LEE KONG CHIAN FACULTY OF ENGINEERING & SCIENCE

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GROUP ASSIGNMENT

UECM3243 TIME SERIES ANALYSIS

BACHELOR OF SCIENCE (HONOURS) ACTUARIAL SCIENCE
BACHELOR OF SCIENCE (HONOURS) FINANCIAL MATHEMATICS

TOP GLOVE CORPORATION BERHAD

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GROUP ASSIGNMENT (30%)

Assessment Form:

Criteria	**Distribution of score**	**Score**
Preliminary Study	35%	
GARCH Modelling	40%	
Alternative Approach for GARCH Modelling	10%	
Overall Assignment Criteria	5%	
Oral Presentation	10%	
TOTAL MARKS	100%	

* Points will be deducted based on the following aspects

Unethical practice/plagiarism.	(10%)
Not meeting the deadline.	(10%)
Not following the instructions.	(10%)

TOTAL MARKS AFTER DEDUCTION (IF ANY): __________

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Part I

(A) INTRODUCTION

Top Glove Corporation Bhd, operation base in Malaysia, was founded in 1991 and is the world's largest glove manufacturer. Top Gloves began as a small local firm with one factory and one glove production line has grown to account for 26% of the global rubber glove market. Top Glove's manufacturing plant is located in Malaysia, Thailand, Vietnam, and China, also with marketing offices in the United States, Germany, and Brazil. Top Glove is a one-stop glove sourcing center that offers more than a dozen latex and nitrile glove varieties. Top Glove's products are essential in the healthcare business, since they ensure human safety and aid in the saving of lives. Top Glove was listed on the Second Board of Bursa Malaysia in March 2001, then promoted within 14 months to the Main Board in May 2002 ("TOP GLOVE - Malaysian Brands", n.d.).

Over the years, Top Glove has grown at an enormous speed. Over 2,000 customers in 195 countries throughout Asia, Europe, the Middle East, Africa, and the Americas are served by the firm today. Their extensive selection of high-quality gloves helps them to satisfy the demands of the company's growing consumer base. Top Glove gloves are known for their high quality and affordable cost, and they comply with internationally recognized standards such as ASTM, EN, and ISO. Customers like the vast selection of items offered as well as the low-cost options that allow them to experience high quality without paying top dollar. Graph below show the share price of Top Glove over 20 years since listing in 2001 ("TOP GLOVE - Malaysian Brands", n.d.).

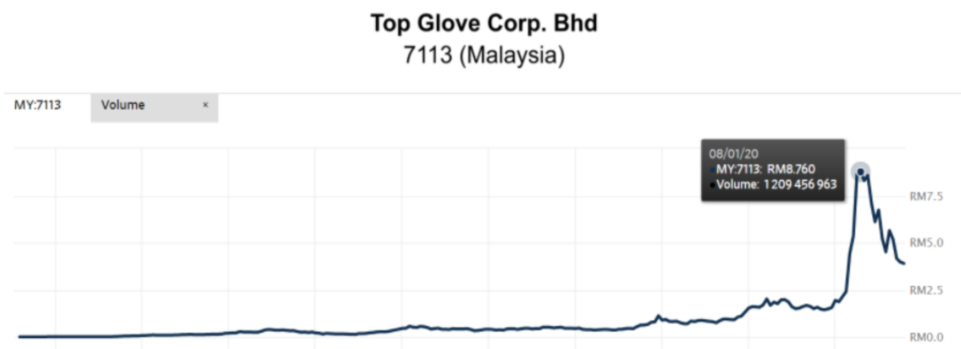


Figure 1.1.1 Share prices of Top Glove over the span of 20 years since 2001

Over the 20 years, Top Glove experience an increasing trend on their share price and experience a surge increase in 2020. The smoothed graph above shows a decreasing trend after the highest peak of share price (RM8.760) in January 2020 ("7113 | Top Glove Corp. Bhd Advanced Charting - WSJ", n.d.). Also, there is no seasonal variation from 2001 to 2019. The significant increase of share price in 2020 is because the global demand for disposable gloves is rapidly rising in these unprecedented times caused by the coronavirus pandemic. However, the share price of Top Glove decreased rapidly after the year 2020 because the supply of gloves had exceeded the demand. This is because all the existing glove makers have added many new production lines in each of their factories and constructed new factories. Moreover, many companies who are traditionally not in the glove business also constructed new factories to make gloves.

On the other hand, daily log returns time series based on the opening price shows that there is significant volatility cluster in year 2018. During this year, share prices experience a big drop and lead to the impact of volatility. Below discusses the reason for the price drop of Top Glove Corporation Bhd .

In July 2018, Top Glove’s share price falls because of its lawsuit against Adventa Capital Pte Ltd. Top Glove claimed that Adventa was reporting an overstatement of valuation and assets in the acquisition of another company, AspionSdn Bhd (The Star, 2018). They asked for a compensation of RM 714.9 million for that fraud. However, if Top Glove did not win this lawsuit, they would have to account the misinterpretation as a full provision, which will then reduce the company’s net profit and eventually the balance sheet. Therefore, investors and shareholders were afraid that losing the lawsuit will badly affect their returns from investing in Top Glove. Thus, they decided to sell the shares and share price fell.

However, one month before the lawsuit, Top Glove had achieved their best share price among the time interval selected (The Star, 2018). The reason that caused the surge of the share price was the increased demand on gloves. In the third financial quarter ended at 31 May, 2018, Top Glove earned sales revenue of RM 1.1 billion, which is 26.6% better as compared to third financial quarter in 2017. Also, Top Glove earned a net profit of RM 117.57 million. This is a 51.4% greater than the net profit of third quarter in 2017. At the same time, their sales volume also increased by 37% as compared to the third quarter in 2017. Therefore, investors believed that buying Top Glove's shares will guarantee a return since they were having an increasing profit at that time. Thus, the demand on the shares in that moment also increased, leading to an increment in the share prices.

(B) INITIAL ANALYSIS

Graphical Analysis

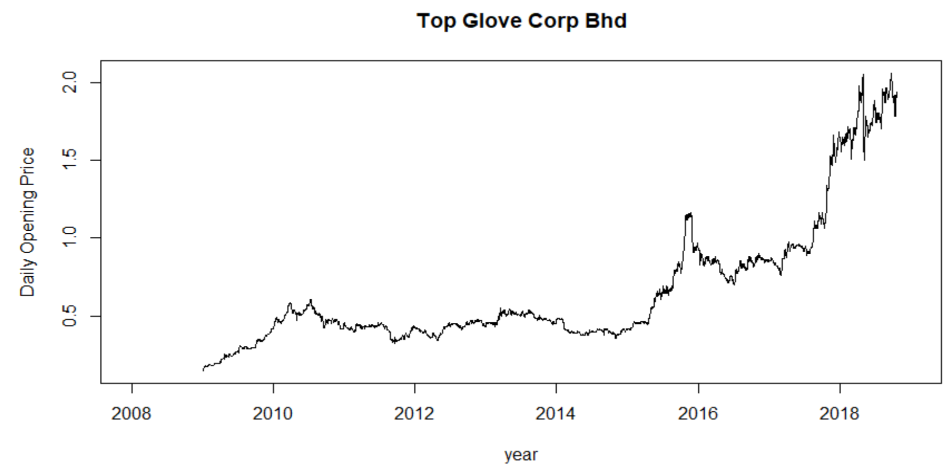


Figure 1.2.1 Time plot of daily opening prices of Top Glove Corp Bhd from Jan 2009 to Dec 2018

The time plot of the daily Top Glove Corporation Berhad opening price shows an overall of increasing trend. It is non-stationary in mean and variance. From the time plot of original series, it can be seen clearly that the fluctuation increase as one moves from left to the right on the graph. Until Aug 2015, the opening price was low as well as the fluctuations. From Aug 2015 until Jan 2016, the opening price increased and so did their variations. The same pattern continues from September 2017 until July 2018 where both opening price and variation are the largest. Thus, the variation in the magnitude of fluctuation with time is referred as non-stationary in variance.

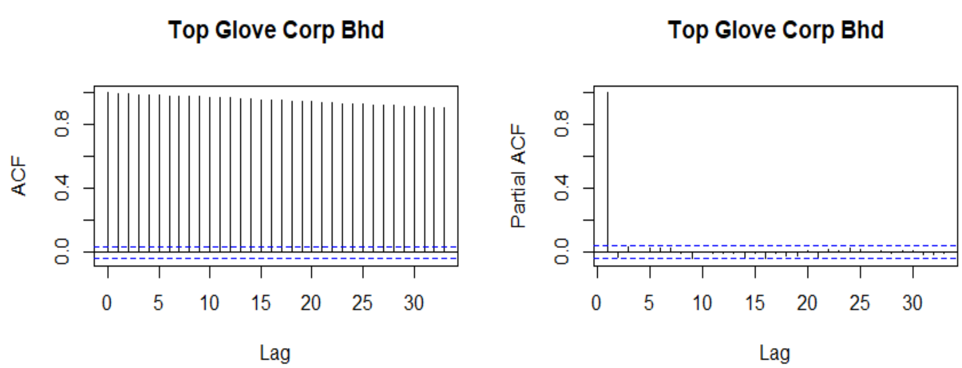


Figure 1.2.2 ACF and PACF of daily opening price of Top Glove Corp Bhd from Jan 2009 to Dec 2018

The ACF plot also displays the pattern of non-stationarity series, with a slow decrease in the size of autocorrelations. Besides, the PACF shown is also a typical nonstationary series with large spike close to 1 at lag 1. Thus, logarithmic transformation of data is suggested to achieve the stationarity of variance and first order differencing is required to transform the data into a stationary series which resembles white noise.

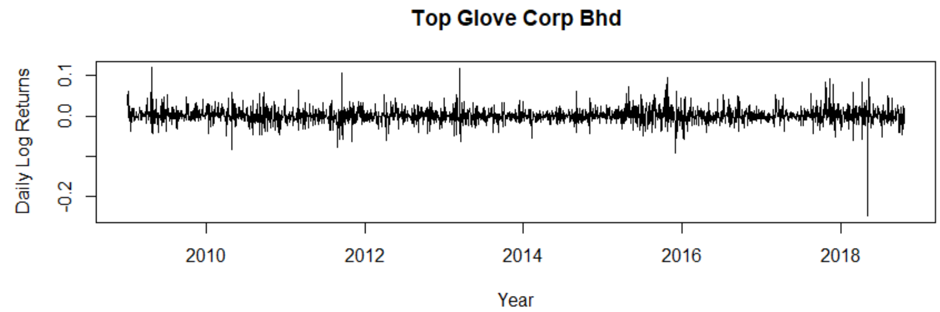


Figure 1.2.3 Time plot of daily log returns of Top Glove Corp Bhd from Jan 2009 to Dec 2018

The logged and differenced series appears to be stationary in mean and variance. Besides, the variation in the magnitude of fluctuation with time decrease. Furthermore, there are a few of volatility clusters exist which clearly show that volatility exist in the time series. However, the most significant volatility cluster was shown in July 2018. This is because of the leverage effect in which a big price drop has a greater impact on volatility than a big price increase. In July 2018, significant price drops from RM2.05 to RM 1.50, thus showing the impact on volatility.

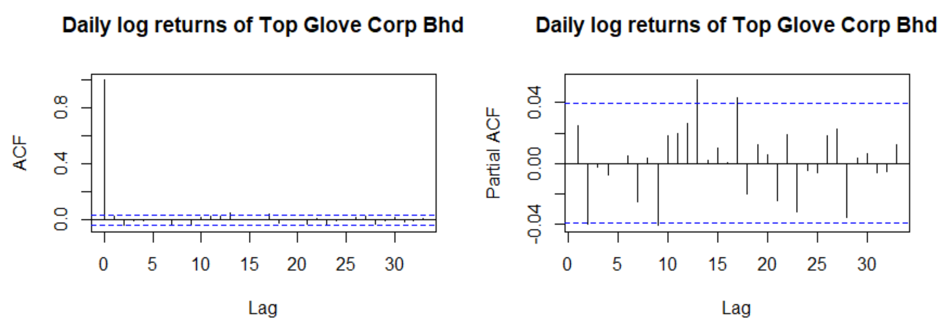


Figure 1.2.4 ACF and PACF of daily log returns of Top Glove Corp Bhd from Jan 2009 to Dec 2018

By considering the first 12 lags of the series, all of the ACF and PACF lies in the critical value. The pattern in the ACF plot shows that the data has transformed into a stationary series which resembles white noise. This shows that the daily changes of opening price are essentially a random amount uncorrelated with the previous day.

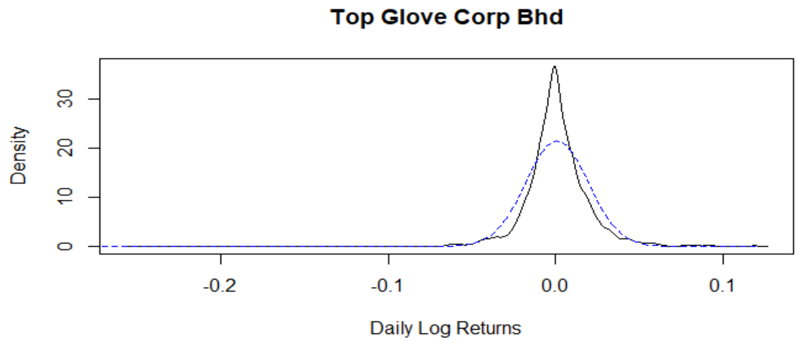


Figure 1.2.5 Empirical density function of daily log returns of Top Glove Corp Bhd from Jan 2009 to Dec 2018. Dashed line denotes the density function of a normal distribution with the same mean and variance.

The empirical density function of the daily log returns of Top Glove Corporation Berhad stock is shown by the solid line and the dashed line denotes the density function of a normal distribution with same mean and variance. The empirical density function has a very high peak and appears to be slightly skewed to the left with heavy tails than the normal density.

Test for the Significance of the Mean, μ

$\mathrm{H}_0: \mu = 0$

$\mathrm{H}_1: \mu \neq 0$

From the command basicStats of fBasics in Rmetrics, the test statistic, $t = 2.7514$.

$\alpha = 0.05, p - value = 0.005977 < \alpha$

Since p-value is less than alpha, we reject H_0 and conclude that the mean of daily Top Glove log returns is significant.

Besides, the 95% confidence interval which is (0.0002966297 , 0.0017682686) excludes zero suggesting to reject H_0.

Test for Skewness, S

$\mathrm{H}_0: S = 0$

$\mathrm{H}_1: S \neq 0$

From the command basicStats of fBasics in Rmetrics, the test statistic, $t_s = -9.837754$.

$with\ \alpha = 0.05, p - value \approx 0$ is less than α, we reject H_0 and conclude that the distribution of daily Top Glove log returns is skewed to the left. This supports the interpretation based on the empirical density function.

Test for Kurtosis, K

$\mathrm{H}_0: K = 3$

$\mathrm{H}_1: K \neq 3$

From the command basicStats of fBasics in Rmetrics, the test statistic, $t_k = 171.2987$.

With $\alpha = 0.05, p - value = 0$ which is lesser than α, we reject $H_0$and conclude that the distribution of daily Top Glove log returns has a heavy tail.

Test for Normality

H_0: The normality assumption of daily Top Glove log returns is true

H_1: The normality assumption of daily Top Glove log returns is not true

From the command normalTest in R, the test statistic, JB = $t_s^2 + t_k^2$ = 29496.1503

With $\alpha = 0.05, p - value \approx 0$ which is less than α, we reject H_0 and conclude that the normality assumption of daily Top Glove log returns assumption is not true.

(C) TESTS ON {Y_t}: SERIAL UNCORRELATION, DEPENDENCY, ARCH EFFECTS

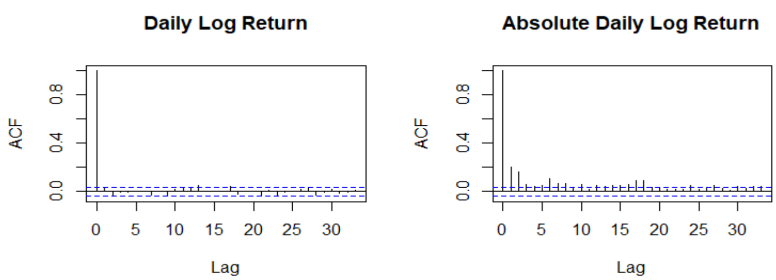


Figure 1.3.1 ACF of daily log return and absolute daily log return

Test for Serial Correlation

From the left side of figure above, ACF of first 12 lag lies in the critical value suggesting that the daily log return $\{Y_t\}$ series is serially uncorrelated. There exists only a marginally serially correlation at lag 13. Other than lag 13 all the lags do not exceed $\pm\frac{1.96}{\sqrt{2470}} = \pm 0.03945$.

We can further prove this statement using Ljung-Box test with lag=12.

$H_0: \rho_1 = \rho_2 = \cdots = \rho_{12} = 0 \; \#serially\ uncorrelated$

$H_1: \rho_i \neq 0 \; for\ i \in \{1,2,..,12\}$

From the Ljung-Box test, we get Q (12) =14.601 and p-value=0.264. Since p-value > α=0.05, therefore we do not reject H_0 and conclude that the daily log returns series is serially uncorrelated.

Dependency Test

From the right side of figure above, it suggests that the absolute daily log returns $\{|Y_t|\}$ is serially correlated. We can view from the ACF graph all the spikes are exceed $\pm\frac{1.96}{\sqrt{2470}} = \pm 0.03945$, which indicates that it is serially correlated.

We proceed further for Ljung-Box test with lag=12.

$H_0: \rho_1 = \rho_2 = \cdots = \rho_{12} = 0 \; \#serially\ uncorrelated$

$H_1: \rho_i \neq 0 \; for\ i \in \{1,2,..,12\}$

The statistics returns by the Ljung-Box shows Q (12) = 256.85 with p-value < 2.2 x 10^{-16}. Since p-value< α=0.05, therefore, we reject H_0 and conclude that the absolutes log return is serially correlated and it is a dependent series.

According the above two tests, we conclude that the daily log returns of Top Glove stock are serially uncorrelated but dependent.

ARCH Effect Test

From the t-test we perform on the mean of log return of Top Glove concludes that the mean is statistically significant from zero. We are going to take into consideration of the mean in building our model. Therefore, we use $\epsilon_t = Y_t - \overline{Y_t}$ be the residuals of the mean equation. The series of $\{\epsilon_t^2\}$ is used to check for conditional heteroscedasticity, Ljung-Box test is chosen.

$H_0: \rho_1 = \rho_2 = \cdots = \rho_{12} = 0$ $\#serially\ uncorrelated$

$H_1: \rho_i \neq 0\ for\ i \in \{1,2,..,12\}$

We reject H_0 as Q (12) =67.935 and p-value < 7.782 x 10^{-10}. Since p-value< α=0.05, therefore we reject H_0 and conclude that $\{\epsilon_t^2\}$ series is not serially uncorrelated.

We can say that the log return series of the Top Glove stock exhibits an ARCH effect.

Part II

(A) GARCH MODELLING FOR {Y_t}

(1) Gaussian GARCH (1,2)

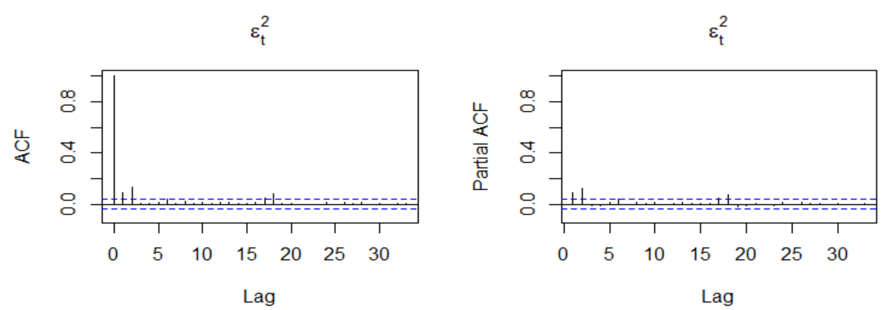


Figure 2.1.1 ACF and PACF of the squared series of mean-adjusted returns

Based on the ACF of the squared series of mean-adjusted returns, we see significant correlations at lag 1, and lag 2. Besides, based on the PACF of the squared series of mean-adjusted returns, we see significant correlations at lag 1, and lag 2. However, only marginal significant in PACF plot were shown Thus, we entertain a GARCH (1,2) model for the Daily log returns of Top Glove Corporation Berhad stock.

Consequently, we specify the model

$$Y_t = 0.00053 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim N(0,1)$$

$$\sigma_t^2 = 0.00001 + 0.110997\epsilon_{t-1}^2 + 0.52059\sigma_{t-1}^2 + 0.34852\sigma_{t-2}^2$$

Where the estimates meet the general requirement of an GARCH (1,2) model, the estimate μ appears to be statistically insignificant at the 5% level. Therefore, the model can be simplified.

Dropping the insignificant parameter, we obtain the revised model

$$Y_t = \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim N(0,1)$$

$$\sigma_t^2 = 0.00001 + 0.11248\epsilon_{t-1}^2 + 0.51795\sigma_{t-1}^2 + 0.34963\sigma_{t-2}^2$$

Where the standard error of the parameters $\{\alpha_0, \alpha_1, \beta_1, \beta_2\}$ are 0.000002, 0.01641, 01378, and 0.1262. All the estimates are statistically significant at the 5% level.

Indeed, the Ljung-Box statistics of standardized residuals give Q(10) = 6.039479 with p-value = 0.8119355, and Q(15) = 13.46536 with p-value = 0.566401. On the other hand, the Q- statistics of $\{\tilde{\varepsilon}_t^2\}$ give Q(10) = 4.427704 with p-value = 0.9259971, and Q(15) = 5.543855 with p-value = 0.9864345.

Except for the normality test, model checking statistics indicate that this Gaussian GARCH (1,2) model is adequate for Y_t. AIC for this model is -5.240867

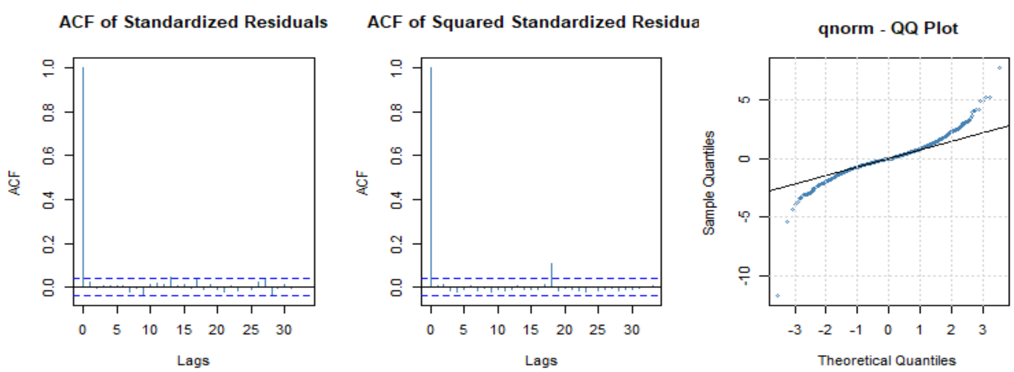


Figure 2.1.2 ACF of standardized residuals, ACF of squared standardized residuals and QQ Plot (Gaussian GARCH(1,2))

Based on the ACF of standardized residuals and squared standardized residuals, by considering the first 12 lags, both ACF plots shows that acf of $\{\tilde{\varepsilon}_t\}$ and acf of $\{\tilde{\varepsilon}_t^2\}$ are serially uncorrelated and indicate that the mean equation and volatility equation are adequate. The QQ plot of standardized residuals shows that the points deviate from straight line suggesting model is not appropriate and normality assumptions is rejected.

(2) Student *t* GARCH (1,2)

Thus, we obtain another model using the student t innovations.

we specify the model as

$$Y_t = 0.00026 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t_{v=3.36}^*$$

$$\sigma_t^2 = 0.00004 + 0.22947\epsilon_{t-1}^2 + 0.49412\sigma_{t-1}^2 + 0.21566\sigma_{t-2}^2$$

Where the estimates meet the general requirement of an GARCH (1,2) model, the estimate μ appears to be statistically insignificant at the 5% level. Therefore, the model can be simplified.

Dropping the insignificant parameters, we obtain the revised model

$$Y_t = \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t^*_{v=3.34}$$

$$\sigma_t^2 = 0.00004 + 0.23247\epsilon_{t-1}^2 + 0.49063\sigma_{t-1}^2 + 0.21754\sigma_{t-2}^2$$

Where the standard error of the parameters $\{\alpha_0, \alpha_1, \beta_1, \beta_2\}$are $0.00001,\ 0.04867,\ 01217,$ and $0.2547.$ All the estimates are statistically significant at the 5% level, and t_v^* denotes a standardized Student t distribution with v degrees of freedom,

Indeed, the Ljung-Box statistics of standardized residuals give Q(10) = 5.808096 with p-value = 0.8311201, and Q(15) = 15.02972 with p-value = 0.4492788. On the other hand, the Q- statistics of $\{\tilde{\varepsilon}_t^2\}$ give Q(10) = 1.926546 with p-value = 0.9968727, and Q(15) = 2.332181 with p-value = 0.9999187.

Model checking statistics show that this fitted GARCH (1,2) model is adequate for log return series. The AIC for this model is -5.449111 and implied unconditional variance of Y_t is

$$\frac{\alpha_0}{1-(\alpha_1+\beta_1+\beta_2)} = \frac{0.00004}{1-(0.23247+\ 0.49063+0.21754)} = 0.00674$$

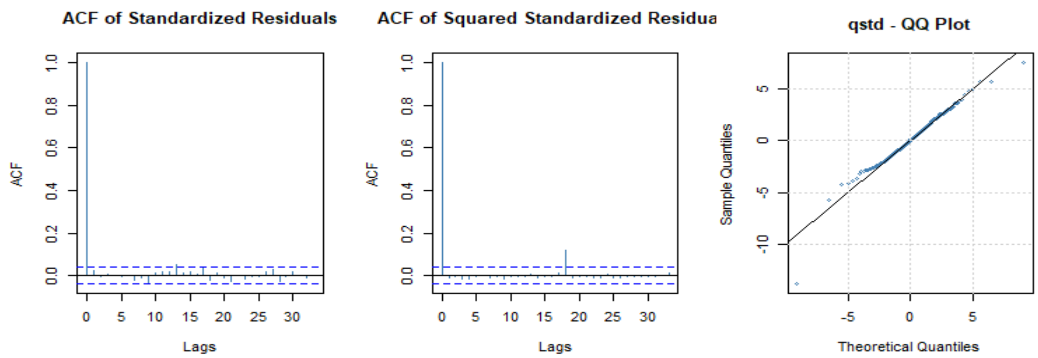


Figure 2.1.3 ACF of standardized residuals, ACF of squared standardized residuals and QQ Plot (Student t GARCH(1,2))

Based on the ACF of standardized residuals and squared standardized residuals, by considering the first 12 lags, both ACF plots shows that acf of $\{\tilde{\varepsilon}_t\}$ and acf of $\{\tilde{\varepsilon}_t^2\}$ are serially uncorrelated and indicate that the mean equation and volatility equation are adequate. The QQ plot of standardized residuals shows that the points deviate lesser from straight line compared to the gaussian model suggesting model seems to be appropriate.

(3) Skew Student *t* GARCH (1,1)

Since the skewness of log returns is -0.4848676, which has a t-ratio of -9.837754 shows that the daily log returns are negatively skewed, we model this skewness with the skew Student t distribution for the innovations e_t.

Thus, we obtain another model using the skew student t innovations.

we specify the model as

$$Y_t = 0.0007 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t^*_{\xi=1.06,\ v=3.38}$$

$$\sigma_t^2 = 0.00004 + 0.2208\epsilon_{t-1}^2 + 0.50382\sigma_{t-1}^2 + 0.2087\sigma_{t-2}^2$$

Where the estimates meet the general requirement of an GARCH (1,2) model, the estimate β_2 appears to be statistically insignificant at the 5% level. Therefore, the model can be simplified.

Dropping the insignificant parameter, we obtain the revised model

$$Y_t = 0.00072 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t^*_{\xi=1.07,\ v=3.38}$$

$$\sigma_t^2 = 0.00004 + 0.19326\epsilon_{t-1}^2 + 0.74323\sigma_{t-1}^2$$

Where the standard error of the parameters $\{\mu, \alpha_0, \alpha_1, \beta_1\}$ are $0.00032, 0.00001, 0.04103,$ and 0.04934. All the estimates are statistically significant at the 5% level, and $t^*_{\xi,v}$ denotes a standardized skew Student t distribution with skew parameter, ξ and degrees of freedom,v.

Indeed, the Ljung-Box statistics of standardized residuals give Q(10) = 6.040436 with p-value = 0.8118546, and Q(15) = 15.68598 with p-value = 0.4032227 On the other hand, the Q- statistics of $\{\tilde{\varepsilon}_t^2\}$ give Q(10) = 1.587939 with p-value = 0.9986344, and Q(15) = 1.907979 with p-value = 0.9999783

Model checking statistics show that this GARCH (1,1) model is adequate for log return series. The AIC for this model is -5.450186.

Note that the estimate of skew parameter is 1.066 with standard error of 0.02679. The hypothesis of interest is

<u>Testing for skew parameter</u>

$H_0: \xi = 1$

$H_1: \xi \neq 1$

$t = \frac{1.066-1}{0.02679}$ = 2.4636

With two-sided p-value 0.0138, we reject null hypothesis and conclude that distribution is not symmetrical. Since the assumption of the symmetry distribution rejected, we conclude that the model is adequate.

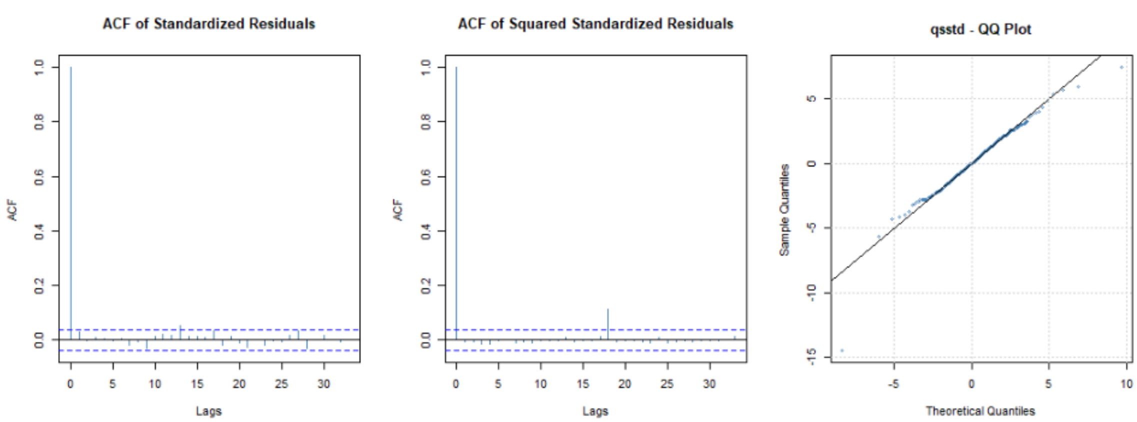


Figure 2.1.4 ACF of standardized residuals, ACF of squared standardized residuals and QQ Plot (Skew Student t GARCH(1,1))

Based on the ACF of standardized residuals and squared standardized residuals, by considering the first 12 lags, both ACF plots shows that acf of $\{\tilde{\varepsilon}_t\}$ and acf of $\{\tilde{\varepsilon}_t^2\}$ are serially uncorrelated and indicate that the mean equation and volatility equation are adequate. The QQ plot of standardized residuals shows that most points lie in the straight-line suggesting model to be appropriate.

(4) Gaussian GARCH (1,1)

Since GARCH(1,1) model with skew Student t innovations shows the lowest AIC value, we further look into the GARCH(1,1) model with gaussian and Student t innovation distributions.

For gaussian distribution of GARCH(1,1) model, we specify the model

$$Y_t = 0.00055 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim N(0,1)$$

$$\sigma_t^2 = 0.000008 + 0.08381\epsilon_{t-1}^2 + 0.90113\sigma_{t-1}^2$$

Where the estimates meet the general requirement of an GARCH (1,1) model, the estimate μ appears to be statistically insignificant at the 5% level. Therefore, the model can be simplified.

Dropping the insignificant parameter, we obtain the revised model

$$Y_t = \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim N(0,1)$$

$$\sigma_t^2 = 0.000008 + 0.084954\epsilon_{t-1}^2 + 0.89997\sigma_{t-1}^2$$

Where the standard error of the parameters $\{\alpha_0, \alpha_1, \beta_1\}$ are $0.000002, 0.01036,$ and 0.01029. All the estimates are statistically significant at the 5% level.

Indeed, the Ljung-Box statistics of standardized residuals give Q(10) = 6.312325 with p-value = 0.7883761, and Q(15) = 13.41876 with p-value = 0.5699874 On the other hand, the Q- statistics of $\{\tilde{\varepsilon}_t^2\}$ give Q(10) = 4.878793 with p-value = 0.8991262, and Q(15) = 5.977056 with p-value = 0.9801306.

Except for the normality test, model checking statistics indicate that this Gaussian GARCH (1,1) model is adequate for Y_t. AIC for this model is -5.239471

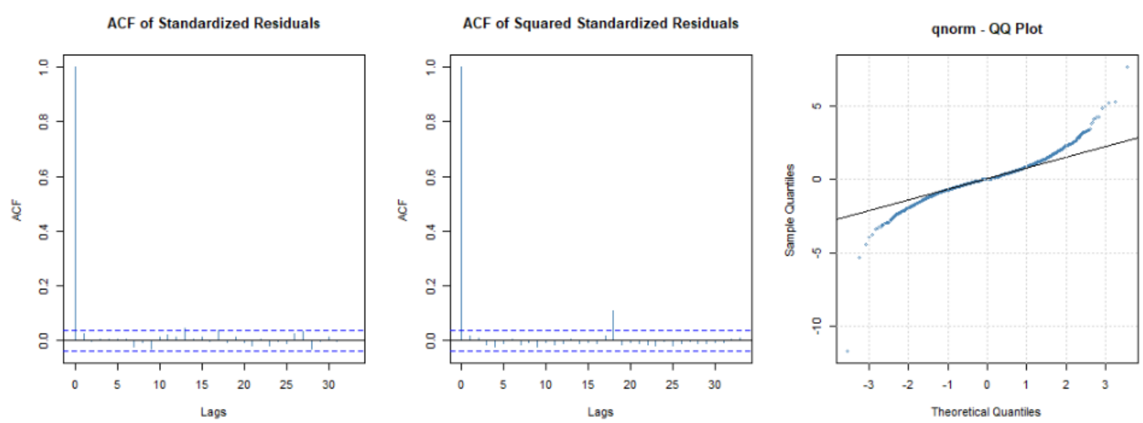


Figure 2.1.5 ACF of standardized residuals, ACF of squared standardized residuals and QQ Plot (GARCH(1,1) – Gaussian)

Based on the ACF of standardized residuals and squared standardized residuals, by considering the first 12 lags, both ACF plots shows that acf of $\{\tilde{\varepsilon}_t\}$ and acf of $\{\tilde{\varepsilon}_t^2\}$ are serially uncorrelated and indicate that the mean equation and volatility equation are adequate. The QQ plot of standardized residuals shows that the points deviate from straight line suggesting model is not appropriate and normality assumptions is rejected.

(5) Student *t* GARCH (1,1)

Thus, we obtain another model using the student t innovations.

we specify the model as

$$Y_t = 0.00027 + \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t_{v=3.36}^*$$

$$\sigma_t^2 = 0.00004 + 0.2019\epsilon_{t-1}^2 + 0.7387\sigma_{t-1}^2$$

Where the estimates meet the general requirement of an GARCH (1,1) model, the estimate μ appear to be statistically insignificant at the 5% level. Therefore, the model can be simplified.

Dropping the insignificant parameters, we obtain the revised model

$$Y_t = \epsilon_t$$

$$\epsilon_t = \sigma_t e_t, \qquad e_t \sim t_{v=3.34}^*$$

$$\sigma_t^2 = 0.00004 + 0.20503\epsilon_{t-1}^2 + 0.73639\sigma_{t-1}^2$$

Where the standard error of the parameters $\{\alpha_0, \alpha_1, \beta_1\}$ are $0.00001, 0.04466,$ and 0.05254. All the estimates are statistically significant at the 5% level, and t_v^* denotes a standardized Student t distribution with v degrees of freedom,

Indeed, the Ljung-Box statistics of standardized residuals give Q(10) = 5.852306 with p-value = 0.8275154, and Q(15) = 15.20764 with p-value = 0.4365668. On the other hand, the Q- statistics of $\{\tilde{\varepsilon}_t^2\}$ give Q(10) = 1.734913 with p-value = 0.9979978, and Q(15) = 2.090704 with p-value = 0.9999602.

Model checking statistics show that this fitted GARCH (1,1) model is adequate for log return series. The AIC for this model is -5.448725 and implied unconditional variance of Y_t is

$$\frac{\alpha_0}{1-(\alpha_1+\beta_1)} = \frac{0.00004}{1-(0.20503+\ 0.73639)} = 0.00068$$

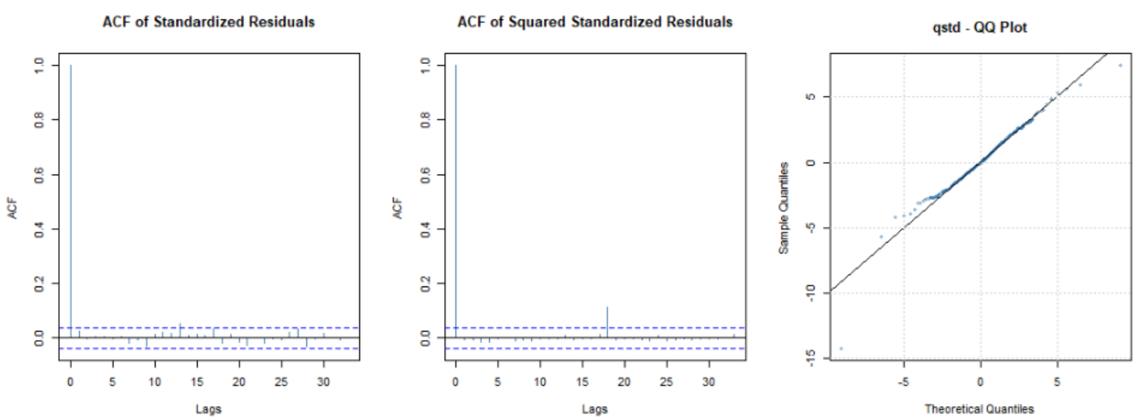


Figure 2.1.6 ACF of standardized residuals, ACF of squared standardized residuals and QQ Plot (GARCH(1,1) – Student t)

Based on the ACF of standardized residuals and squared standardized residuals, by considering the first 12 lags, both ACF plots shows that acf of $\{\tilde{\varepsilon}_t\}$ and acf of $\{\tilde{\varepsilon}_t^2\}$ are serially uncorrelated and indicate that the mean equation and volatility equation are adequate. The QQ plot of standardized residuals shows that the points deviate lesser from straight line compared to the gaussian model suggesting model seems to be appropriate.

(6) COMPARISON

Thus, by comparing the AIC value of the five models, GARCH (1,1) model with skew Student t innovations is the best model for the data. This selection is also supported by the preliminary analysis which shows significant skewness in the returns.

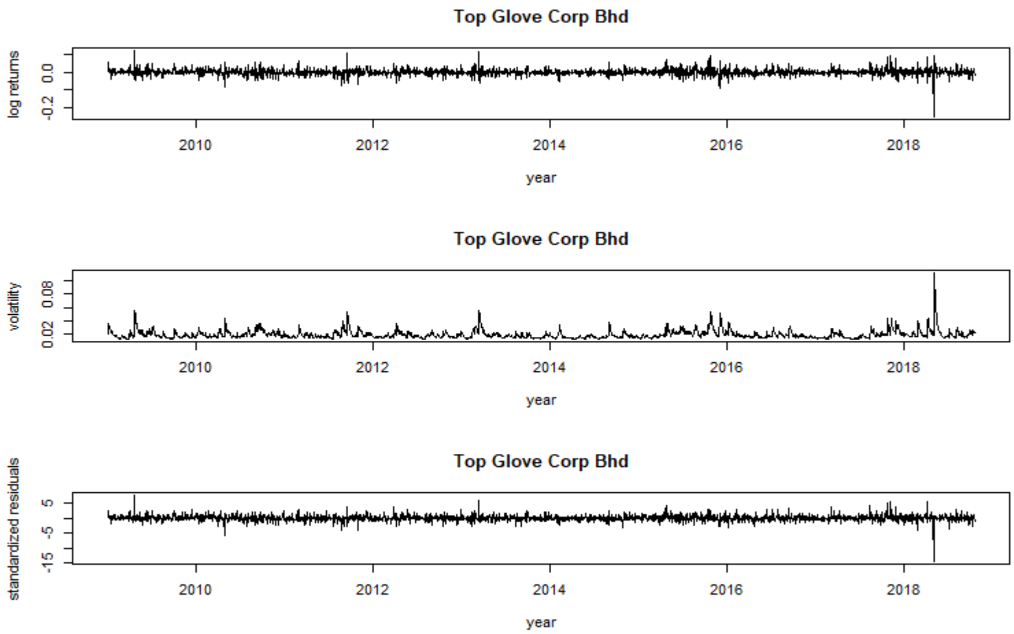


Figure 2.1.7 Time plot of daily log returns, volatility and standardized residuals of GARCH(1,1) with skew Student t

The figure above shows time plot for GARCH (1,1) model with skew Student t distribution to the daily log returns of Top Glove Corporation Berhad. When there is volatility cluster in the log returns series, the fitted volatility series also shows high volatility. Besides, the standardized residuals series appears to be stationary in mean and looks reasonable except for the one or two outliers.

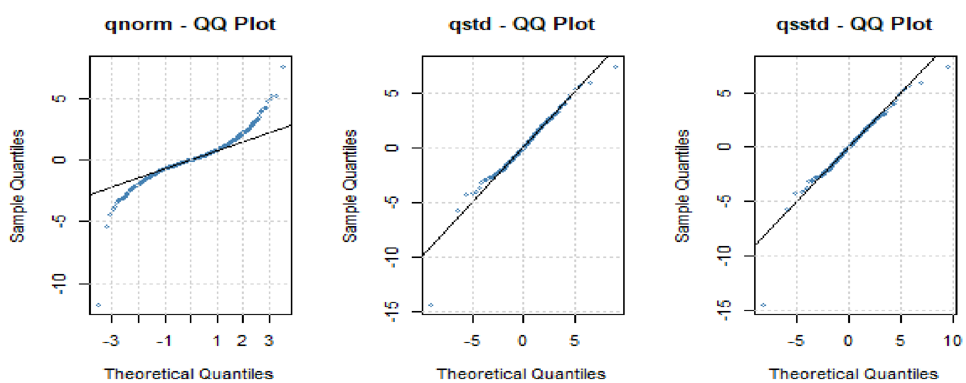


Figure 2.1.8 QQ Plot of Gaussian, Student t, and skew Student t of GARCH(1,1)

The figure above shows the QQ plot for standardized residuals of Gaussian, Student t and skew Student t distribution of GARCH(1,1) model. By comparing QQ plot of three distributions, skew Student t seems to be more adequate as lesser points deviates from the straight line and most of the points lies in the straight line.

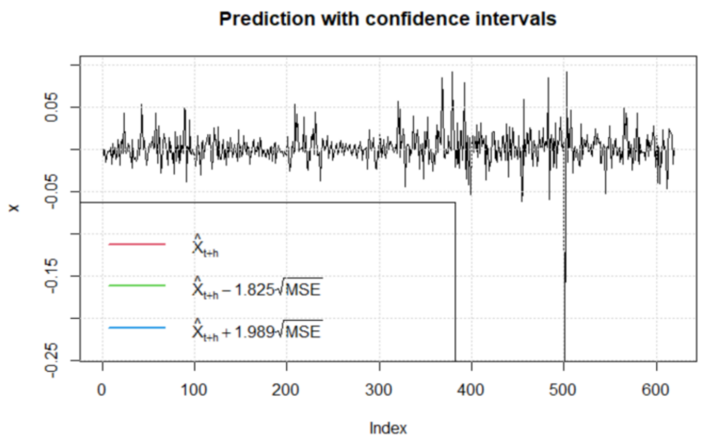
(B) PREFERRED MODEL & 1-STEP AHEAD FORECAST

In model selection, we use AIC to select the model with skew Student t innovation as the best model for our data which is GARCH(1,1). The AIC of the model is -5.450186 which is the lowest among all the model we tested. From the QQ plot and the hypothesis test for GARCH(1,1) skew parameter, it shown the model is adequate.

1-step ahead forecast of the preferred fitted GARCH(1,1) model and assume that the forecast origin is h.

$$\hat{\sigma}_{h+1}^2 = \alpha_0 + \alpha_1 \varepsilon_h^2 + \beta_1 \sigma_h^2$$

$$\hat{\sigma}_{h+1}^2 = 0.000036463 + 0.19326\varepsilon_h^2 + 0.74323\sigma_h^2$$



The mean forecast and mean standard error for this 1-step ahead forecast skew student t model is 0.0007183 and 0.020725 respectively. By using Skew Student-t Distribution and Parameter Estimation in R, the critical values of this two-sided skew Student t distribution are -1.82443 and 1.989323.

$$Lower\ Bound = \ 0.0007182676 - (1.82443 \times 0.02072517) = -0.03710246$$

$$Upper\ Bound = \ 0.0007182676 + (1.989323 \times 0.02072517) = 0.04193786$$

Hence, the 95% prediction intervals for this 1-step ahead forecast skew Student t model is $(-0.03710, 0.04194)$

(C) 95% PREDICTIVE INTERVAL

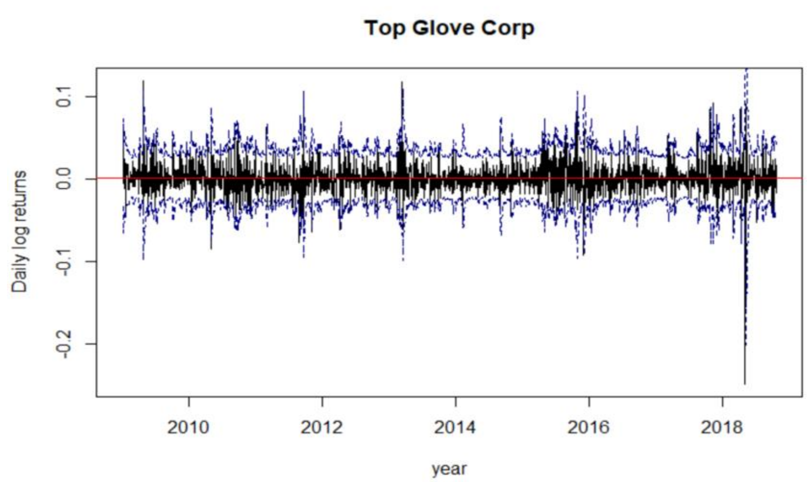


Figure 2.3.1 *Time plot of the daily log returns of Top Glove Corp Bhd. The two dashed lines indicate pointwise 95% predictive intervals based on the Skew Student t GARCH(1,1) model.*

The 95% predictive intervals based on the preferred $\mathrm{GARCH}(1,1)$ model is shown in the $\{Y_t\}$ time plot above which indicated within the two dashed blue line. The intervals are calculated by $\hat{\mu} \pm z_{0.025}\widehat{\sigma_t}$, $\hat{\mu} = 0.0007183$ is the constant term of the mean equation. With some extreme exceptions, all returns are within the 95% predictive intervals.

Part III

TWO-PASS ESTIMATION

From the RStudio, we get that

$$\mu_t = 0.001032449$$

$$\Rightarrow Y_t = 0.001032449 + \varepsilon_t$$

$$\hat{\delta} = \mu(1 - \phi_1)$$

$$\mu = 0.0003 \Rightarrow \ \hat{\delta} = 0.0003(1 - 0.6637) = 0.00010089$$

$$\varepsilon_t^2 = 0.00010089 \ + 0.6637\varepsilon_{t-1}^2 + \eta_t - 0.5661\eta_{t-1} \text{ , } \sigma_\eta^2 = 2.247 \times 10^{-6}$$

$$\widehat{\beta_1} = \widehat{\theta_1} = 0.5661$$

$$\widehat{\alpha_1} = \widehat{\phi_1} - \widehat{\theta_1} = 0.6637 - 0.5661 = 0.0976$$

Findings:

- The estimate of $\widehat{\alpha_1}$ is close to its actual value of GARCH(1,1) but estimate of $\widehat{\beta_1}$ is not close to its actual value of GARCH(1,1).
- The fitted volatility of this two-pass procedure is close to the GARCH(1,1) model.
- The correlation of fitted volatility between GARCH (1, 1) and ARMA (1, 1) is 0.9384323

GARCH (1, 1)	α_0	α_1	β_1
Norm	8.1935×10^{-6}	8.4954×10^{-2}	9.000×10^{-1}
Student-t	3.7061×10^{-5}	2.0503×10^{-1}	7.3639×10^{-1}
Skew student-t (preferred)	3.6463×10^{-5}	1.9326×10^{-1}	7.4323×10^{-1}
ARMA	1.0089×10^{-4}	0.9760×10^{-1}	5.6610×10^{-1}

LIMITATION & FINDINGS

Limitations:

As we mentioned in the previous part, the most preferred model is the GARCH (1, 1) model with skew Student t innovation. However, by applying the two-pass estimation method, we can see that the estimates found are slightly different from the actual values.

$$For\ \alpha_1, difference = 0.19326 - 0.0976 = 0.09566$$

$$For\ \beta_1, difference = 0.74323 - 0.56610 = 0.17713$$

We say that an estimate is close to its actual value if it is 0.1 differing from the actual value. Thus, we can say that the estimate of alpha is close to its actual value, but beta is not. Therefore, based on the findings of estimate, we say that the two-pass estimation method is not good and inaccurate.

Also, if we use the estimates in GARCH model, it may lead to very different results. For example, if we wish to use the estimates to look for the volatility in the financial markets, it may be much different from the actual volatility and in turn causing the investors to lose their money.

Besides that, some problems may also arise even if we get very close estimates. According to Ahn and Gadarowski (1999), if we apply the estimated values into the regression model, it will cause a problem known as error-in-variable. With this problem, the estimates will lose their ordinary or generalized least squares properties. The least square properties are important to minimise the sum of squares of the residuals that appear in every equation. Therefore, using estimates in regression model will lose its accuracy and the results are not really reliable.

Besides that, the correlation between the GARCH (1, 1) model and the ARMA model is positive and the magnitude close to 1. When the magnitude of correlation is close to 1 and positive, it means that the results obtained from the one model are moving in same direction and slightly weaker than another. Although the correlation seems to be fine, but due to the estimates are not close to the actual values, we conclude that two-pass estimation is not a good method to estimate a GARCH model.

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Ahn, S.C. and Gadarowski, C. (1999). Two-Pass cross-sectional regression of factor pricing models: minimum distance approach. Retrieved from http://www.public.asu.edu/~miniahn/archive/capm.pdf

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R OUTPUT

```
> library(fBasics)
> library(fGarch)
> library(forecast)
>
> tg0 = read.csv("UECM3243_TopGloveCorporationBerhad.csv", header = T)
> tg1=tg0[249:2720,]
> # Option 1
> # to eliminate null value(s) and check numerical
> sapply(X = tg1, FUN = function(x) sum(x=="null"))
     Date      Open      High       Low     Close Adj.Close    Volume
        0         1         1         1         1         1         1
> tg = tg1[tg1$Open!="null",]
> #tp_open = as.numeric(levels(tg$Open))[tg$Open]
> tp_open=as.numeric((tg$Open))
> str(tp_open)
 num [1:2471] 0.148 0.152 0.16 0.17 0.171 ...
>
> ###### PART I #####
> # daily log returns
> lrtn = diff(log(tp_open))
>
> ######   time series plot       #####
> # time stamp
> year= c(1:2471)/252 + 2009
>
> par(mfrow=c(1,1))
> plot(year, tp_open, main = "Top Glove Corp Bhd", type = "l",
+      ylab = "Daily Opening Price")
>
> year1= c(1600:2471)/252 + 2009
> plot(year1, tp_open[1600:2471], main = "Top Glove Corp Bhd", type =
"l",
+      ylab = "Daily Opening Price",xlim=c(2015,2019))
>
> ######   ACF PACF tp_open      ######
> par(mfrow=c(1,2))
> acf(tp_open, main="Top Glove Corp Bhd")
> pacf(tp_open, main="Top Glove Corp Bhd")
> #acf decays very slowly
> #pacf lag-1 is approximately 1.0, first reg diff required
>
> ######   log return plot        #######
> par(mfrow=c(1,1))
> plot(year[-1], lrtn, main = "Top Glove Corp Bhd", type = "l", xlab=
"Year", ylab = "Daily Log Returns")
> #appears to be weekly stationary in mean and variance
> #volatility cluster exists in 2018
>
> year1= c(1600:2471)/252 + 2009
> plot(year1[-1], diff(log(tp_open[1600:2471])), main = "Top Glove Corp
Bhd", type = "l",
+      ylab = "Daily Opening Price",xlim=c(2015,2019))
>
>
> ######   ACF PACF lrtn          ######
```

```
> par(mfrow=c(1,2))
> acf(lrtn, main = "Daily log returns of Top Glove Corp Bhd")
> pacf(lrtn, main = "Daily log returns of Top Glove Corp Bhd")
>
> # First 12-lags of acf lie within the error band
> # suggesting white noise series and no evidence of non-randomness
>
> ######   Histogram & density plot  lrtn   #############
> par(mfrow=c(1,1))
> hist(lrtn, nclass=40, xlab="Daily Log Returns", main="Top Glove Corp
Bhd")
> plot(density(lrtn)$x, density(lrtn)$y, type="l", xlab="Daily Log
Returns", ylab="Density", main="Top Glove Corp Bhd")
> range(lrtn)
[1] -0.2494607  0.1198028
> x = seq(-0.3, 0.12, 0.001)
> y = dnorm(x, mean(lrtn), sd(lrtn))
> lines(x, y, lty=2, col="blue")
>
> ######   Statistical Testings (Analysis)   ######
> basicStats(lrtn)
                   lrtn
nobs        2470.000000
NAs            0.000000
Minimum       -0.249461
Maximum        0.119803
1. Quartile   -0.007867
3. Quartile    0.009211
Mean           0.001032
Median         0.000000
Sum            2.550149
SE Mean        0.000375
LCL Mean       0.000297
UCL Mean       0.001768
Variance       0.000348
Stdev          0.018649
Skewness      -0.484868
Kurtosis      16.885390
>
> # Mean testing
> t.test(lrtn)


One Sample t-test

data:  lrtn
t = 2.7514, df = 2469, p-value = 0.005977
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 0.0002966297 0.0017682686
sample estimates:
  mean of x
0.001032449

> # Mean is significant. Need to include mean
>
> # Skewness testing
```

```
> t1 = skewness(lrtn)/sqrt(6/length(lrtn))
> t1
[1] -9.837754
attr(,"method")
[1] "moment"
> pv1 = 2*pnorm(t1)
> pv1
[1] 7.741957e-23
attr(,"method")
[1] "moment"
> #  The daily log returns is skewed to the left
>
> # Tail thickness testing
> t2 = kurtosis(lrtn)/sqrt(24/length(lrtn))
> t2
[1] 171.2987
attr(,"method")
[1] "excess"
> pv2 = 2*(1-pnorm(t2))
> pv2
[1] 0
attr(,"method")
[1] "excess"
> # Heavy tails
>
> # JB test
> normalTest(lrtn, method = "jb")

Title:
 Jarque - Bera Normalality Test

Test Results:
  STATISTIC:
    X-squared: 29496.1503
  P VALUE:
    Asymptotic p Value: < 2.2e-16

Description:
 Mon Aug 30 18:05:13 2021 by user: User

> # Normality assumption for lrtn is rejected.
>
> ######   Data Testing           ######
>
> Box.test(lrtn, lag = 12, type = "Ljung")


Box-Ljung test

data:  lrtn
X-squared = 14.601, df = 12, p-value = 0.264

> # Do not rej H_0, serially uncorrelated
>
> par(mfrow=c(1,2))
>
> acf(lrtn,main="Daily Log Return")
```

```
> # From first 12 acf and pacf, weakly stationary and white noise
>
> acf(abs(lrtn), main = "Absolute Daily Log Return")
> Box.test(abs(lrtn), lag = 12, type = "Ljung")


Box-Ljung test

data:  abs(lrtn)
X-squared = 256.85, df = 12, p-value < 2.2e-16

> # Rej H_0, it is dependent series
>
> x1 = lrtn - mean(lrtn) #estimate of epsilon_t
>
> Box.test(x1^2, lag = 12, type = "Ljung")


Box-Ljung test

data:  x1^2
X-squared = 67.935, df = 12, p-value = 7.782e-10

> # Rej H_0, exist ARCH effect
>
>
> ####   PART II      #####
> par(mfrow=c(1,2))
> acf(x1^2, main=expression(epsilon[t]^2),ylim=c(-0.1,1))
> pacf(x1^2, main=expression(epsilon[t]^2),ylim=c(-0.1,1))
>
> #######   GARCH (1,2)        ######
> #based on acf and pacf
> a1.1 = garchFit(~garch(1,2), data = lrtn, include.mean = T, trace =
F)
> summary(a1.1) #mean is insignificant

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 2), data = lrtn, include.mean = T,
    trace = F)

Mean and Variance Equation:
 data ~ garch(1, 2)
<environment: 0x0000024878e66348>
 [data = lrtn]

Conditional Distribution:
 norm

Coefficient(s):
        mu       omega      alpha1       beta1       beta2
0.00053107  0.00001062  0.11099734  0.52059366  0.34851949

Std. Errors:
```

```
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     5.311e-04   3.221e-04    1.649 0.099225 .
omega  1.062e-05   2.446e-06    4.341 1.42e-05 ***
alpha1 1.110e-01   1.637e-02    6.781 1.20e-11 ***
beta1  5.206e-01   1.407e-01    3.701 0.000215 ***
beta2  3.485e-01   1.288e-01    2.705 0.006825 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6477.833    normalized:  2.622604

Description:
 Mon Aug 30 18:17:47 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  14187.72  0
 Shapiro-Wilk Test  R    W      0.92393   0
 Ljung-Box Test     R    Q(10)  6.14967   0.8025357
 Ljung-Box Test     R    Q(15)  13.85607  0.536472
 Ljung-Box Test     R    Q(20)  18.16618  0.576462
 Ljung-Box Test     R^2  Q(10)  4.234723  0.9361376
 Ljung-Box Test     R^2  Q(15)  5.34568   0.9887729
 Ljung-Box Test     R^2  Q(20)  36.50653  0.01340127
 LM Arch Test       R    TR^2   4.712939  0.9668863

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.241160 -5.229395 -5.241168 -5.236886

> a1.1 = garchFit(~garch(1,2), data = lrtn, include.mean = F, trace =
F)
> summary(a1.1)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 2), data = lrtn, include.mean = F,
    trace = F)

Mean and Variance Equation:
 data ~ garch(1, 2)
<environment: 0x000002486e27deb0>
 [data = lrtn]

Conditional Distribution:
 norm

Coefficient(s):
     omega       alpha1       beta1        beta2
1.0729e-05  1.1248e-01  5.1795e-01  3.4963e-01
```

```
Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
omega  1.073e-05   2.457e-06    4.366 1.26e-05 ***
alpha1 1.125e-01   1.641e-02    6.854 7.18e-12 ***
beta1  5.179e-01   1.378e-01    3.758 0.000171 ***
beta2  3.496e-01   1.262e-01    2.771 0.005581 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6476.47    normalized:  2.622053

Description:
 Mon Aug 30 18:17:48 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  13865.95  0
 Shapiro-Wilk Test  R    W      0.9240809 0
 Ljung-Box Test     R    Q(10)  6.039479  0.8119355
 Ljung-Box Test     R    Q(15)  13.46536  0.566401
 Ljung-Box Test     R    Q(20)  17.64983  0.6104633
 Ljung-Box Test     R^2  Q(10)  4.427704  0.9259971
 Ljung-Box Test     R^2  Q(15)  5.543855  0.9864345
 Ljung-Box Test     R^2  Q(20)  36.88327  0.01208487
 LM Arch Test       R    TR^2   4.895722  0.9613714

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.240867 -5.231455 -5.240872 -5.237448

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a1.1)

Selection: 10
Selection: 11
Selection: 13 #QQ plot deviates, normality assumption fails

Selection: 0
>
> a1.2 = garchFit(~garch(1,2), data = lrtn, include.mean = T, trace =
F, cond.dist = "std")
> summary(a1.2) #mean is insignificant

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 2), data = lrtn, cond.dist = "std",
    include.mean = T, trace = F)
```

```
Mean and Variance Equation:
 data ~ garch(1, 2)
<environment: 0x0000024870aa87b0>
 [data = lrtn]

Conditional Distribution:
 std

Coefficient(s):
        mu       omega      alpha1       beta1       beta2       shape
2.5641e-04  3.8794e-05  2.2947e-01  4.9412e-01  2.1566e-01  3.3587e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     2.564e-04   2.591e-04    0.990 0.322280
omega  3.879e-05   1.135e-05    3.419 0.000628 ***
alpha1 2.295e-01   4.795e-02    4.786 1.70e-06 ***
beta1  4.941e-01   1.226e-01    4.030 5.58e-05 ***
beta2  2.157e-01   1.073e-01    2.010 0.044459 *
shape  3.359e+00   2.573e-01   13.054  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6735.144    normalized:  2.726779

Description:
 Mon Aug 30 18:17:48 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  45326.32  0
 Shapiro-Wilk Test  R    W      0.901041  0
 Ljung-Box Test     R    Q(10)  5.871917  0.8259069
 Ljung-Box Test     R    Q(15)  15.2022   0.4369528
 Ljung-Box Test     R    Q(20)  19.8824   0.4653073
 Ljung-Box Test     R^2  Q(10)  1.86837   0.997253
 Ljung-Box Test     R^2  Q(15)  2.2633    0.9999331
 Ljung-Box Test     R^2  Q(20)  38.34878  0.008025523
 LM Arch Test       R    TR^2   1.985265  0.9994281

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.448699 -5.434581 -5.448711 -5.443571

> a1.2 = garchFit(~garch(1,2), data = lrtn, include.mean = F, trace =
F, cond.dist = "std")
> summary(a1.2)

Title:
 GARCH Modelling

Call:
```

```
 garchFit(formula = ~garch(1, 2), data = lrtn, cond.dist = "std",
    include.mean = F, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 2)
<environment: 0x000002486e9e05d8>
 [data = lrtn]

Conditional Distribution:
 std

Coefficient(s):
     omega      alpha1       beta1       beta2       shape
3.9047e-05  2.3247e-01  4.9063e-01  2.1754e-01  3.3414e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
omega  3.905e-05   1.150e-05    3.396 0.000683 ***
alpha1 2.325e-01   4.867e-02    4.777 1.78e-06 ***
beta1  4.906e-01   1.217e-01    4.030 5.58e-05 ***
beta2  2.175e-01   1.069e-01    2.035 0.041852 *
shape  3.341e+00   2.547e-01   13.120  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6734.653    normalized:  2.72658

Description:
 Mon Aug 30 18:17:49 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  44375.11  0
 Shapiro-Wilk Test  R    W      0.9013466 0
 Ljung-Box Test     R    Q(10)  5.808096  0.8311201
 Ljung-Box Test     R    Q(15)  15.02972  0.4492788
 Ljung-Box Test     R    Q(20)  19.65211  0.4798725
 Ljung-Box Test     R^2  Q(10)  1.926546  0.9968727
 Ljung-Box Test     R^2  Q(15)  2.332181  0.9999187
 Ljung-Box Test     R^2  Q(20)  38.49635  0.007696753
 LM Arch Test       R    TR^2   2.044193  0.999335

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.449111 -5.437346 -5.449120 -5.444837

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a1.2)

Selection: 10
Selection: 11
```

```
Selection: 13 #QQ plot seems to be adequate
Selection: 0
>
> skewness(lrtn)
[1] -0.4848676
attr(,"method")
[1] "moment"
> a1.3 = garchFit(~garch(1,2), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> summary(a1.3) #beta 2 insignificant,reduce to garch (1,1)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 2), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 2)
<environment: 0x000002486fe11cc8>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1       beta1       beta2        skew
7.0222e-04  3.9228e-05  2.2080e-01  5.0382e-01  2.0870e-01  1.0649e+00
     shape
3.3808e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.022e-04   3.146e-04    2.232 0.025628 *
omega  3.923e-05   1.118e-05    3.510 0.000448 ***
alpha1 2.208e-01   4.584e-02    4.817 1.46e-06 ***
beta1  5.038e-01   1.248e-01    4.038 5.39e-05 ***
beta2  2.087e-01   1.081e-01    1.931 0.053463 .
skew   1.065e+00   2.680e-02   39.738  < 2e-16 ***
shape  3.381e+00   2.592e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6738.344    normalized:  2.728074

Description:
 Mon Aug 30 18:17:50 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  47409.06  0
```

```
 Shapiro-Wilk Test  R    W      0.9004511 0
 Ljung-Box Test     R    Q(10)  5.971228  0.8176747
 Ljung-Box Test     R    Q(15)  15.55424  0.412279
 Ljung-Box Test     R    Q(20)  20.35984  0.435632
 Ljung-Box Test     R^2  Q(10)  1.727316  0.9980351
 Ljung-Box Test     R^2  Q(15)  2.094476  0.9999598
 Ljung-Box Test     R^2  Q(20)  37.53582  0.01008523
 LM Arch Test       R    TR^2   1.833499  0.9996217

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC 
-5.450481 -5.434010 -5.450497 -5.444497 

> a1.3 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> summary(a1.3)

Title:
 GARCH Modelling 

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "sstd", 
    include.mean = T, trace = F) 

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000002486e1f72e8>
 [data = lrtn]

Conditional Distribution:
 sstd 

Coefficient(s):
        mu       omega      alpha1       beta1        skew       shape  
7.1826e-04  3.6463e-05  1.9326e-01  7.4323e-01  1.0656e+00  3.3767e+00  

Std. Errors:
 based on Hessian 

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)    
mu     7.183e-04   3.154e-04    2.277 0.022760 *  
omega  3.646e-05   1.093e-05    3.335 0.000854 ***
alpha1 1.933e-01   4.103e-02    4.711 2.47e-06 ***
beta1  7.432e-01   4.934e-02   15.064  < 2e-16 ***
skew   1.066e+00   2.679e-02   39.778  < 2e-16 ***
shape  3.377e+00   2.589e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6736.979    normalized:  2.727522 

Description:
 Mon Aug 30 18:17:51 2021 by user: User 
```

```
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  53824.82  0
 Shapiro-Wilk Test  R    W      0.8975015 0
 Ljung-Box Test     R    Q(10)  6.040436  0.8118546
 Ljung-Box Test     R    Q(15)  15.68598  0.4032227
 Ljung-Box Test     R    Q(20)  20.57352  0.4226056
 Ljung-Box Test     R^2  Q(10)  1.587939  0.9986344
 Ljung-Box Test     R^2  Q(15)  1.907979  0.9999783
 Ljung-Box Test     R^2  Q(20)  35.22975  0.01891424
 LM Arch Test       R    TR^2   1.659406  0.9997763

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.450186 -5.436068 -5.450198 -5.445057

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a1.3)

Selection: 10
Selection: 11
Selection: 13 #QQ plot adequate
Selection: 0
>
> # all coef sig at 5%, pass SRT , SSRT for Gaussian  mean insig  AIC -
5.240867
> # all coef sig at 5%, pass SRT , SSRT for std       mean insig  AIC -
5.449111
> # all coef sig at 5%, pass SRT , SSRT for sstd     beta2 insig  AIC -
5.450186
>
> #skew parameter testing
> t_a1=(1.066e+00-1)/ 2.679e-02
> t_a1
[1] 2.463606
> pv_a1=2*(1-pnorm(t_a1))
> pv_a1
[1] 0.01375473
> #rej, model adequate.
>
> v1.3 = volatility(a1.3)
> resi1 = residuals(a1.3, standardize = T)
> par(mfrow=c(3,1))
> plot(year[-1], lrtn, type="l", xlab="year", ylab="log returns", main
="Top Glove Corp Bhd")
> plot(year[-1], v1.3, type="l", xlab="year", ylab="volatility", main
="Top Glove Corp Bhd")
> plot(year[-1], resi1, type="l", xlab="year", ylab="standardized
residuals", main ="Top Glove Corp Bhd")
>
> par(mfrow=c(1,3))
> plot(a1.1)
Selection: 13
Selection: 0
> plot(a1.2)
Selection: 13
```

```
Selection: 0
> plot(a1.3)

Selection: 13
Selection: 0
>
> #model a1.3 preferred
>
> #######   GARCH (1,1)        ######
>
> a2.1 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F)
> summary(a2.1) #mean is insignificant

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, include.mean = T,
    trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x0000024878febde8>
 [data = lrtn]

Conditional Distribution:
 norm

Coefficient(s):
        mu       omega      alpha1       beta1
5.4763e-04  8.1111e-06  8.3810e-02  9.0113e-01

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     5.476e-04   3.227e-04    1.697   0.0897 .
omega  8.111e-06   1.708e-06    4.749 2.05e-06 ***
alpha1 8.381e-02   1.022e-02    8.199 2.22e-16 ***
beta1  9.011e-01   1.015e-02   88.791  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6475.19    normalized:  2.621534

Description:
 Mon Aug 30 18:30:30 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  13892.35  0
 Shapiro-Wilk Test  R    W      0.9241998 0
 Ljung-Box Test     R    Q(10)  6.424033  0.7784693
```

```
 Ljung-Box Test     R    Q(15)  13.81443  0.5396475
 Ljung-Box Test     R    Q(20)  18.26216  0.5701433
 Ljung-Box Test     R^2  Q(10)  4.673042  0.9119225
 Ljung-Box Test     R^2  Q(15)  5.768141  0.9833847
 Ljung-Box Test     R^2  Q(20)  37.13455  0.01127476
 LM Arch Test       R    TR^2   5.130453  0.9534791

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC 
-5.239830 -5.230418 -5.239835 -5.236411 

> a2.1 = garchFit(~garch(1,1), data = lrtn, include.mean = F, trace = 
F)
> summary(a2.1)

Title:
 GARCH Modelling 

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, include.mean = F, 
    trace = F) 

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000002486e04a6f0>
 [data = lrtn]

Conditional Distribution:
 norm 

Coefficient(s):
     omega      alpha1       beta1  
8.1935e-06  8.4954e-02  8.9997e-01  

Std. Errors:
 based on Hessian 

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)    
omega  8.194e-06   1.722e-06    4.759 1.94e-06 ***
alpha1 8.495e-02   1.036e-02    8.202 2.22e-16 ***
beta1  9.000e-01   1.029e-02   87.500  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6473.747    normalized:  2.62095 

Description:
 Mon Aug 30 18:30:30 2021 by user: User 


Standardised Residuals Tests:
                                Statistic p-Value  
 Jarque-Bera Test   R    Chi^2  13576.2   0        
 Shapiro-Wilk Test  R    W      0.9243546 0        
 Ljung-Box Test     R    Q(10)  6.312325  0.7883761
```

```
 Ljung-Box Test     R    Q(15)  13.41876  0.5699874
 Ljung-Box Test     R    Q(20)  17.73727  0.6047105
 Ljung-Box Test     R^2  Q(10)  4.878793  0.8991262
 Ljung-Box Test     R^2  Q(15)  5.977056  0.9801306
 Ljung-Box Test     R^2  Q(20)  37.45329  0.01031988
 LM Arch Test       R    TR^2   5.324062  0.9462702

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC 
-5.239471 -5.232412 -5.239474 -5.236907 

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a2.1)

Selection: 10
Selection: 11
Selection: 13 #QQ plot deviates, normality assumption fails
Selection: 0
> 
> a2.2 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F, cond.dist = "std")
> summary(a2.2) #mean is insignificant

Title:
 GARCH Modelling 

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "std", 
    include.mean = T, trace = F) 

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000002486ed3d190>
 [data = lrtn]

Conditional Distribution:
 std 

Coefficient(s):
        mu       omega      alpha1       beta1       shape  
2.6574e-04  3.6621e-05  2.0186e-01  7.3866e-01  3.3553e+00  

Std. Errors:
 based on Hessian 

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)    
mu     2.657e-04   2.598e-04    1.023  0.30630    
omega  3.662e-05   1.137e-05    3.221  0.00128 ** 
alpha1 2.019e-01   4.371e-02    4.618 3.88e-06 ***
beta1  7.387e-01   5.165e-02   14.300  < 2e-16 ***
shape  3.355e+00   2.572e-01   13.047  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:
```

```
 6733.7    normalized:  2.726194

Description:
 Mon Aug 30 18:30:31 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  52606.92  0
 Shapiro-Wilk Test  R    W      0.8975757 0
 Ljung-Box Test     R    Q(10)  5.923557  0.8216442
 Ljung-Box Test     R    Q(15)  15.36966  0.4251322
 Ljung-Box Test     R    Q(20)  20.15249  0.4484276
 Ljung-Box Test     R^2  Q(10)  1.689034  0.9982158
 Ljung-Box Test     R^2  Q(15)  2.033005  0.9999669
 Ljung-Box Test     R^2  Q(20)  35.67616  0.01678501
 LM Arch Test       R    TR^2   1.763409  0.9996916

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.448340 -5.436575 -5.448348 -5.444066

> a2.2 = garchFit(~garch(1,1), data = lrtn, include.mean = F, trace =
F, cond.dist = "std")
> summary(a2.2)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "std",
    include.mean = F, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000002486fdfecc0>
 [data = lrtn]

Conditional Distribution:
 std

Coefficient(s):
     omega       alpha1        beta1        shape
3.7061e-05  2.0503e-01  7.3639e-01  3.3369e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
omega  3.706e-05   1.161e-05    3.192  0.00141 **
alpha1 2.050e-01   4.466e-02    4.591 4.42e-06 ***
beta1  7.364e-01   5.254e-02   14.015  < 2e-16 ***
shape  3.337e+00   2.544e-01   13.116  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Log Likelihood:
 6733.175    normalized:  2.725982

Description:
 Mon Aug 30 18:30:31 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  51788.05  0
 Shapiro-Wilk Test  R    W      0.8977447 0
 Ljung-Box Test     R    Q(10)  5.852306  0.8275154
 Ljung-Box Test     R    Q(15)  15.20764  0.4365668
 Ljung-Box Test     R    Q(20)  19.93666  0.4618981
 Ljung-Box Test     R^2  Q(10)  1.734913  0.9979978
 Ljung-Box Test     R^2  Q(15)  2.090704  0.9999602
 Ljung-Box Test     R^2  Q(20)  35.72654  0.01655911
 LM Arch Test       R    TR^2   1.807968  0.9996485

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.448725 -5.439312 -5.448730 -5.445305

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a2.2)

Selection: 10
Selection: 11
Selection: 13 #QQ plot seems to be adequate
Selection: 0
>
> a2.3 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> summary(a2.3)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x0000024870708220>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1       beta1        skew       shape
7.1826e-04  3.6463e-05  1.9326e-01  7.4323e-01  1.0656e+00  3.3767e+00

Std. Errors:
 based on Hessian
```

```
Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.183e-04   3.154e-04    2.277 0.022760 *
omega  3.646e-05   1.093e-05    3.335 0.000854 ***
alpha1 1.933e-01   4.103e-02    4.711 2.47e-06 ***
beta1  7.432e-01   4.934e-02   15.064  < 2e-16 ***
skew   1.066e+00   2.679e-02   39.778  < 2e-16 ***
shape  3.377e+00   2.589e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6736.979    normalized:  2.727522

Description:
 Mon Aug 30 18:30:32 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  53824.82  0
 Shapiro-Wilk Test  R    W      0.8975015 0
 Ljung-Box Test     R    Q(10)  6.040436  0.8118546
 Ljung-Box Test     R    Q(15)  15.68598  0.4032227
 Ljung-Box Test     R    Q(20)  20.57352  0.4226056
 Ljung-Box Test     R^2  Q(10)  1.587939  0.9986344
 Ljung-Box Test     R^2  Q(15)  1.907979  0.9999783
 Ljung-Box Test     R^2  Q(20)  35.22975  0.01891424
 LM Arch Test       R    TR^2   1.659406  0.9997763

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.450186 -5.436068 -5.450198 -5.445057

> #Pass SRT,SSRT for first 15 lags.
> par(mfrow=c(1,3))
> plot(a2.3)
Selection: 10
Selection: 11
Selection: 13 # QQ plot shows adequate
Selection: 0
>
> # all coef sig at 5%, pass SRT , SSRT for Gaussian  mean insig  AIC -
5.239471
> # all coef sig at 5%, pass SRT , SSRT for std       mean insig  AIC -
5.448725
> # all coef sig at 5%, pass SRT , SSRT for sstd                  AIC -
5.450186
>
> t_a2=(1.066e+00-1)/2.679e-02
> t_a2
[1] 2.463606
> pv_a2=2*(1-pnorm(t_a2))
> pv_a2
[1] 0.01375473
> #rej h0, model adequate
```

```
>
> v2.3 = volatility(a2.3)
> resi2 = residuals(a2.3, standardize = T)
> par(mfrow=c(3,1))
> plot(year[-1], lrtn, type="l", xlab="year", ylab="log returns", main
="Top Glove Corp Bhd")
> plot(year[-1], v2.3, type="l", xlab="year", ylab="volatility", main
="Top Glove Corp Bhd")
> plot(year[-1], resi2, type="l", xlab="year", ylab="standardized
residuals", main ="Top Glove Corp Bhd")
>
> par(mfrow=c(1,3))
> plot(a2.1)
Selection: 13
Selection: 0
> plot(a2.2)
Selection: 13
Selection: 0
> plot(a2.3)
Selection: 13
Selection: 0
>
> #model a2.3 preferred
>
> #######   GARCH (2,0)        ######
> ar.mle(x1^2)$order
[1] 2
> #suggest GARCH(2,0)
> auto.arima(x1^2)
Series: x1^2
ARIMA(0,0,2) with non-zero mean

Coefficients:
         ma1     ma2    mean
      0.0806  0.1330  3e-04
s.e.  0.0199  0.0202  0e+00

sigma^2 estimated as 2.233e-06:  log likelihood=12566.49
AIC=-25124.98   AICc=-25124.97   BIC=-25101.73
> #suggest GARCH(0,2), for garch model must at least p =1 , model fails
>
> a3.1 = garchFit(~garch(2,0), data = lrtn, include.mean = T, trace =
F)
Error in solve.default(fit$hessian) :
  system is computationally singular: reciprocal condition number =
5.28207e-21
> #cannot run as distribution of yt has heavier tail than normal
distribution
> summary(a3.1)
Error in h(simpleError(msg, call)) :
  error in evaluating the argument 'object' in selecting a method for
function 'summary': object 'a3.1' not found
> #cannot run
>
> a3.2 = garchFit(~garch(2,0), data = lrtn, include.mean = T, trace =
F, cond.dist = "std")
> summary(a3.2)  #mean insignificant
```

```
Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(2, 0), data = lrtn, cond.dist = "std",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(2, 0)
<environment: 0x000002487a01b0b8>
 [data = lrtn]

Conditional Distribution:
 std

Coefficient(s):
        mu       omega      alpha1      alpha2       shape
0.00025146  0.00023331  0.34136331  0.18965749  3.18999960

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     2.515e-04   2.623e-04    0.959    0.338
omega  2.333e-04   2.463e-05    9.474  < 2e-16 ***
alpha1 3.414e-01   7.040e-02    4.849 1.24e-06 ***
alpha2 1.897e-01   4.633e-02    4.094 4.24e-05 ***
shape  3.190e+00   2.378e-01   13.416  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6720.71    normalized:  2.720935

Description:
 Mon Aug 30 18:42:26 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  95296.1   0
 Shapiro-Wilk Test  R    W      0.8810853 0
 Ljung-Box Test     R    Q(10)  4.474369  0.9234211
 Ljung-Box Test     R    Q(15)  16.83997  0.3285207
 Ljung-Box Test     R    Q(20)  23.47019  0.2663011
 Ljung-Box Test     R^2  Q(10)  4.021316  0.9463803
 Ljung-Box Test     R^2  Q(15)  4.751034  0.9940327
 Ljung-Box Test     R^2  Q(20)  27.08929  0.1327705
 LM Arch Test       R    TR^2   4.173192  0.9801044

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.437822 -5.426057 -5.437830 -5.433548
```

```
> a3.2 = garchFit(~garch(2,0), data = lrtn, include.mean = F, trace =
F, cond.dist = "std")
> summary(a3.2)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(2, 0), data = lrtn, cond.dist = "std",
    include.mean = F, trace = F)

Mean and Variance Equation:
 data ~ garch(2, 0)
<environment: 0x00000248708a48a0>
 [data = lrtn]

Conditional Distribution:
 std

Coefficient(s):
     omega      alpha1      alpha2       shape
0.00023409  0.34667390  0.19125013  3.17158897

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
omega  0.0002341   0.0000250    9.364  < 2e-16 ***
alpha1 0.3466739   0.0713099    4.862 1.16e-06 ***
alpha2 0.1912501   0.0468288    4.084 4.43e-05 ***
shape  3.1715890   0.2348670   13.504  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6720.249    normalized:  2.720748

Description:
 Mon Aug 30 18:42:26 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  93754.82  0
 Shapiro-Wilk Test  R    W      0.881327  0
 Ljung-Box Test     R    Q(10)  4.42059   0.9263856
 Ljung-Box Test     R    Q(15)  16.70203  0.3369871
 Ljung-Box Test     R    Q(20)  23.28849  0.2748522
 Ljung-Box Test     R^2  Q(10)  4.143406  0.9406458
 Ljung-Box Test     R^2  Q(15)  4.904274  0.9929063
 Ljung-Box Test     R^2  Q(20)  27.5446   0.1206254
 LM Arch Test       R    TR^2   4.298368  0.9774308

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.438258 -5.428846 -5.438263 -5.434839
```

```
> #Pass SRT,SSRT for first 15 lags.
> plot(a3.2)
Selection: 10
Selection: 11

Selection: 13
Selection: 0
> #QQ plot seems to be adequate
>
> a3.3 = garchFit(~garch(2,0), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> summary(a3.3)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(2, 0), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(2, 0)
<environment: 0x000002487089e398>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1      alpha2        skew       shape
0.00079538  0.00023405  0.32307955  0.18421821  1.07320698  3.22386514

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.954e-04   3.266e-04    2.435   0.0149 *
omega  2.340e-04   2.431e-05    9.627  < 2e-16 ***
alpha1 3.231e-01   6.673e-02    4.842 1.29e-06 ***
alpha2 1.842e-01   4.478e-02    4.114 3.89e-05 ***
skew   1.073e+00   2.731e-02   39.293  < 2e-16 ***
shape  3.224e+00   2.408e-01   13.389  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6724.667    normalized:  2.722537

Description:
 Mon Aug 30 18:42:27 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  97033.34  0
```

```
 Shapiro-Wilk Test  R    W      0.8811823 0
 Ljung-Box Test     R    Q(10)  4.613811  0.91544
 Ljung-Box Test     R    Q(15)  17.15011  0.3099702
 Ljung-Box Test     R    Q(20)  23.83838  0.2495235
 Ljung-Box Test     R^2  Q(10)  3.785148  0.9565192
 Ljung-Box Test     R^2  Q(15)  4.451381  0.9958404
 Ljung-Box Test     R^2  Q(20)  26.07135  0.1634682
 LM Arch Test       R    TR^2   3.932834  0.9846181

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC 
-5.440216 -5.426098 -5.440228 -5.435087 

> #Pass SRT,SSRT for first 15 lags.
> plot(a3.3)
Selection: 10
Selection: 11
Selection: 13 #QQ plot seems to be adequate
Selection: 0
>
> # Fail  for Gaussian
> # all coef sig at 5%, pass SRT first 12 lags, SSRT  for std   mean
insig  AIC -5.438258
> # all coef sig at 5%, pass SRT first 12 lags, SSRT  for sstd  AIC -
5.440216
>
> t_a3=( 1.073e+00-1)/2.731e-02
> t_a3
[1] 2.673014
> pv_a3 = 2*(1-pnorm(t_a3))
> pv_a3
[1] 0.007517321
> # rej H0, model adequate
>
>
> v3.3 = volatility(a3.3)
> resi3 = residuals(a3.3, standardize = T)
> par(mfrow=c(3,1))
> plot(year[-1], lrtn, type="l", xlab="year", ylab="log returns", main
="Top Glove Corp Bhd")
> plot(year[-1], v3.3, type="l", xlab="year", ylab="volatility", main
="Top Glove Corp Bhd")
> plot(year[-1], resi3, type="l", xlab="year", ylab="standardized
residuals", main ="Top Glove Corp Bhd")
>
> par(mfrow=c(1,2))
>
> plot(a3.2)
Selection: 13
Selection: 0
> plot(a3.3)
Selection: 13
Selection: 0
> #model a3.3 preferred
>
> #######   Model Preferred          #####
> a1.3  #GARCH(1,1) AIC -5.450186
```

```
Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x000002486e1f72e8>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1       beta1        skew       shape
7.1826e-04  3.6463e-05  1.9326e-01  7.4323e-01  1.0656e+00  3.3767e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.183e-04   3.154e-04    2.277 0.022760 *
omega  3.646e-05   1.093e-05    3.335 0.000854 ***
alpha1 1.933e-01   4.103e-02    4.711 2.47e-06 ***
beta1  7.432e-01   4.934e-02   15.064  < 2e-16 ***
skew   1.066e+00   2.679e-02   39.778  < 2e-16 ***
shape  3.377e+00   2.589e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6736.979    normalized:  2.727522

Description:
 Mon Aug 30 18:17:51 2021 by user: User

> a2.3  #GARCH(1,1) AIC -5.450186

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x0000024870708220>
 [data = lrtn]

Conditional Distribution:
 sstd
```

```
Coefficient(s):
        mu       omega      alpha1       beta1        skew       shape
7.1826e-04  3.6463e-05  1.9326e-01  7.4323e-01  1.0656e+00  3.3767e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.183e-04   3.154e-04    2.277 0.022760 *
omega  3.646e-05   1.093e-05    3.335 0.000854 ***
alpha1 1.933e-01   4.103e-02    4.711 2.47e-06 ***
beta1  7.432e-01   4.934e-02   15.064  < 2e-16 ***
skew   1.066e+00   2.679e-02   39.778  < 2e-16 ***
shape  3.377e+00   2.589e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6736.979    normalized:  2.727522

Description:
 Mon Aug 30 18:30:32 2021 by user: User

> a3.3  #GARCH(2,0) AIC -5.440216

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(2, 0), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(2, 0)
<environment: 0x000002487089e398>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1      alpha2        skew       shape
0.00079538  0.00023405  0.32307955  0.18421821  1.07320698  3.22386514

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.954e-04   3.266e-04    2.435   0.0149 *
omega  2.340e-04   2.431e-05    9.627  < 2e-16 ***
alpha1 3.231e-01   6.673e-02    4.842 1.29e-06 ***
alpha2 1.842e-01   4.478e-02    4.114 3.89e-05 ***
skew   1.073e+00   2.731e-02   39.293  < 2e-16 ***
shape  3.224e+00   2.408e-01   13.389  < 2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6724.667    normalized:  2.722537

Description:
 Mon Aug 30 18:42:27 2021 by user: User

>
> #Lowest AIC , GARCH(1,1)
> # one-step ahead
> par(mfrow=c(1,1))
> predict(a1.3, n.ahead=1, plot = T)
     meanForecast  meanError standardDeviation lowerInterval upperInterval
skew 0.0007182607 0.02072522        0.02072522   -0.03710256    0.04193793
>
> #######   Predictive Interval         ####
>
> a1.3 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> summary(a1.3)

Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(1, 1), data = lrtn, cond.dist = "sstd",
    include.mean = T, trace = F)

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x00000248795f6e90>
 [data = lrtn]

Conditional Distribution:
 sstd

Coefficient(s):
        mu       omega      alpha1       beta1        skew       shape
7.1826e-04  3.6463e-05  1.9326e-01  7.4323e-01  1.0656e+00  3.3767e+00

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     7.183e-04   3.154e-04    2.277 0.022760 *
omega  3.646e-05   1.093e-05    3.335 0.000854 ***
alpha1 1.933e-01   4.103e-02    4.711 2.47e-06 ***
beta1  7.432e-01   4.934e-02   15.064  < 2e-16 ***
skew   1.066e+00   2.679e-02   39.778  < 2e-16 ***
shape  3.377e+00   2.589e-01   13.044  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 6736.979    normalized:  2.727522
```

```
Description:
 Mon Aug 30 18:56:47 2021 by user: User


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  53824.82  0
 Shapiro-Wilk Test  R    W      0.8975015 0
 Ljung-Box Test     R    Q(10)  6.040436  0.8118546
 Ljung-Box Test     R    Q(15)  15.68598  0.4032227
 Ljung-Box Test     R    Q(20)  20.57352  0.4226056
 Ljung-Box Test     R^2  Q(10)  1.587939  0.9986344
 Ljung-Box Test     R^2  Q(15)  1.907979  0.9999783
 Ljung-Box Test     R^2  Q(20)  35.22975  0.01891424
 LM Arch Test       R    TR^2   1.659406  0.9997763

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-5.450186 -5.436068 -5.450198 -5.445057

> v1.3 = volatility(a1.3)
> mu=7.183e-04
> lcv=qsstd(0.025,nu=3.377e+00,xi=1.066e+00)
> lcv
[1] -1.82443
> rcv=qsstd(0.975,nu=3.377e+00,xi=1.066e+00)
> rcv
[1] 1.989323
> UL = mu + rcv*v1.3
> LL = mu + lcv*v1.3
>
> year= c(1:2471)/252 + 2009
> plot(year[-1],lrtn,type="l",xlab="year",ylab="Daily log returns",
+      main="Top Glove Corp")
> lines(year[-1],UL,lty=2 , col="navy")
> lines(year[-1],LL,lty=2 , col="navy")
> abline(h=mu,col='red',lwd=1.5)
>
> ####   Part III           ####
> am1 = arima(x1^2, order = c(1,0,1), include.mean = T)
> am1

Call:
arima(x = x1^2, order = c(1, 0, 1), include.mean = T)

Coefficients:
         ar1      ma1  intercept
      0.6637  -0.5661      3e-04
s.e.  0.0937   0.1033      0e+00

sigma^2 estimated as 2.247e-06:  log likelihood = 12557.78,  aic = -
25107.55
>
> mean(lrtn)     #for the purpose of mean equation
[1] 0.001032449
>
```

```
> a1.3 = garchFit(~garch(1,1), data = lrtn, include.mean = T, trace =
F, cond.dist = "sstd")
> ex1 = x1^2 - am1$residuals
> v1.3 = volatility(a1.3)
> cor(v1.3, sqrt(ex1))
[1] 0.9384323
```