Final Exam Project - Option 1

William Han

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Part 1 (Steps 1-3)

Model 1: Disney (DIS)

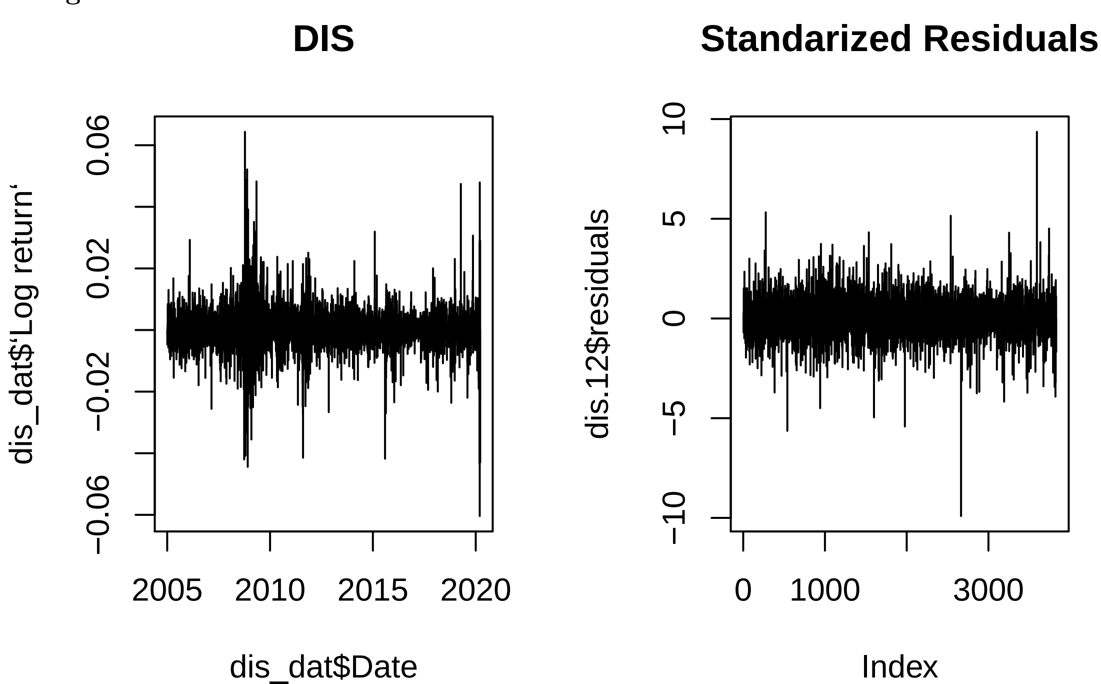
GARCH Model

The final model is a Garch(1,2) model.

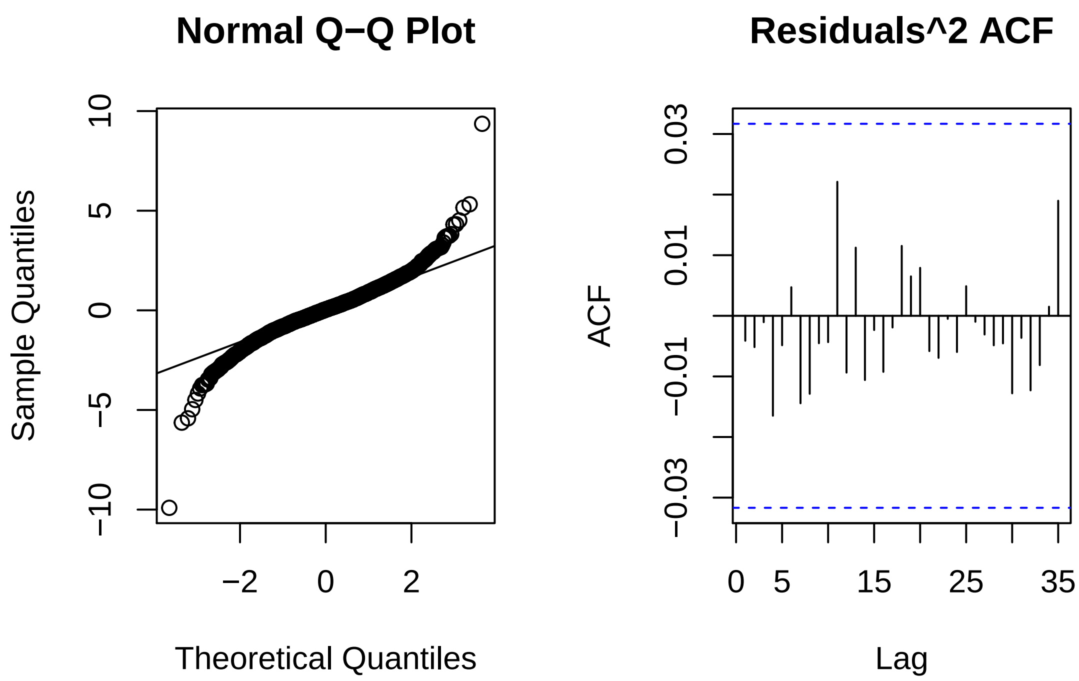
	Estimate	Std. Error	t value	Pr(>|t|)
a0	1.869318e-06	1.850803e-07	10.100038	0.000000e+00
a1	8.190889e-02	1.333698e-02	6.141485	8.175354e-10
a2	2.589590e-02	1.565596e-02	1.654060	9.811528e-02
b1	8.508995e-01	1.190572e-02	71.469831	0.000000e+00

- The sum of squared error is 3825.522.
- Although the final model did not have the lowest SSE, it was the only model that actually converged. The other three models did not converge, and thus were not considered. All of its variables were significant.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020




```
    Shapiro-Wilk normality test

data:  na.omit(residuals(dis.12))
W = 0.9591, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(dis.12))
X-squared = 6538.6, df = 2, p-value < 2.2e-16
```

```
skewness(na.omit(residuals(dis.12)))
```

```
[1] -0.1269025
```

```
kurtosis(na.omit(residuals(dis.12)))
```

```
[1] 6.398491
```

Model 2: Adobe (ADBE)

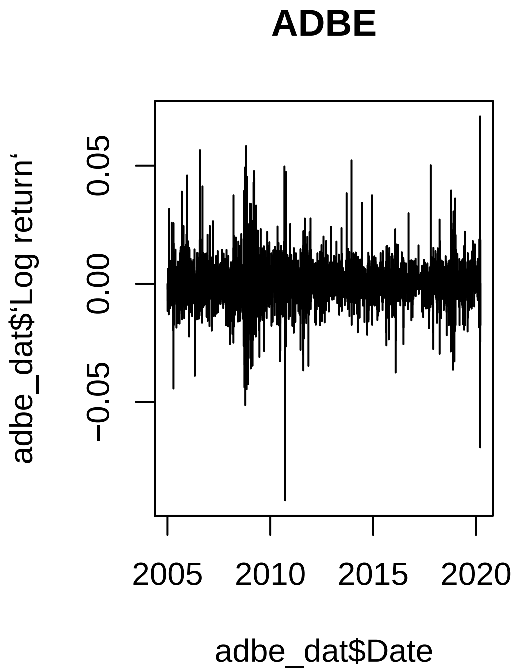
GARCH Model

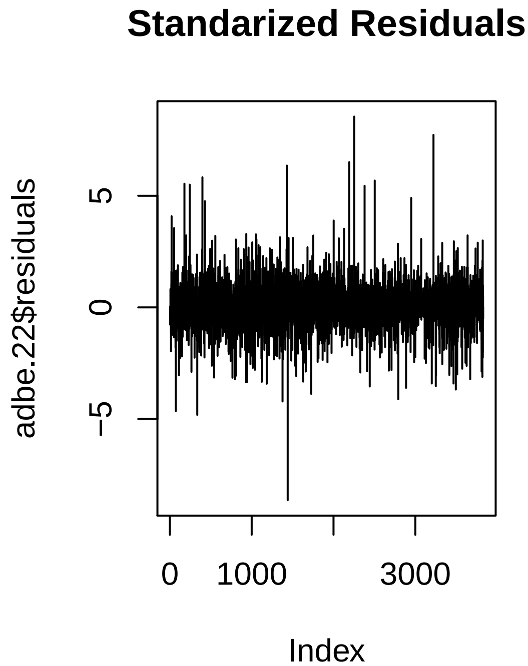
The final model is a Garch(1,1) model.

```
       Estimate   Std. Error   t value Pr(>|t|)
a0 3.511536e-06 2.210647e-07  15.88465        0
a1 1.052361e-01 7.210232e-03  14.59538        0
b1 8.546801e-01 7.807902e-03 109.46347        0
```

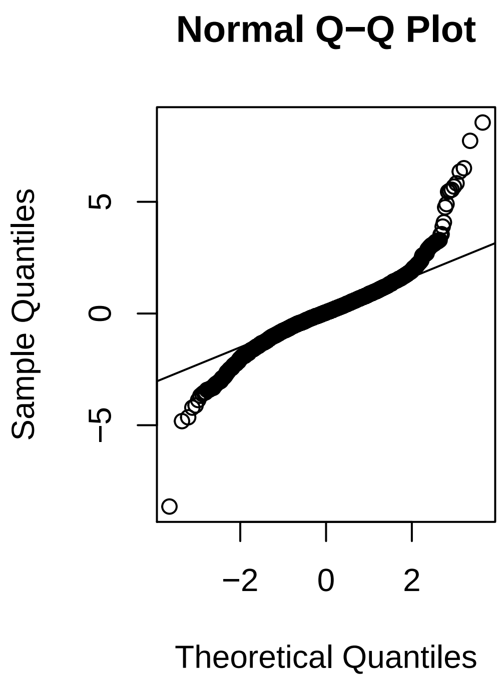
- The sum of squared error is 3824.794.
- There were only two models that converged: GARCH(1,1) and GARCH(2,2). Although the GARCH(2,2) model had a slightly lower SSE (by about .5), it did not produce any standard errors or t-values, so I decided to go with GARCH(1,1), and all of its variables were significant.

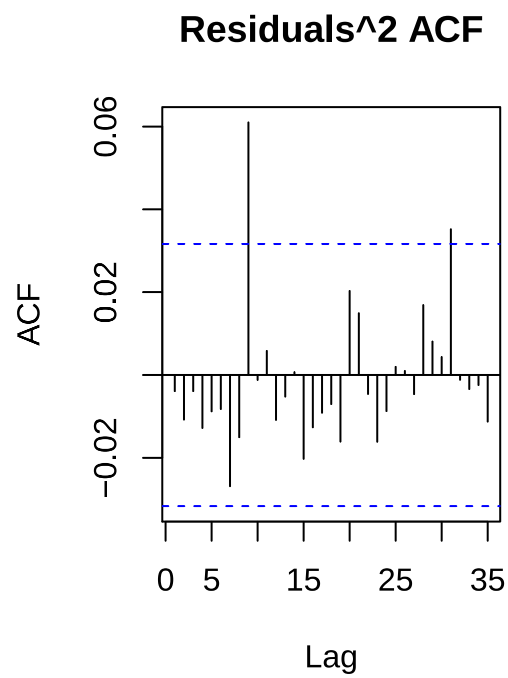
Model Diagnoistics





The data is from stock data collected between 1/1/2005 to 3/21/2020






```
    Shapiro-Wilk normality test

data:  na.omit(residuals(adbe.22))
W = 0.94155, p-value < 2.2e-16


    Jarque Bera Test
```

```
data:  na.omit(residuals(adbe.22))
X-squared = 7735.4, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(adbe.22)))
```

```
[1] 0.2714071
```

```r
kurtosis(na.omit(residuals(adbe.22)))
```

```
[1] 6.94376
```

Model 3: Cisco (CSCO)

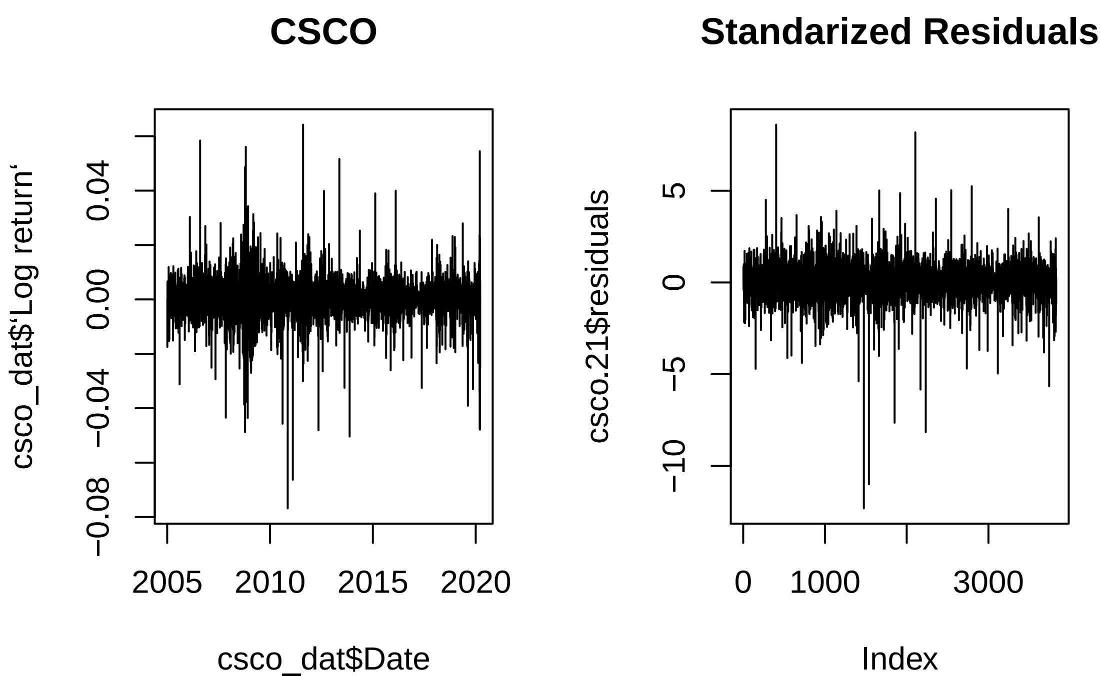
GARCH Model

The final model is a Garch(2,1) model.

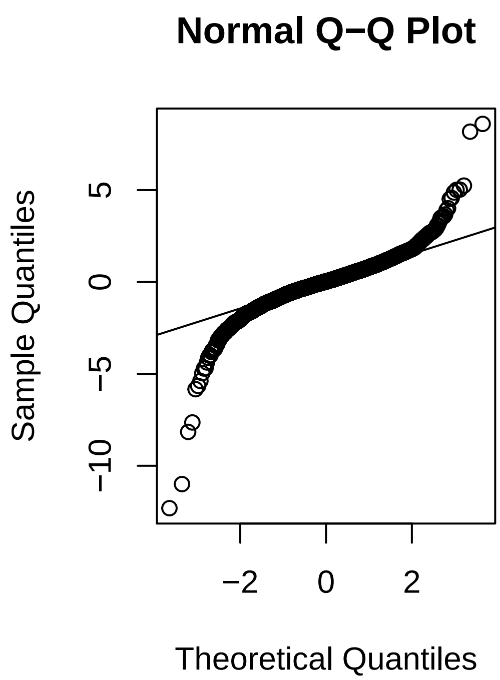
```
       Estimate   Std. Error   t value     Pr(>|t|)
a0 6.163295e-06 5.088307e-07 12.112664 0.000000e+00
a1 1.516865e-01 1.020014e-02 14.871017 0.000000e+00
b1 1.702086e-01 2.574565e-02  6.611161 3.813172e-11
b2 5.864871e-01 2.731273e-02 21.473035 0.000000e+00
```

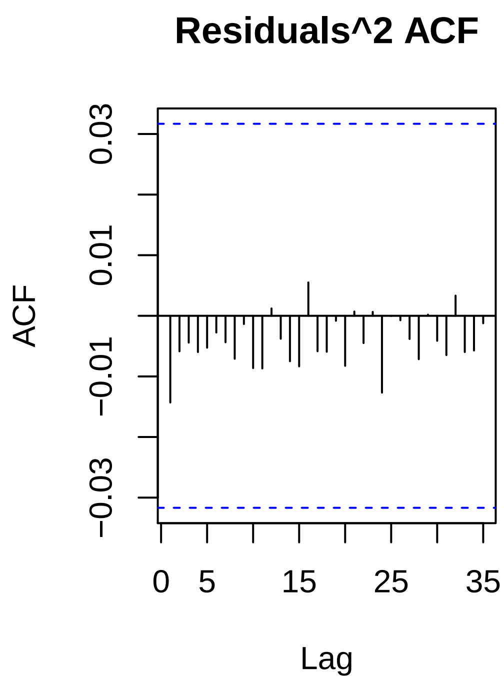
- The sum of squared error is 3824.945.
- There were three models that converged: GARCH(1,1), GARCH(1,2), and GARCH(2,1). GARCH(2,1) had the lowest SSE and all of its variables were significant.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020






```
	Shapiro-Wilk normality test

data:  na.omit(residuals(csco.21))
W = 0.89588, p-value < 2.2e-16


	Jarque Bera Test

data:  na.omit(residuals(csco.21))
X-squared = 45046, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(csco.21)))
```

```
[1] -0.9648425
```

```r
kurtosis(na.omit(residuals(csco.21)))
```

```
[1] 16.69635
```

Model 4: Fiserv (FISV)

GARCH Model

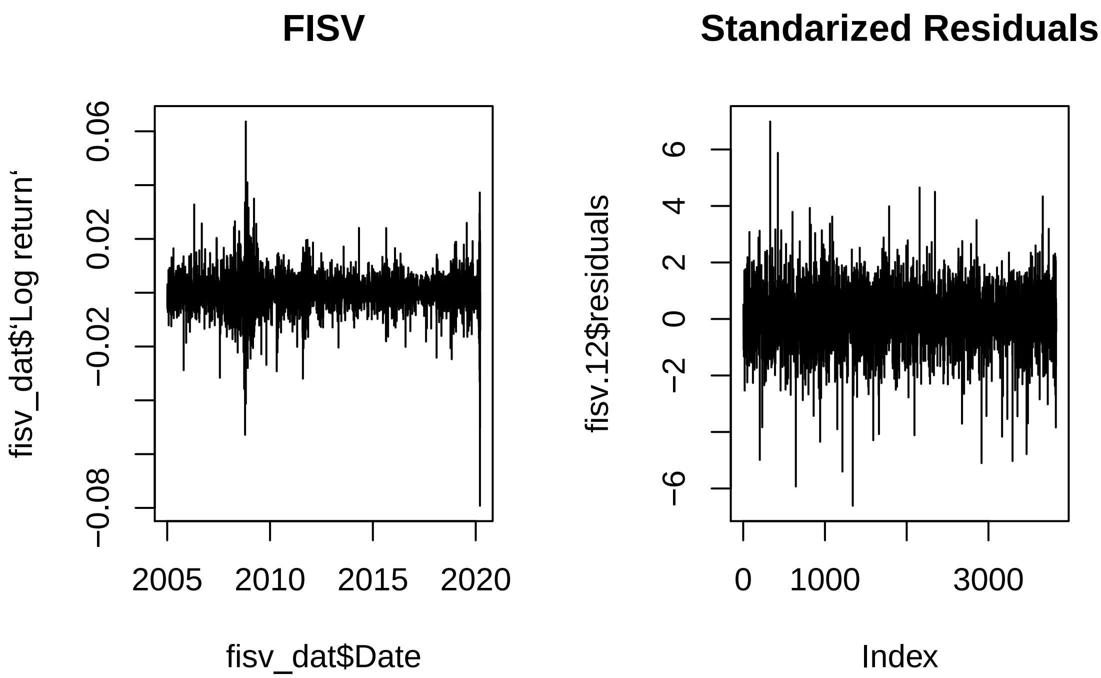
The final model is a Garch(1,2) model.

```
       Estimate   Std. Error      t value     Pr(>|t|)
a0 1.268281e-06 1.550670e-07 8.178921e+00 2.220446e-16
a1 9.971008e-02 1.330026e-02 7.496849e+00 6.528111e-14
a2 8.473346e-09 1.470886e-02 5.760711e-07 9.999995e-01
b1 8.706098e-01 1.083793e-02 8.032986e+01 0.000000e+00
```

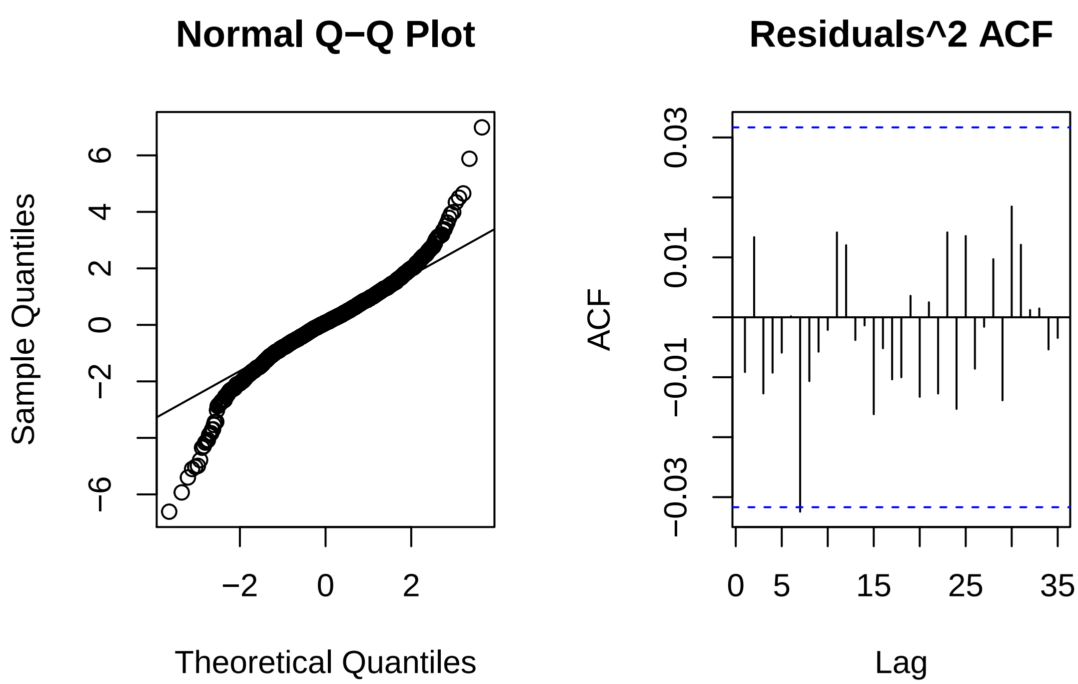
- The sum of squared error is 3817.583

- The only model that converged was the GARCH(2,1) model, but it did not produce any std. errors. It also did not have the lowest SSE. The model that had the lowest SSE, but did not converge, was GARCH(1,2), and was the model selected for FISV.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020




```
Shapiro-Wilk normality test
```

```
data:  na.omit(residuals(fisv.12))
W = 0.96789, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(fisv.12))
X-squared = 2111.4, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(fisv.12)))
```

```
[1] -0.2616223
```

```r
kurtosis(na.omit(residuals(fisv.12)))
```

```
[1] 3.601004
```

Model 5: Alaska Airlines (ALK)

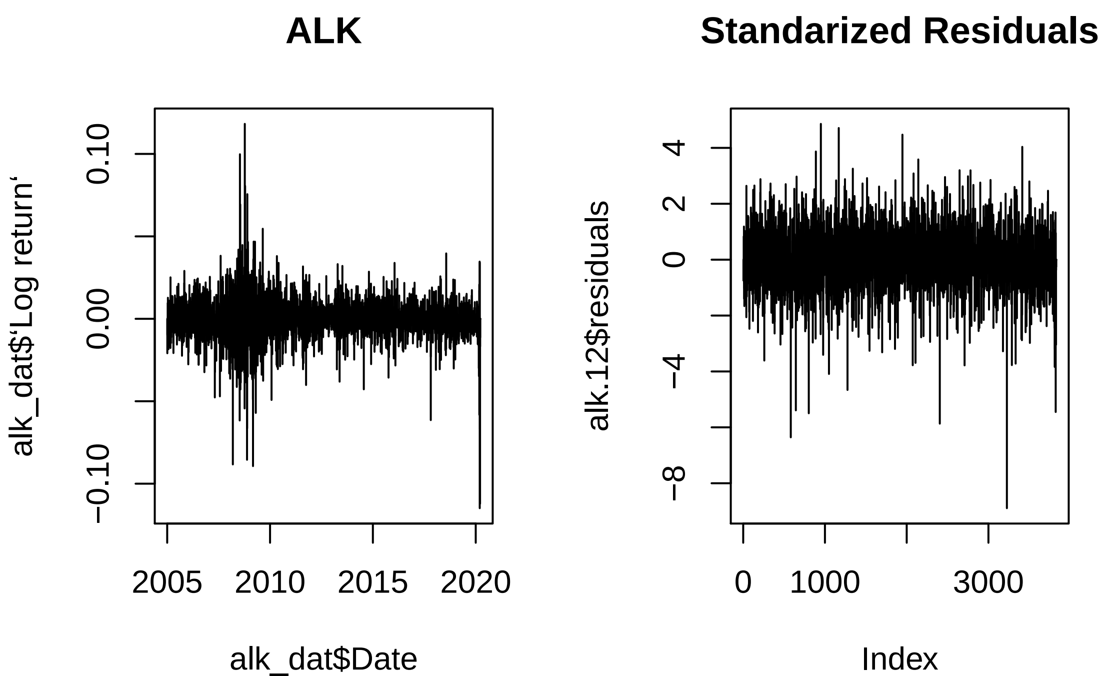
GARCH Model

The final model is a Garch(1,2) model.

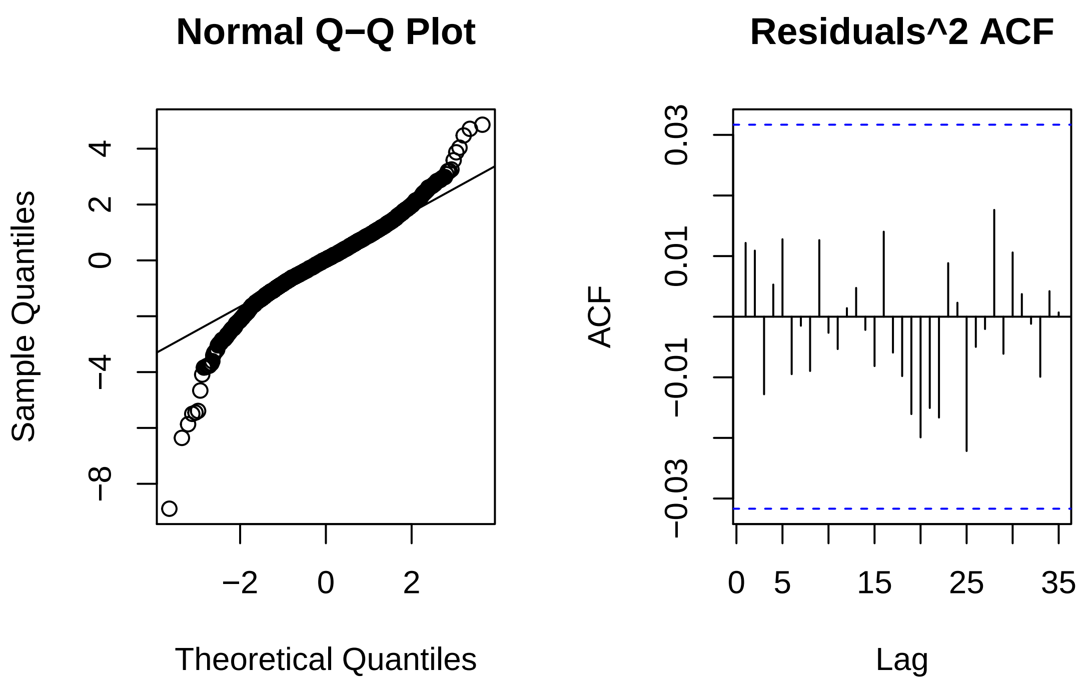
```
       Estimate   Std. Error      t value     Pr(>|t|)
a0 1.541389e-06 2.120735e-07 7.268180e+00 3.643752e-13
a1 6.629609e-02 1.355866e-02 4.889576e+00 1.010535e-06
a2 6.921862e-09 1.381987e-02 5.008629e-07 9.999996e-01
b1 9.240572e-01 5.503248e-03 1.679113e+02 0.000000e+00
```

- The sum of squared error is 3787.506.
- The two models that converged was GARCH(2,1) and GARCH(2,2), however both of these produced coefficients with no standard errors/pvalues. The lowest SSE was produced by the GARCH(1,2) model, however it has an insignificant variable a2.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020




```
    Shapiro-Wilk normality test

data:  na.omit(residuals(alk.12))
W = 0.96727, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(alk.12))
```

```
X-squared = 2932.1, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(alk.12)))
```

```
[1] -0.5151183
```

```r
kurtosis(na.omit(residuals(alk.12)))
```

```
[1] 4.162498
```

Model 6: Boeing (BA)

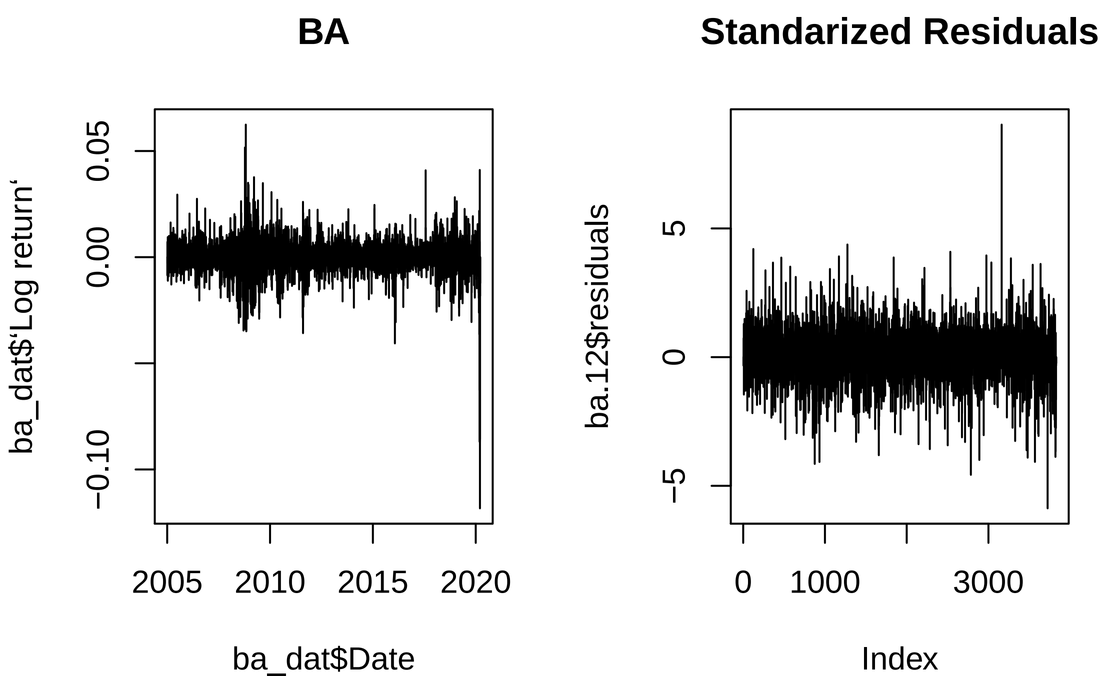
GARCH Model

The final model is a Garch(1,2) model.

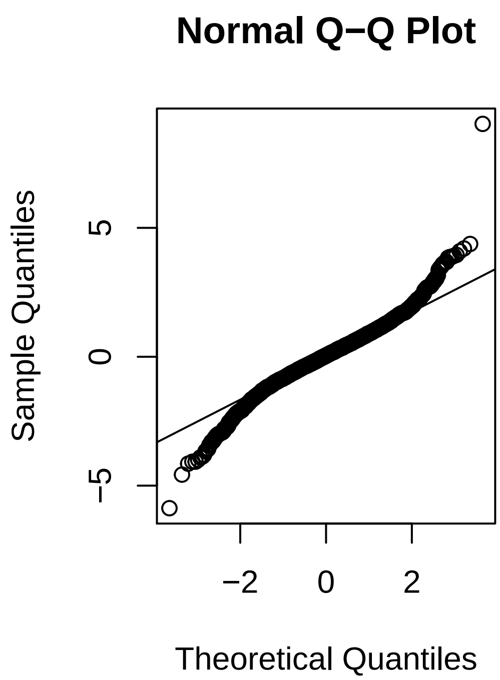
```
       Estimate   Std. Error      t value     Pr(>|t|)
a0 1.637669e-06 1.670706e-07 9.802256e+00 0.000000e+00
a1 1.038462e-01 1.573010e-02 6.601750e+00 4.063327e-11
a2 2.500606e-09 1.622361e-02 1.541338e-07 9.999999e-01
b1 8.754020e-01 9.007712e-03 9.718362e+01 0.000000e+00
```

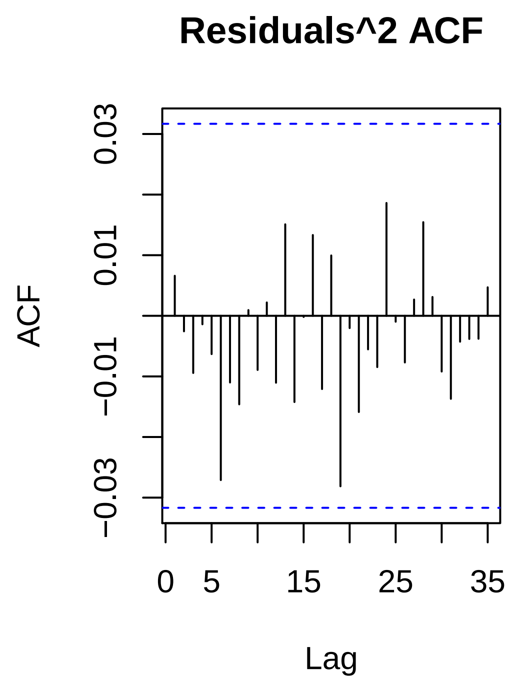
- The sum of squared error is 3749.124.
- The only model that converged was the GARCH(2,1), however this again produced NA for its std.error and p value. Although GARCH(2,2) produced the lowest SSE, it too did not produce any values for its std error. The final model choosen was thus GARCH(1,2), as it had the lowest SSE out of the remaining models. However, it does have an insignificant parameter a2.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020






```
    Shapiro-Wilk normality test

data:  na.omit(residuals(ba.12))
W = 0.97273, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(ba.12))
X-squared = 2072.8, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(ba.12)))
```

```
[1] 0.030378
```

```r
kurtosis(na.omit(residuals(ba.12)))
```

```
[1] 3.604865
```

Model 7: MolsonCoors (TAP)

GARCH Model

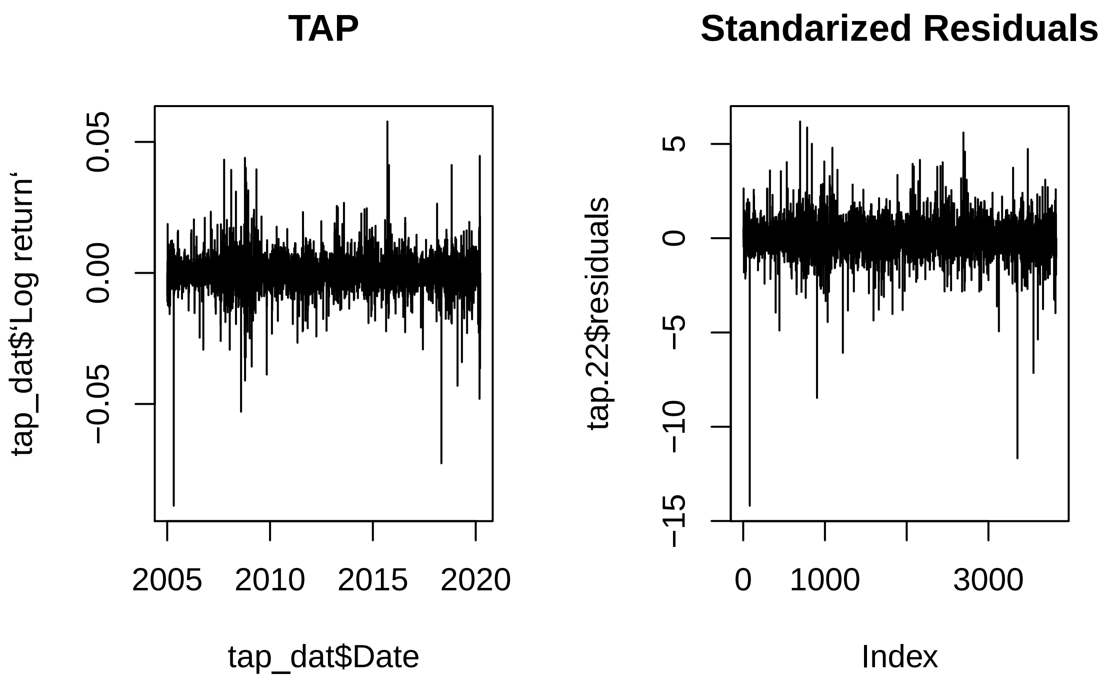
The final model is a Garch(2,2) model.

```
       Estimate    Std. Error       t value      Pr(>|t|)
a0 1.587091e-05 2.172564e-06 7.305150e+00 2.768896e-13
a1 1.468592e-01 9.954803e-03 1.475260e+01 0.000000e+00
a2 5.707406e-02 2.537952e-02 2.248824e+00 2.452372e-02
b1 1.817623e-09 9.191266e-02 1.977555e-08 1.000000e+00
b2 4.931051e-01 4.689198e-02 1.051577e+01 0.000000e+00
```

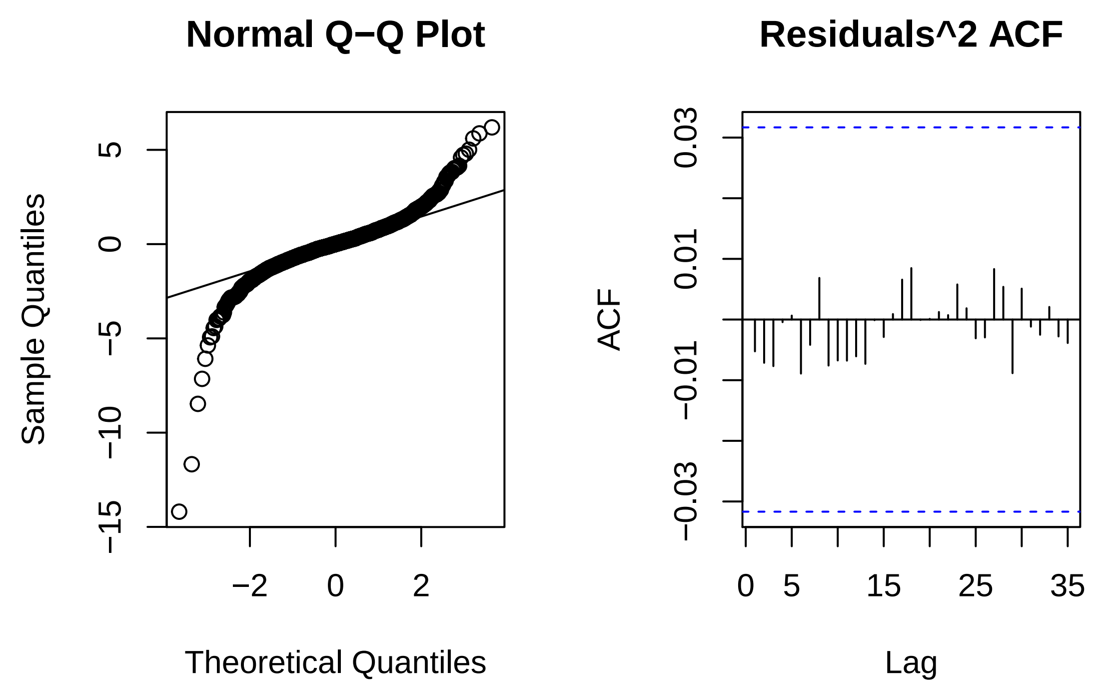
- The sum of squared error is 3825.273

- The only model that converged was GARCH(2,1), however it did not produce any values for std error or pvalue. It also did not have the lowest SSE. The model with the lowest SSE was GARCH(2,2), however it did not converge. This was chosen as the final model, and all of its coeficients were significant.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020




```
Shapiro-Wilk normality test
```

```
data:  na.omit(residuals(tap.22))
W = 0.88907, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(tap.22))
X-squared = 68039, df = 2, p-value < 2.2e-16
```

```
skewness(na.omit(residuals(tap.22)))
```

```
[1] -1.297804
```

```
kurtosis(na.omit(residuals(tap.22)))
```

```
[1] 20.49265
```

Model 8: Lowes (LOW)

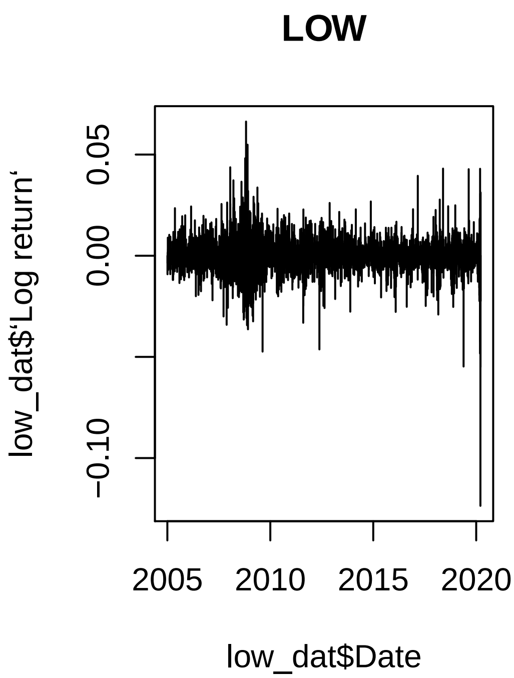
GARCH Model

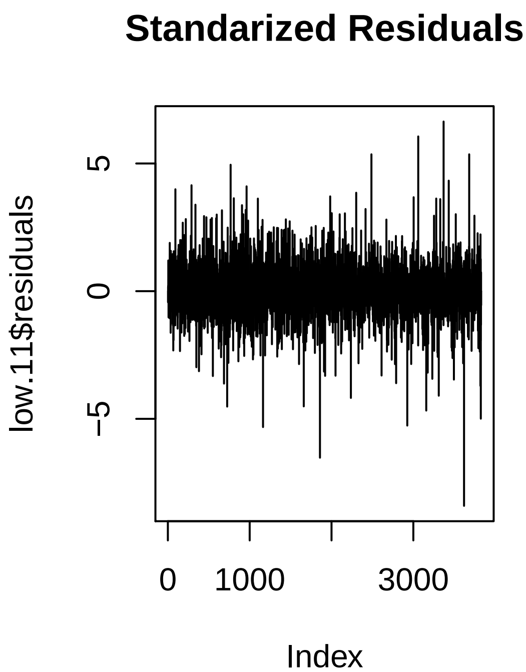
The final model is a Garch(1,1) model.

```
       Estimate   Std. Error   t value Pr(>|t|)
a0 2.249343e-06 2.401645e-07  9.365844        0
a1 9.544847e-02 6.302415e-03 15.144746        0
b1 8.728833e-01 8.891129e-03 98.174635        0
```

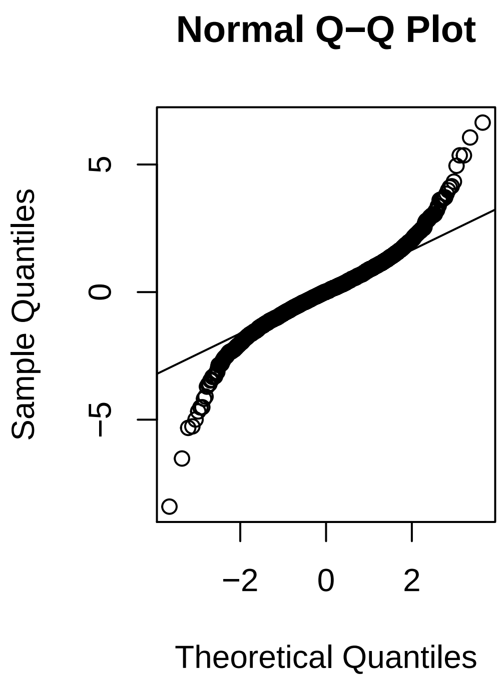
- The sum of squared error is 3822.868.
- Although the GARCH(2,2) model produced the lowest SSE of 3753, it did not converge. Out of the models that converged, only GARCH(1,1) produced a model with values for std error and pvalue. Furthermore, all of its coeficients were significant.

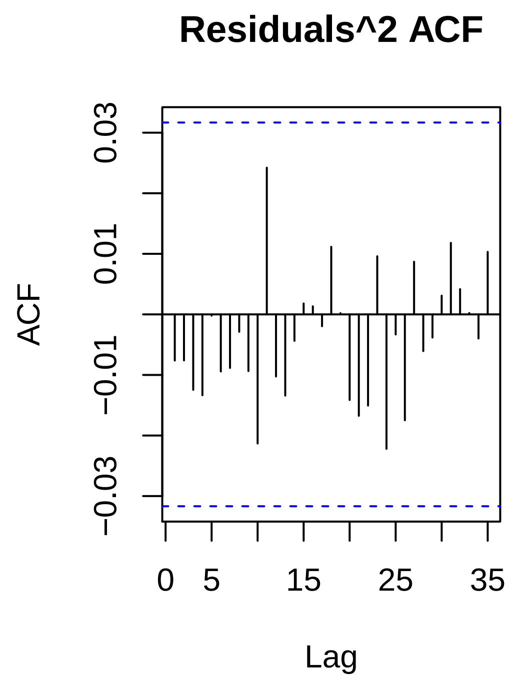
Model Diagnoistics





The data is from stock data collected between 1/1/2005 to 3/21/2020






```
    Shapiro-Wilk normality test

data:  na.omit(residuals(low.11))
W = 0.95929, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(low.11))
X-squared = 3651.1, df = 2, p-value < 2.2e-16
```

```
skewness(na.omit(residuals(low.11)))
```

```
[1] -0.08611368
```

```
kurtosis(na.omit(residuals(low.11)))
```

```
[1] 4.781353
```

Model 9: Allstate Insurance (ALL)

The following two stocks are new stocks that I added to replace FANG and DLTR, which were publicaly listed after 1/1/2005.

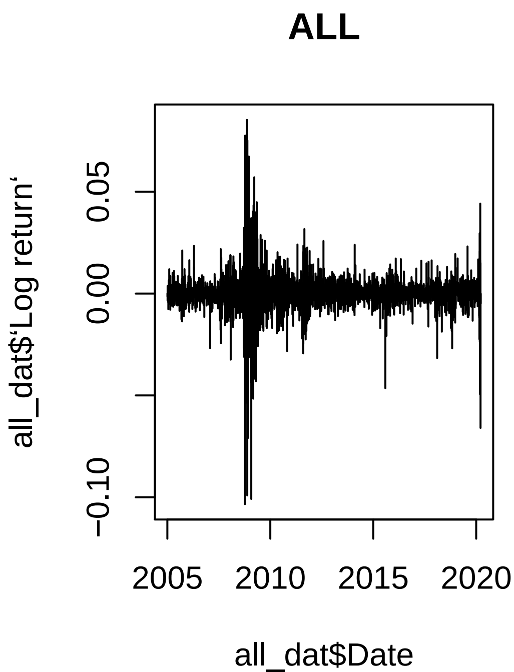
GARCH Model

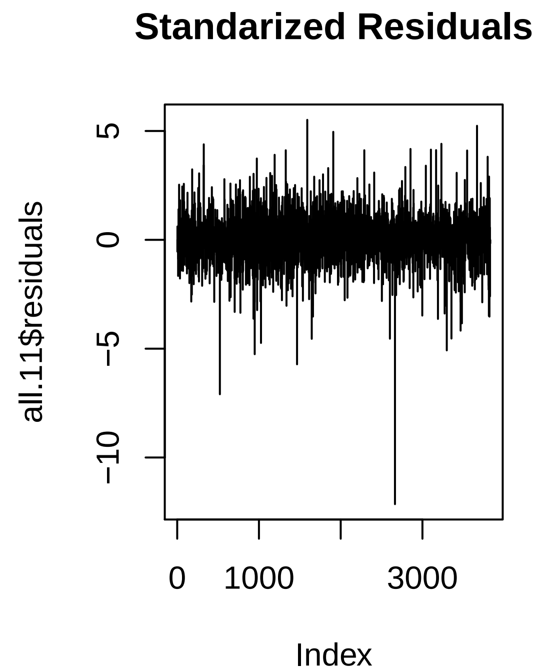
The final model is a Garch(1,1) model.

```
       Estimate   Std. Error   t value Pr(>|t|)
a0 9.003864e-07 8.183449e-08  11.00253        0
a1 8.657967e-02 4.230779e-03  20.46424        0
b1 8.926960e-01 5.408826e-03 165.04432        0
```

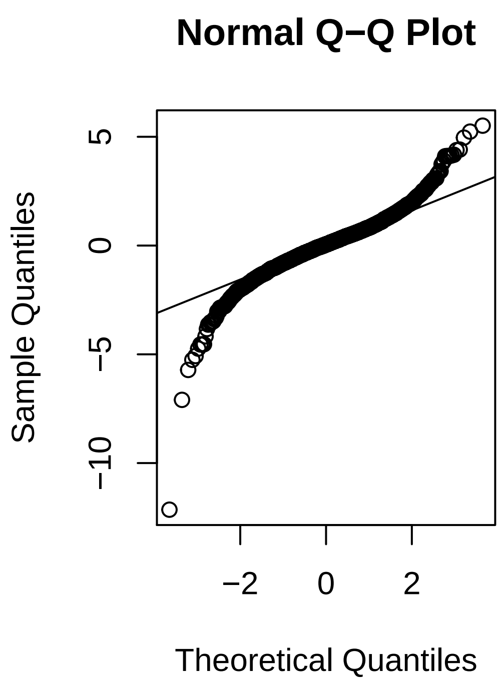
- The sum of squared error is 3823.317
- Out of the two models that converged, GARCH(1,1) was the only one that produced values for std error and the pvalue. It did not, however, have the lowest SSE.

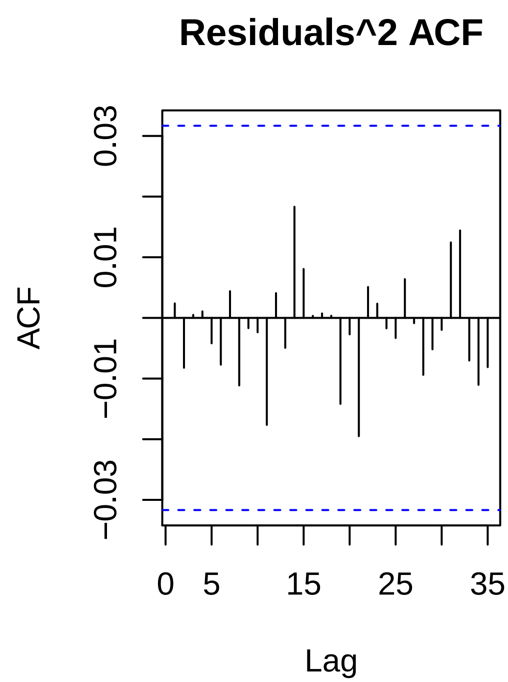
Model Diagnoistics





The data is from stock data collected between 1/1/2005 to 3/21/2020






```
Shapiro-Wilk normality test
```

```
data:  na.omit(residuals(all.11))
W = 0.94427, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(all.11))
X-squared = 13016, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(all.11)))
```

```
[1] -0.6144504
```

```r
kurtosis(na.omit(residuals(all.11)))
```

```
[1] 8.949676
```

Model 10: AT&T (T)

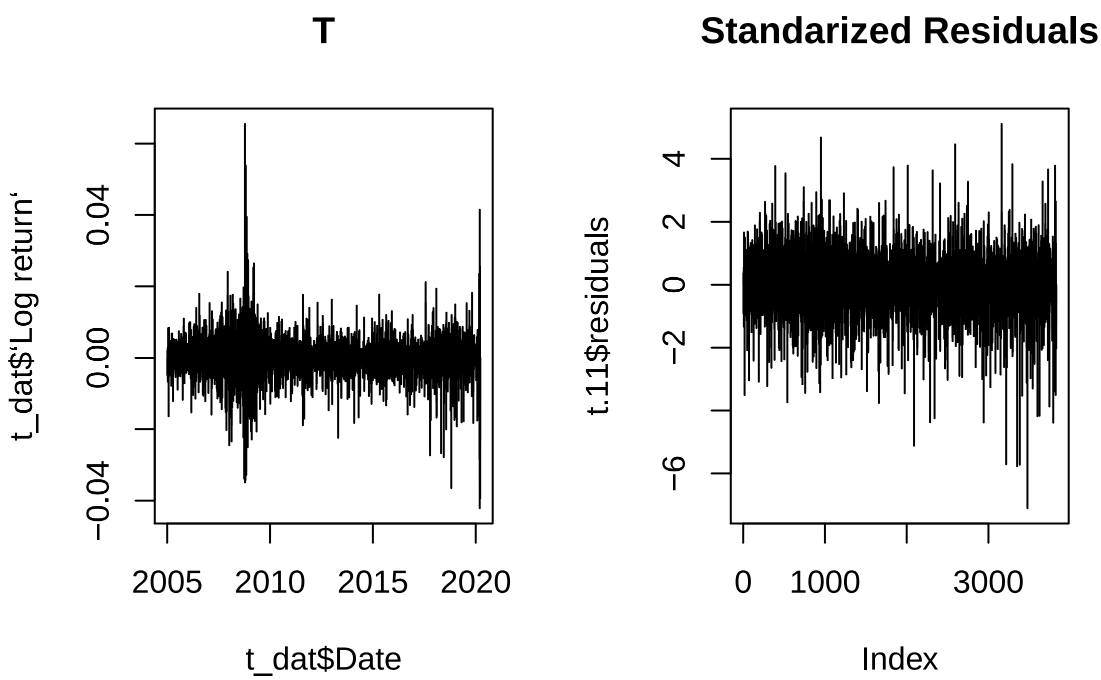
GARCH Model

The final model is a Garch(1,1) model.

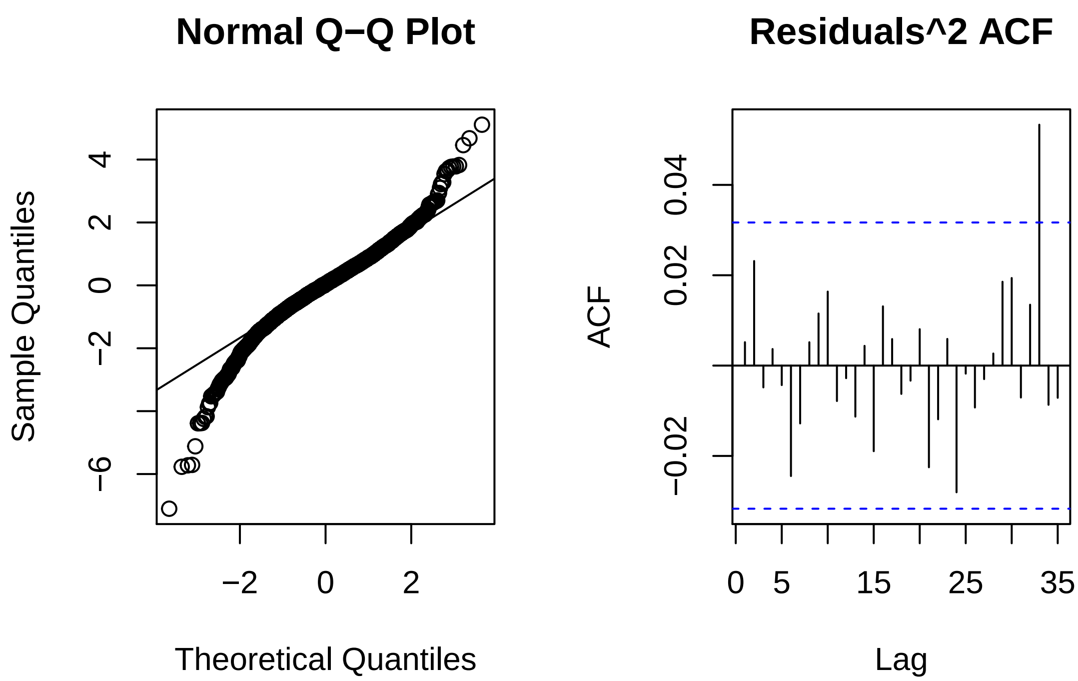
```
       Estimate   Std. Error    t value     Pr(>|t|)
a0 6.256953e-07 9.328411e-08   6.707416 1.981015e-11
a1 6.369119e-02 4.812132e-03  13.235543 0.000000e+00
b1 9.167090e-01 6.669605e-03 137.445775 0.000000e+00
```

- The sum of squared error is 3827.396
- GARCH(1,2) produced the lowest SSE, however it did not converge. GARCH(1,1) was the only model out of the remaining that produced values for std.error and pvalue of the coeficients, and therefore is choosen as the final model.

Model Diagnoistics



The data is from stock data collected between 1/1/2005 to 3/21/2020




```
    Shapiro-Wilk normality test

data:  na.omit(residuals(t.11))
W = 0.96907, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(t.11))
```

```
X-squared = 1713.2, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(t.11)))
```

```
[1] -0.4807952
```

```r
kurtosis(na.omit(residuals(t.11)))
```

```
[1] 3.133152
```

Comments on all fitted models

- Based on the shapiro-wilk and jarque bera tests, the residuals from all of the final models are normally distributed. However, rom the QQ plots and test for skewness/kurtosis, there are problems with skewness and right/left tails.
- When selecting the final model, the first criteria was to choose the lowest SSE among the GARCH(p,q) models that converged. When these models did not produce any values for the std. error, I did not use the model. In these cases, I would select from the models that did not converge, produced coeficient values, and had the lowest SSE. Out of the 10 models, 4 of them were GARCH models that did not converge: FISV, ALK, BA, TAP.
- In most models, the ACF of the residuals squared did not have any significant lags. In three of the models, only one of the lags were significant.

Question 5 - Return

Baseline(1/10 weights)

```r
(mean(crt))
```

```
[1] 0.0001028839
```

```r
(sd.base <- sd(crt))
```

```
[1] 0.005768263
```

The mean return for equal portfolio weights of 1/10 is .000102, with a standard deviation of .0058.

Optimization

```r
(return_max <- max(port_returns[port_sd<=sd.base]))
```

```
[1] 0.0001477532
```

```r
(weights_max <- all_wts[which(port_returns == return_max),])
```

```
 [1] 0.08295994 0.24880708 0.03348786 0.22729007 0.02577842 0.02742646
 [7] 0.13542431 0.10943922 0.01588946 0.09349717
```

```r
(std_max <- port_sd[which(port_returns == return_max)])
```

```
[1] 0.005752969
```

The best weight combination (rounded to two significant digits) is: (0.08295994, 0.24880708, 0.03348786, 0.22729007, 0.02577842, 0.02742646, 0.13542431, 0.10943922, 0.01588946, 0.09349717). This resulted in a sample mean of .00015 and a sd of .00575.

To find the best weights for the portfolio, I generated 5000 random weight combinations using a uniform distribution, and divided the weights by their sum to ensure that they sum to 1. Out of the 5000 different weight combinations, I screened them to show only the returns with standard deviations less than the baseline. Then I found the highest mean return from these remaining weight combinations.

Question 6 - Residuals

Baseline(1/10 weights)

```
(mean(cet))
```

```
[1] 0.02228479
```

```
(sd.base <- sd(cet))
```

```
[1] 0.6502719
```

The mean residuals for equal portfolio weights of 1/10 is .0223, with a standard deviation of .650

Optimization

```
(residual_max <- max(port_residuals[port_sd<=sd.base]))
```

```
[1] 0.0229694
```

```
(weights_max <- all_wts[which(port_residuals == residual_max),])
```

```
 [1] 0.09039547 0.13750944 0.04711100 0.11164706 0.09029237 0.12555648
 [7] 0.12951653 0.12435095 0.03600397 0.10761674
```

```
(std_max <- port_sd[which(port_residuals == residual_max)])
```

```
[1] 0.6501697
```

The best weight combination is: (0.09039547 0.13750944 0.04711100 0.11164706 0.09029237 0.12555648 0.12951653 0.12435095 0.03600397 0.10761674). This resulted in a sample mean of .023 and a sd of .0650

I used the same optimization technique as in Question 5.

Question 7 - Log(price)

Baseline(1/10 weights)

```
(mean(cpt))
```

```
[1] 0.0002721163
```

```
(sd.base <- sd(cpt))
```

```
[1] 0.0133303
```

The mean return for equal portfolio weights of 1/10 is .00027, with a standard deviation of .0133

Optimization

```r
(logp_max <- max(port_logp[port_sd<=sd.base]))
```

```
[1] 0.0003655041
```

```r
(weights_max <- all_wts[which(port_logp == logp_max),])
```

```
 [1] 0.235269105 0.191079615 0.015214001 0.200594743 0.040605754 0.001328097
 [7] 0.232533069 0.022225874 0.016816476 0.044333267
```

```r
(std_max <- port_sd[which(port_logp == logp_max)])
```

```
[1] 0.01330878
```

The best weight combination is: (0.235269105 0.191079615 0.015214001 0.200594743 0.040605754 0.001328097 0.232533069 0.022225874 0.016816476 0.044333267). This resulted in a sample mean of .00037 and a sd of .0133

I used the same optimization technique as in Question 5/6.

Question 8

Equally weighted log prices

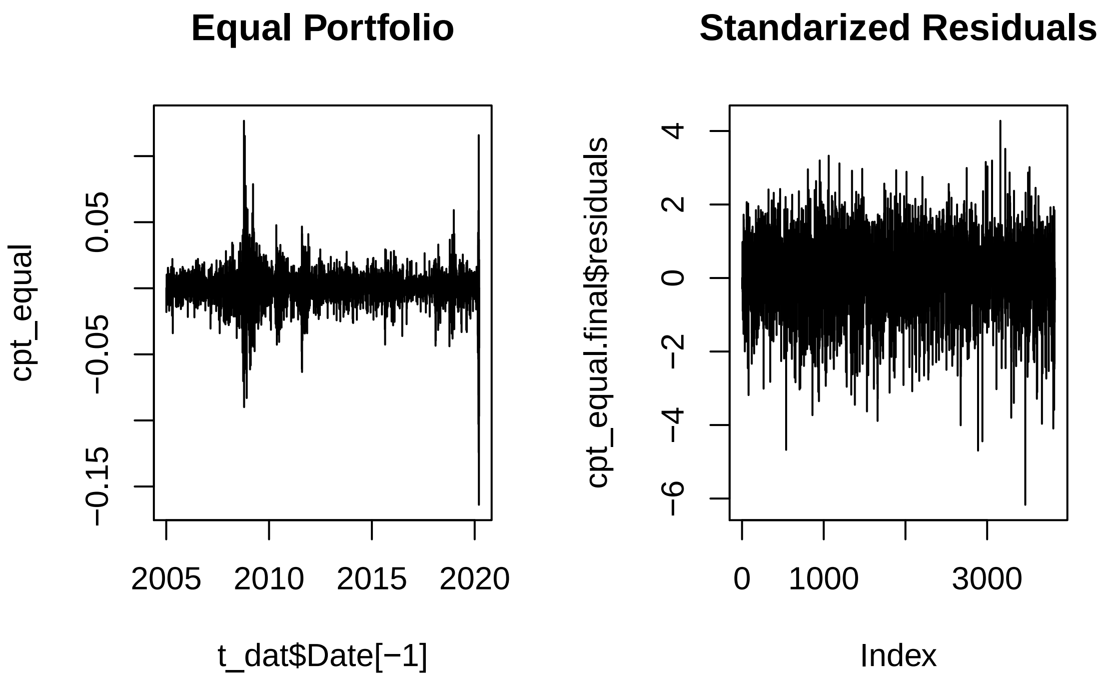
GARCH Model

The final model is a Garch(1,1) model.

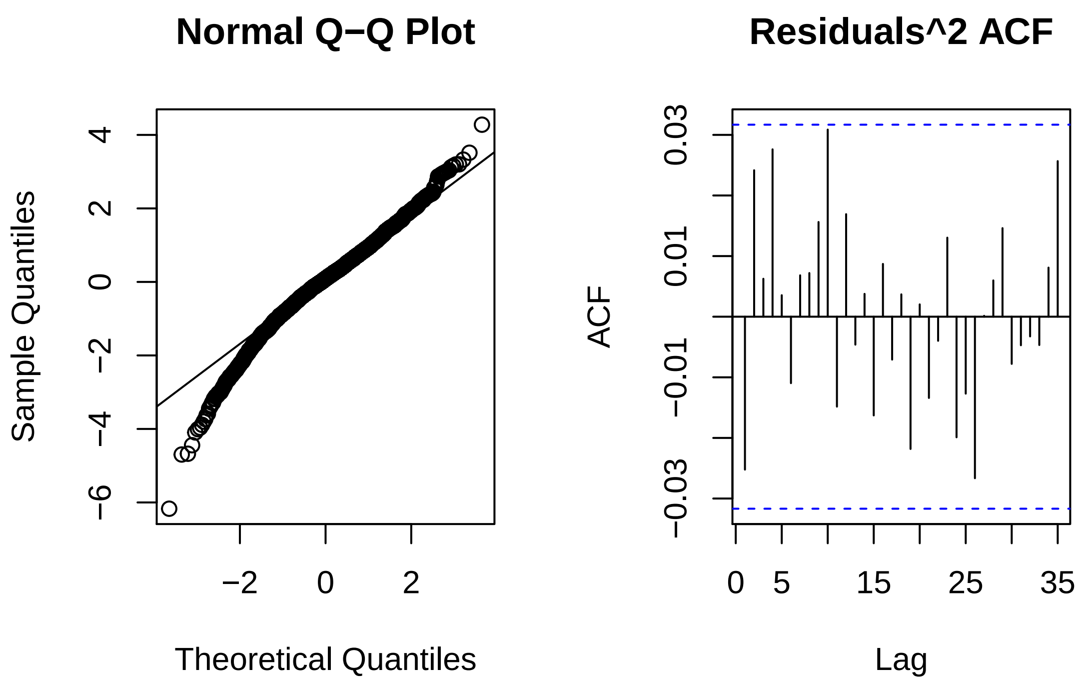
```
       Estimate   Std. Error   t value Pr(>|t|)
a0 3.248386e-06 3.882952e-07  8.365765        0
a1 1.148599e-01 9.055811e-03 12.683557        0
b1 8.619740e-01 1.039791e-02 82.898793        0
```

- The sum of squared error is 3825.024
- The only model that converged was the GARCH(1,1) model and it was choosen as the final model. However, GARCH(2,1) had the lowest SSE, I did not use it as it had a false convergence.

Model Diagnoistics



The data is from a equally weighted stock portfolio collected between 1/1/2005 to 3/21/2020




```
    Shapiro-Wilk normality test

data:  na.omit(residuals(cpt_equal.final))
W = 0.9841, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(cpt_equal.final))
```

```
X-squared = 485.83, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(cpt_equal.final)))
```

```
[1] -0.4323457
```

```r
kurtosis(na.omit(residuals(cpt_equal.final)))
```

```
[1] 1.515995
```

Analysis

```r
mean(na.omit(cpt_equal.final$residuals))
```

```
[1] 0.03891434
```

```r
sd(na.omit(cpt_equal.final$residuals))
```

```
[1] 0.998984
```

- The sample mean of the residuals from the final GARCH model is .039, with a sd of 1.

Question 9

Optimized weighted log prices

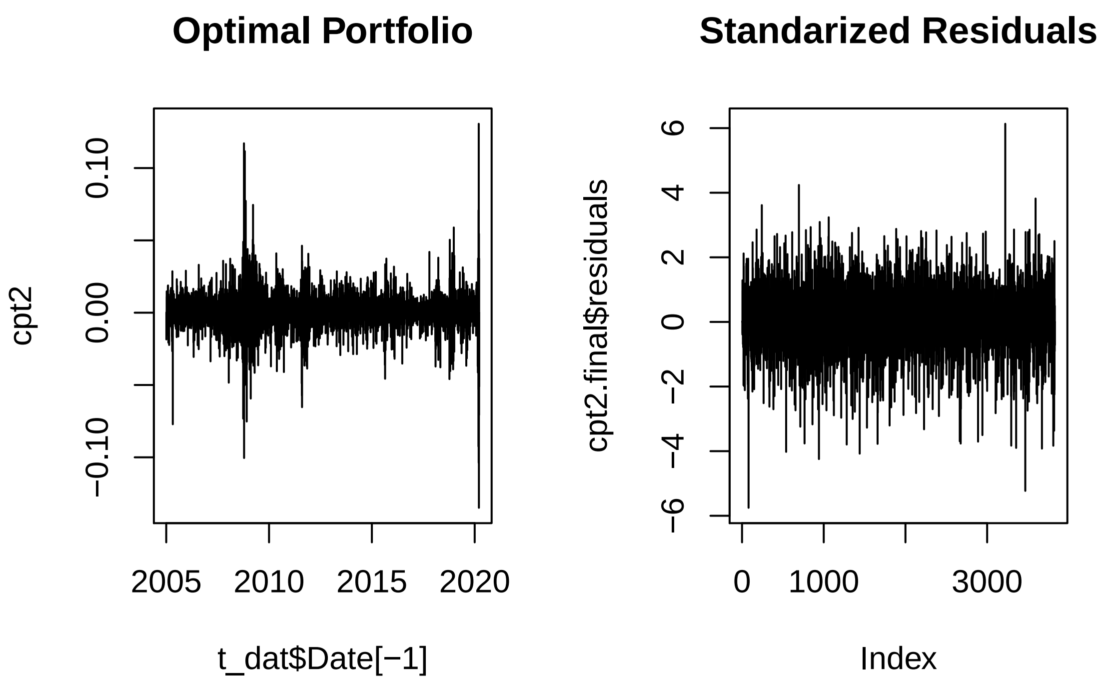
GARCH Model

The final model is a Garch(1,2) model.

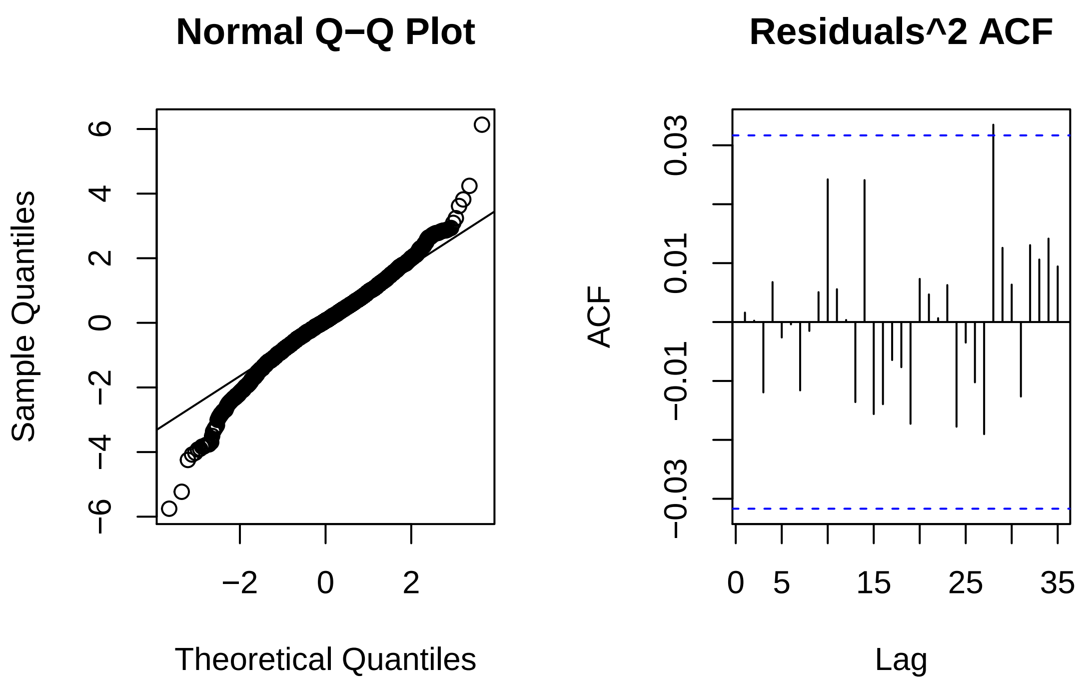
```
       Estimate   Std. Error   t value     Pr(>|t|)
a0 5.356784e-06 6.248832e-07  8.572457 0.000000e+00
a1 7.133747e-02 1.527635e-02  4.669799 3.014948e-06
a2 6.043681e-02 1.758322e-02  3.437187 5.877894e-04
b1 8.336334e-01 1.321599e-02 63.077650 0.000000e+00
```

- The sum of squared error is 3824.59
- There were two models that converged, however neither had the lowest SSE. The lowest SSE out of the two models that converged was the GARCH(1,2) model, which was selected as the final model.

Model Diagnoistics



The data is from a equally weighted stock portfolio collected between 1/1/2005 to 3/21/2020




```
    Shapiro-Wilk normality test

data:  na.omit(residuals(cpt2.final))
W = 0.98386, p-value < 2.2e-16


    Jarque Bera Test

data:  na.omit(residuals(cpt2.final))
```

```
X-squared = 566.49, df = 2, p-value < 2.2e-16
```

```r
skewness(na.omit(residuals(cpt2.final)))
```

```
[1] -0.2826009
```

```r
kurtosis(na.omit(residuals(cpt2.final)))
```

```
[1] 1.798094
```

Analysis

```r
mean(na.omit(cpt2.final$residuals))
```

```
[1] 0.04099326
```

```r
sd(na.omit(cpt2.final$residuals))
```

```
[1] 0.9989753
```

- The sample mean of the residuals from the final GARCH model is .041, with a sd of 1.

Question 10

Problems with Code

A major problem that came up with the second half of the project was show to handle residuals that were NA. To handle them in my portfolio analysis in question 6, I converted the Na's to zero, in order to perform the optimization. In reality, this may not have been the best way to handle this, maybe a better way would be to remove the dates that included NA's.

I also could not find a good code online to optimize the best linear combination of portfolio weights. I did not want to rely on a package that I did not totaly understand. To combat this, I just relied on randomly generating numbers based on the uniform distribution, and then making sure they sum to 1. I ran 5000 of these simulations with different seeds for each problem, however there is still a chance that I did not find the best combination.

Comparison between #8 & #9

The mean return for the optimal portfolio is about .01 higher than the equally weighted portfolio, and both share about the same standard deviation of 1.

Looking at the residual analysis, both residuals are normally distributed, however the the residuals for the equally weighted portfolio shows more skewness in the QQplot and from the test. The equally weighted portfolio shows more residuals on the left side, while the optimal portfolio shows more of a balance for both sides.