R Notebook

Code

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```
#Loading the data

library(quantmod)
```

```
Loading required package: xts
Loading required package: zoo

Attaching package: ‘zoo’

The following objects are masked from ‘package:base’:

    as.Date, as.Date.numeric

Loading required package: TTR
Registered S3 method overwritten by 'quantmod':
  method            from
  as.zoo.data.frame zoo
```

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```
getSymbols("EA",src="yahoo",from=as.Date("2018-02-06"),to=as.Date("2023-02-06"))
```

```
[1] "EA"
```

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```
head(EA)
```

```
           EA.Open EA.High EA.Low EA.Close EA.Volume EA.Adjusted
2018-02-06  118.86  123.35 117.76   123.13   4652300    121.6679
2018-02-07  122.86  125.00 122.18   123.05   4066900    121.5889
2018-02-08  123.00  123.00 116.52   116.54   5478900    115.1562
2018-02-09  117.96  122.14 114.67   120.64   5945100    119.2075
2018-02-12  121.78  124.16 121.53   122.22   3695100    120.7687
2018-02-13  120.85  123.13 120.58   122.28   2388700    120.8280
```

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```
tail(EA)
```

```
           EA.Open EA.High EA.Low EA.Close EA.Volume EA.Adjusted
2023-01-27  129.14  130.57 128.79   128.87   1786200      128.87
2023-01-30  128.92  129.47 128.11   128.99   2446900      128.99
2023-01-31  129.19  129.99 128.38   128.68   3067700      128.68
2023-02-01  116.78  117.22 112.58   116.76  14492300      116.76
2023-02-02  117.50  117.52 114.10   115.99   6355600      115.99
2023-02-03  115.15  115.54 113.78   113.92   4390400      113.92
```

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```
getSymbols("ATVI",src="yahoo",from=as.Date("2018-02-06"),to=as.Date("2023-02-06"))
```

```
[1] "ATVI"
```

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```
head(ATVI)
```

```
           ATVI.Open ATVI.High ATVI.Low ATVI.Close ATVI.Volume ATVI.Adjusted
2018-02-06     66.00     69.84    65.72      69.70    10524300      67.60927
2018-02-07     69.62     70.86    69.43      69.46     6255200      67.37648
2018-02-08     69.63     69.79    65.76      65.83    11179300      63.85536
2018-02-09     66.99     67.78    63.32      67.08    18582300      65.06787
2018-02-12     67.16     69.20    67.16      68.32     8315700      66.27068
2018-02-13     67.96     68.21    67.18      68.03     5373600      65.98937
```

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```
tail(ATVI)
```

```
           ATVI.Open ATVI.High ATVI.Low ATVI.Close ATVI.Volume ATVI.Adjusted
2023-01-27     75.50     76.76    75.22      76.61     4381700         76.61
2023-01-30     76.63     77.08    75.84      75.96     4247400         75.96
2023-01-31     76.13     77.00    75.85      76.57     4118000         76.57
2023-02-01     76.00     76.82    75.58      76.70     4575400         76.70
2023-02-02     76.50     77.39    76.07      77.11     4696100         77.11
2023-02-03     76.64     76.78    75.03      75.24     5779400         75.24
```

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```
#EA - Electronic Arts
#ATVI - Activision Blizzard
```

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```
#1-Daily close prices columns
head(EA[,4])
```

```
           EA.Close
2018-02-06   123.13
2018-02-07   123.05
2018-02-08   116.54
2018-02-09   120.64
2018-02-12   122.22
2018-02-13   122.28
```

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```
head(ATVI[,4])
```

```
           ATVI.Close
2018-02-06      69.70
2018-02-07      69.46
2018-02-08      65.83
2018-02-09      67.08
2018-02-12      68.32
2018-02-13      68.03
```

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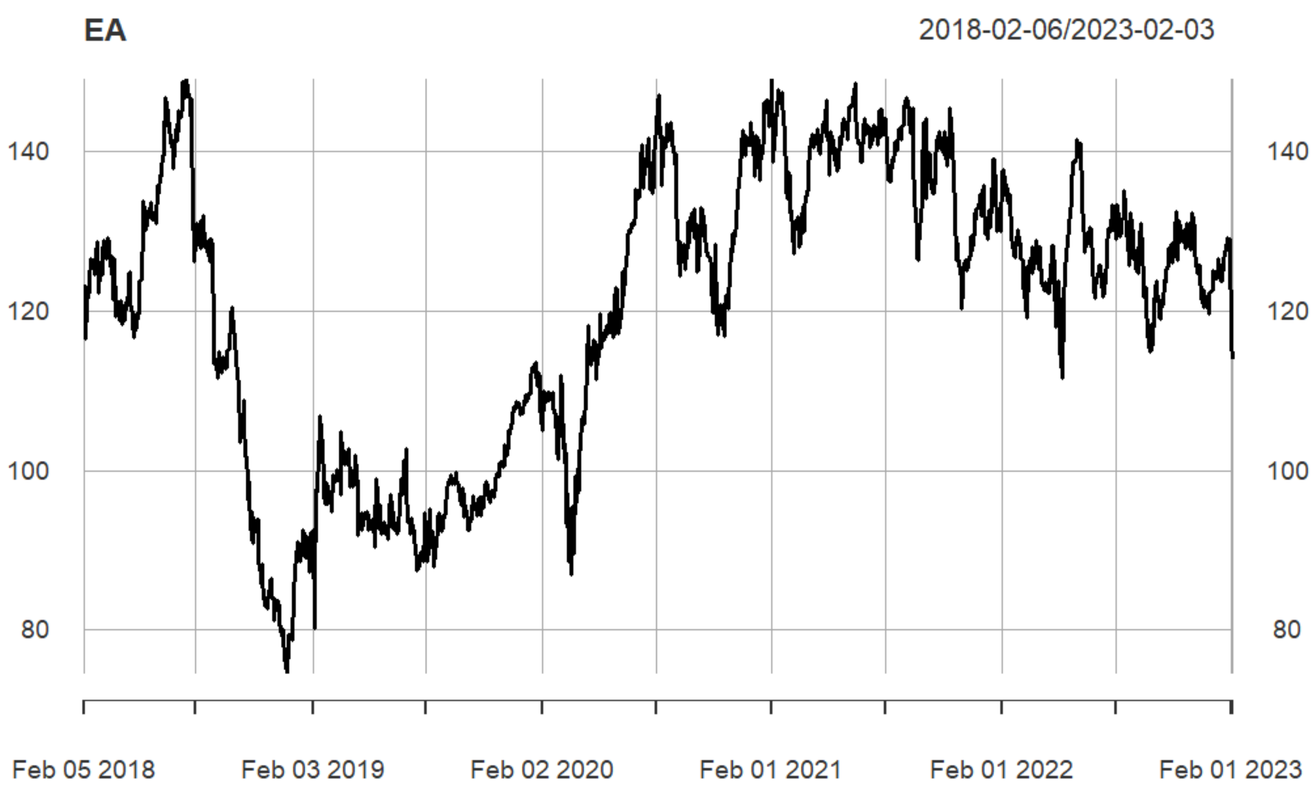
```
#EA and ATVI daily close prices plot

plot(EA[,4], type="l", main="EA") # first plot
```



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```
plot(ATVI[,4], type="l", main="ATVI") # second plot
```

Hide

```
# Looking at the characteristics of the both graphs. We are analyzing the of a 5-year period
of the closing prices of EA and ATVI.

#I would describe both plots as non-stationary, as both show evidence of fluctuations in mean
and variance. On the ea plot there are certain periods of time that looked to be stationary w
hereas the ATVI not.

# Over the years the volatility fluctuates over time, so for this set o year its complex to d
ecide if they are on up or down trend.
```

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```
#2-Log Return plots of EA and ATVI

#EA Log Return Calculation
EA_log_return_1<-diff(log(EA[,6]))
EA_log_return<-EA_log_return_1[-1]
head(as.numeric(EA_log_return))
```

```
[1] -0.0006498483 -0.0543562350  0.0345762122  0.0130118824  0.0004908013
[6]  0.0121115460
```

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```
#Mean EA Log Return Calculation
mean(EA_log_return)
```

```
[1] -5.234598e-05
```

Hide

```
#EA Log Return Calculation
ATVI_log_return_1<-diff(log(ATVI[,6]))
ATVI_log_return<-ATVI_log_return_1[-1]
head(as.numeric(ATVI_log_return))
```

```
[1] -0.003449079 -0.053675439  0.018810337  0.018316612 -0.004253808  0.023533983
```

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```
#Mean EA Log Return Calculation
mean(ATVI_log_return)
```

```
[1] 8.507391e-05
```

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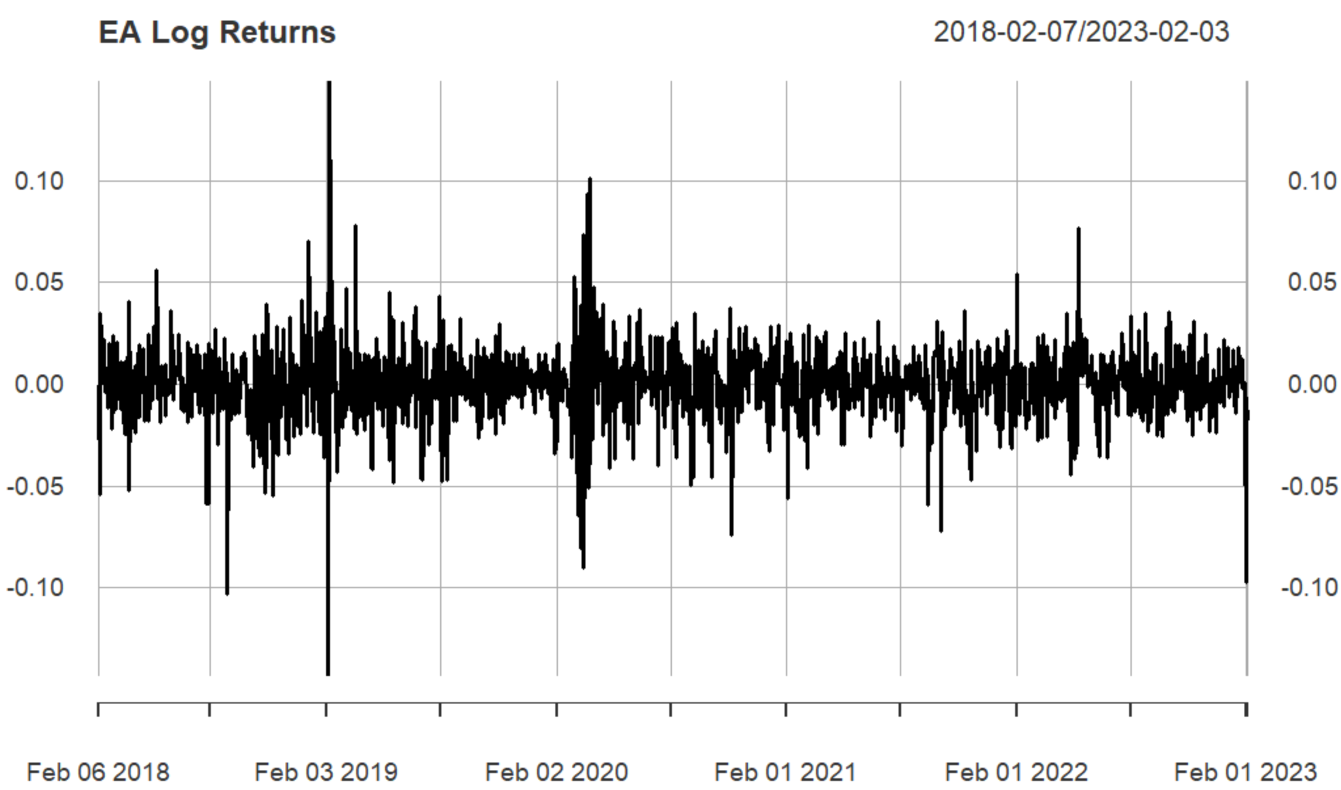
```
# Log Return plot

plot(EA_log_return, type="l", main="EA Log Returns") # first plot
```



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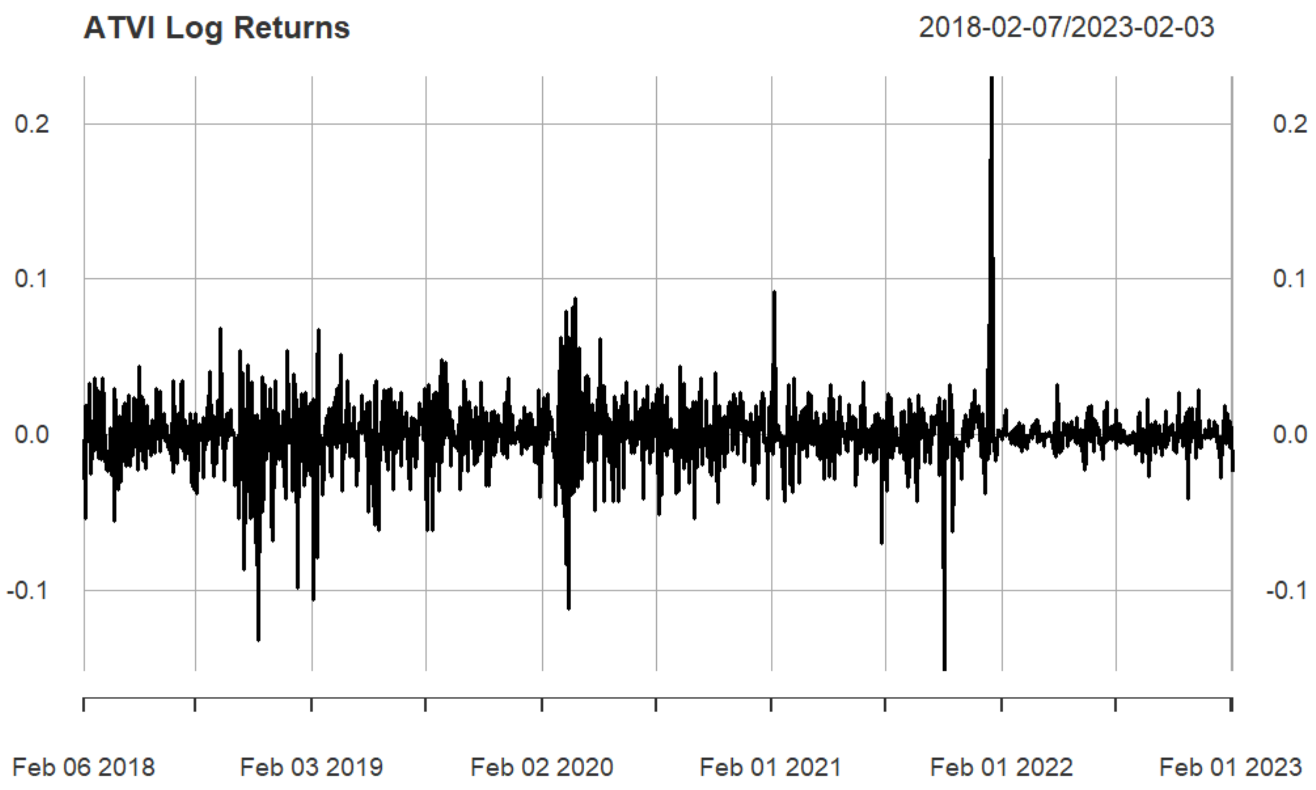
```
plot(ATVI_log_return, type="l", main="ATVI Log Returns") # second plot
```



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```
#Looking at the characteristics of the both graphs. We are analyzing the of a 5-year period o
f the log returns of EA and ATVI. Basically, the graphs are generated using theoretical formu
la wt=ln(x(t)/x(t-1))
```

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```
#3- Quantile Plots generation

#Length of EA and ATVI Log Returns
length(as.numeric(EA_log_return))
```

```
[1] 1257
```

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```
length(as.numeric(ATVI_log_return))
```

```
[1] 1257
```

Hide

```
#Norm quantiles generation based of the length of EA and ATVI

normquantiles<-qnorm(1:1257/1258)
length(normquantiles)
```

```
[1] 1257
```

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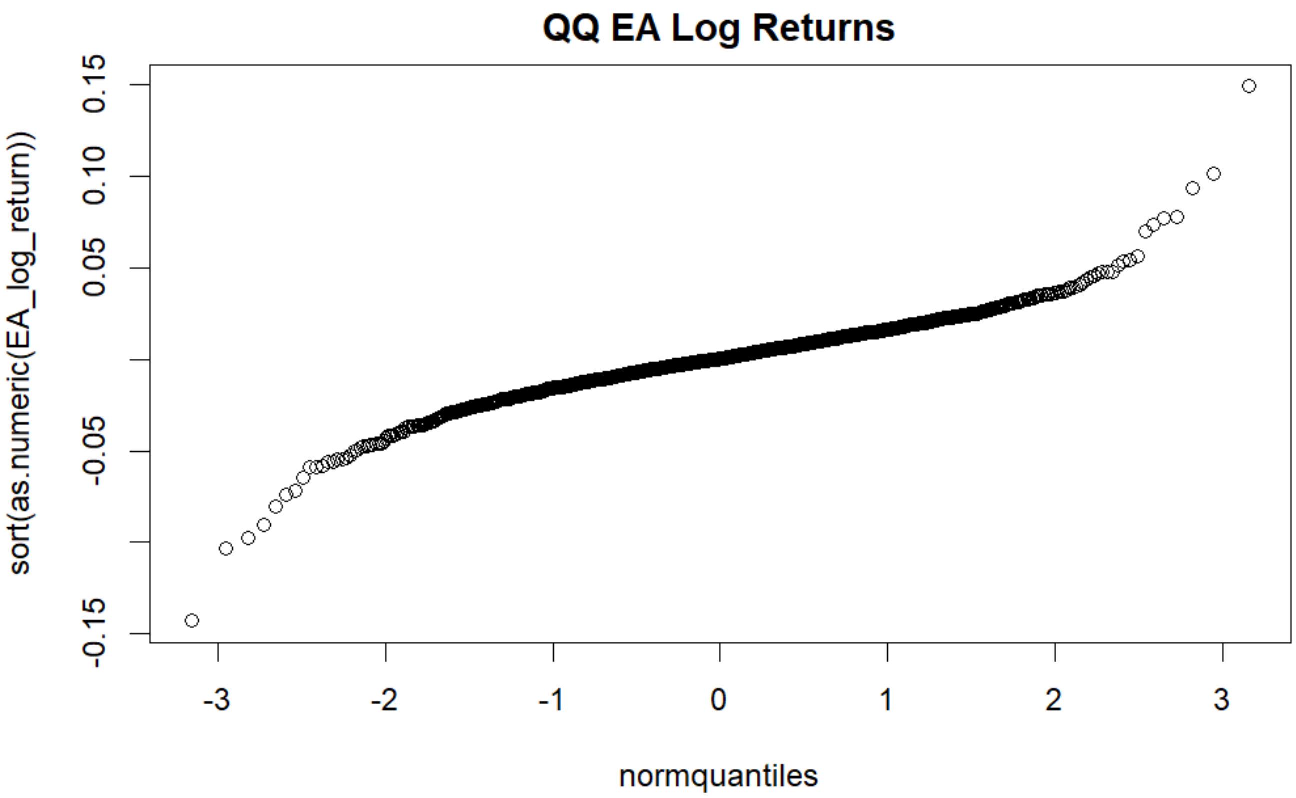
```
qqplot(normquantiles, sort(as.numeric(EA_log_return)), main="QQ EA Log Returns") # first plot
```



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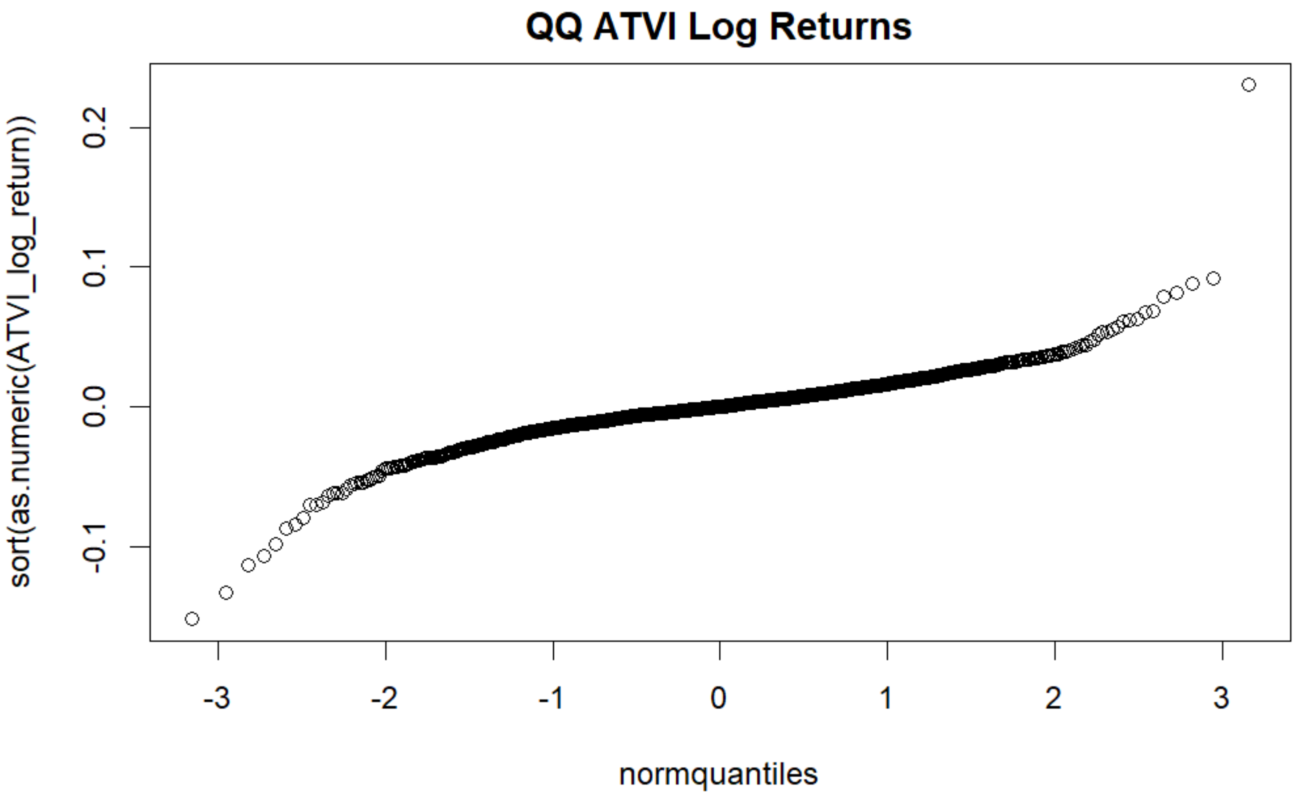
```
qqplot(normquantiles, sort(as.numeric(ATVI_log_return)), main="QQ ATVI Log Returns") # second
plot
```



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```
# Since the plots do not align on straight line it means that the data its not normally distr
ibuted, but both of them show an upward trend meaning that both stocks have a positive skewne
ss meaning that there are more returns with larger positive values compared to negative value
s. Furthermore, Other techniques such as probability density functions and histograms may be
useful in understanding the distribution of the log returns and drawing more accurate conclus
ions.
```

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```
#4-Student-t(quantile-quantile) df=1
theoretical_quantiles <- qt(seq(0.01, 0.99, 0.01), df = 1)
```

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```
empirical_quantiles_EA <- quantile(as.numeric(EA_log_return), seq(0.01, 0.99, 0.01))
empirical_quantiles_ATVI <- quantile(as.numeric(ATVI_log_return), seq(0.01, 0.99, 0.01))
```

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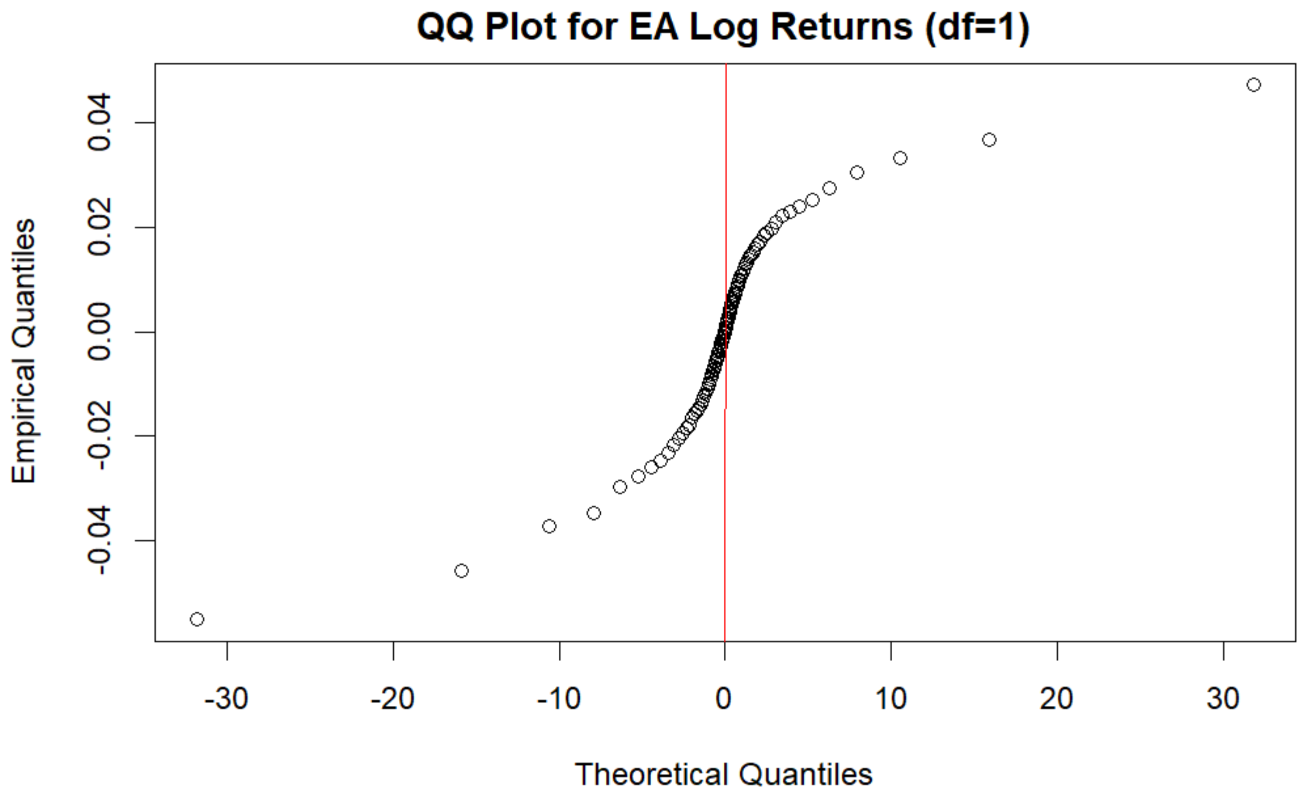
```
# Plot for EA_log_return
plot(theoretical_quantiles, empirical_quantiles_EA,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for EA Log Returns (df=1)")
abline(0, 1, col = "red")
```



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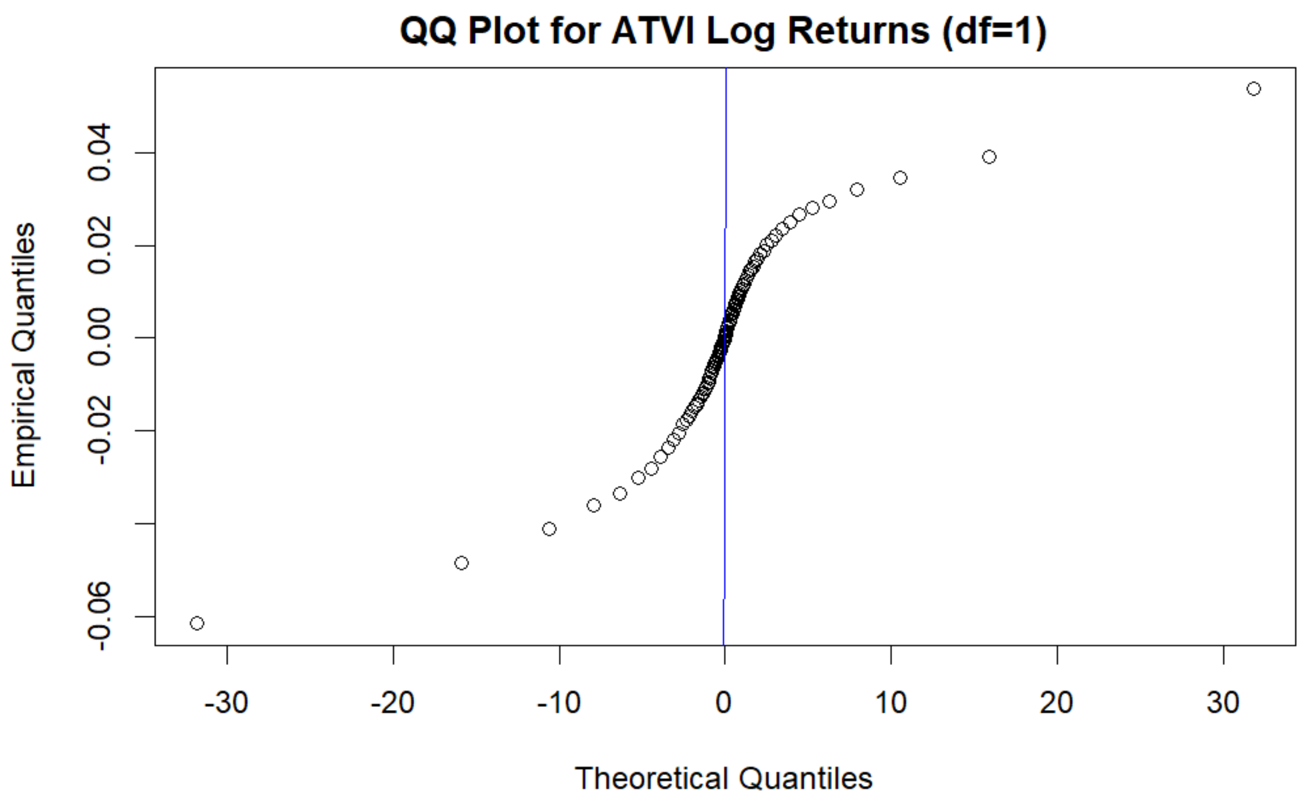
```
# Plot for ATVI_log_return
plot(theoretical_quantiles, empirical_quantiles_ATVI,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for ATVI Log Returns (df=1)")
abline(0, 1, col = "blue")
```



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```
#Student-t(quantile-quantile) df=4
theoretical_quantiles2 <- qt(seq(0.01, 0.99, 0.01), df = 4)
```

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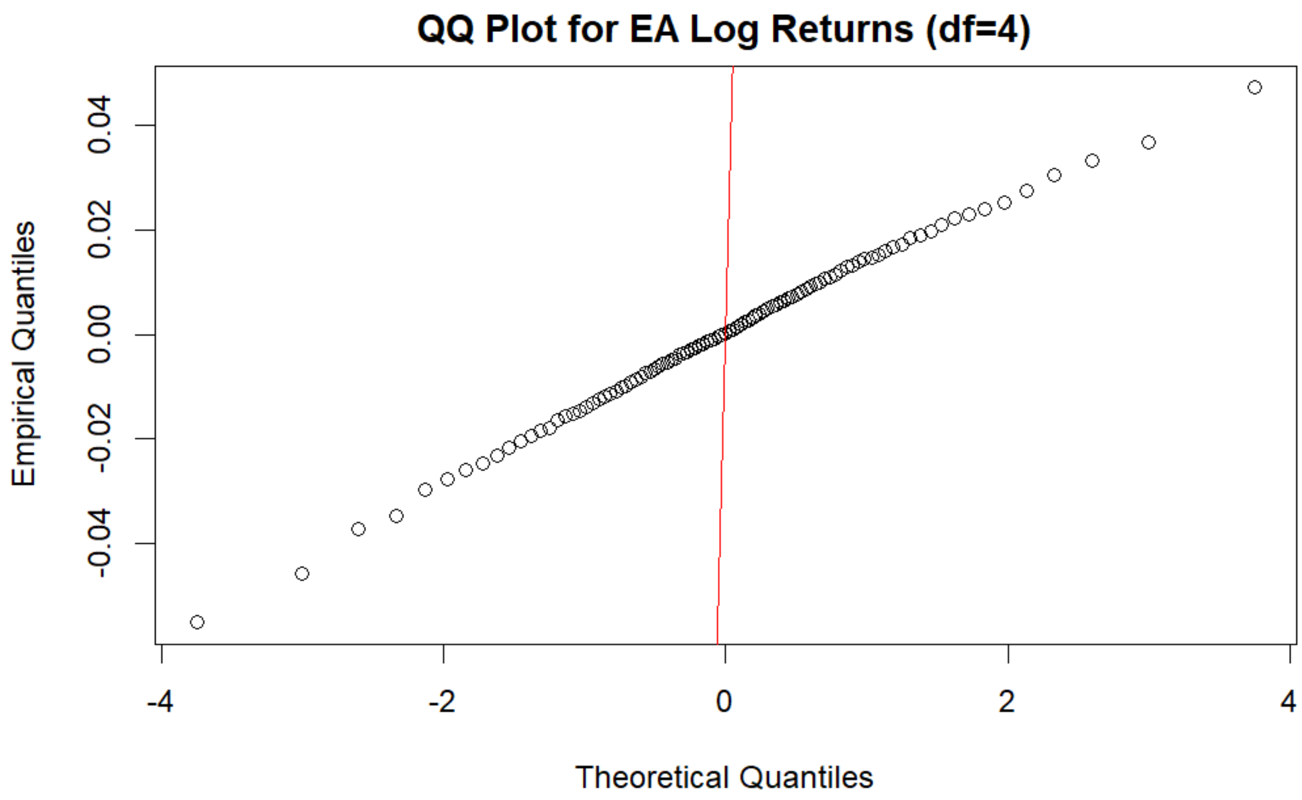
```
# Plot for EA_log_return
plot(theoretical_quantiles2, empirical_quantiles_EA,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for EA Log Returns (df=4)")
abline(0, 1, col = "red")
```



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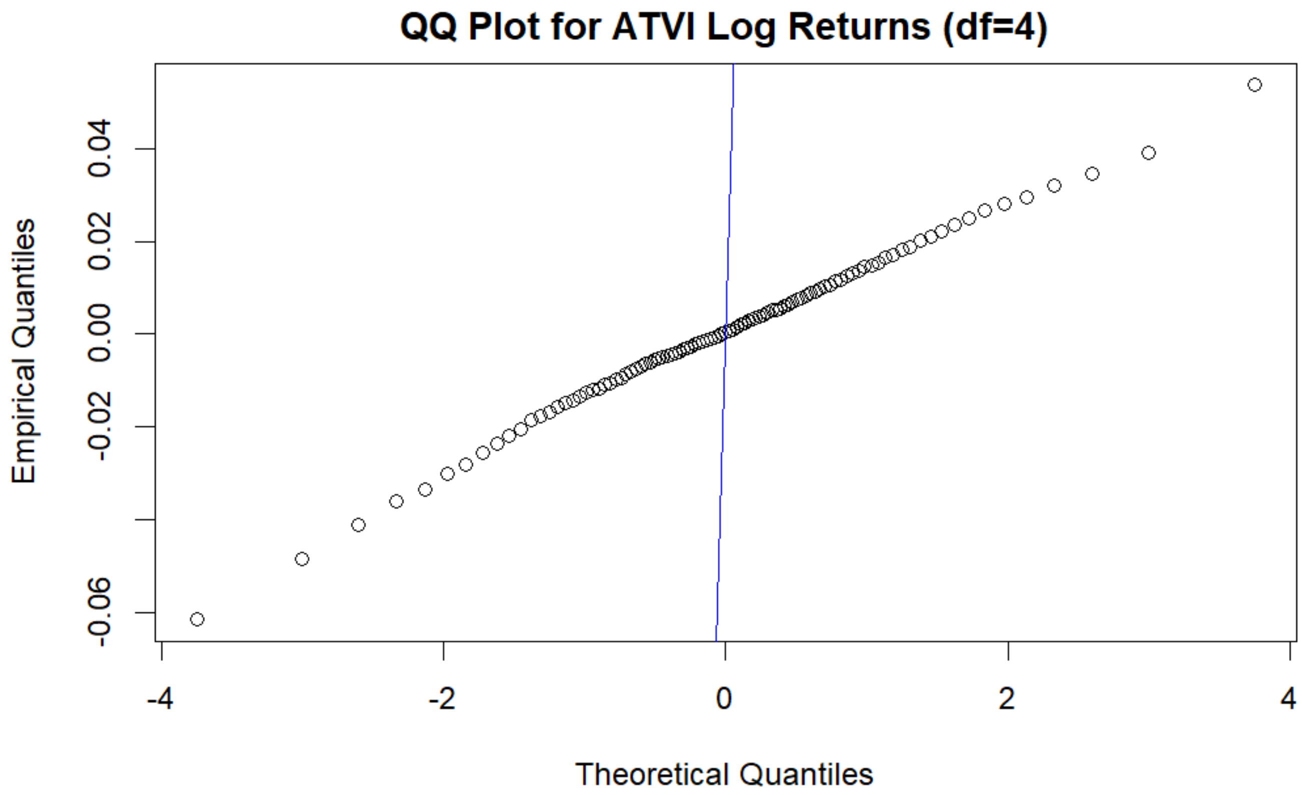
```
# Plot for ATVI_log_return
plot(theoretical_quantiles2, empirical_quantiles_ATVI,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for ATVI Log Returns (df=4)")
abline(0, 1, col = "blue")
```



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```
#Student-t(quantile-quantile) df=6
theoretical_quantiles3 <- qt(seq(0.01, 0.99, 0.01), df = 6)
```

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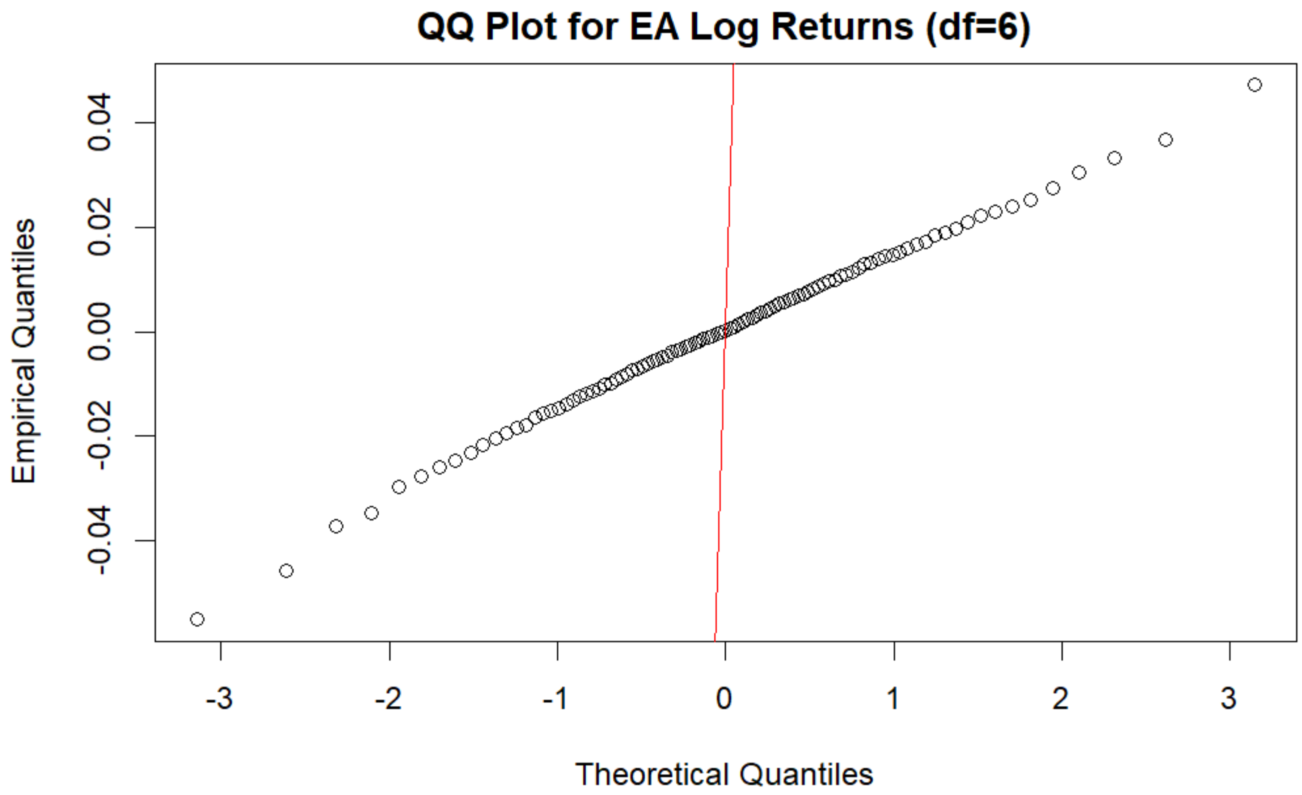
```
# Plot for EA_log_return
plot(theoretical_quantiles3, empirical_quantiles_EA,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for EA Log Returns (df=6)")
abline(0, 1, col = "red")
```



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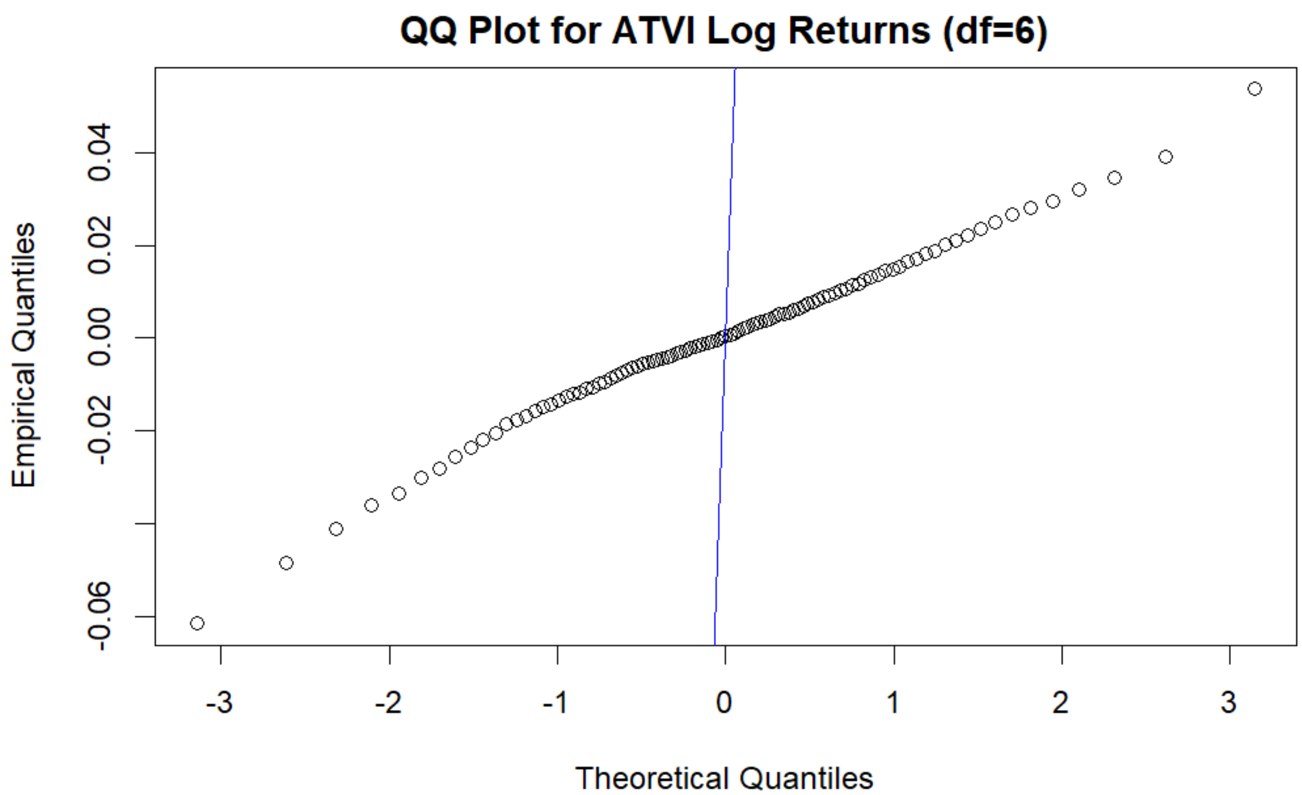
```
# Plot for ATVI_log_return
plot(theoretical_quantiles3, empirical_quantiles_ATVI,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for ATVI Log Returns (df=6)")
abline(0, 1, col = "blue")
```



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```
#Student-t(quantile-quantile) df=10
theoretical_quantiles4 <- qt(seq(0.01, 0.99, 0.01), df = 10)
```

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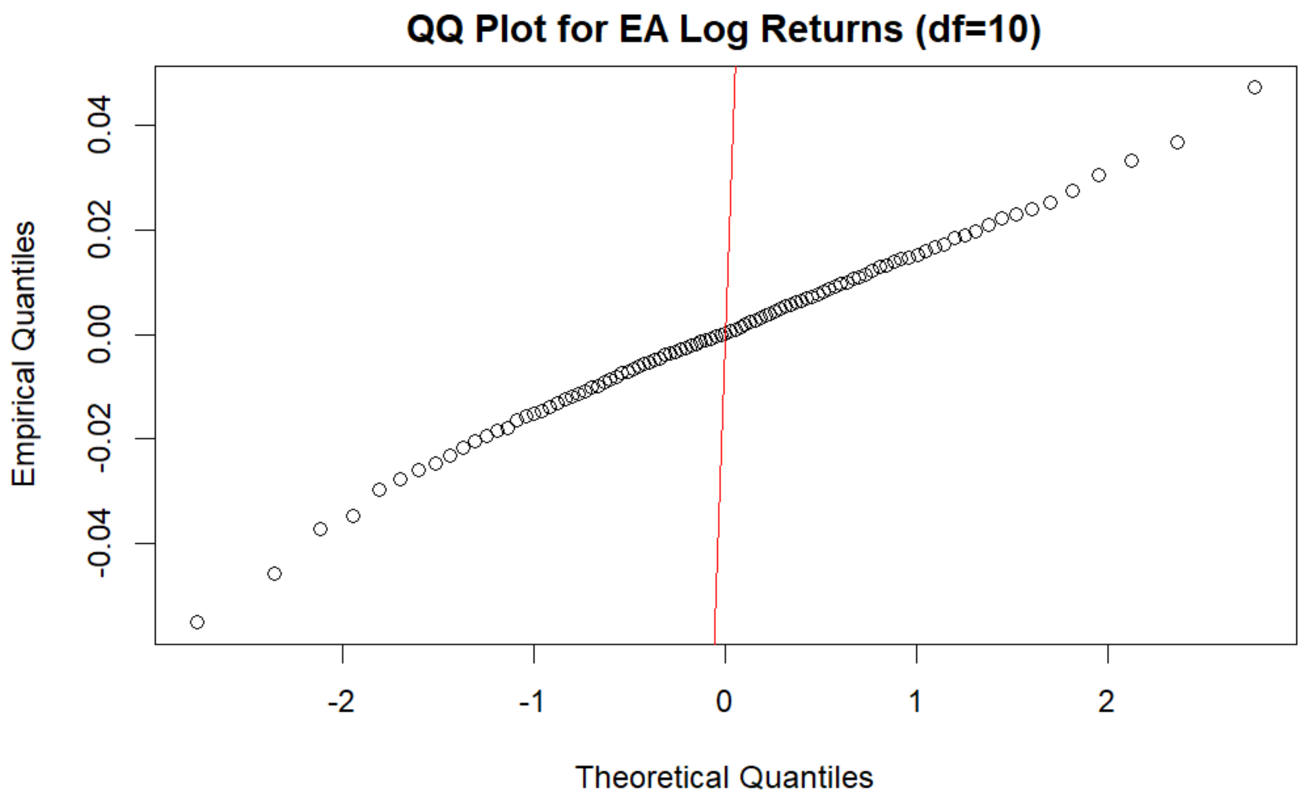
```
# Plot for EA_log_return
plot(theoretical_quantiles4, empirical_quantiles_EA,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for EA Log Returns (df=10)")
abline(0, 1, col = "red")
```



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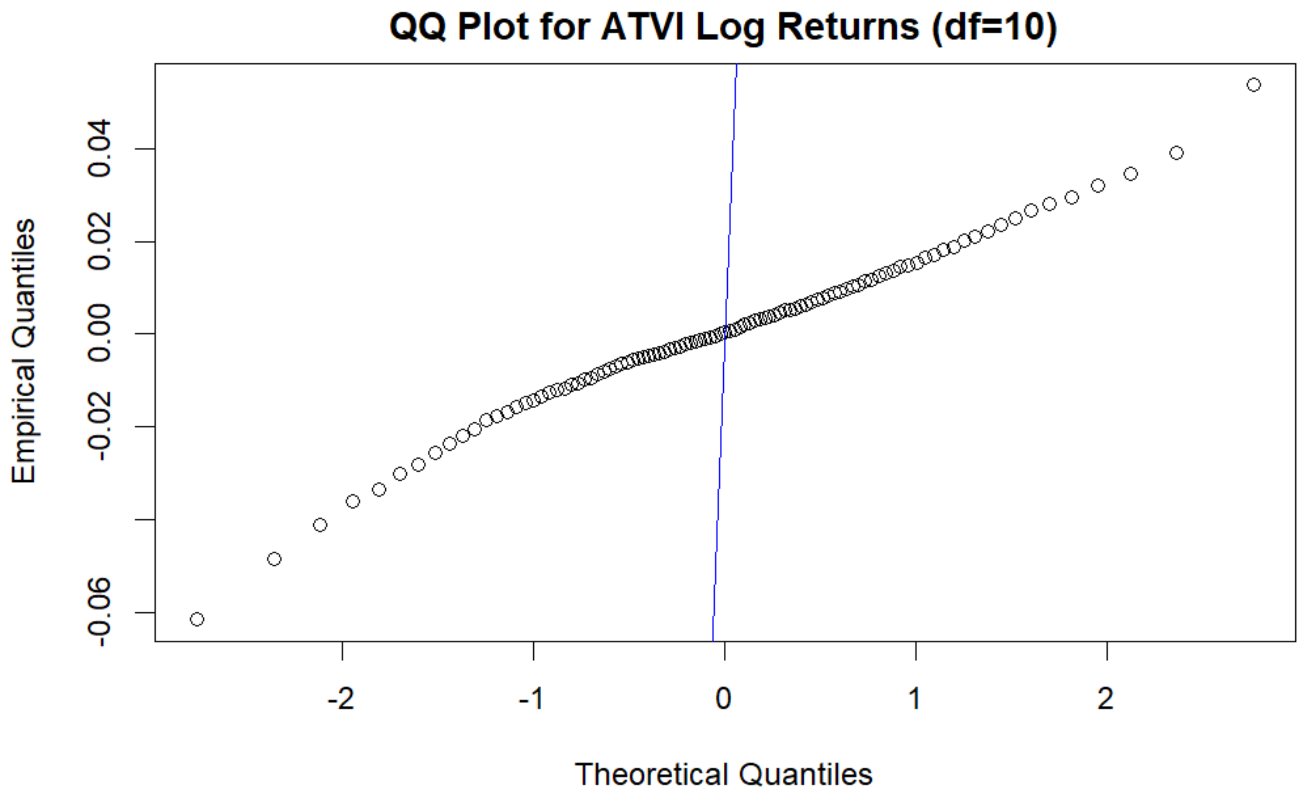
```
# Plot for ATVI_log_return
plot(theoretical_quantiles4, empirical_quantiles_ATVI,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for ATVI Log Returns (df=10)")
abline(0, 1, col = "blue")
```



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```
#Student-t(quantile-quantile) df=20
theoretical_quantiles5 <- qt(seq(0.01, 0.99, 0.01), df = 20)
```

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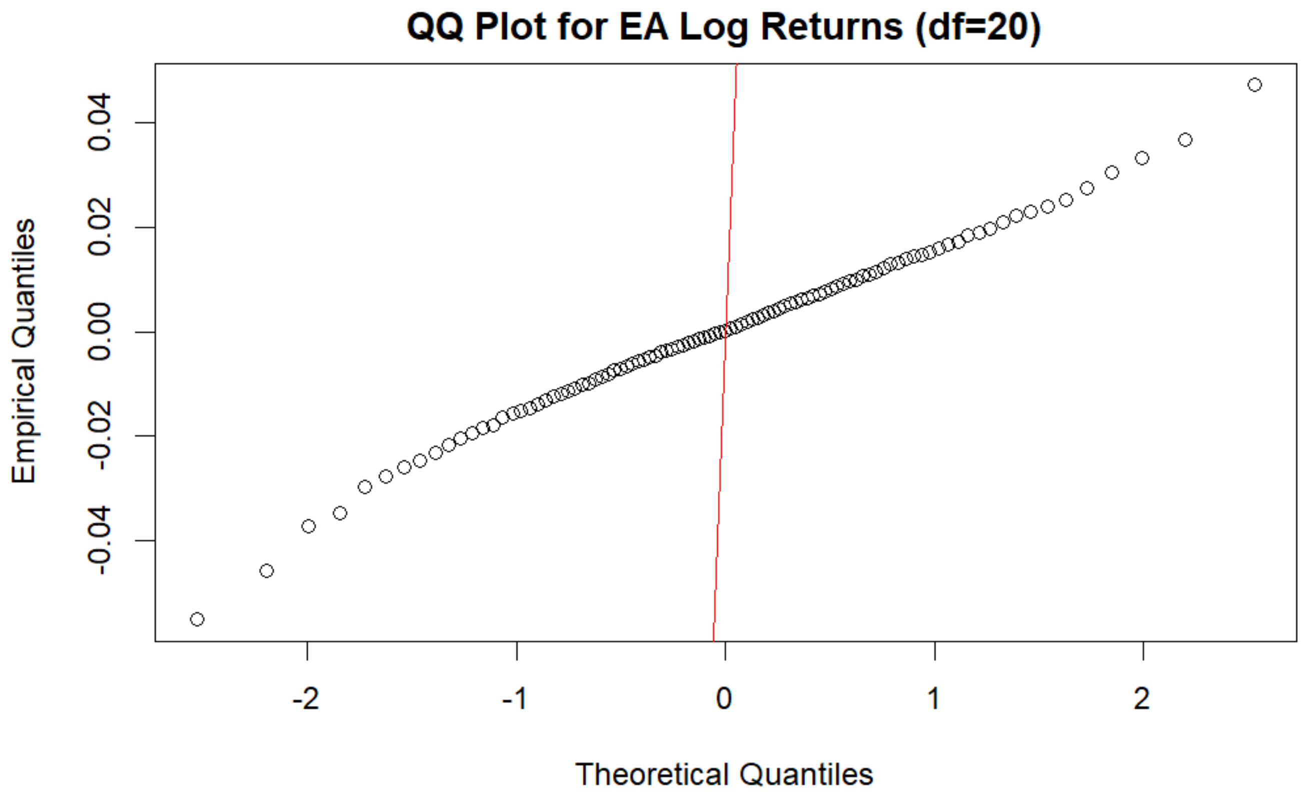
```
# Plot for EA_log_return
plot(theoretical_quantiles5, empirical_quantiles_EA,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for EA Log Returns (df=20)")
abline(0, 1, col = "red")
```



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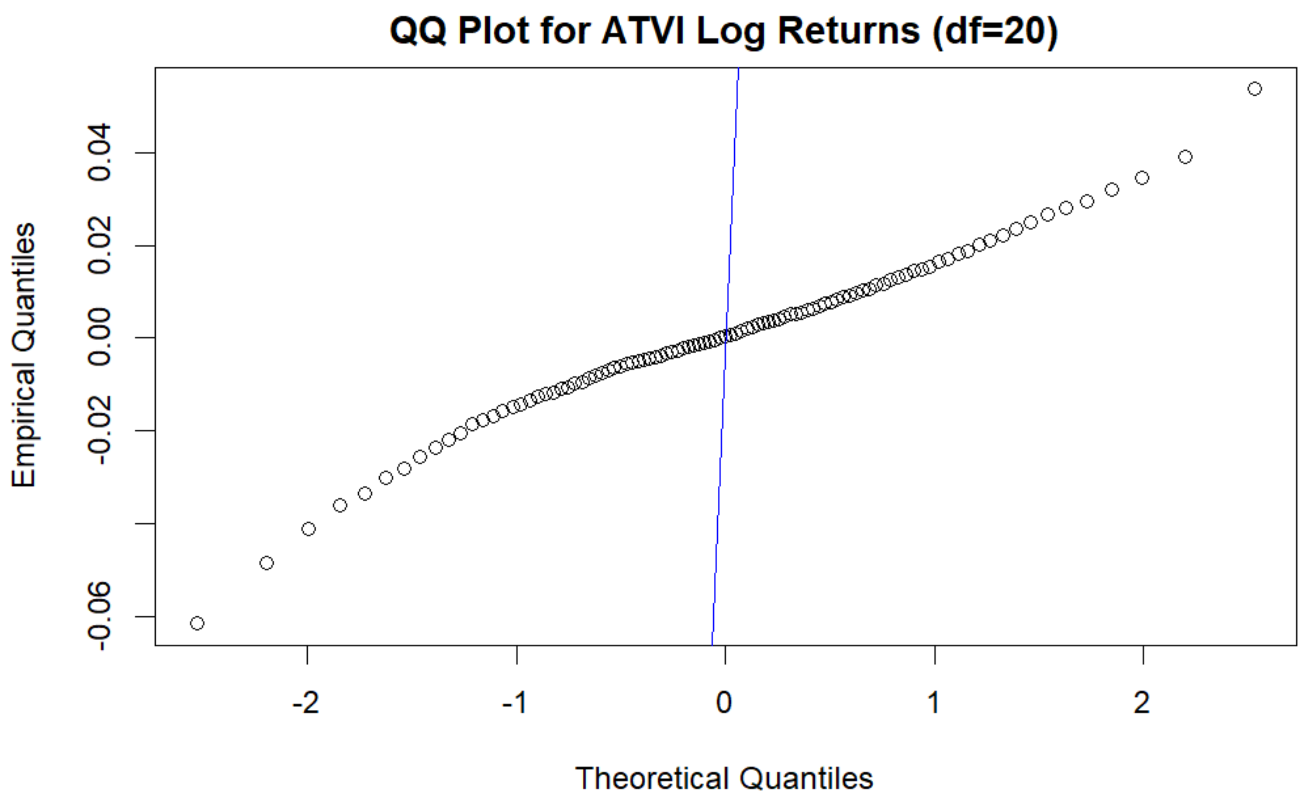
```
# Plot for ATVI_log_return
plot(theoretical_quantiles5, empirical_quantiles_ATVI,
     xlab = "Theoretical Quantiles", ylab = "Empirical Quantiles",
     main = "QQ Plot for ATVI Log Returns (df=20)")
abline(0, 1, col = "blue")
```



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```
#From the plots generated, it is possible to say that 4 degrees of freedom gives us a more li
near relationship although it doesnt really align as a straight line and as we increase the d
egrees of freedom we get more evidence. In addition, when using 4 df EA log returns are close
r to a straight line comparing to ATVI log returns.
```

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```
#5- Summarizing the two Stock (EA and ATVI)
library(e1071)
library(tseries)

# Calculate the mean and standard deviation of each series
mean1 <- mean(EA_log_return)
mean2 <- mean(ATVI_log_return)
sd1 <- sd(EA_log_return)
sd2 <- sd(ATVI_log_return)
cat("EA: Mean =", mean1, " SD =", sd1, "\n")
cat("ATVI: Mean =", mean2, " SD =", sd2, "\n")

# Calculate the skewness and kurtosis of each series
skew1 <- skewness(EA_log_return)
skew2 <- skewness(ATVI_log_return)
kurt1 <- kurtosis(EA_log_return)
kurt2 <- kurtosis(ATVI_log_return)
cat("EA: Skewness =", skew1, " Kurtosis =", kurt1, "\n")
cat("ATVI: Skewness =", skew2, " Kurtosis =", kurt2, "\n")


# Calculate the correlation between the two series
correlation <- cor(EA_log_return, ATVI_log_return)
cat("Correlation between the two series:", correlation, "\n")

# Starting at their differences:

#a)- The EA Stock log returns is different then the mean of the ATVI Stock log returns with t
he value of EA being negative and close to 0 (meaning its centred at around a small negative
value) whereas the ATVI has a positive value close to 0 which means its centred at a small po
sitive number.

#b) Looking at their standard deviation we can conclude that the ATVI's is slightly higher co
mpared to EA suggesting that the ATVI log returns are more spread out compared to EA log retu
rn, therefore could be more volatile than EA but their SD's are close to each other.

#c) Now looking at skewness and kurtosis, we could conclude that both Stocks present a high K
urtosis > 3 meaning that they have sharp peaks and heavy tails, but the ATVI is way 2 times h
igher compared to EA's, and EA has negative skewness which means the stock's returns are skew
ed towards negative values, meaning that there are more frequent small losses than large gain
s suggesting that the stock may be more volatile, whereas the ATVI's skewness is positive ind
ication that there are more frequent small gains than large losses, suggesting that the stock
may have more upside potential but in extreme events may experience large losses.

# Similarities

#d) Looking at correlation between the two series EA and ATVI being at 0.59811, it shows that
they have a moderately positive relationship with similar means therefore, it is possible to
assume that they could moving in the same direction.
```