Assignment3

Kareem Alameen - 0831119

```r
library(quantmod)
library(rugarch)
library(rmgarch)
library(fGarch)
```

```r
date_from = as.Date("2009-07-18")
date_to = as.Date("2024-08-09")
```

```r
getSymbols('JNJ', from = date_from, to = date_to)
```

```
[1] "JNJ"
```

```r
getSymbols('KO', from = date_from, to = date_to)
```

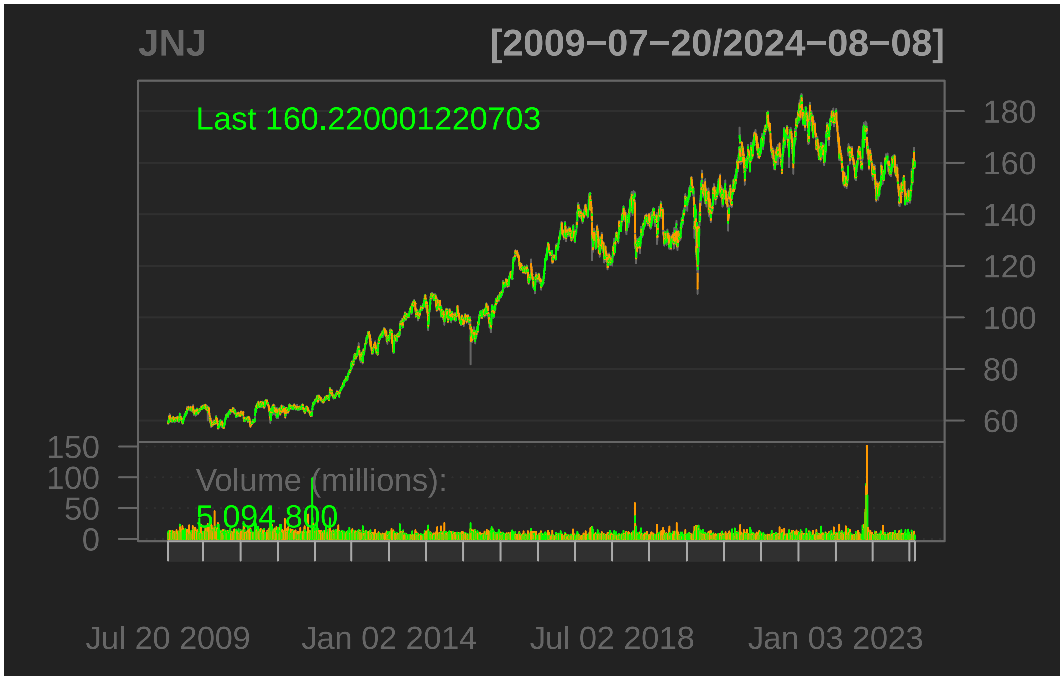
```
[1] "KO"
```

```r
getSymbols('GE', from = date_from, to = date_to)
```

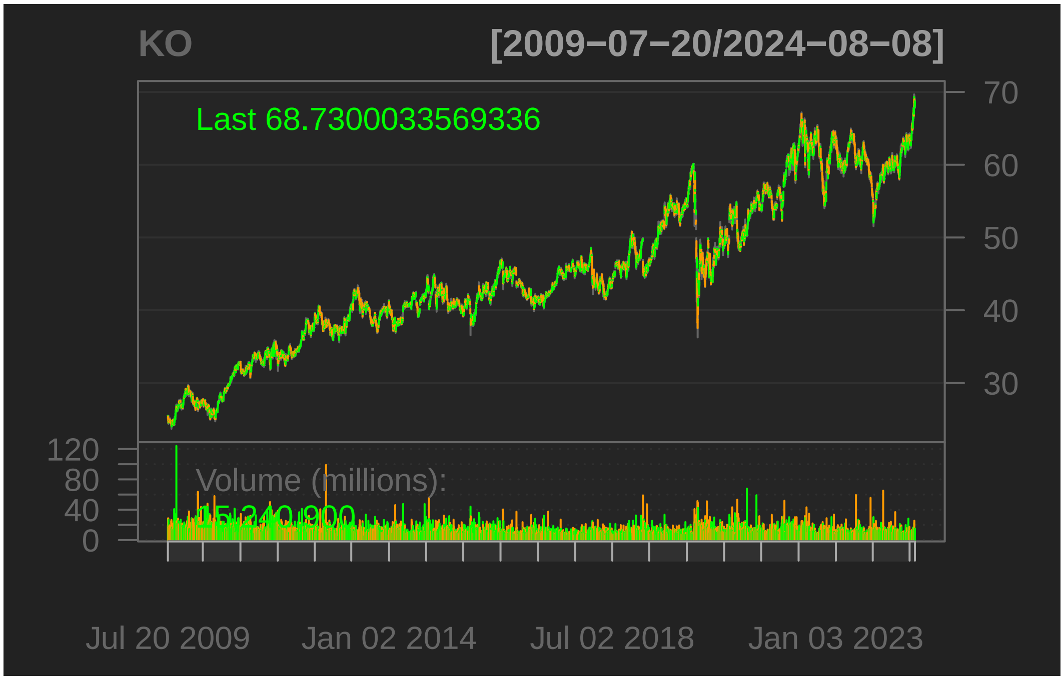
```
[1] "GE"
```

2)

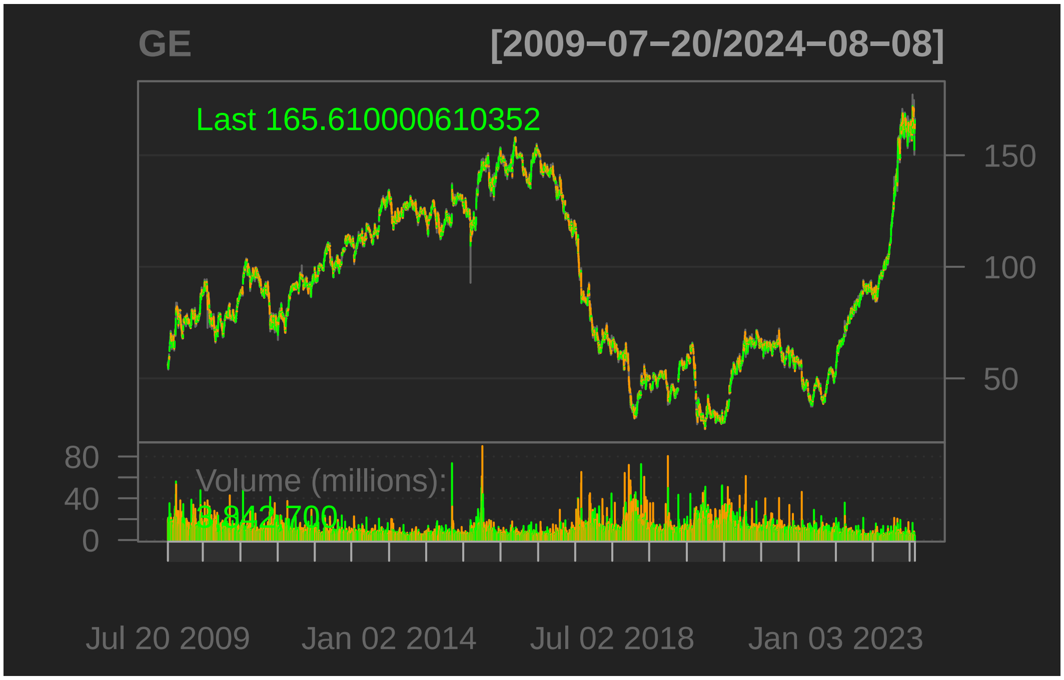
```r
chartSeries(JNJ)
```




```r
chartSeries(KO)
```



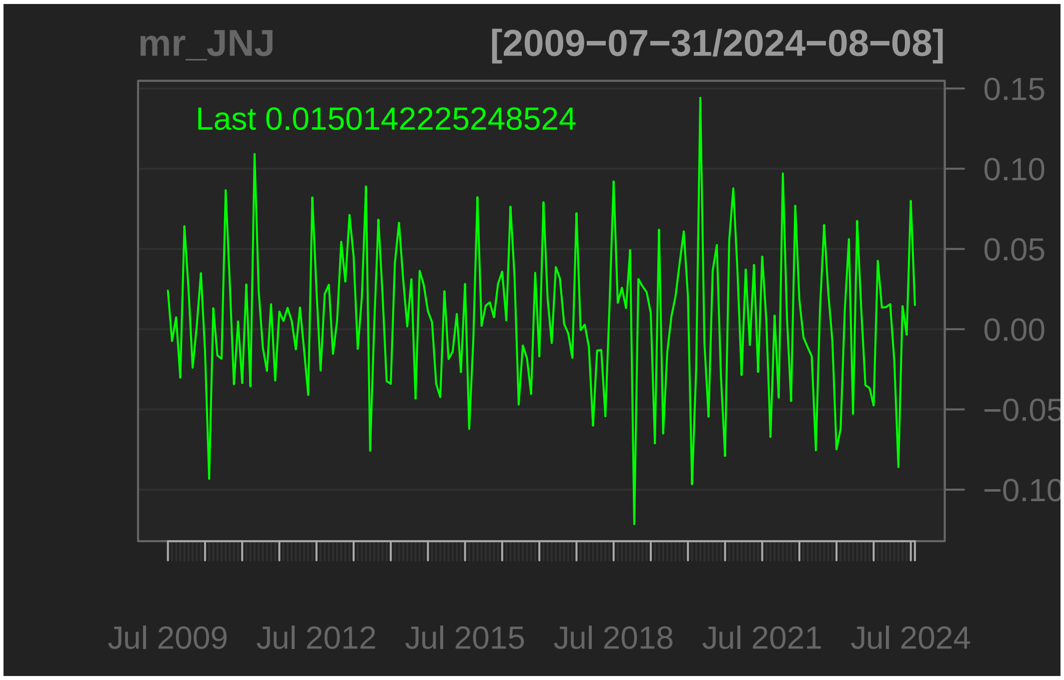
```r
chartSeries(GE)
```



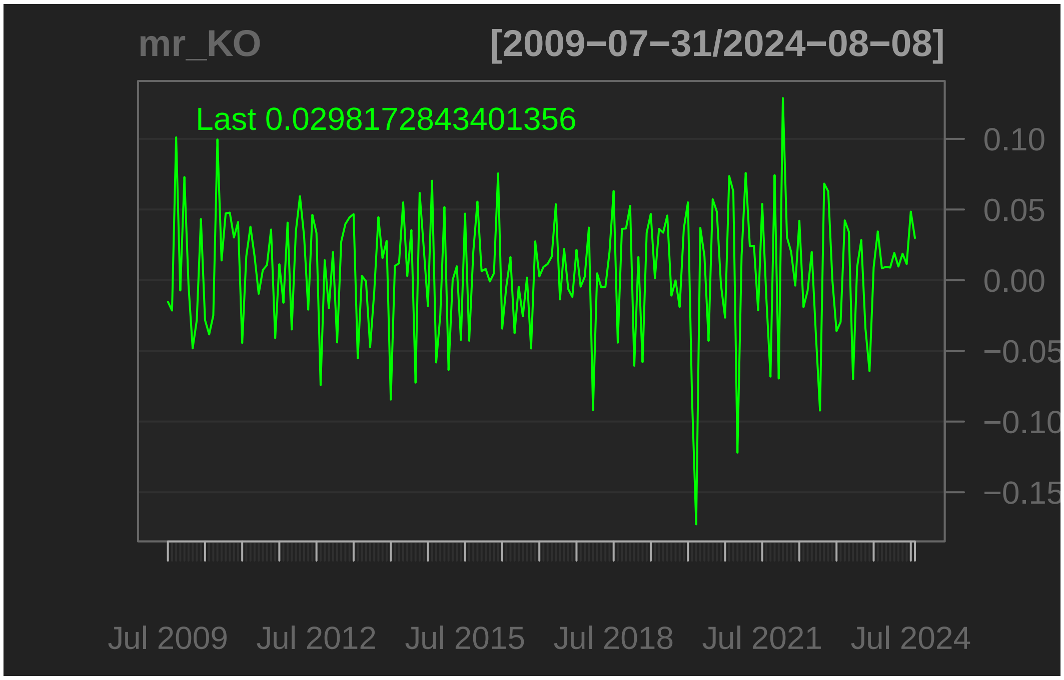
On a strictly visual basis the 3 series appears to be non-stationary in mean and variance. Though stationarity can be observed in certain time periods but overall the time series is non-stationary. i.e the stock's value is trending upward over time and is highly volatile.

```r
mr_JNJ <- monthlyReturn(JNJ)
mr_KO <- monthlyReturn(KO)
mr_GE <- monthlyReturn(GE)
```

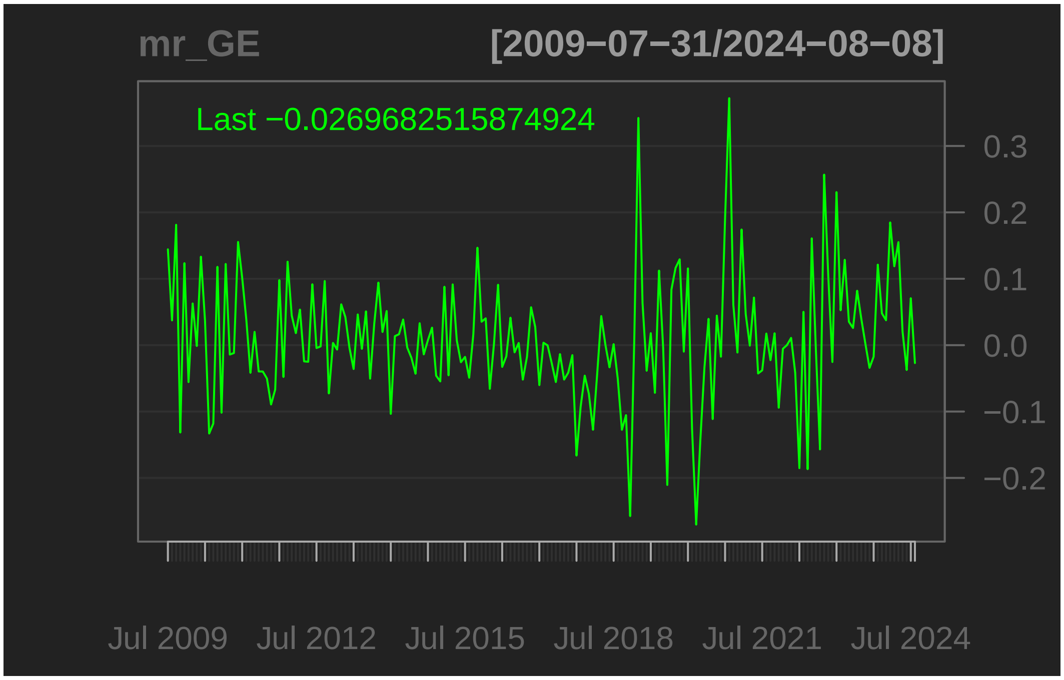
```r
chartSeries(mr_JNJ)
```




```
chartSeries(mr_KO)
```



```r
chartSeries(mr_GE)
```




```r
dataA3 <- merge(mr_JNJ, mr_KO, mr_GE)
names(dataA3)[1] <- "mr_JNJ"
names(dataA3)[2] <- "mr_KO"
names(dataA3)[3] <- "mr_GE"
```

On a strictly visual basis the chart for monthly returns for Johnson & Johnson, Coca-Cola, and General Electric appear to be stationary in mean i.e The plot of the time series hovers around a horizontal line (representing the mean) without drifting upward or downward, but non stationary in variance i.e The series shows periods of increasing or decreasing variability. Non stationary in variance meaning the degree of variation in the data points changes over time and stationary in mean meaning central tendency of the series remains constant throughout the period or central tendency of the series remains constant throughout the period.

3)

```r
mean(mr_JNJ)
```

```
[1] 0.00638668
```

```r
mean(mr_KO)
```

```
[1] 0.00645409
```

```r
mean(mr_GE)
```

```
[1] 0.01014723
```

```r
uspec = ugarchspec(mean.model = list(armaOrder = c(0,0)), variance.model = list(garchOrder =
spec1 = dccspec(uspec = multispec( replicate(3, uspec) ),  dccOrder = c(1,1),  distribution =
fit1 = dccfit(spec1, data = dataA3, fit.control = list(eval.se=T))
fit1
```

```
*---------------------------------*
*          DCC GARCH Fit          *
*---------------------------------*

Distribution          :  mvnorm
Model                 :  DCC(1,1)
No. Parameters        :  17
[VAR GARCH DCC UncQ] : [0+12+2+3]
No. Series            :  3
No. Obs.              :  182
Log-Likelihood        :  857.5466
Av.Log-Likelihood     :  4.71

Optimal Parameters
-----------------------------------
                 Estimate  Std. Error    t value Pr(>|t|)
[mr_JNJ].mu      0.006457    0.002928   2.205656 0.027408
[mr_JNJ].omega   0.000004    0.000007   0.495927 0.619946
[mr_JNJ].alpha1  0.000000    0.002777   0.000011 0.999991
[mr_JNJ].beta1   0.999000    0.002019 494.715248 0.000000
[mr_KO].mu       0.005615    0.003228   1.739480 0.081950
[mr_KO].omega    0.000177    0.000409   0.433385 0.664735
[mr_KO].alpha1   0.067802    0.165060   0.410774 0.681239
[mr_KO].beta1    0.835682    0.356229   2.345910 0.018981
```

```
[mr_GE].mu       0.009909    0.005533   1.790955 0.073301
[mr_GE].omega    0.000212    0.000265   0.800164 0.423616
[mr_GE].alpha1   0.125910    0.084634   1.487698 0.136830
[mr_GE].beta1    0.853308    0.096531   8.839711 0.000000
[Joint]dcca1     0.007655    0.017994   0.425450 0.670508
[Joint]dccb1     0.948030    0.037635  25.190380 0.000000

Information Criteria
---------------------

Akaike       -9.2368
Bayes        -8.9375
Shibata      -9.2523
Hannan-Quinn -9.1155


Elapsed time : 2.660005
```

```
uspec = ugarchspec(mean.model = list(armaOrder = c(0,0)), variance.model = list(garchOrder =
spec1 = dccspec(uspec = multispec( replicate(3, uspec) ),  dccOrder = c(1,2),  distribution =
fit1 = dccfit(spec1, data = dataA3, fit.control = list(eval.se=T))
fit1
```

```
*---------------------------------*
*          DCC GARCH Fit          *
*---------------------------------*

Distribution         :  mvnorm
Model                :  DCC(1,2)
No. Parameters       :  21
[VAR GARCH DCC UncQ] : [0+15+3+3]
No. Series           :  3
No. Obs.             :  182
Log-Likelihood       :  859.5356
Av.Log-Likelihood    :  4.72

Optimal Parameters
-----------------------------------
                 Estimate  Std. Error   t value Pr(>|t|)
[mr_JNJ].mu      0.006461    0.002991   2.159880 0.030782
[mr_JNJ].omega   0.000005    0.000037   0.140670 0.888131
```

```
[mr_JNJ].alpha1  0.000000    0.096201   0.000000 1.000000
[mr_JNJ].beta1   0.038117    0.101788   0.374479 0.708048
[mr_JNJ].beta2   0.960883    0.006181 155.445397 0.000000
[mr_KO].mu       0.006115    0.002982   2.050520 0.040314
[mr_KO].omega    0.001183    0.000474   2.497843 0.012495
[mr_KO].alpha1   0.314385    0.242974   1.293906 0.195698
[mr_KO].beta1    0.089884    0.244508   0.367611 0.713163
[mr_KO].beta2    0.000000    0.072369   0.000000 1.000000
[mr_GE].mu       0.010048    0.005568   1.804621 0.071134
[mr_GE].omega    0.000208    0.000251   0.828328 0.407485
[mr_GE].alpha1   0.124255    0.081547   1.523722 0.127578
[mr_GE].beta1    0.844924    0.213916   3.949797 0.000078
[mr_GE].beta2    0.010373    0.177523   0.058432 0.953405
[Joint]dcca1     0.012654    0.025682   0.492720 0.622210
[Joint]dccb1     0.380498    0.260907   1.458365 0.144740
[Joint]dccb2     0.545482    0.240088   2.272010 0.023086

Information Criteria
---------------------

Akaike       -9.2147
Bayes        -8.8450
Shibata      -9.2378
Hannan-Quinn -9.0648


Elapsed time : 4.209632
```

```r
uspec = ugarchspec(mean.model = list(armaOrder = c(0,0)), variance.model = list(garchOrder =
spec1 = dccspec(uspec = multispec( replicate(3, uspec) ),  dccOrder = c(2,1),  distribution =
fit1 = dccfit(spec1, data = dataA3, fit.control = list(eval.se=T))
fit1
```

```
*---------------------------------*
*          DCC GARCH Fit          *
*---------------------------------*

Distribution         :  mvnorm
Model                :  DCC(2,1)
No. Parameters       :  21
[VAR GARCH DCC UncQ] : [0+15+3+3]
```

```
No. Series          :  3
No. Obs.            :  182
Log-Likelihood      :  859.4463
Av.Log-Likelihood   :  4.72

Optimal Parameters
-----------------------------------
                  Estimate  Std. Error    t value Pr(>|t|)
[mr_JNJ].mu       0.006458    0.002928   2.206011 0.027383
[mr_JNJ].omega    0.000004    0.000005   0.776346 0.437545
[mr_JNJ].alpha1   0.000000    0.079121   0.000000 1.000000
[mr_JNJ].alpha2   0.000000    0.077731   0.000001 0.999999
[mr_JNJ].beta1    0.999000    0.001611 620.082875 0.000000
[mr_KO].mu        0.006115    0.002897   2.110868 0.034784
[mr_KO].omega     0.001183    0.002253   0.525308 0.599369
[mr_KO].alpha1    0.314385    0.238551   1.317891 0.187540
[mr_KO].alpha2    0.000000    0.591603   0.000000 1.000000
[mr_KO].beta1     0.089883    1.630981   0.055110 0.956051
[mr_GE].mu        0.010002    0.005537   1.806207 0.070886
[mr_GE].omega     0.000205    0.000253   0.812768 0.416351
[mr_GE].alpha1    0.111323    0.122917   0.905671 0.365110
[mr_GE].alpha2    0.013627    0.121542   0.112116 0.910731
[mr_GE].beta1     0.855099    0.095742   8.931299 0.000000
[Joint]dcca1      0.006561    0.031438   0.208709 0.834676
[Joint]dcca2      0.000000    0.035638   0.000001 0.999999
[Joint]dccb1      0.953286    0.035900  26.554159 0.000000

Information Criteria
---------------------

Akaike       -9.2137
Bayes        -8.8440
Shibata      -9.2368
Hannan-Quinn -9.0638


Elapsed time : 4.046057
```

```
uspec = ugarchspec(mean.model = list(armaOrder = c(0,0)), variance.model = list(garchOrder =
spec1 = dccspec(uspec = multispec( replicate(3, uspec) ),  dccOrder = c(2,2),  distribution =
fit1 = dccfit(spec1, data = dataA3, fit.control = list(eval.se=T))
fit1
```

```
*---------------------------------*
*          DCC GARCH Fit          *
*---------------------------------*

Distribution         :  mvnorm
Model                :  DCC(2,2)
No. Parameters       :  25
[VAR GARCH DCC UncQ] : [0+18+4+3]
No. Series           :  3
No. Obs.             :  182
Log-Likelihood       :  860.9511
Av.Log-Likelihood    :  4.73

Optimal Parameters
-----------------------------------
                 Estimate  Std. Error   t value Pr(>|t|)
[mr_JNJ].mu      0.006524    0.003076  2.120794 0.033939
[mr_JNJ].omega   0.000063    0.000153  0.410741 0.681262
[mr_JNJ].alpha1  0.000000    0.040637  0.000000 1.000000
[mr_JNJ].alpha2  0.026433    0.037360  0.707528 0.479239
[mr_JNJ].beta1   0.000000    0.081241  0.000001 0.999999
[mr_JNJ].beta2   0.942786    0.085181 11.067992 0.000000
[mr_KO].mu       0.006115    0.002912  2.099863 0.035741
[mr_KO].omega    0.001183    0.005823  0.203247 0.838942
[mr_KO].alpha1   0.314386    0.239951  1.310209 0.190125
[mr_KO].alpha2   0.000000    1.592680  0.000000 1.000000
[mr_KO].beta1    0.089874    4.680814  0.019200 0.984681
[mr_KO].beta2    0.000002    0.338386  0.000006 0.999995
[mr_GE].mu       0.009562    0.005425  1.762724 0.077947
[mr_GE].omega    0.000294    0.000340  0.862918 0.388183
[mr_GE].alpha1   0.078537    0.106399  0.738134 0.460433
[mr_GE].alpha2   0.108757    0.094316  1.153107 0.248866
[mr_GE].beta1    0.337616    0.180893  1.866392 0.061987
[mr_GE].beta2    0.447153    0.178886  2.499654 0.012431
[Joint]dcca1     0.012618    0.109217  0.115531 0.908025
[Joint]dcca2     0.000000    0.197530  0.000000 1.000000
[Joint]dccb1     0.376998    4.132249  0.091233 0.927307
[Joint]dccb2     0.546562    3.959180  0.138049 0.890201

Information Criteria
---------------------
```

```
Akaike       -9.1863
Bayes        -8.7462
Shibata      -9.2183
Hannan-Quinn -9.0079


Elapsed time : 4.813902
```

INTERPRETATIONS

A higher log-likelihood value indicates a better fit to the data. Among the models, the specification GARCH(2,2) and DCC(2,2) has the highest log-likelihood value (856.7095), suggesting a better fit compared to the others, followed by GARCH(1,2) and DCC(1,2) with a log-likelihood value of (855.0154), suggesting a better fit compared to the other 2 models. Followed by GARCH(2,1) and DCC(2,1)with a log-likelihood value (854.9192) which is higher than, GARCH(1,1) and DCC(1,1) with a log-likelihood value (851.8387).

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to compare models. Lower values indicate a better model fit. The model with GARCH(1,1) and DCC(1,1) has the lowest AIC (-9.22) and BIC (-8.92) values, The model with GARCH(1,2) and DCC(1,2) has the second lowest AIC (-9.21) and BIC (-8.84) values, the model with GARCH(2,1) and DCC(2,1) has the third lowest AIC (-9.21) and BIC (-8.84) values,while the model with GARCH(1,1) and DCC(1,1) has the highest AIC (-9.19) and BIC (-8.74) values.

1. GARCH(1,1) and DCC(1,1) Model

JNJ:

MEAN=($p= 0.036103$): Statistically significant.

CONSTANT=($p = 0.357740$): Not Statistically significant.

GARCH Term=($p = 0.999980$): Not statistically significant.

ARCH TERM= ($p =0.000000$): Statistically significant.

KO:

MEAN=($p = 0.050495$): Statistically significant.

CONSTANT=($p = 0.206538$): Not statistically significant.

GARCH Term= ($p = 1.000$): Not statistically significant.

ARCH TERM= ($p = 0.000000$): Statistically significant.

GE:

MEAN=($p = 0.006$): Statistically significant.

CONSTANT=($p = 0.418165$): Not statistically significant.

GARCH Term=($p = 0.133013$): Not statistically significant.

ARCH Term=($p = 0.000000$): Not statistically significant.

2. GARCH(1,2) and DCC(1,2) Model

JNJ:

MEAN =($p = 0.051807$): Statistically significant.

CONSTANT ($p = 0.929127$): Not statistically significant.

GARCH Term ($p = 1.000000$): Not statistically significant.

ARCH Term ($p = 0.813195$): Not statistically significant.

KO:

MEAN ($p = 0.049756$): Statistically significant.

CONSTANT ($p = 0.013771$): Not statistically significant.

GARCH Term ($p = 0.186159$): Not statistically significant.

ARCH Term = 0.018810 ($p = 0.173$): Not statistically significant.

GE:

MEAN ($p = 0.074807$): Statistically significant.

CONSTANT ($p = 0.407546$): Not statistically significant.

GARCH Term =($p = 0.125278$): Not statistically significant.

ARCH Term =($p = 0.000072$): Not statistically significant.

3. GARCH(2,1) and DCC(2,1) Model

JNJ:

MEAN= ($p = 0.035303$): Statistically significant.

CONSTANT ($p = 0.280929$): Statistically significant.

GARCH Term ($p = 1.000000$): Not statistically significant.

ARCH Term ($p = 0.000000$): Statistically significant.

KO:

MEAN =($p = 0.042781$): Statistically significant.

CONSTANT=($p = 0.560605$): Not statistically significant.

GARCH Term=($p = 0.177337$): Not statistically significant.

ARCH Term = ($p = 0.943819$): Statistically significant.

GE:

MEAN= ($p = 0.074525$): Statistically significant.

CONSTANT= ($p = 0.415872$): Not statistically significant.

GARCH Term=($p = 0.368939$): Not statistically significant.

ARCH Term=($p = 0.000000$): Not statistically significant.

4. GARCH(2,2) and DCC(2,2) Model

JNJ:

MEAN= ($p = 0.043046$): Statistically significant.

CONSTANT= ($p = 0.898318$): Not statistically significant.

GARCH Term=($p = 1.000000$): Not statistically significant.

ARCH Term= ($p = 1.000000$): Not statistically significant.

KO:

MEAN= ($p = 0.046470$): Statistically significant.

CONSTANT= ($p = 0.813226$): Not statistically significant.

GARCH Term= ($p = 0.182952$): Not statistically significant.

ARCH Term= ($p = 0.979828$): Not statistically significant.

GE:

MEAN=($p = 0.086809$): Statistically significant.

CONSTANT=($p = 0.387145$): Not statistically significant.

GARCH Term=($p = 0.469443$): Not statistically significant.

ARCH Term=($p = 0.073499$): Not statistically significant.

GARCH(1,1) and DCC(1,1) Model: 4 significant parameters GARCH(1,2) and DCC(1,2) Model: 2 significant parameters GARCH(2,1) and DCC(2,1) Model: 6 significant parameters GARCH(2,2) and DCC(2,2) Model: 2 significant parameters

GARCH (2,1) and DCC(2,1) model appears to be the best overall based on the following reasons:

Log-Likelihood: It is not the highest but is relatively close.

AIC and BIC: It has the lowest values, indicating the best fit relative to model complexity.

The GARCH(2,1) and DCC(2,1) model has 6 significant parameters, which suggests that more of the model's coefficients are relevant.

GARCH(2,1) and DCC(2,1) model appears to be the best overall. It has a relatively high log-likelihood, a competitive AIC and BIC, and the highest number of statistically significant parameters, making it a strong candidate for explaining the data effectively.

D)

Based on the results from part (c), we identified that the GARCH(2,1) and DCC(2,1) models are the best fit for our data. These models help us forecast two crucial components for the next period: the expected returns (conditional means) and the variance-covariance matrix.

The DCC-GARCH model provides forecasts of the conditional means, denoted as MEAN. These values represent the distribution that the expected returns for the next month is going to be drawn from.

Formulae = W' * r

They also also provides forecasts of the conditional variance-covariance matrix, this matrix shows the variance of the distribution from which the next shock is going to be drawn from.

formulae : W * v * W

Using the estimation results from the GARCH(2,1) and DCC(2,1) models, you can accurately forecast the expected returns and variance-covariance matrix for the three stocks. This allows the calculation of both the expected return and the risk (variance) associated with the portfolio in the next month.

E)

```r
# 1-month forecasts
forecasts <- dccforecast(fit1, n.ahead = 1)
# conditional variance-covariance forecasts
forecasts@mforecast$H
```

```
[[1]]
, , 1

             [,1]         [,2]        [,3]
[1,] 0.0018586729 0.0009107361 0.000563929
[2,] 0.0009107361 0.0015279589 0.001000325
[3,] 0.0005639290 0.0010003248 0.007706139
```

```r
# conditional correlation forecasts
forecasts@mforecast$R
```

```
[[1]]
, , 1

          [,1]      [,2]      [,3]
[1,] 1.0000000 0.5404248 0.1490063
[2,] 0.5404248 1.0000000 0.2915190
[3,] 0.1490063 0.2915190 1.0000000
```

```
# conditional mean forecasts
forecasts@mforecast$mu
```

```
, , 1

            [,1]        [,2]        [,3]
[1,] 0.006523582 0.006115484 0.009562135
```

F)

Methodology:

To maximize the Sharpe Ratio, we have to find the optimal weights for Johnson & Johnson, Coca-Cola, and General Electric that maximize the difference between the portfolio's expected return and the risk-free rate, relative to the portfolio's standard deviation (volatility).

Expected Return Calculation: W'* r

Expected return is the weighted average of the expected returns of the individual assets.

Portfolio Variance Calculation: W * v * W The portfolio variance depends on the weights of the assets, their variances, and the covariances between them.

SharpeRatio= E(ret)−Risk-FreeRate/$\sqrt{variance}$

To ensure no short-selling means all weights must be non-negative.

to ensure an optimized sharp ratio the Weights can be derived from excels solver.

RESULT

Expected Return: 0.007140379462= 0.714%

Is the weighted average return of the portfolio based on the optimal weights.

Portfolio Variance: 0.001670754526

Is the dispersion of the portfolio's returns around the mean return, representing the risk level.

Risk-Free Rate: 0.0035=or 0.35%

Sharpe Ratio: 0.08906156707 Is the dispersion of the portfolio's returns around the mean return, representing the risk level.

WEIGHT

johnson and Johnson=0.3563733795=35.64%

Coca Cola=0.3434477719=34.34%

General electric0.3001788486=30.02%

Conclusion

The Sharpe Ratio-maximizing portfolio for the next month, under the constraints provided (no short-selling), comprises approximately 35.64% in Johnson & Johnson stock, 34.34% in Coca-Cola stock, and 30.02% in General Electric stock. With a Sharpe Ratio of 0.089, this portfolio offers a balanced risk-adjusted return compared to a risk-free asset.