GARCH Model GBP And USD

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Forcasting Exchange Rate Using GARCH Model for GBP And USDollar

Reading GBP and USD Currency into r

```
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
GBPUSDGARCH <-  read.csv ("GBPUSD_Candlestick_1_D_BID_01.01.2000-31.12.2020.csv")%>%
  select('GMT.TIME', CLOSE)%>%
  rename(Date = ('GMT.TIME'), RateUSD = ("CLOSE"))


tail(GBPUSDGARCH)
```

```
##            Date RateUSD
## 6394 2020-12-25 1.35408
## 6395 2020-12-27 1.35694
## 6396 2020-12-28 1.34640
## 6397 2020-12-29 1.34967
## 6398 2020-12-30 1.36286
## 6399 2020-12-31 1.36630
```

Conversion of Gmt time to date format

```r
library(dplyr)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'
```

```
## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union
```

```r
GBPUSDGARCH$Date <- lubridate::ymd(GBPUSDGARCH$Date)
head(GBPUSDGARCH)
```

```
##         Date RateUSD
## 1 2000-01-03  1.6355
## 2 2000-01-04  1.6357
## 3 2000-01-05  1.6423
## 4 2000-01-06  1.6469
## 5 2000-01-07  1.6391
## 6 2000-01-10  1.6369
```

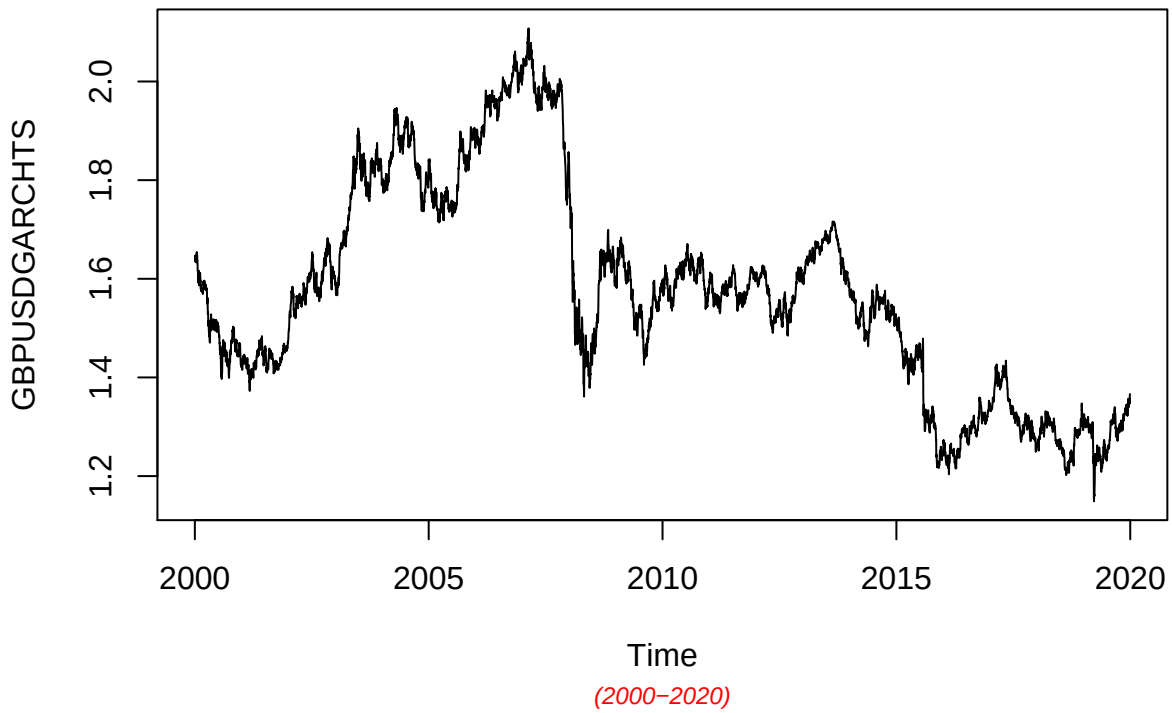
##Checking for obvious errors or missingg value

```r
#Checking for obvious errors
which(is.na(GBPUSDGARCH))
```

```
## integer(0)
```

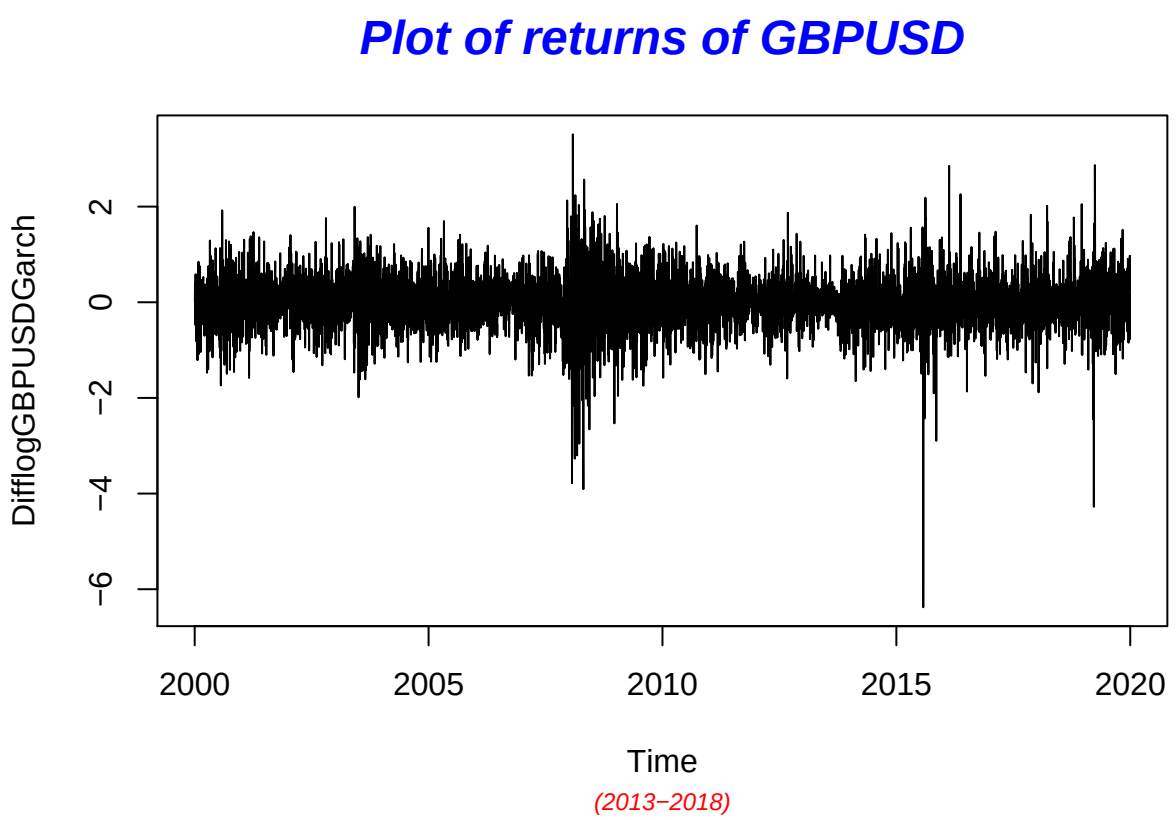
##Converting the data set into time series object

```r
#Converting the data set into time series object
GBPUSDGARCHTS<- ts(as.vector(GBPUSDGARCH$Rate),  frequency = 320, start= c(2000,01,03))
plot.ts(GBPUSDGARCHTS)
title("Time Series plot of GBPUSDTimeseries ", sub = "(2000-2020)",
      cex.main = 1.5,   font.main= 4, col.main= "blue",
      cex.sub = 0.75, font.sub = 3, col.sub = "red")
```



##Dealing with Conditional Heteroscedaticity:

```
DifflogGBPUSDGarch= diff(log(GBPUSDGARCHTS))*100
plot(DifflogGBPUSDGarch)
title("Plot of returns of GBPUSD", sub = "(2013-2018)",
      cex.main = 1.5,   font.main= 4, col.main= "blue",
      cex.sub = 0.75, font.sub = 3, col.sub = "red")
```



##nature as almost at all lags the p-values fall below the significance levels.

```
library(TSA)
```

```
## Warning: package 'TSA' was built under R version 4.0.5
```

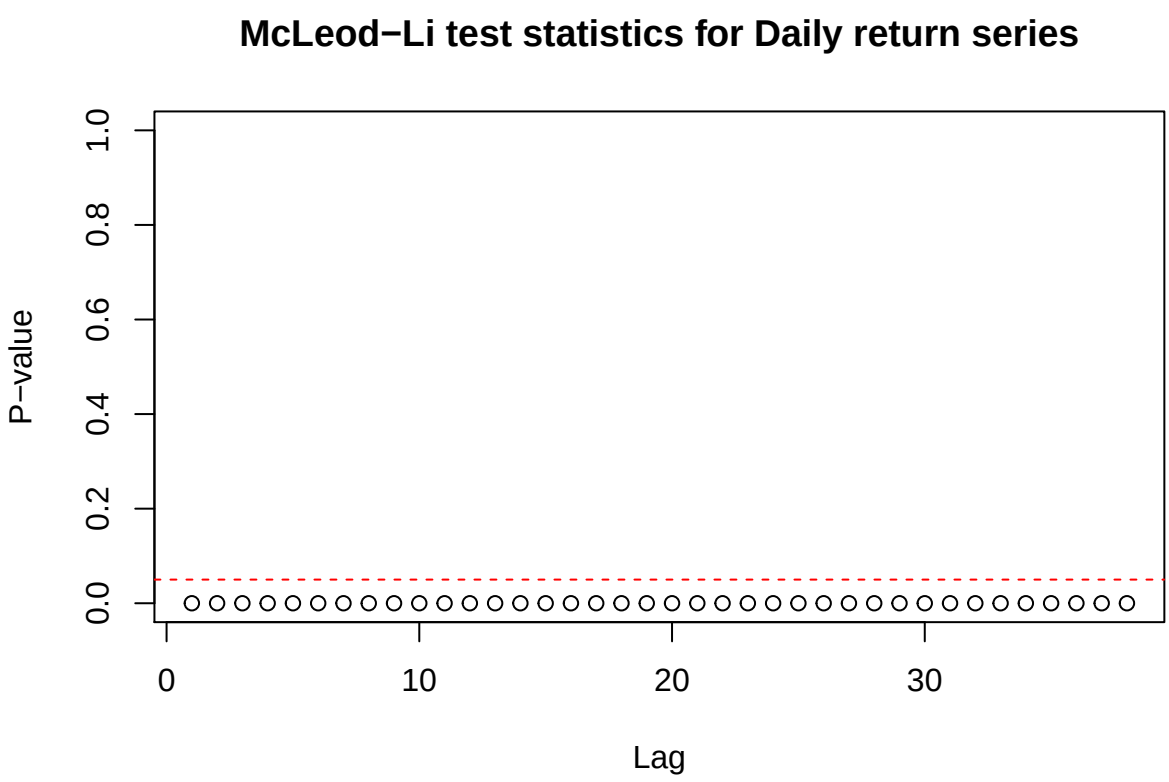
```
##
## Attaching package: 'TSA'
```

```
## The following object is masked from 'package:readr':
##
##     spec
```

```
## The following objects are masked from 'package:stats':
##
##     acf, arima
```

```
## The following object is masked from 'package:utils':
##
##     tar
```

```
McLeod.Li.test(y= DifflogGBPUSDGarch,main="McLeod-Li test statistics for Daily return series")
```

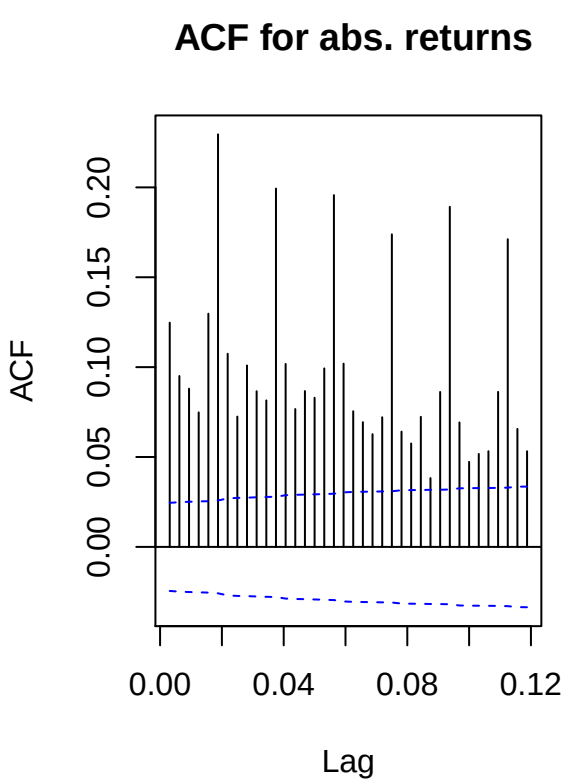


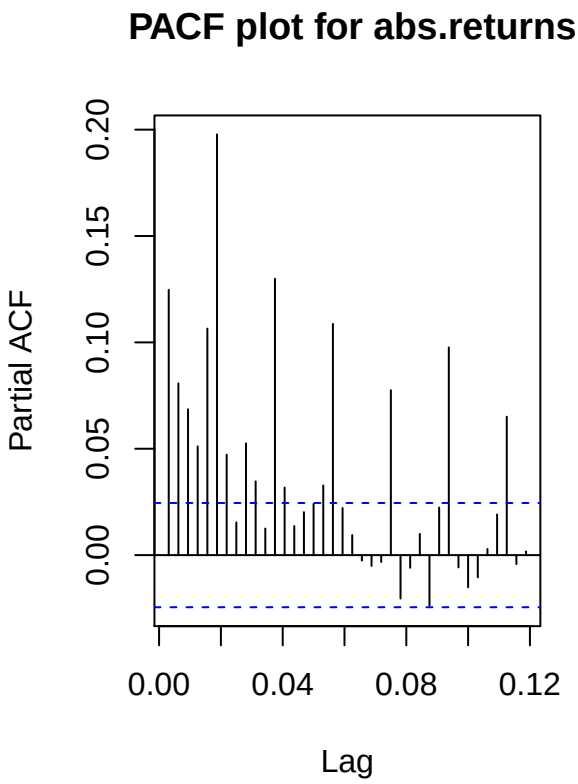
In order to get an order of GARCH , we further transform the return series into absolute values and squared return values.

```
abs = abs(DifflogGBPUSDGarch)
sqr = DifflogGBPUSDGarch^2
```

GARCH Model specification:

```
par(mfrow=c(1,2))
acf(abs, ci.type="ma",main=" ACF for abs. returns")
pacf(abs, main=" PACF plot for abs.returns")
```





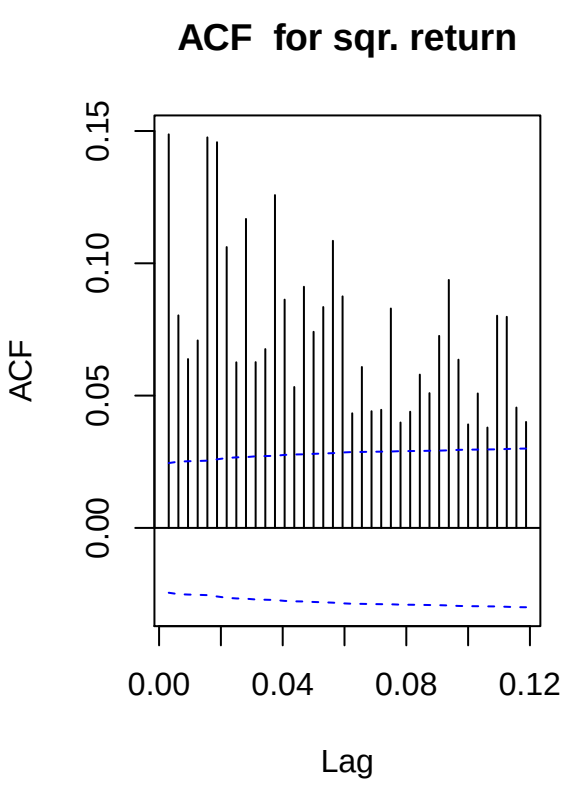
##From ACF and PACF we see many lags are significant. Hence, we plot EACF to get the candidate models

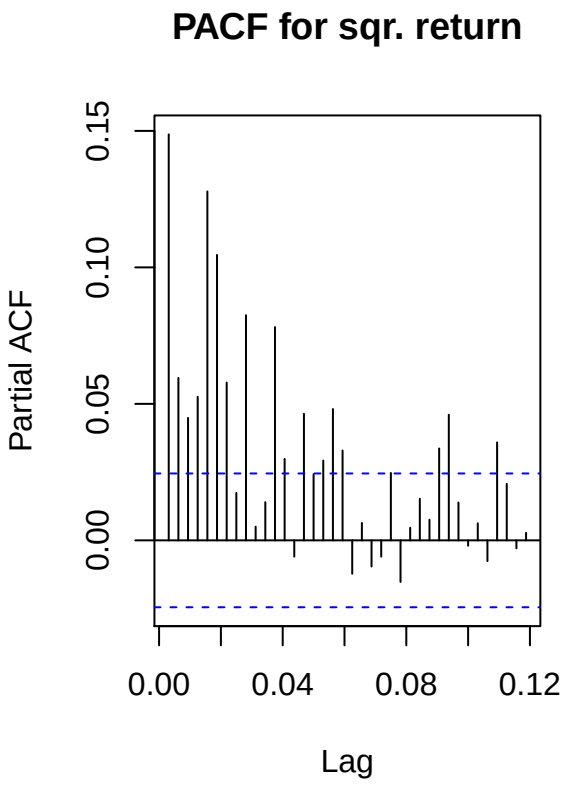
```
eacf(abs)
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 x x x x x x x x x x x  x  x  x
## 1 x o o o o x x x x o o  x  x  o
## 2 x x o o o x x x o o o  x  x  x
## 3 x x x o o x x x o o o  x  x  x
## 4 x x x x o x x o x o o  x  x  o
## 5 x x x x x x o o x o x  x  x  o
## 6 x o x x o x o o o o x  o  o  o
## 7 x o x o o x x o o o x  o  o  o
```

##From the squared returns ACF and PACF plot, it is not that clear to derive the order of p and q. Hence, I approach EACF and the order of ARMA are ARMA (2,3), ARMA (3,3), ARMA (2,4). Thus, GARCH candidate models would be GARCH (3,2) GARCH (3,3) GARCH (4,2)

```
par(mfrow=c(1,2))
acf(sqr, ci.type="ma",main="ACF  for sqr. return")
pacf(sqr, main="PACF for sqr. return")
```






```
eacf(sqr)
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 x x x x x x x x x x x  x  x  x
## 1 x x o o x x o x x x o  x  o  x
## 2 x x o o x o o x x x o  x  o  x
## 3 x x x x x o x x o x o  o  o  x
## 4 x x x x o x x x o x o  o  o  x
## 5 x x o x o x x x o x o  o  o  x
## 6 x x o x x x o x x x x  o  o  o
## 7 x x x x x x x x x x x  x  o  o
```

With reference to the Dickey-Fuller Test, p-value is less than the 0.02 and we can reject the null hypothesis stating the non-stationarity. Hence , we can proceed further for model selection .

#MODEL ESTIMATION: ##GARCH (2,1): for GBP and CAD Curruency Pair

```
# GARCH(2,1)
library(tseries)
```

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

```
GBPUSDGARCHFit.21 = garch(DifflogGBPUSDGarch,order=c(2,1),trace =FALSE)
summary(GBPUSDGARCHFit.21)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(2, 1), trace = FALSE)
##
## Model:
## GARCH(2,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9.06476 -0.53868  0.01043  0.54353  5.31781
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 0.0030439   0.0005533    5.501 3.77e-08 ***
## a1 0.0516624   0.0048431   10.667  < 2e-16 ***
## b1 0.5928849   0.1594611    3.718 0.000201 ***
## b2 0.3454036   0.1541030    2.241 0.025001 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1698.6, df = 2, p-value < 2.2e-16
##
##
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 1.386, df = 1, p-value = 0.2391
```

GARCH (2,2):

##This model can be interpreted as an overfit model of GARCH(2,1) and p values from residual tests confirms that residuals are highly correlated. Thus this model is not consider to be a good fit.

```
GBPUSDGARCHFit.22 = garch(DifflogGBPUSDGarch, order =c(2,2),trace =FALSE)
summary(GBPUSDGARCHFit.22)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(2, 2), trace = FALSE)
##
## Model:
```

```
## GARCH(2,2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.0440 -0.5378  0.0104  0.5442  5.3663
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 3.203e-03   1.087e-03    2.948   0.0032 **
## a1 5.454e-02   6.656e-03    8.194 2.22e-16 ***
## a2 2.601e-15   2.174e-02    0.000   1.0000
## b1 4.750e-01   4.070e-01    1.167   0.2432
## b2 4.599e-01   3.874e-01    1.187   0.2353
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1695.8, df = 2, p-value < 2.2e-16
##
##
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 1.0946, df = 1, p-value = 0.2954
```

##GARCH (3,1): ##This model can be interpreted as an overfit model of GARCH(2,1) and GARCH (2,2). This model may not be consider to be a good fit.

```
GBPUSDGARCHFit.31 = garch(DifflogGBPUSDGarch,order=c(3,1),trace =FALSE)
summary(GBPUSDGARCHFit.31)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(3, 1), trace = FALSE)
##
## Model:
## GARCH(3,1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.86949 -0.53854  0.01007  0.54475  5.23982
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 3.455e-03   6.326e-04    5.461 4.74e-08 ***
## a1 5.906e-02   5.219e-03   11.315  < 2e-16 ***
## b1 6.474e-01   1.672e-01    3.872 0.000108 ***
## b2 5.946e-15   2.209e-01    0.000 1.000000
## b3 2.821e-01   1.287e-01    2.192 0.028388 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1555.3, df = 2, p-value < 2.2e-16
##
##
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 0.58236, df = 1, p-value = 0.4454
```

##GARCH (3,2): ##This model can be interpreted as an overfitting model and p values from residual tests confirms that residuals are highly correlated. Thus this model is not consider to be a good fit.

GARCH(3,2)

```
GBPUSDGARCHFit.32 = garch(DifflogGBPUSDGarch,order=c(3,2),trace =FALSE)
summary(GBPUSDGARCHFit.32)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(3, 2), trace = FALSE)
##
## Model:
## GARCH(3,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9.02544 -0.53882  0.01026  0.54397  5.13766
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 3.597e-03   1.170e-03    3.074  0.00211 **
## a1 4.663e-02   6.003e-03    7.767 7.99e-15 ***
## a2 2.080e-02   2.155e-02    0.965  0.33442
## b1 5.224e-01   4.018e-01    1.300  0.19360
## b2 2.745e-16   3.317e-01    0.000  1.00000
## b3 3.985e-01   1.621e-01    2.459  0.01392 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1637.8, df = 2, p-value < 2.2e-16
##
##
```

```
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 2.1623, df = 1, p-value = 0.1414
```

GARCH (3,3):

This model can be interpreted as an overfitting model and p values from residual tests confirms that residuals are highly correlated. Thus, this model is not consider to be a good fit.

GARCH(3,3)

```
GBPUSDGARCHFit.33 = garch(DifflogGBPUSDGarch,order=c(3,3),trace =FALSE)
summary(GBPUSDGARCHFit.33)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(3, 3), trace = FALSE)
##
## Model:
## GARCH(3,3)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -9.03788 -0.53928  0.01022  0.54504  5.20437
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 4.872e-03   1.494e-03    3.261  0.00111 **
## a1 5.101e-02   6.586e-03    7.745 9.55e-15 ***
## a2 2.932e-02   2.103e-02    1.394  0.16332
## a3 2.068e-16   2.099e-02    0.000  1.00000
## b1 2.026e-01   3.705e-01    0.547  0.58448
## b2 2.815e-01   4.707e-01    0.598  0.54976
## b3 4.191e-01   3.438e-01    1.219  0.22279
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1637, df = 2, p-value < 2.2e-16
##
##
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 1.4135, df = 1, p-value = 0.2345
```

##GARCH (4,2): ##This model can be interpreted as an overfitting model and p values from residual tests confirms that residuals are highly correlated. Thus, this model is not considered to be a good fit.

```
GBPUSDGARCHFit.42 = garch(DifflogGBPUSDGarch,order=c(4,2),trace =FALSE)
summary(GBPUSDGARCHFit.42)
```

```
##
## Call:
## garch(x = DifflogGBPUSDGarch, order = c(4, 2), trace = FALSE)
##
## Model:
## GARCH(4,2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.68794 -0.54430  0.01023  0.54538  4.95973
##
## Coefficient(s):
##     Estimate  Std. Error  t value Pr(>|t|)
## a0 6.827e-03   1.552e-03    4.398 1.09e-05 ***
## a1 5.473e-02   6.533e-03    8.376  < 2e-16 ***
## a2 6.378e-02   1.848e-02    3.451 0.000559 ***
## b1 1.741e-01   2.829e-01    0.615 0.538365
## b2 6.675e-16   2.816e-01    0.000 1.000000
## b3 1.937e-01   2.495e-01    0.776 0.437611
## b4 4.916e-01   2.255e-01    2.180 0.029264 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Diagnostic Tests:
##  Jarque Bera Test
##
## data:  Residuals
## X-squared = 1456.5, df = 2, p-value < 2.2e-16
##
##
##  Box-Ljung test
##
## data:  Squared.Residuals
## X-squared = 1.2584, df = 1, p-value = 0.2619
```

Model Selection:

##Best possible model is selected by AIC scores of the models. From the below sort function, GARCH(3,1) would be the best model for the return series. From the p-value, 3.1 also has the lowest correlation

```
library(dLagM)
```

```
## Warning: package 'dLagM' was built under R version 4.0.5
```

```
## Loading required package: nardl
```

```
## Warning: package 'nardl' was built under R version 4.0.5
```

```
## Loading required package: dynlm
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
GARCHModelSelectionGBPUSD = AIC(GBPUSDGARCHFit.21,GBPUSDGARCHFit.22 ,GBPUSDGARCHFit.31,GBPUSDGARCHFit.3
sortScore(GARCHModelSelectionGBPUSD, score ="aic")
```

```
##                    df      AIC
## GBPUSDGARCHFit.42   7 9353.608
## GBPUSDGARCHFit.31   5 9370.845
## GBPUSDGARCHFit.32   6 9373.686
## GBPUSDGARCHFit.21   4 9376.383
## GBPUSDGARCHFit.22   5 9378.868
## GBPUSDGARCHFit.33   7 9380.119
```

Model Fitting:

```
library(rugarch)
```

```
## Warning: package 'rugarch' was built under R version 4.0.5
```

```
## Loading required package: parallel
```

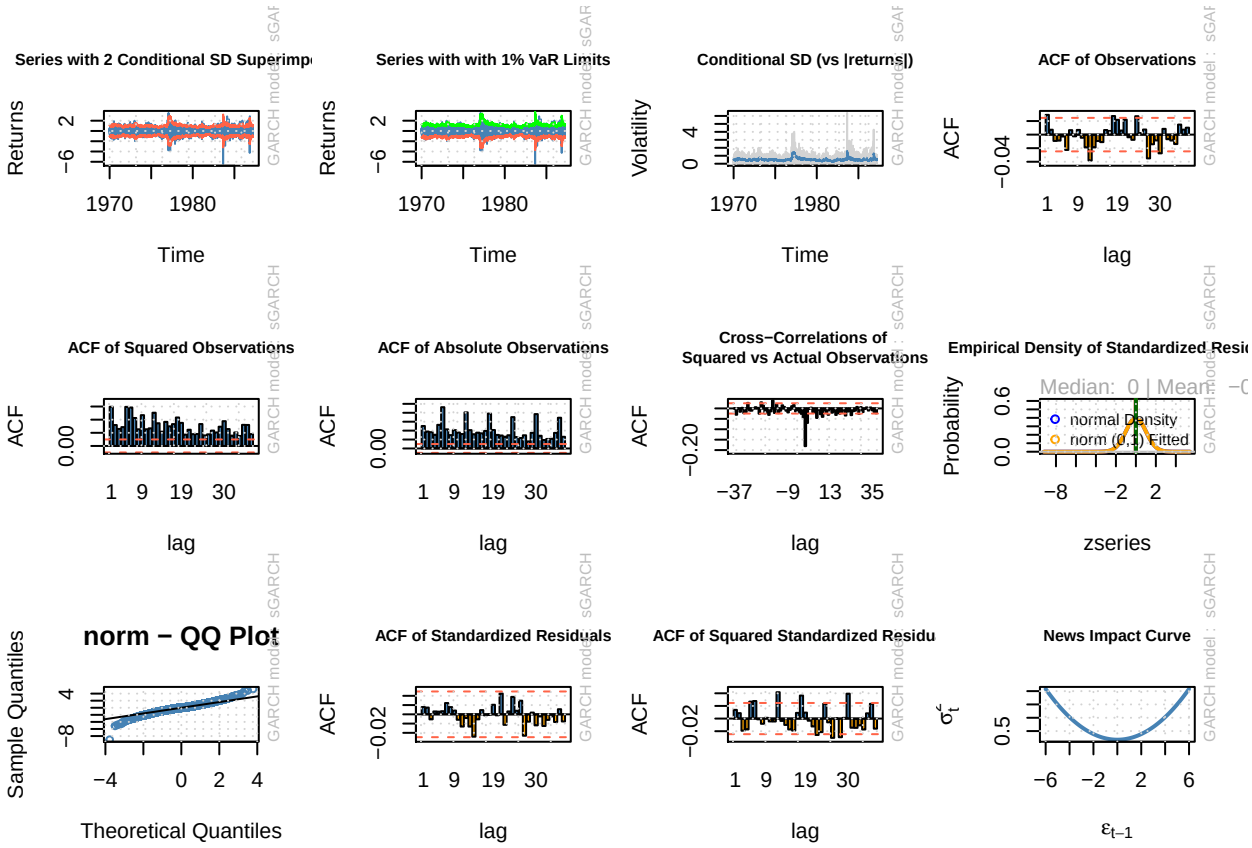
```
##
## Attaching package: 'rugarch'
```

```
## The following object is masked from 'package:stats':
##
##     sigma
```

```
GBPUSDmodel2.2<-ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(2,2)),
                  mean.model = list(armaOrder = c(1, 1), include.mean = TRUE),
                  distribution.model = "norm")

GBPUSDgarchMODEL2.2<-ugarchfit(spec=GBPUSDmodel2.2,data=DifflogGBPUSDGarch, out.sample = 100)
plot(GBPUSDgarchMODEL2.2,which="all")
```

```
##
## please wait...calculating quantiles...
```



##Model Diagnostics

```
GBPUSDgarchMODEL2.2
```

```
##
## *----------------------------------*
## *          GARCH Model Fit         *
## *----------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(2,2)
## Mean Model   : ARFIMA(1,0,1)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error     t value Pr(>|t|)
## mu      0.003026    0.005940  5.0935e-01 0.610507
## ar1    -0.992999    0.001312 -7.5704e+02 0.000000
## ma1     0.994154    0.000019  5.3306e+04 0.000000
## omega   0.003115    0.000486  6.4099e+00 0.000000
## alpha1  0.052932    0.010662  4.9646e+00 0.000001
## alpha2  0.000000    0.010585  6.0000e-06 0.999995
## beta1   0.573113    0.006219  9.2154e+01 0.000000
## beta2   0.363649    0.005887  6.1776e+01 0.000000
```

```
##
## Robust Standard Errors:
##         Estimate  Std. Error     t value Pr(>|t|)
## mu      0.003026    0.006084  4.9731e-01 0.618970
## ar1    -0.992999    0.002223 -4.4660e+02 0.000000
## ma1     0.994154    0.000053  1.8896e+04 0.000000
## omega   0.003115    0.000997  3.1234e+00 0.001788
## alpha1  0.052932    0.022410  2.3620e+00 0.018177
## alpha2  0.000000    0.021854  3.0000e-06 0.999998
## beta1   0.573113    0.002787  2.0566e+02 0.000000
## beta2   0.363649    0.002606  1.3954e+02 0.000000
##
## LogLikelihood : -4602.548
##
## Information Criteria
## ------------------------------------
##
## Akaike       1.4641
## Bayes        1.4727
## Shibata      1.4641
## Hannan-Quinn 1.4671
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.3938  0.5303
## Lag[2*(p+q)+(p+q)-1][5]    0.8118  1.0000
## Lag[4*(p+q)+(p+q)-1][9]    1.3554  0.9984
## d.o.f=2
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                          statistic p-value
## Lag[1]                       1.201 0.27304
## Lag[2*(p+q)+(p+q)-1][11]    10.652 0.07082
## Lag[4*(p+q)+(p+q)-1][19]    19.760 0.01419
## d.o.f=4
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[5]     4.536 0.500 2.000 0.03319
## ARCH Lag[7]     8.719 1.473 1.746 0.01780
## ARCH Lag[9]     9.169 2.402 1.619 0.04010
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  1.2946
## Individual Statistics:
## mu     0.15267
## ar1    0.10468
## ma1    0.09414
## omega  0.12383
```

```
## alpha1 0.05793
## alpha2 0.05245
## beta1  0.04682
## beta2  0.04647
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.89 2.11 2.59
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## -----------------------------------
##                    t-value    prob sig
## Sign Bias          0.02222 0.98227
## Negative Sign Bias 2.25557 0.02413  **
## Positive Sign Bias 0.74841 0.45424
## Joint Effect       9.77524 0.02058  **
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     377.1    2.521e-68
## 2    30     410.6    5.382e-69
## 3    40     430.1    2.211e-67
## 4    50     455.8    2.410e-67
##
##
## Elapsed time : 0.9078691
```

Forecasting

```
forcgarchGBPUSD= ugarchforecast(GBPUSDgarchMODEL2.2, data = DiffGBPUSDLogTran, n.ahead = 100, n.roll =1
print(forcgarchGBPUSD)
```

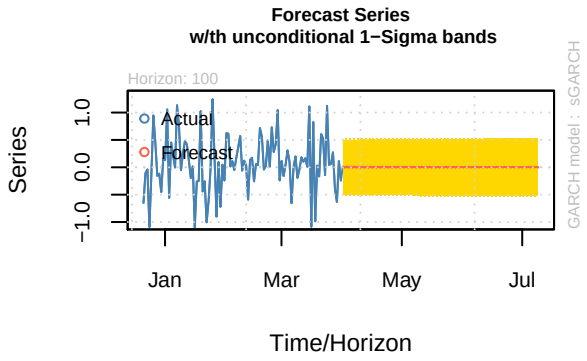
```
##
## *----------------------------------*
## *       GARCH Model Forecast       *
## *----------------------------------*
## Model: sGARCH
## Horizon: 100
## Roll Steps: 10
## Out of Sample: 100
##
## 0-roll forecast [T0=1987-03-31 03:00:00]:
##          Series  Sigma
## T+1    0.014516 0.5097
## T+2   -0.008384 0.5118
## T+3    0.014355 0.5114
## T+4   -0.008225 0.5119
## T+5    0.014197 0.5122
## T+6   -0.008068 0.5125
## T+7    0.014042 0.5128
```

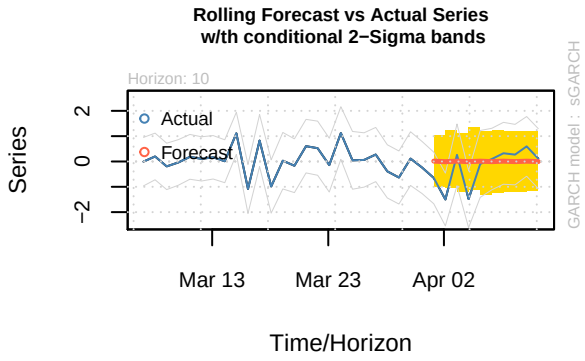
```
## T+8   -0.007913 0.5131
## T+9    0.013888 0.5133
## T+10  -0.007760 0.5136
## T+11   0.013736 0.5139
## T+12  -0.007610 0.5142
## T+13   0.013587 0.5145
## T+14  -0.007462 0.5147
## T+15   0.013439 0.5150
## T+16  -0.007315 0.5153
## T+17   0.013294 0.5156
## T+18  -0.007171 0.5158
## T+19   0.013151 0.5161
## T+20  -0.007029 0.5163
## T+21   0.013010 0.5166
## T+22  -0.006888 0.5169
## T+23   0.012870 0.5171
## T+24  -0.006750 0.5174
## T+25   0.012733 0.5176
## T+26  -0.006614 0.5179
## T+27   0.012598 0.5181
## T+28  -0.006479 0.5184
## T+29   0.012464 0.5186
## T+30  -0.006347 0.5189
## T+31   0.012332 0.5191
## T+32  -0.006216 0.5193
## T+33   0.012203 0.5196
## T+34  -0.006087 0.5198
## T+35   0.012074 0.5200
## T+36  -0.005960 0.5203
## T+37   0.011948 0.5205
## T+38  -0.005834 0.5207
## T+39   0.011824 0.5209
## T+40  -0.005711 0.5212
## T+41   0.011701 0.5214
## T+42  -0.005589 0.5216
## T+43   0.011580 0.5218
## T+44  -0.005469 0.5220
## T+45   0.011461 0.5223
## T+46  -0.005350 0.5225
## T+47   0.011343 0.5227
## T+48  -0.005233 0.5229
## T+49   0.011227 0.5231
## T+50  -0.005118 0.5233
## T+51   0.011112 0.5235
## T+52  -0.005005 0.5237
## T+53   0.011000 0.5239
## T+54  -0.004892 0.5241
## T+55   0.010888 0.5243
## T+56  -0.004782 0.5245
## T+57   0.010779 0.5247
## T+58  -0.004673 0.5249
## T+59   0.010670 0.5251
## T+60  -0.004566 0.5253
## T+61   0.010564 0.5255
```

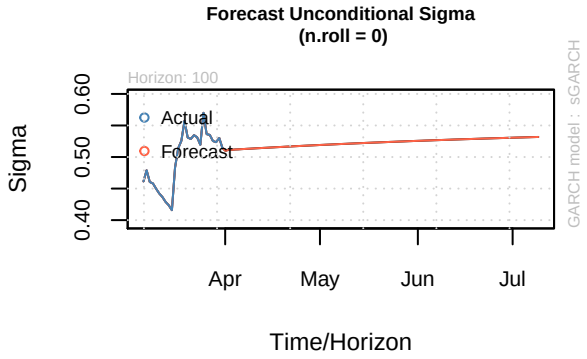
```
## T+62  -0.004460 0.5257
## T+63   0.010459 0.5258
## T+64  -0.004355 0.5260
## T+65   0.010355 0.5262
## T+66  -0.004252 0.5264
## T+67   0.010253 0.5266
## T+68  -0.004151 0.5268
## T+69   0.010152 0.5269
## T+70  -0.004051 0.5271
## T+71   0.010052 0.5273
## T+72  -0.003952 0.5275
## T+73   0.009954 0.5276
## T+74  -0.003855 0.5278
## T+75   0.009858 0.5280
## T+76  -0.003759 0.5281
## T+77   0.009762 0.5283
## T+78  -0.003664 0.5285
## T+79   0.009668 0.5286
## T+80  -0.003571 0.5288
## T+81   0.009576 0.5290
## T+82  -0.003479 0.5291
## T+83   0.009484 0.5293
## T+84  -0.003388 0.5294
## T+85   0.009394 0.5296
## T+86  -0.003298 0.5297
## T+87   0.009305 0.5299
## T+88  -0.003210 0.5301
## T+89   0.009218 0.5302
## T+90  -0.003123 0.5304
## T+91   0.009131 0.5305
## T+92  -0.003037 0.5307
## T+93   0.009046 0.5308
## T+94  -0.002953 0.5309
## T+95   0.008962 0.5311
## T+96  -0.002869 0.5312
## T+97   0.008879 0.5314
## T+98  -0.002787 0.5315
## T+99   0.008798 0.5317
## T+100 -0.002706 0.5318
```

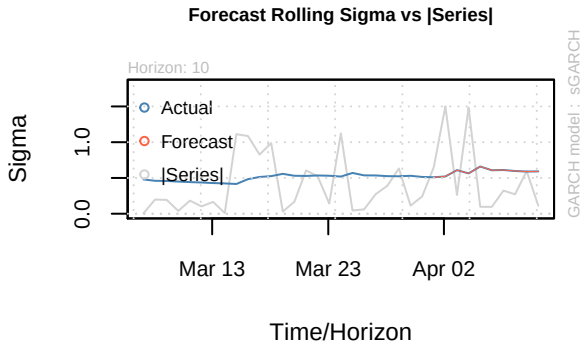
plotting

```
plot(forcgarchGBPUSD, which= "all")
```









Forecasting the rate

```
p.t_1 =1.36630
  R_t <- c( 0.014516, -0.008384, 0.014355, -0.008225, 0.014197, -0.008068, 0.014042, -0.007913, 0.013888
-0.006888, 0.012870, -0.006750, 0.012733, -0.006614, 0.012598, -0.006479, 0.012464, -0.006347, 0.012332
0.012203, -0.006087, 0.012074, -0.005960, 0.011948, -0.005834, 0.011824, -0.005711, 0.011701, -0.005589
0.010888,  -0.004782, 0.010779, -0.004673, 0.010670, -0.004566, 0.010564, -0.004460, 0.010459, -0.00435
0.009762, -0.003664, 0.009668, -0.003571, 0.009576, -0.003479, 0.009484, -0.003388, 0.009394, -0.003298
)
  p_t= 0
  for (i in 1:100){
    p_t =  p.t_1  *((2.71828)^(R_t[i]/100))
   print(p_t)
    p.t_1=p_t
  }
```

```
## [1] 1.366498
## [1] 1.366384
## [1] 1.36658
## [1] 1.366468
## [1] 1.366662
## [1] 1.366551
## [1] 1.366743
## [1] 1.366635
## [1] 1.366825
## [1] 1.366719
## [1] 1.366907
## [1] 1.366803
## [1] 1.366988
## [1] 1.366886
## [1] 1.36707
## [1] 1.36697
## [1] 1.367152
## [1] 1.367054
## [1] 1.367233
## [1] 1.367137
## [1] 1.367315
## [1] 1.367221
## [1] 1.367397
## [1] 1.367305
## [1] 1.367479
## [1] 1.367388
## [1] 1.367561
## [1] 1.367472
## [1] 1.367643
## [1] 1.367556
## [1] 1.367724
## [1] 1.367639
## [1] 1.367806
## [1] 1.367723
## [1] 1.367888
## [1] 1.367807
## [1] 1.36797
## [1] 1.36789
## [1] 1.368052
## [1] 1.367974
## [1] 1.368134
## [1] 1.368058
## [1] 1.368216
## [1] 1.368141
## [1] 1.368298
## [1] 1.368225
## [1] 1.36838
## [1] 1.368308
## [1] 1.368462
## [1] 1.368392
## [1] 1.368544
## [1] 1.368475
## [1] 1.368626
## [1] 1.368559
```

```
## [1] 1.368708
## [1] 1.368643
## [1] 1.36879
## [1] 1.368726
## [1] 1.368872
## [1] 1.36881
## [1] 1.368954
## [1] 1.368893
## [1] 1.369036
## [1] 1.368977
## [1] 1.369119
## [1] 1.36906
## [1] 1.369201
## [1] 1.369144
## [1] 1.369283
## [1] 1.369228
## [1] 1.369365
## [1] 1.369311
## [1] 1.369447
## [1] 1.369395
## [1] 1.36953
## [1] 1.369478
## [1] 1.369612
## [1] 1.369562
## [1] 1.369694
## [1] 1.369645
## [1] 1.369776
## [1] 1.369729
## [1] 1.369859
## [1] 1.369812
## [1] 1.369941
## [1] 1.369896
## [1] 1.370023
## [1] 1.369979
## [1] 1.370105
## [1] 1.370063
## [1] 1.370188
## [1] 1.370146
## [1] 1.37027
## [1] 1.37023
## [1] 1.370352
## [1] 1.370313
## [1] 1.370435
## [1] 1.370397
## [1] 1.370517
## [1] 1.37048
```

```
RateGBPJPYGarch = 141.168
  RGBPJPYGARCH <-c(0.007108, 0.008990, 0.009627, 0.009843, 0.009916, 0.009940, 0.009949, 0.009951, 0.009

)
  GBPJPYgarch= 0
  for (i in 1:100){
    USCanadagarch =  RateGBPJPYGarch *((2.71828)^(RGBPJPYGARCH[i]/100))
```

```
    print(GBPJPYgarch)
    RateUSGBPJPY=GBPJPYgarch
  }
```

```
## [1] 0
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```