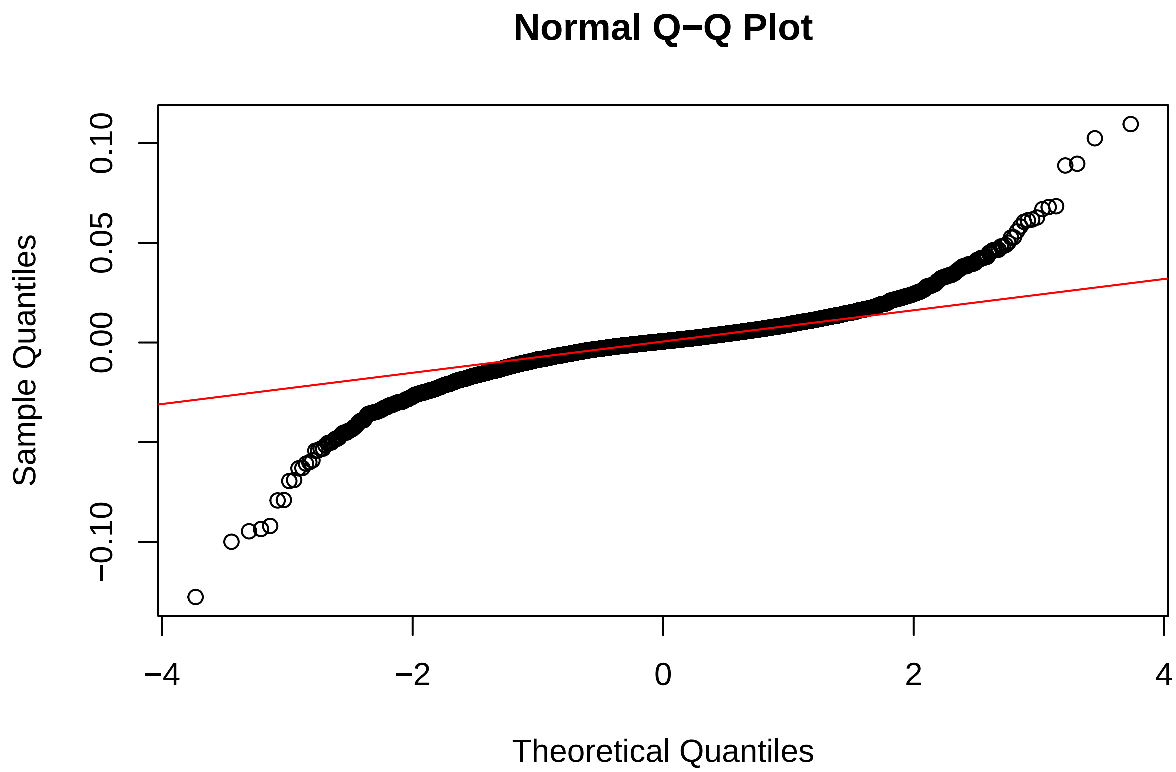


The returns look like they follow a normal distribution. So, we will make qq-plots to further confirm this:

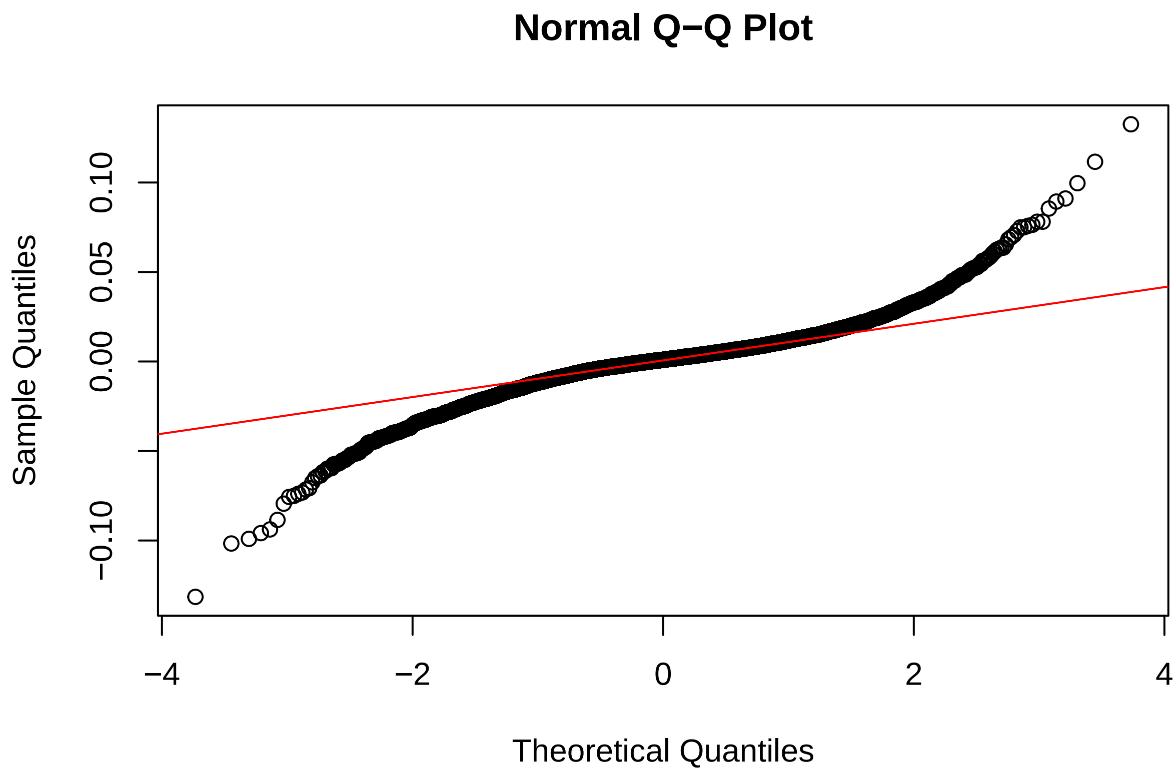
```
qqnorm(sp_logret)
qqline(sp_logret,col='red')
```




```
qqnorm(ny_logret)
qqline(ny_logret,col='red')
```




```
qqnorm(nas_logret)
qqline(nas_logret,col='red')
```



The log-returns have much heavier tails than the normal distribution, which suggests that it might follow a Student's t-distribution.

Calculating summary statistics

Let us now obtain some sample statistics of our data. We will first use summary():

```
summary(sp_logret)
```

```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -0.1276521 -0.0045195  0.0006476  0.0002135  0.0057220  0.1095720
```

```
summary(ny_logret)
```

```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -0.1276521 -0.0047659  0.0005935  0.0001795  0.0058089  0.1095720
```

```
summary(nas_logret)
```

```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.
## -0.1314915 -0.0062893  0.0009564  0.0002154  0.0075183  0.1325465
```

Now we will calculate the skewness of our data:

```
skewness(sp_logret)
```

```
## [1] -0.4178326
```

```
skewness(ny_logret)
```

```
## [1] -0.393156
```

```
skewness(nas_logret)
```

```
## [1] -0.1333754
```

The skewness of our indexes are not equal to 0 which indicates that our log-returns might not be normally distributed. Let's also look at the tails of the distribution by calculating the sample kurtosis:

```
kurtosis(sp_logret)
```

```
## [1] 14.67896
```

```
kurtosis(ny_logret)
```

```
## [1] 13.94
```

```
kurtosis(nas_logret)
```

```
## [1] 9.621652
```

The sample kurtosis is much higher than 3 meaning our log-returns have much fatter tails than the normal distribution!

Doing basic time-series tests

We will carrying out tests to check if our series is stationary and auto-correlated.

We first test if our series is stationary:

```
lag.length = 25

Box.test(sp_logret, lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  sp_logret
## X-squared = 182.6, df = 25, p-value < 2.2e-16
```

```
Box.test(ny_logret, lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  ny_logret
## X-squared = 179.72, df = 25, p-value < 2.2e-16
```

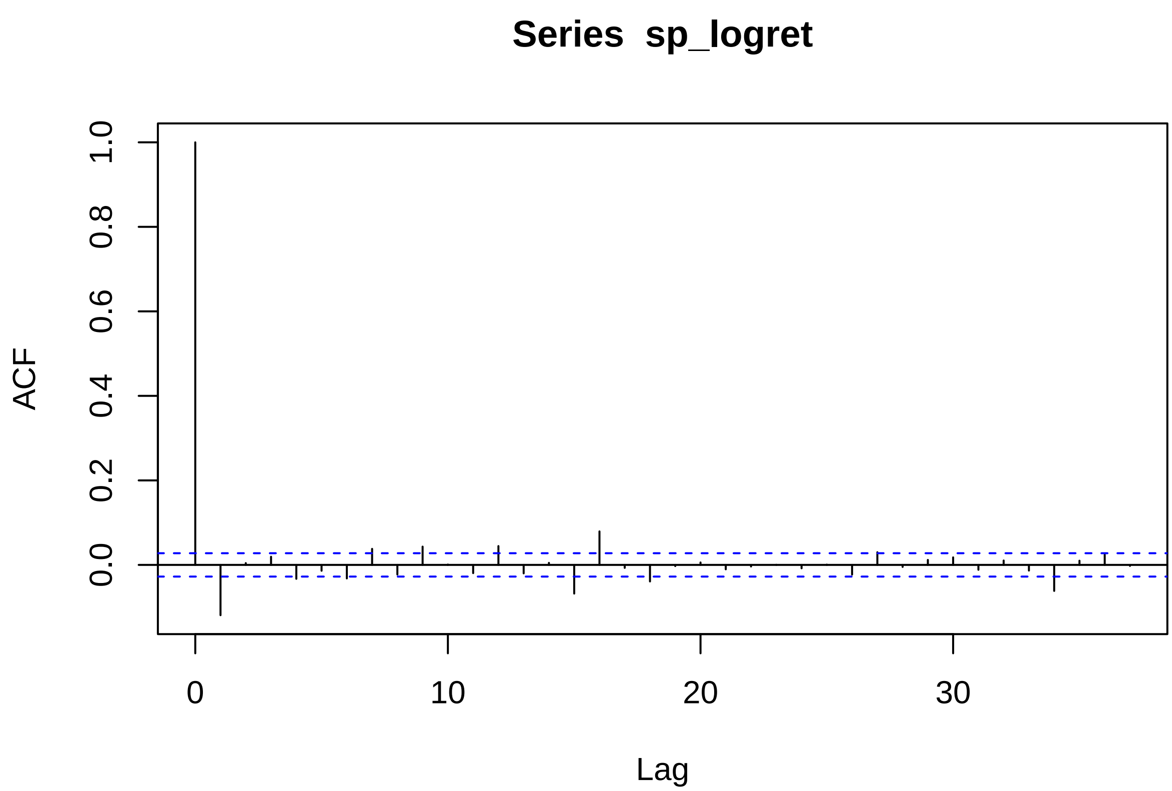
```
Box.test(nas_logret, lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  nas_logret
## X-squared = 133.38, df = 25, p-value < 2.2e-16
```

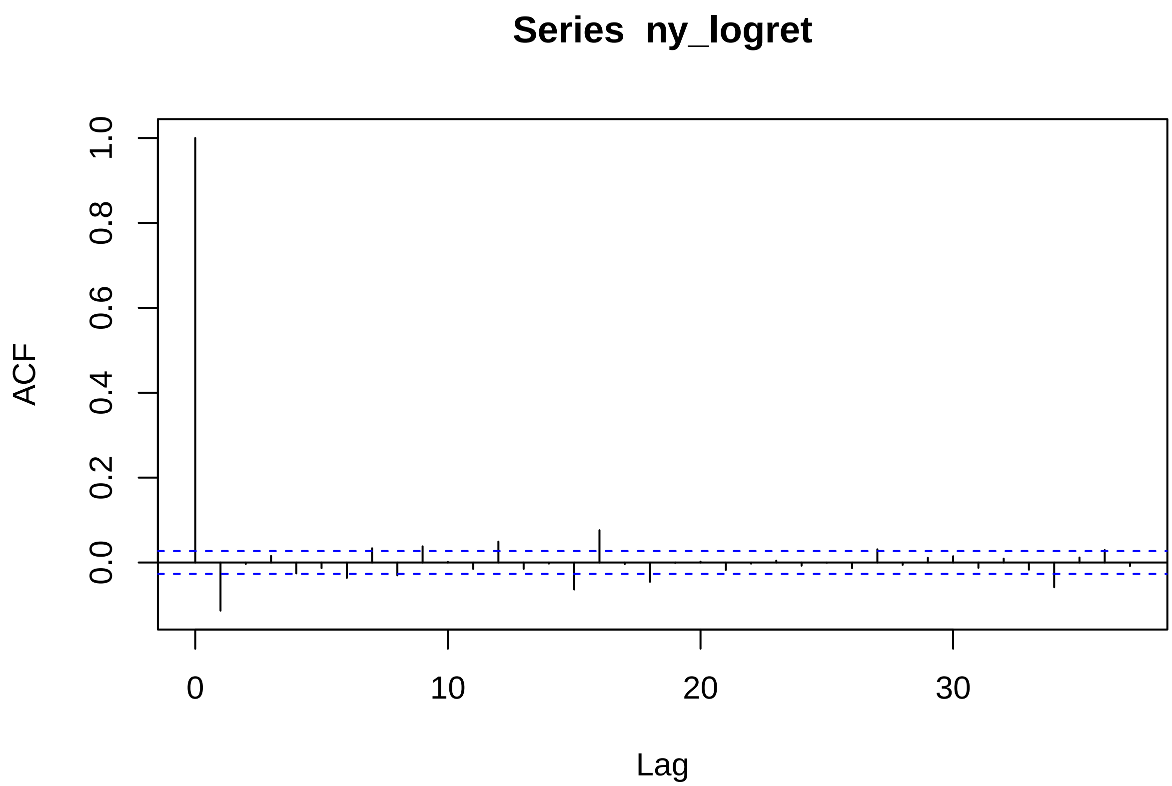
The p-value is very small which means we reject the null hypothesis that our correlations are 0. This means our data is not stationary and we might not use a GARCH model on log-returns directly.

We also plot the ACF of our indexes to see how our data is correlated:

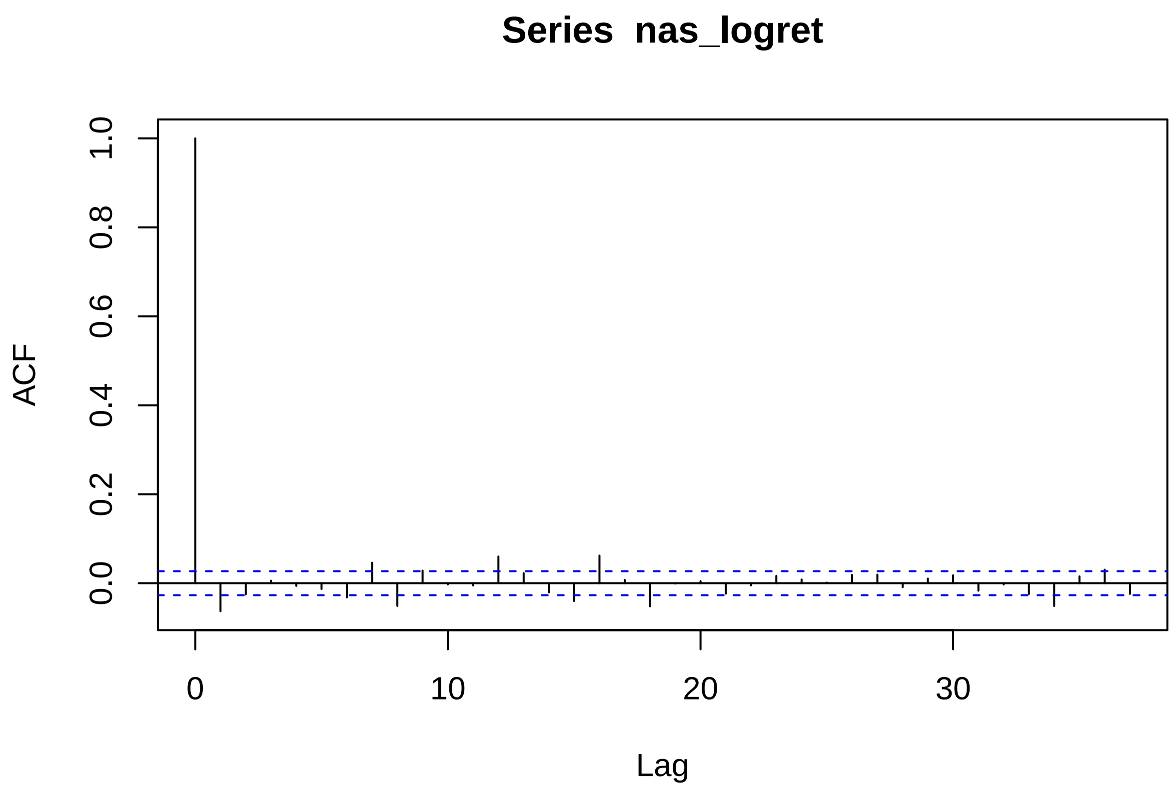
```
acf(sp_logret)
```



```
acf(ny_logret)
```




```
acf(nas_logret)
```



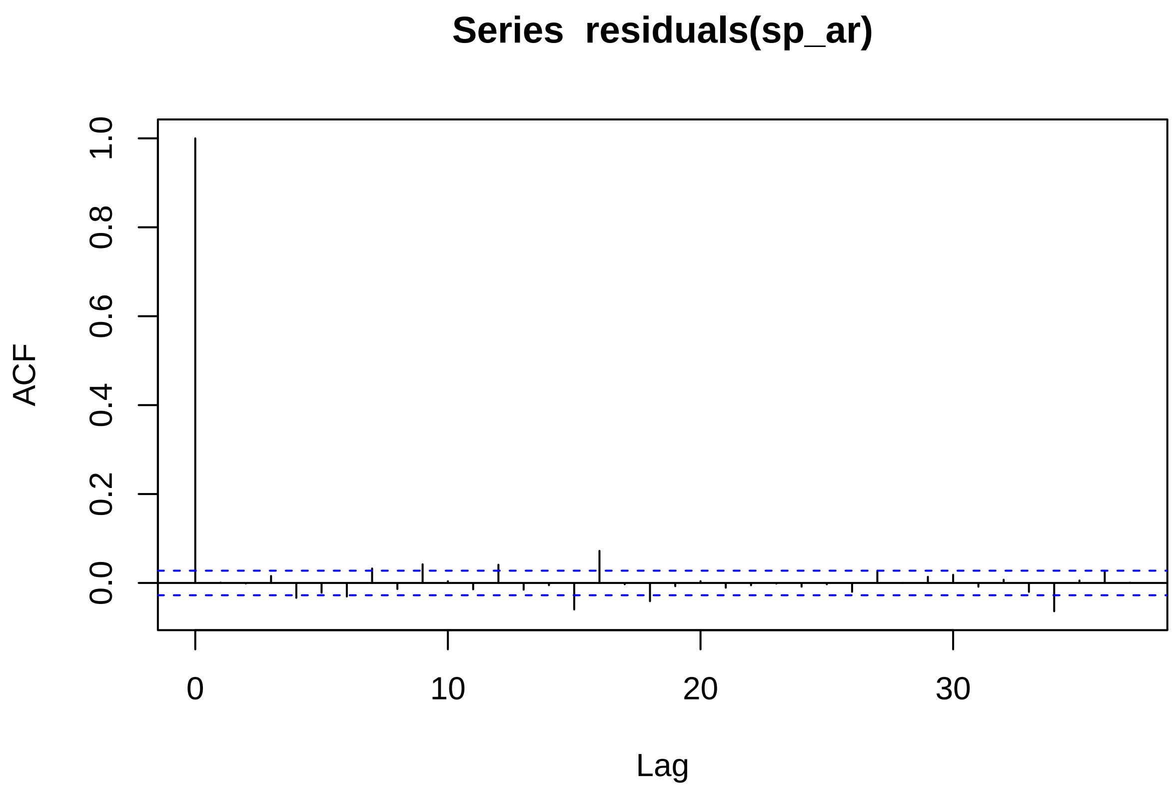
As you can see above there is serious correlation on the first lag, again confirm that our series is not stationary. So instead, we will build a mean equation and try to convert our residuals into a stationary white noise.

Building a mean-equation

```
sp_ar <- arima(sp_logret , order = c(1, 0, 1))
sp_ar
```

```
##
## Call:
## arima(x = sp_logret, order = c(1, 0, 1))
##
## Coefficients:
##           ar1      ma1  intercept
##       -0.0631  -0.0578      2e-04
## s.e.   0.1056   0.1056      2e-04
##
## sigma^2 estimated as 0.0001533:  log likelihood = 14955.89,  aic = -29903.78
```

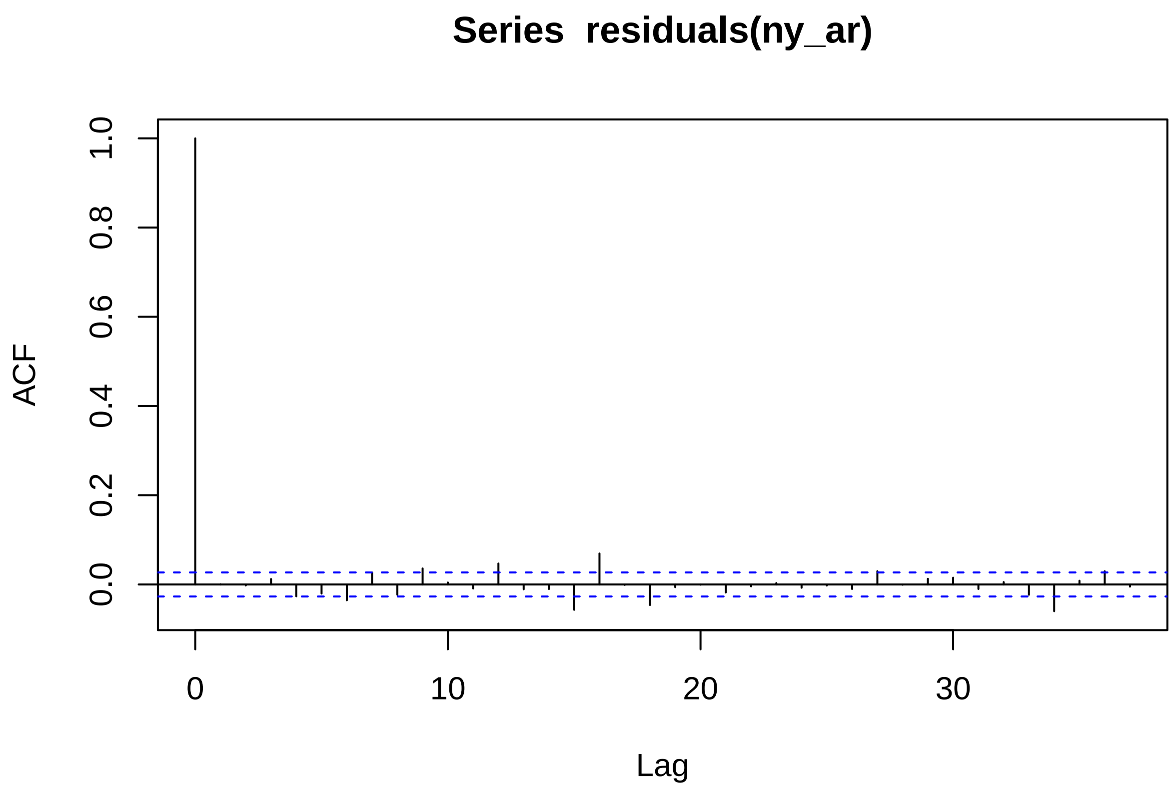
```
acf(residuals(sp_ar))
```




```r
ny_ar <- arima(ny_logret , order = c(1, 0, 1))
ny_ar
```

```
##
## Call:
## arima(x = ny_logret, order = c(1, 0, 1))
##
## Coefficients:
##           ar1      ma1  intercept
##       -0.0020  -0.1135      2e-04
## s.e.   0.1143   0.1136      2e-04
##
## sigma^2 estimated as 0.0001555:  log likelihood = 15667.19,  aic = -31326.38
```

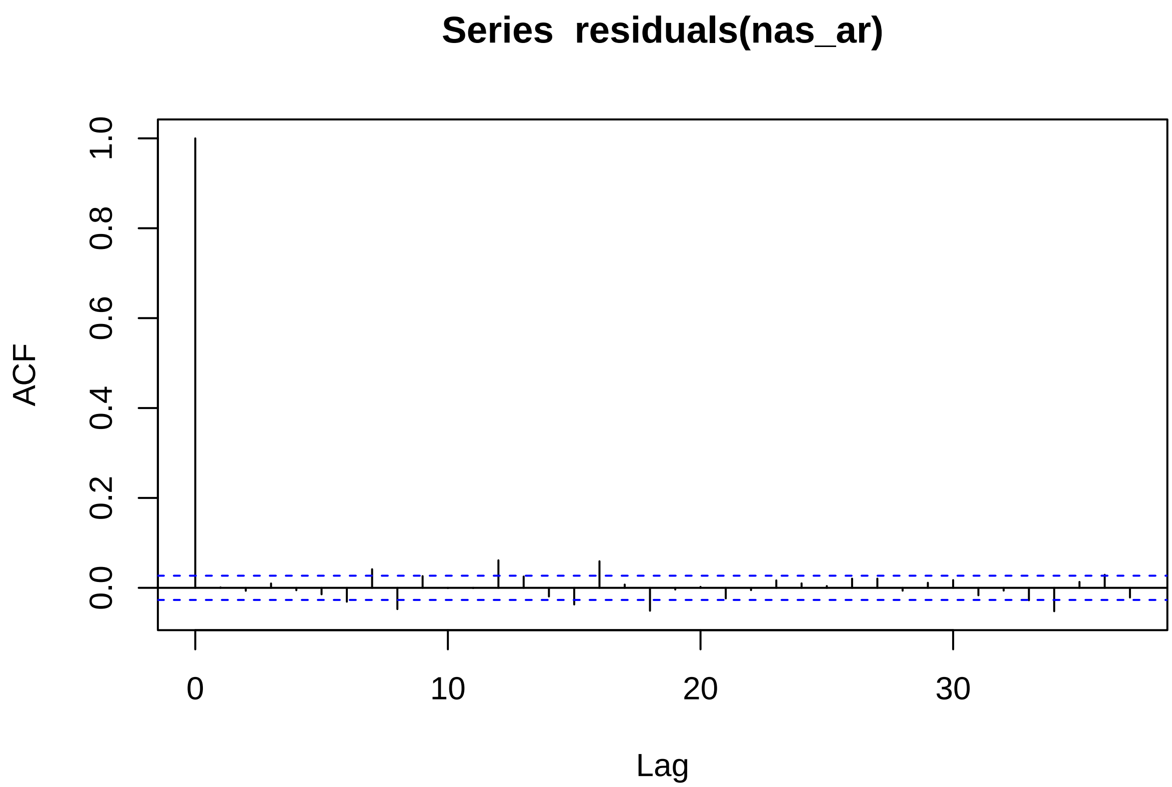
```r
acf(residuals(ny_ar))
```




```
nas_ar <- arima(nas_logret , order = c(1, 0, 1))
nas_ar
```

```
##
## Call:
## arima(x = nas_logret, order = c(1, 0, 1))
##
## Coefficients:
##          ar1      ma1  intercept
##       0.2811  -0.3470      2e-04
## s.e.  0.2102   0.2065      2e-04
##
## sigma^2 estimated as 0.000255:  log likelihood = 14360.11,  aic = -28712.21
```

```
acf(residuals(nas_ar))
```




```r
lag.length = 25

Box.test(residuals(sp_ar), lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(sp_ar)
## X-squared = 94.264, df = 25, p-value = 5.697e-10
```

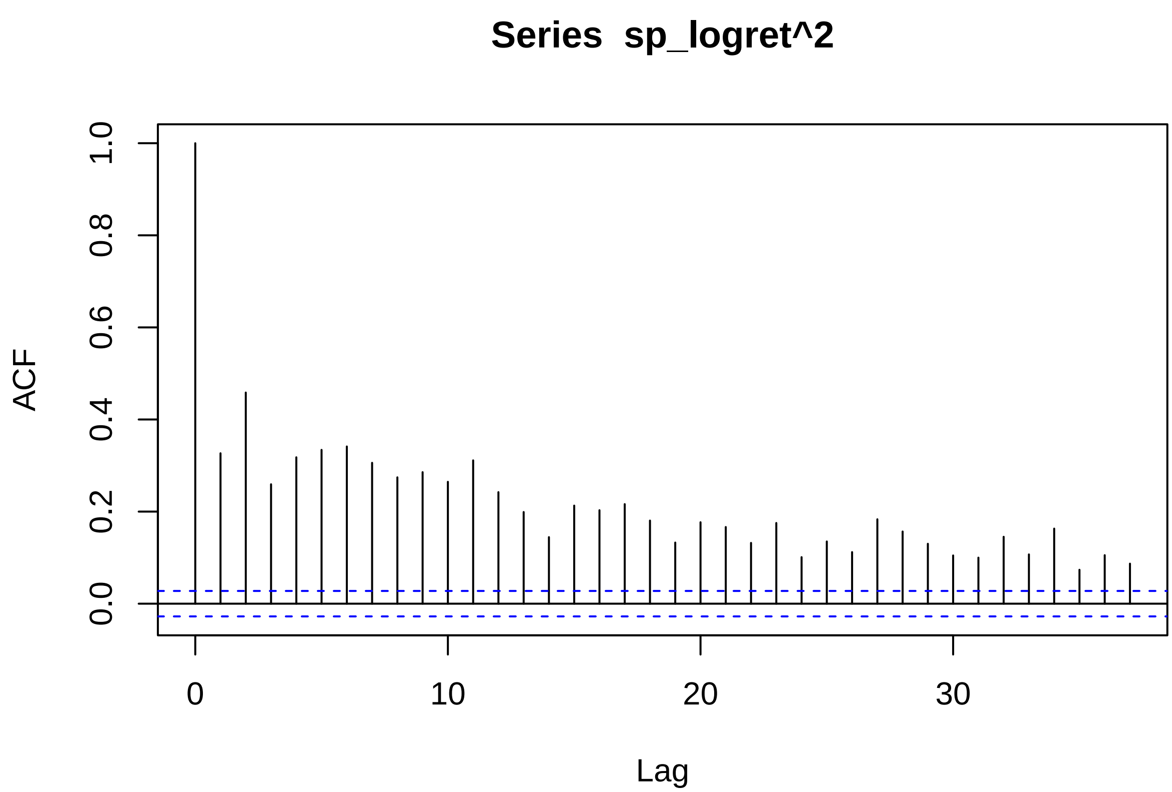
```r
Box.test(residuals(ny_ar), lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(ny_ar)
## X-squared = 96.877, df = 25, p-value = 2.095e-10
```

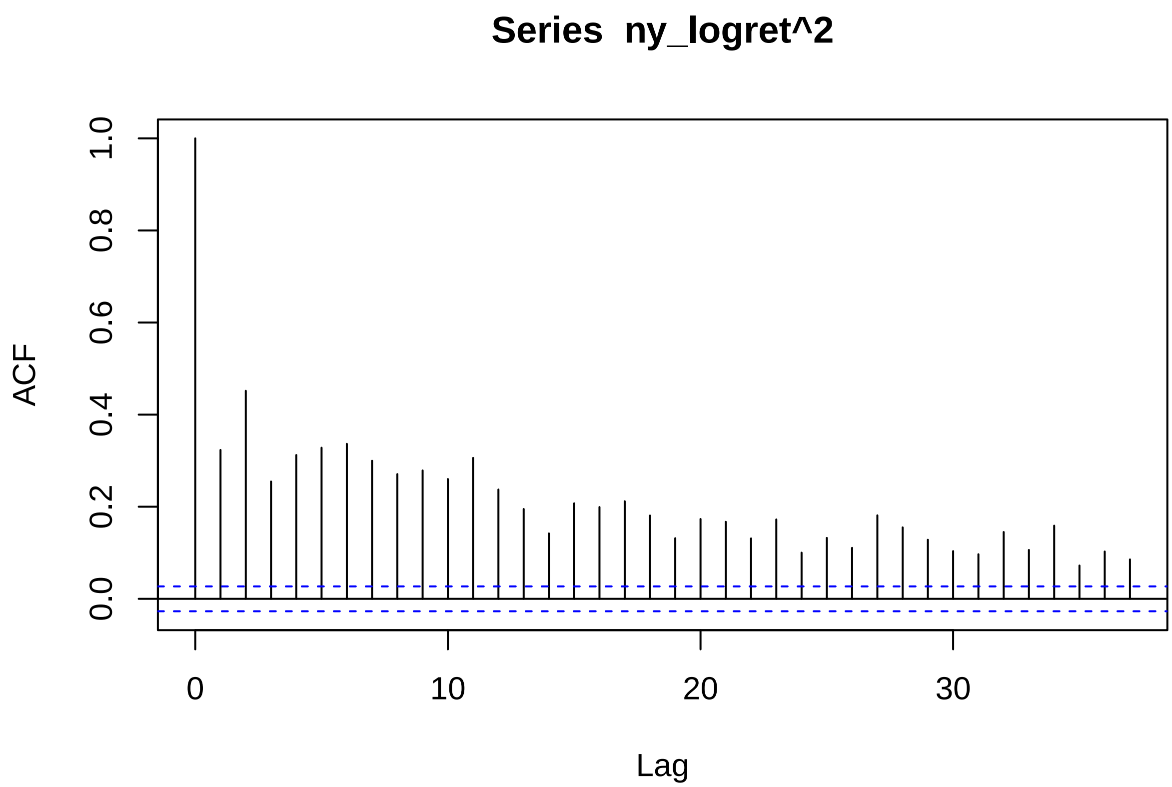
```r
Box.test(residuals(nas_ar), lag=lag.length, type="Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(nas_ar)
## X-squared = 101.92, df = 25, p-value = 2.974e-11
```

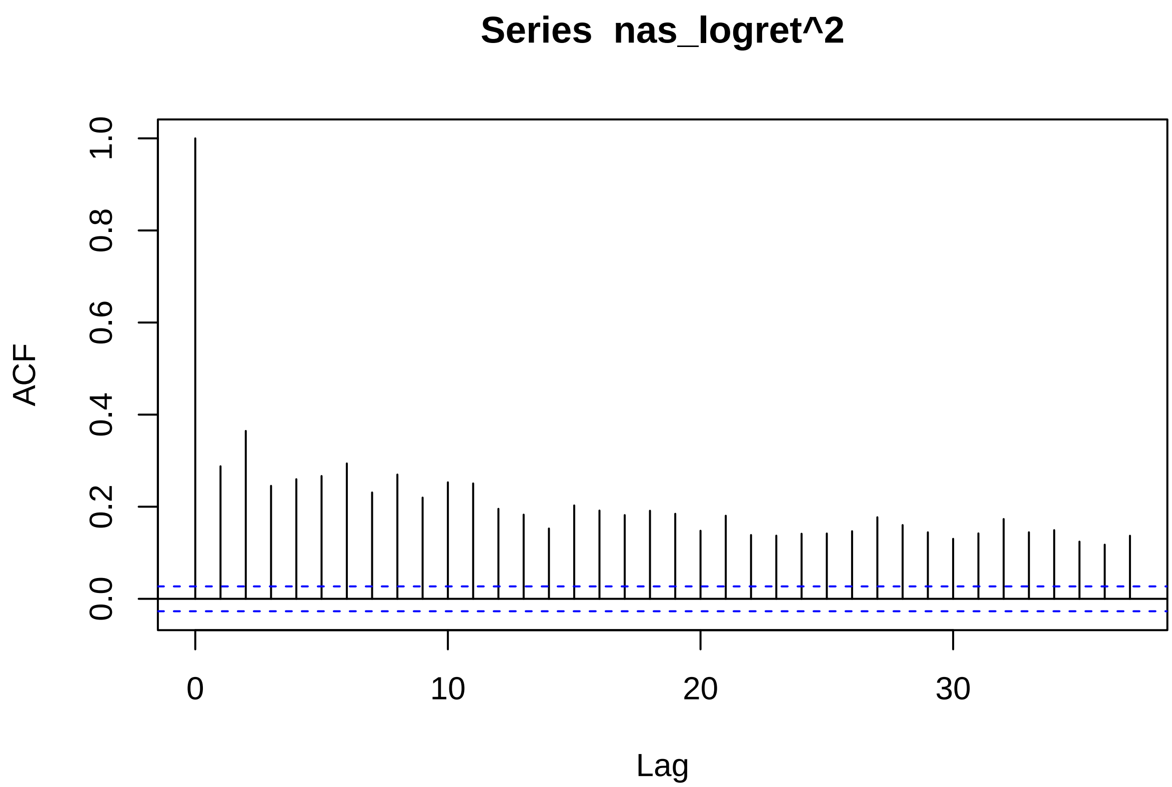
```
acf(sp_logret^2)
```



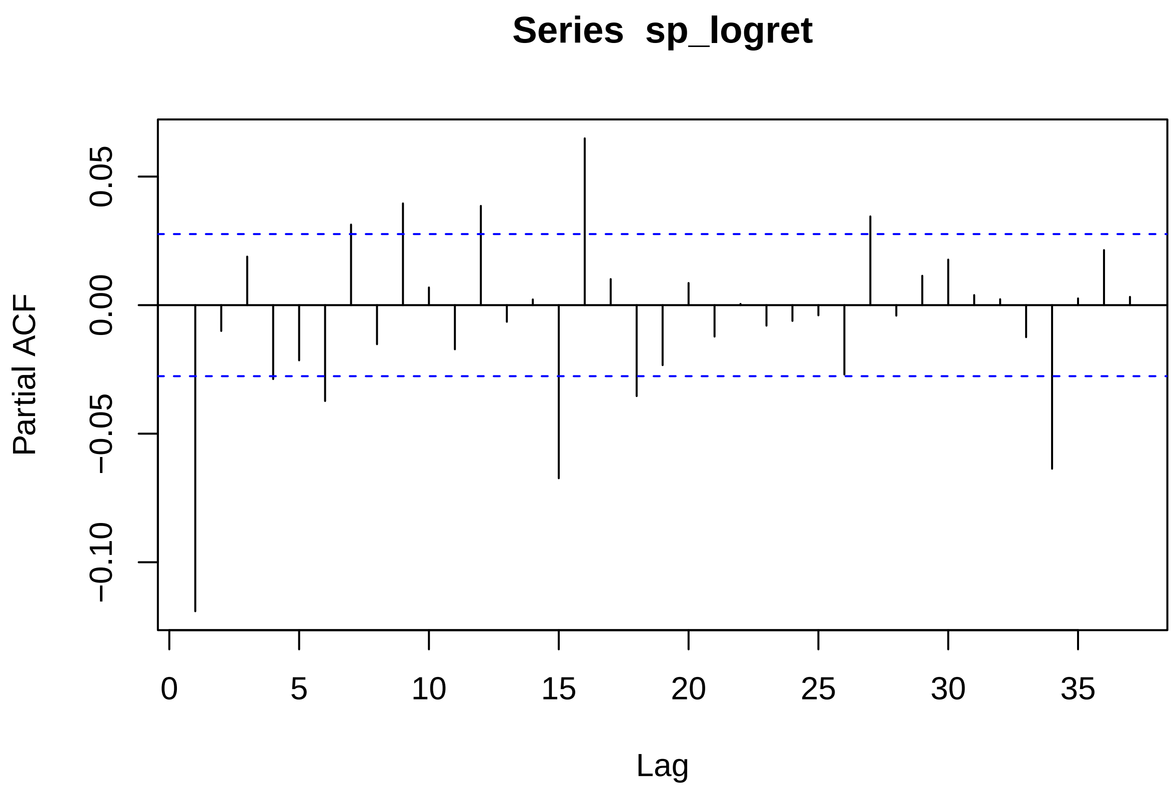

```
acf(ny_logret^2)
```



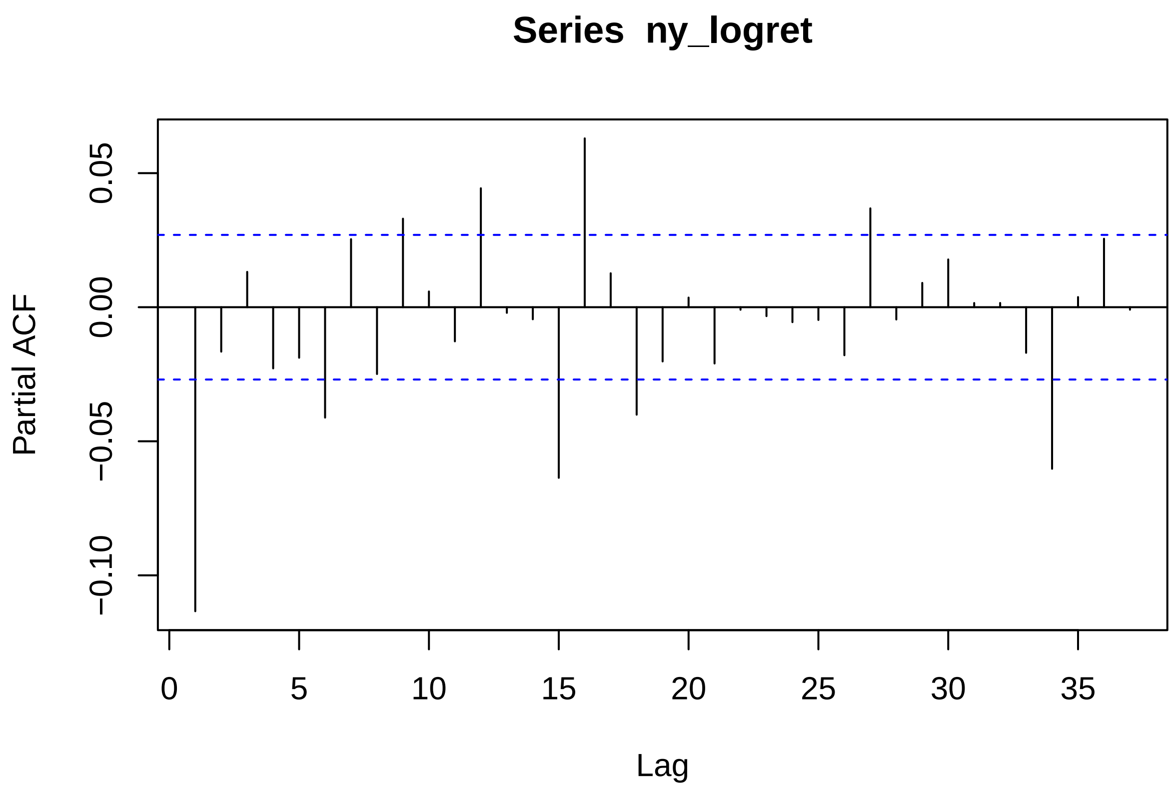

```
acf(nas_logret^2)
```



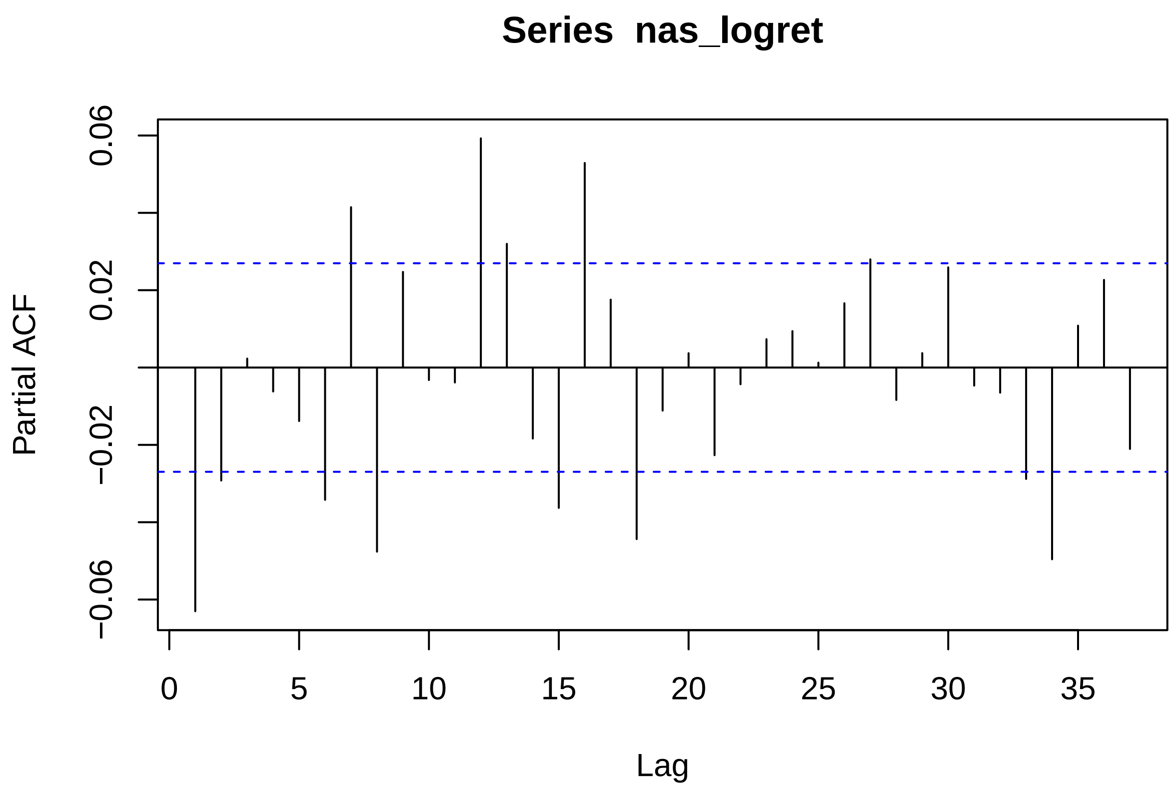

```
pacf(sp_logret)
```




```
pacf(ny_logret)
```




```
pacf(nas_logret)
```



Outputting Files

```
setwd('..')
write.csv(residuals(sp_ar), 'Data/sp_residual.csv', row.names=T)
write.csv(residuals(ny_ar), 'Data/ny_residual.csv', row.names=T)
write.csv(residuals(nas_ar), 'Data/nas_residual.csv', row.names=T)
```