Analyzing AMD and Tesla Stock Prices to Make a Purchase Decision

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1 Abstract

This project aims to identify which stock, AMD or Tesla, is a better idea to purchase. Various models (AR - autoregressive, MA - moving average, and GARCH) will be used to analyze the stocks and gain more insight on which is a better buy. From analysis, it was seen that Tesla stock is trending generally upward. It was also seen that an increase in Tesla's price affects Tesla's volatility less than an increase in AMD's price affects AMD's volatility. In other words, Tesla seems to be going up, and when it does go up, uncertainty in its stock increases less than with AMD. For these reasons, Tesla seems to be the better buy.

2 Introduction

The purpose of this study is to analyze stocks using the skills covered in Stat 461: Financial Statistics. The course covered many types of models that will aid in stock analysis, such as AR, MA, and GARCH models. This project will analyze two stocks, AMD and Tesla, using these models and the statistics they provide to make a decision on which of the two is a better idea to purchase. Analysis is necessary because it is not easy to know just by looking at a stock's historical price how it may perform in the future, or how the price of the stock will fluctuate. With this analysis, I hope to identify which stocks generally trend upwards, and which stocks are more volatile. After analysis, the project will be recommending which stock is a better choice to invest in.

The historical data for these stocks will be collected from the Yahoo Finance site. The time window for historical data that was used for AMD was from 12/05/2000 to 12/05/2020. Data is not available back to 12/05/2000 for Tesla, so instead, data was used from the start of the company going public on the stock market (6/30/2010) to 12/05/2020.

For analysis, as mentioned before, the AR, MA, and GARCH models will be used. These models will be fit where applicable, on the log returns of the AMD and Tesla stocks. Verification that the models are fitting the data well will be done using Ljung-Box tests to check for serial correlations in the residuals of the models. If a model performs well, there should be an observable decrease in the amount of serial correlations in the squared and non-squared terms of log returns, and the models' residuals (i.e. if serial correlations are observed in the log returns, the models applied should learn and 'remove' these serial correlations).

3 Theoretical Analysis

As mentioned before, this project will analyze two stocks separately to be able to check which one is a better idea to invest money in. For this reason, and to make it clear which models/statistics apply to which stocks, there will be separate subsections for each stock.

3.1 AMD

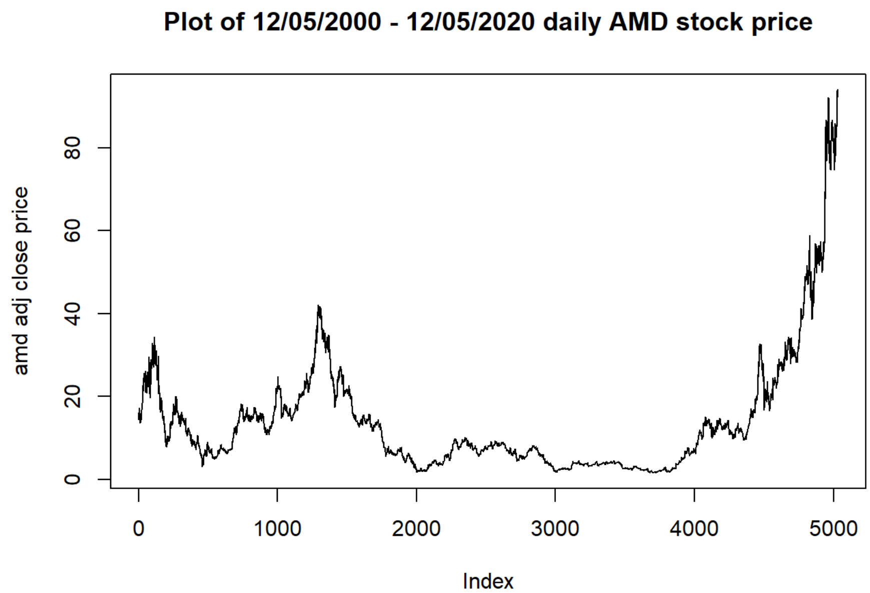

Figure 1: Plot of AMD stock price.

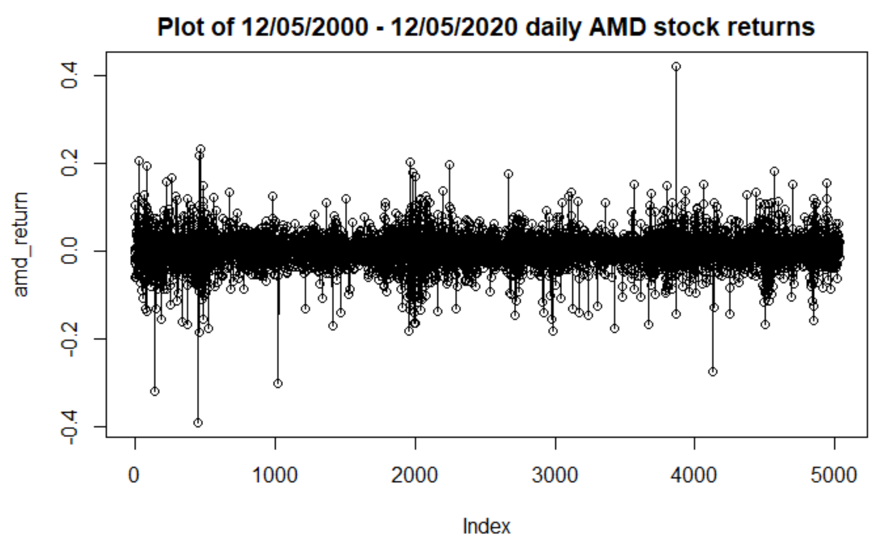

Figure 2: Plot of AMD stock log returns.

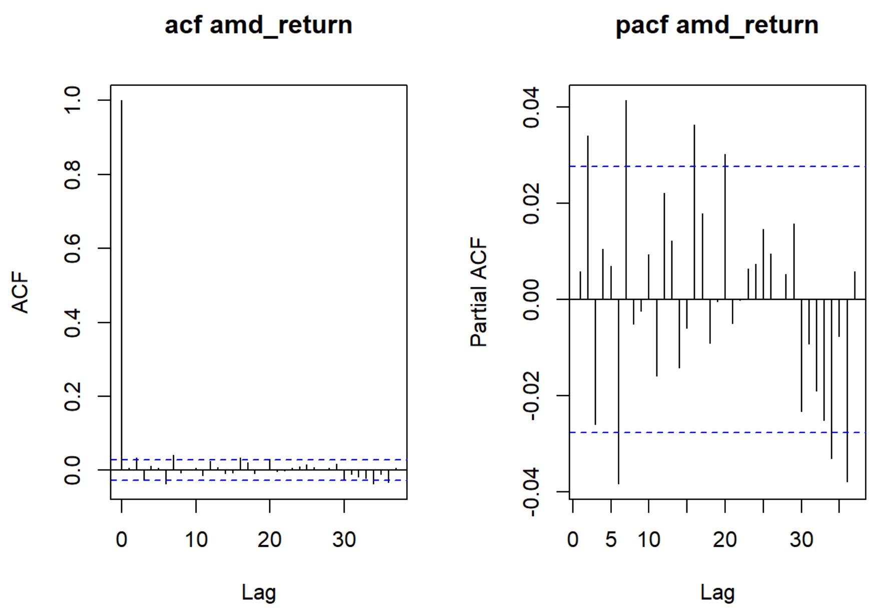

Figure 3: ACF and PACF plots of AMD log returns.

[mean: 0.000372543] [sd: 0.03923543] [skewness: -0.1897285] [kurtosis: 12.57562]

A two-sided t-test was performed to check if the mean of the return series is different from 0. After performing the two-sided t-test, and seeing a p-value of 0.5007, we fail to reject the null hypothesis (that the mean is different from 0). Since the mean of the returns seems to not be significantly different from 0, no MA (moving average) model will be applied.

The above ACF and PACF plots of the log AMD returns seems to indicate that there is serial correlation in the non-squared term. To check if the correlations seen in the plots is significant, the Ljung-Box test will be performed for 20 lags. The p-value of this Box test was 0.001506. Therefore, we must reject the null hypothesis (that the correlation for 20 lags all equal 0). Since the correlations are not equal to 0, an AR (autoregressive) model will be applied.

To check how many lags to include in the AR model, we check the AIC and BIC for AR(1) to AR(20). The best model should have the lowest AIC or BIC value. After fitting all 20 AR models, the one with the lowest AIC was AR(7), and the one with the lowest BIC was AR(1). Since visual inspection of the ACF and PACF plots seems to indicate that there is correlation more than 1 lag back, the AR(7) model will be used.

A Ljung-Box test can be performed on the residuals of the AR(7) model to check if the correlations in the non-squared term were successfully learned by the model. The fitdf parameter was specified as 7 since an AR(7) model was used. After performing the test, a p-value of 0.106 was found. With a significance level of .1, we fail to reject the null hypothesis (meaning that it seems like the correlations were learned by the model).

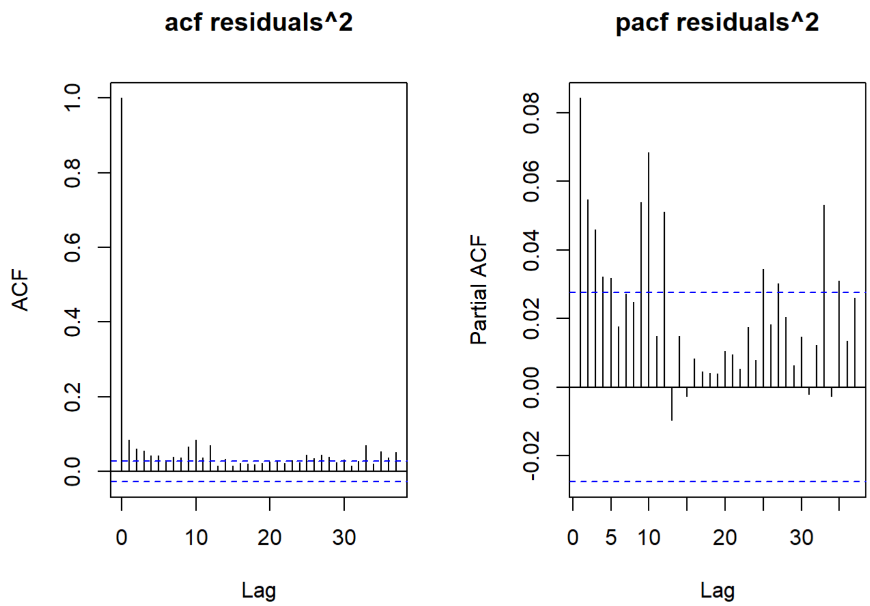

Figure 4: ACF and PACF of AMD AR(7) model residuals squared.

A Ljung-Box test can also be performed on the squared residuals of the AR(7) model to check for serial correlations in the squared term, and again, the fitdf=7 parameter will be used. The test results show a p-value less than 2.2e-16. This means that we reject the null hypothesis (that the correlations between the residuals squared is not 0). Based on the results of the Box test, and the ACF/PACF plots of the squared residuals (shown above), it seems like a GARCH model should be applied.

The first GARCH model that will be fit is the standard GARCH(1,1), with mean model of AR(7), and using the normal distribution. It is clear from the QQ-plot (on right) that when fitting the GARCH model, using normal distribution will not work. The tails of the normal distribution are not heavy enough. This makes sense because the kurtosis (calculated earlier) for the log AMD returns was around 12.

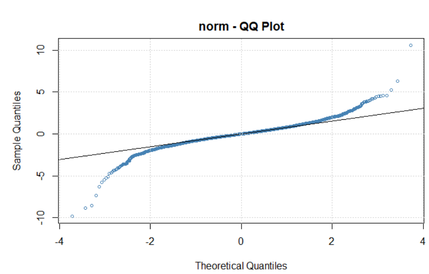

Figure 5: QQ-plot of AMD AR(7)-GARCH(1,1)-norm model.

The second GARCH model that will be fit is the standard GARCH(1,1), with mean model of AR(7), and using the skewed student's t-distribution. The reason for using a skewed t-distribution and not a standard t-distribution is because the skewness of the log AMD returns was around -.2. After fitting the second GARCH model, the parameters for the model's skew and shape are around 1 and 4 respectively, and the QQ-plot (shown below) looks normal.

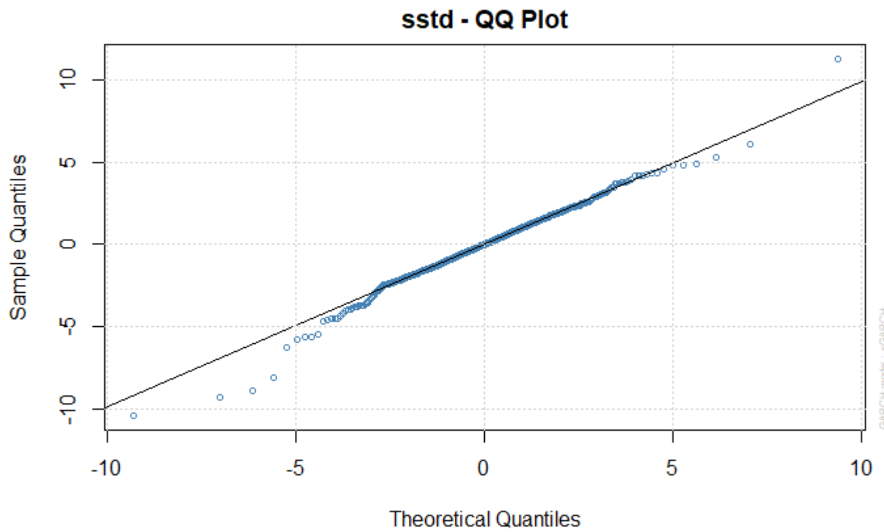

Figure 6: QQ-plot of AMD AR(7)-GARCH(1,1)-sstd model.

The third GARCH model that will be fit is the (exponential) eGARCH(1,1), with mean model of AR(7), and using the skewed student's t-distribution. The reason for fitting this model is because we know that it is common for stock volatility to be affected more from negative returns than positive returns. This is called 'leverage effect'. The standard GARCH model used previously does not capture leverage effects. After fitting the third GARCH model, we can see the news impact curve (shown below). It seems to confirm what is thought to be common with stocks; the effects of negative returns on volatility are greater than the effects of positive returns.

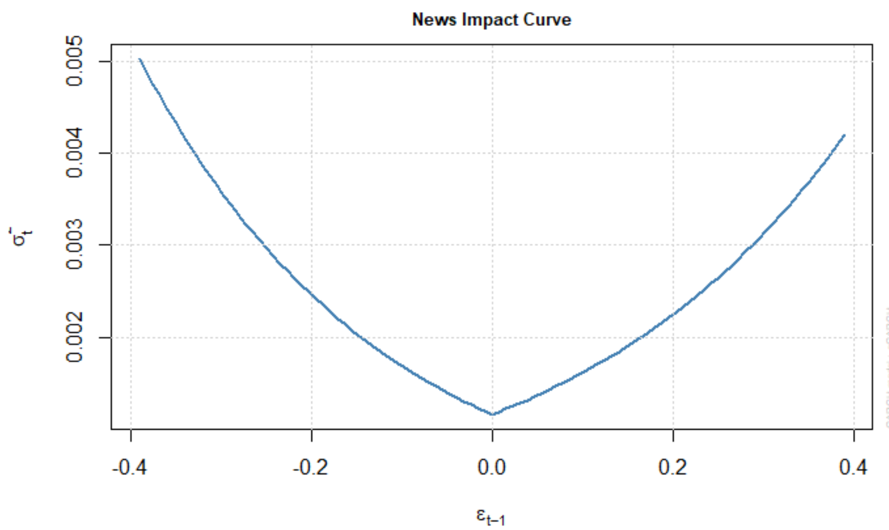

Figure 7: News impact curve of AMD AR(7)-eGARCH(1,1)-sstd model.

3.2 TSLA

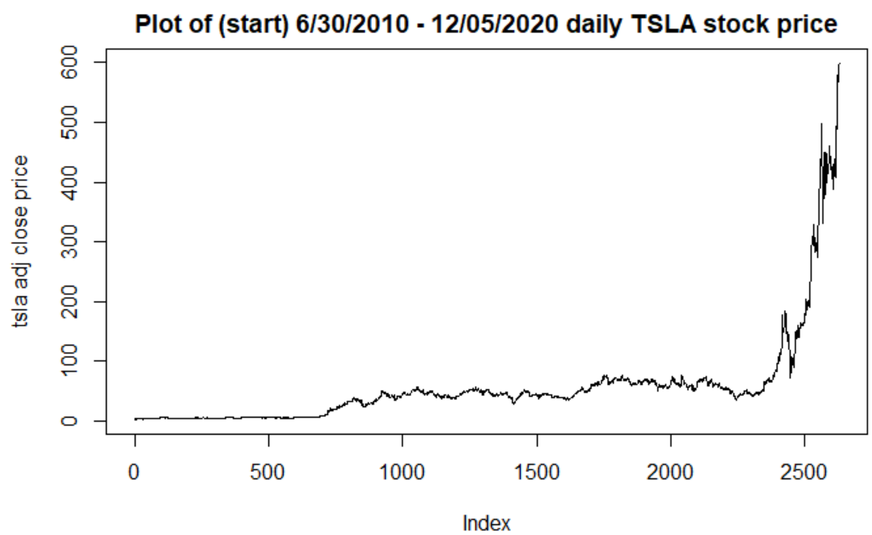

Figure 8: Plot of Telsa stock price.

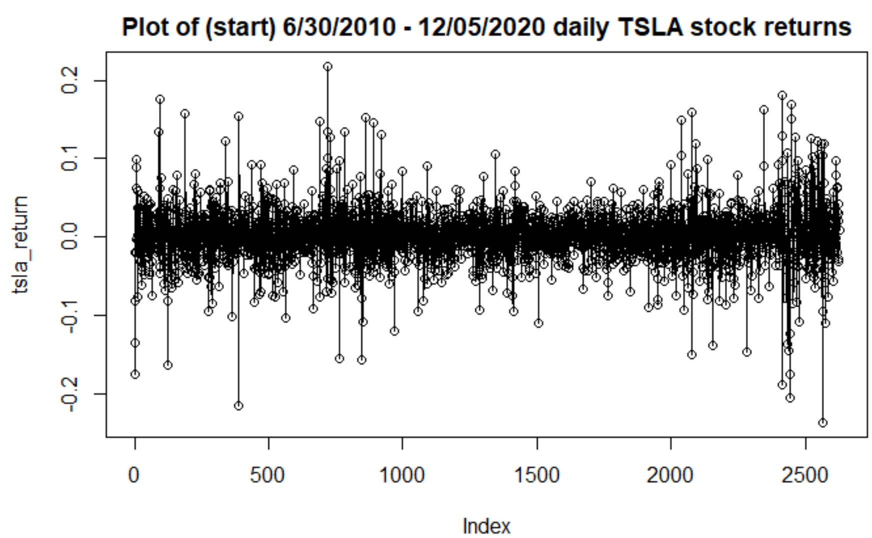

Figure 9: Plot of Tesla stock log returns.

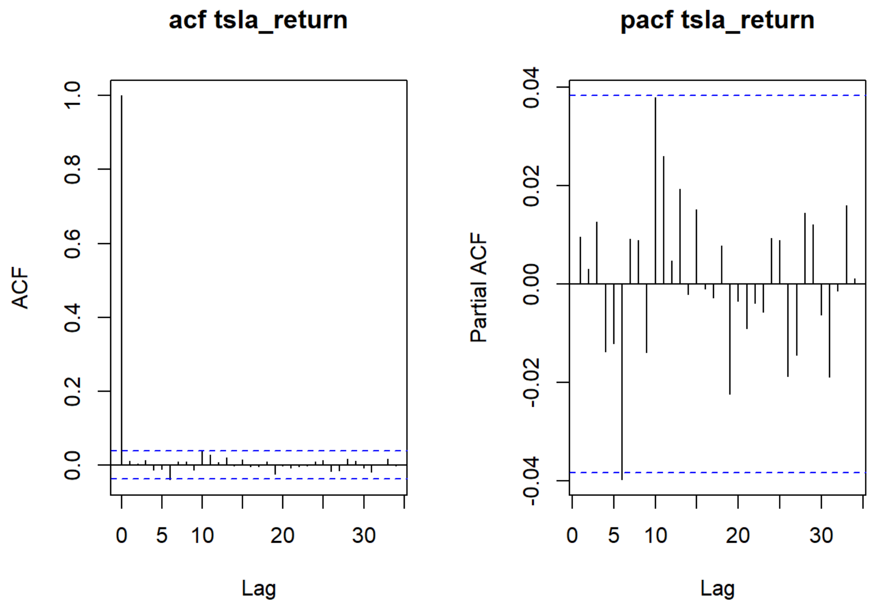

Figure 10: ACF and PACF of Tesla log returns.

[mean: 0.001840054] [sd: 0.0353058] [skewness: -0.03128846] [kurtosis: 9.099144]

After performing a two-sided t-test to check if the mean of the log returns is different from 0, a p-value of 0.0076 was seen. Based on this, we must reject the null hypothesis. Since the mean of the log returns of the Tesla stock appears to be different from 0, a MA (moving average) model will be employed. To check how many lags to include for the MA model, we check the AIC and BIC for MA(1) to MA(5). The model with the lowest AIC and BIC was MA(1).

Checking the above ACF and PACF plots of the log Tesla returns seems to indicate that there is no significant serial correlation in the non-squared term (since none of the bars seem to go far outside the bands of the plots). For this reason, no AR model needs to be applied.

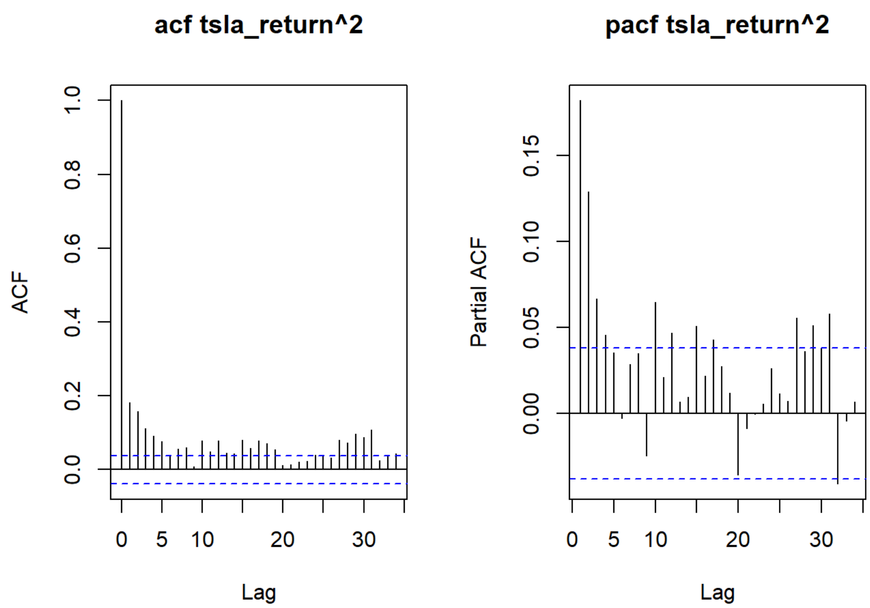

Figure 11: ACF and PACF of Tesla MA(1) model residuals squared.

Since the above ACF and PACF plots of the Tesla squared log returns clearly indicates there is serial correlation in the squared term, a GARCH model will be applied. After fitting an MA(1)-GARCH(1,1) model using the normal distribution, we can observe the norm-QQ Plot, shown to the right. The plot indicates, that using a normal distribution for the GARCH model is not sufficient (the tails of the normal distribution are not heavy enough).

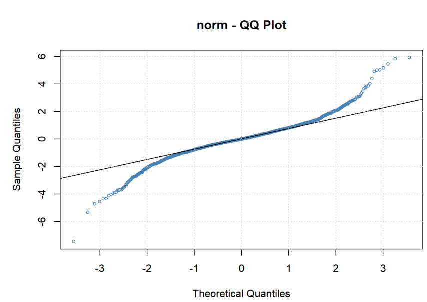

Figure 12: QQ-plot of Tesla MA(1)-GARCH(1,1)-norm model.

The second GARCH model that will be fit is an MA(1)-GARCH(1,1) model using the skewed student's t-distribution. After fitting this model, the parameters for the model's skew and shape are around 1 and 3.5 respectively. We can see from the following QQ-plot, that the tails of the t-distributions are heavy enough.

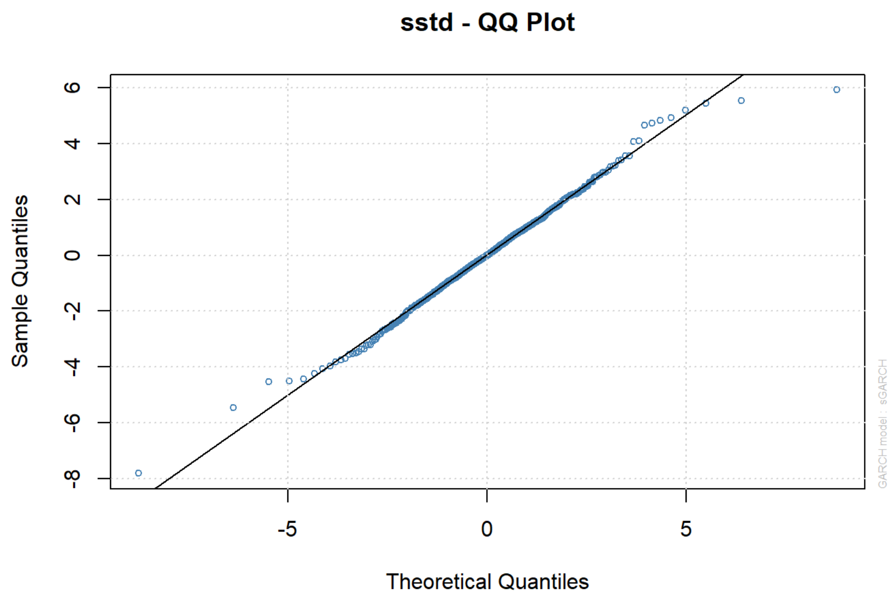

Figure 13: QQ-plot of Tesla MA(1)-GARCH(1,1)-sstd model.

None of the GARCH models fit on the Tesla log returns capture leverage effects, so the third GARCH model that will be fit is an MA(1)-eGARCH(1,1) model with skewed student's t-distribution. After fitting this model, we can observe that the News Impact Curve indicates that negative returns have a greater effect on future volatility. It is interesting to note that (for both AMD and Tesla), the farther the return is from 0, the greater the effect on future volatility.

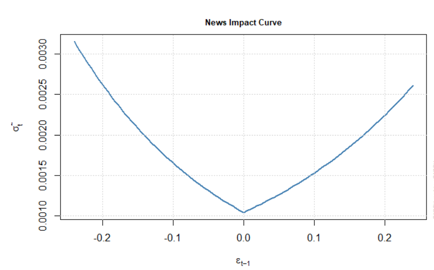

Figure 14: News impact curve for Tesla MA(1)-eGARCH(1,1)-sstd model.

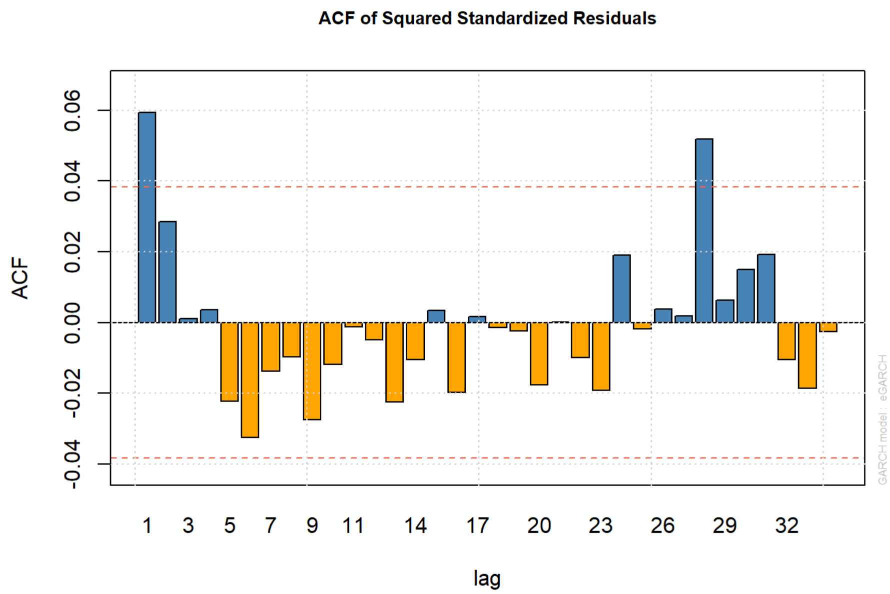

Figure 15: ACF plot of Tesla MA(1)-eGARCH(1,1)-sstd model's squared standardized residuals.

Based on the above ACF plot of squared standardized residuals from the MA(1)-eGARCH(1,1) model with skewed student's t-distribution, it seems like there is still some significant correlation in the squared term that the model was not able to capture. Despite the recommendation to use only GARCH(1,1) type models, we can see what happens if a GARCH(2,1) model is applied (since the correlation appears to be at lag 2).

After fitting an MA(1)-eGARCH(2,1) model with skewed student's t-distribution, we can check the ACF plot (on right) again and observe that there is no longer significant serial correlation in the squared term (there is something around lag 28, but this is very far out in the plot). Another interesting thing to note is that the news impact curve (below) has changed, in that the leverage effect on volatility of negative returns is much stronger than was seen before.

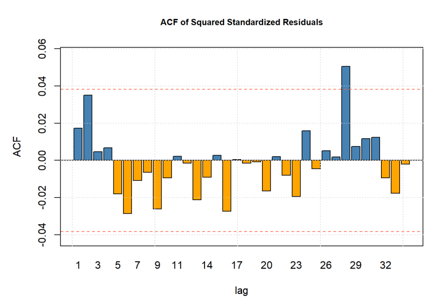

Figure 16: ACF plot of Tesla eGARCH(2,1)-sstd model's squared standardized residuals.

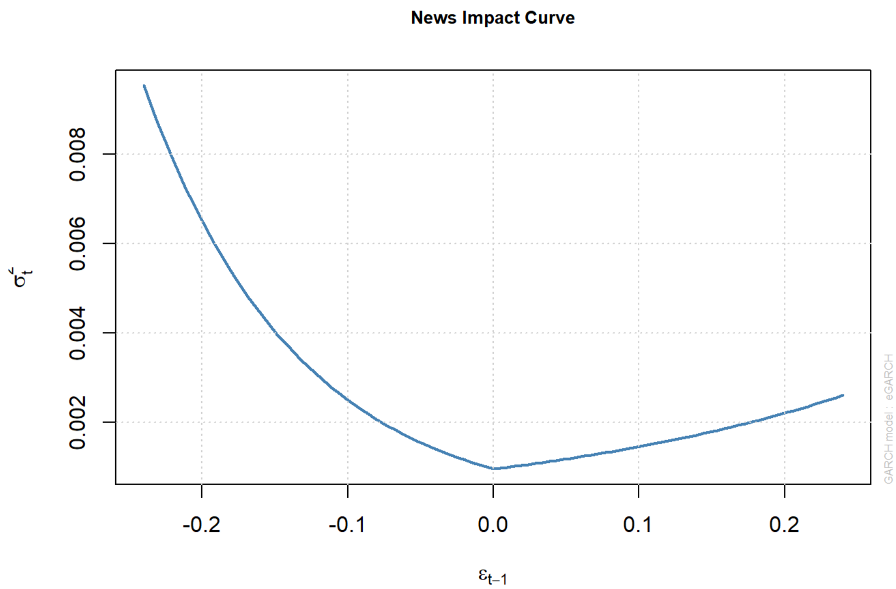

Figure 17: News impact curve for Tesla eGARCH(2,1)-sstd model.

4 Model Validation

Similarly to the 'Theoretical Analysis' this section will be split into separate validation sections for each stock being analyzed.

4.1 AMD

To validate the final AR(7)-eGARCH(1,1) model (with skewed student's t-distribution) that was fit on the AMD log returns, we can look at the ACF plots of the standardized residuals (shown below). Since the correlation bars stay relatively within the red-dotted bands, it seems like the final model has fit the data well.

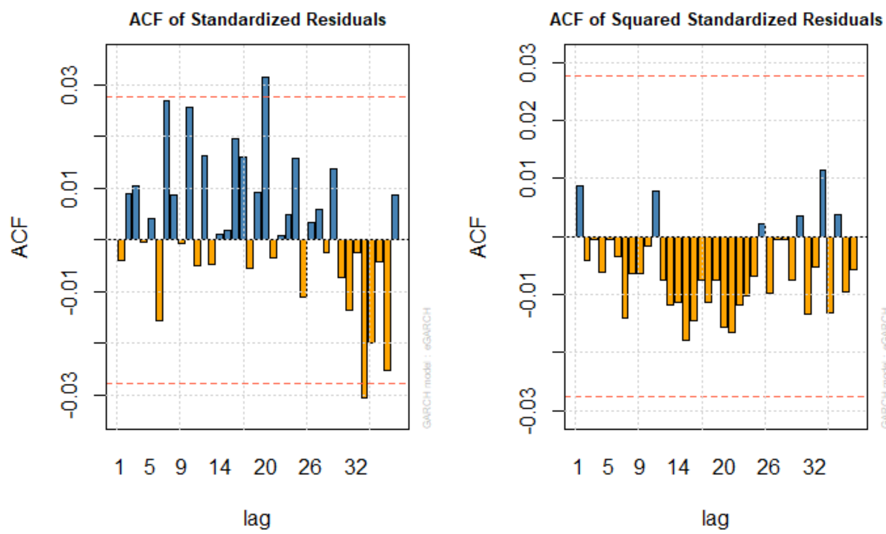

Figure 18: ACFs of AMD eGARCH(1,1)-sstd model standardized residuals.

We can go further to check if the final model has fit the data well by checking the results of the weighted Ljung-Box Tests on the standardized residuals and squared residuals. Since all of the p-values are very high, it appears that the final model has fit the data well.

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                          statistic p-value
Lag[1]                      0.08229  0.7742
Lag[2*(p+q)+(p+q)-1][20]    8.39622  0.9999
Lag[4*(p+q)+(p+q)-1][34]   14.64503  0.8194
d.o.f=7
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                         statistic p-value
Lag[1]                      0.3905  0.5320
Lag[2*(p+q)+(p+q)-1][5]     0.5344  0.9522
Lag[4*(p+q)+(p+q)-1][9]     1.0170  0.9855
d.o.f=2
```

Figure 19: Ljung-Box test results on AMD eGARCH(1,1)-sstd model standardized residuals.

4.2 TSLA

To validate the final MA(1)-eGARCH(2,1) model (with skewed student's t-distribution) that was fit on the Tesla log returns, we can check the results of the weighted Ljung-Box tests on the standardized residuals and squared residuals, as well as the information criteria (below, right side). We can also see the information criteria, and the results of the same Ljung-Box tests for the MA(1)-eGARCH(1,1) model (below, left side). Notice that the eGARCH(1,1) model Ljung-Box tests all had very low p-values for the standardized squared residuals, which indicates that the correlations were not learned by the model, while the Ljung-Box tests for the eGARCH(2,1) model have high p-values. Additionally, we can see the AIC for the eGARCH(1,1) model is worse than the AIC for the eGARCH(2,1) model. Since it looks like the final model has 'learned' the correlations in the squared and non-squared terms, it appears the final model has fit the data well.

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

Akaike       -4.1521
Bayes        -4.1342
Shibata      -4.1521
Hannan-Quinn -4.1456

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                     0.3675  0.5444
Lag[2*(p+q)+(p+q)-1][2]    0.4492  0.9752
Lag[4*(p+q)+(p+q)-1][5]    0.5102  0.9932
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic  p-value
Lag[1]                      9.238 0.002371
Lag[2*(p+q)+(p+q)-1][5]    11.214 0.004471
Lag[4*(p+q)+(p+q)-1][9]    13.547 0.007949
d.o.f=2
```

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

Akaike       -4.1538
Bayes        -4.1314
Shibata      -4.1538
Hannan-Quinn -4.1457

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      1.274  0.2591
Lag[2*(p+q)+(p+q)-1][2]     1.373  0.5101
Lag[4*(p+q)+(p+q)-1][5]     1.445  0.8598
d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                         statistic p-value
Lag[1]                      0.7871  0.3750
Lag[2*(p+q)+(p+q)-1][8]     5.0556  0.3453
Lag[4*(p+q)+(p+q)-1][14]    7.1954  0.4808
d.o.f=3
```

Figure 20: Ljung-Box test results on Tesla eGARCH(1,1)-sstd model standardized residuals (left) and eGARCH(2,1)-sstd model (right).

5 Discussion

GARCH models are useful in analyzing time series data, and in our application, can predict the future volatility of the stock it is applied to. Given that generally, when people invest in stocks, they are not looking to engage in micro-trading (buying and selling stocks based on daily, small fluctuations in price), it seems far more useful to look at the unconditional mean and variance of the model (this is what the predictions trend toward as we predict farther in the future). If one were to keep updating the models, and watch for jumps in predicted volatility (for the near future), you could use that information to decide to sell the stock (or buy) during times of increased volatility.

The unconditional mean for Tesla's log returns is 0.001596622, and the unconditional variance is 0.001133352. The unconditional mean for AMD's log returns is 0.0005177646, and the unconditional variance is 0.001269549. It appears that the unconditional variances for both stocks are about the same (only differ by around 0.00014), but the unconditional mean of the two stocks appear to be different (differing by about 0.001; AMD's u-mean is around 1/3 of Tesla's). This difference in mean makes sense since we chose to use an MA model for Tesla (since a t-test indicated the mean of it's log returns was different from 0).

6 Conclusion

The original question being addressed by this report is, which company's stock is a better idea to buy, AMD or Tesla? To answer this question, we applied models (AR, MA, and various GARCH) to the time series' of both company's returns (calculated from the adjusted closing stock price) in R (a statistical analysis software). After fitting various models, we were able to validate that the models fit the data well by checking the ACF plots of the model's residuals and squared residuals. We were also able to statistically verify that the correlations in the data were learned by the models by performing Ljung-Box tests. Since the goal of this project is to make a long-term purchase decision, there is no benefit in checking the short-term predictions that the models we fit are able to produce. Instead, we can look a the unconditional mean and variance to make a recommendation.

We observed that the unconditional variance for AMD and Tesla were around the same, while the unconditional mean of Tesla was notably higher than AMD (also, we employed an MA model for Tesla). This indicates that Tesla stock is trending more strongly upward than AMD. If we compare the news impact curves of both the AMD (page 5, bottom) and Tesla (page 11, top) models, we can see that the volatility for the Tesla stock is impacted less by 'good news' (positive returns) than AMD. For these reasons, Tesla stock appears to be the better buy when compared to AMD.

7 Acknowledgements

As indicated in the 'References' section, the only source used for this project was the course materials provided by the Stat 461 class.

8 References

[1] Yazhen Wang, 2020, Stat 461 Lecture Material and Supplementary R Code (available through course Canvas page)