Indian Institute of Technology Kanpur

MTH392A

Undergraduate Project

An Analysis of Nifty 50 index in pre-Covid and during Covid crisis

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January - May 2021

ACKNOWLEDGEMENT

I would like to express my gratitude to **Dr. Sharmishtha Mitra** for giving me the opportunity to do this UGP. It has been a great learning experience and has also provided me with a hands-on practical insight of this area. It has also urged me to explore new concepts and apply them in our project. I would further say that I have liked this area very much and request you to give me chance to do more work in this area.

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1 Introduction

India's exchanges equate to less than 2.2% of the total global market capitalization as of Jan. 2020. Most of the trading in the Indian stock market takes place on its two stock exchanges: the **Bombay Stock Exchange (BSE)** and the **National Stock Exchange (NSE)**.

The Bombay Stock Exchange is the oldest stock exchange in Asia. The BSE sensitivity index **(SENSEX)** is launched in 1986. It comprises 30 shares and its base year is 1978-79. The major criteria for selection of a scrip in the BSE Sensex is large market capitalization.

The National stock exchange began equity trading in November 1994. NSE introduced this index to reflect the market movements more accurately, provide for managers with a benchmark for measuring portfolio performance. The **S&P CNX Nifty** launched comprises of 50 scrips which are selected on the basis of low impact cost, high liquidity and market capitalization.

The NIFTY 50 index covers 13 sectors (as on 30 April 2021) of the Indian economy and offers investment managers exposure to the Indian market in one portfolio. Between 2008 & 2012, the NIFTY 50 index's share of NSE's market capitalisation fell from 65% to 29% due to the rise of sectoral indices like NIFTY Bank, NIFTY IT, NIFTY Pharma, NIFTY SERV SECTOR, NIFTY Next 50, etc. The NIFTY 50 Index gives a weightage of 39.47% to financial services, 15.31% to Energy, 13.01% to IT, 12.3% to consumer goods, 6.11% to Automobiles and 0% to the agricultural sector.

2 About the Data

2.1 Data Description

The dataset is a time-series data of **NIFTY 50 Index**. It consits of daily price from 4th January 2016 to 26th February 2021 of Nifty open, close etc values of index. The total observations is 1273 and 7 variables are there.

The associated variables with this data set are as follows:

- **Date** : It is in the format of Year-Month-Day
- **Open** : Open value of index
- **High** : Particular day high value of index
- **Low** : Particular day low value of index
- **Close**: Close value of index
- **Adj. Close**: Its give better idea of the overall value of index
- **Volume**: It is the total volume of each stock in Nifty 50.

We will just use **Date** and **Adj. Close** for further analysis.

2.2 Link to the Data File

Click here or go to the next url: `https://in.finance.yahoo.com/quote/%5ENSEI/history?p=%5E%NSEI`

3 Preliminary Analysis - Data Structure, Summary and Exploratory Analysis

First we will store the data in data frame and remove all the NA values and covert the character variables in numeric.

```
library(dplyr)
library(tidyr)
Nifty <- read.csv("C:/Users/ACER/OneDrive/Desktop/Project/Dat
asets/Nifty.csv")
nifty <- data.frame(Nifty)
nifty$Date <- as.Date(nifty$Date)

nifty[,2] <- as.numeric(nifty[,2])
nifty[,3] <- as.numeric(nifty[,3])
nifty[,4] <- as.numeric(nifty[,4])
nifty[,5] <- as.numeric(nifty[,5])
nifty[,6] <- as.numeric(nifty[,6])
nifty[,7] <- as.numeric(nifty[,7])
nifty <- nifty %>% drop_na()
```

We will look at **head**, **tail** and **summary** of the data sets

```
head(nifty)
tail(nifty)
summary(nifty)
```

head(nifty)

	Date	Open	High	Low	Close	Adj.Close	Volume
1	2016-01-04	7924.55	7937.55	7781.10	7791.30	7791.30	134700
2	2016-01-05	7828.40	7831.20	7763.25	7784.65	7784.65	145200
3	2016-01-06	7788.05	7800.95	7721.20	7741.00	7741.00	147100
4	2016-01-07	7673.35	7674.95	7556.60	7568.30	7568.30	188900
5	2016-01-08	7611.65	7634.10	7581.05	7601.35	7601.35	157400
6	2016-01-11	7527.45	7605.10	7494.35	7563.85	7563.85	189000

tail(nifty)

	Date	Open	High	Low	Close	Adj.Close	Volume
1262	2021-02-19	15074.80	15144.05	14898.20	14981.75	14981.75	712200
1263	2021-02-22	14999.05	15010.10	14635.05	14675.70	14675.70	609900
1264	2021-02-23	14782.25	14854.50	14651.85	14707.80	14707.80	744100
1265	2021-02-24	14729.15	15008.80	14504.50	14982.00	14982.00	403800
1266	2021-02-25	15079.85	15176.50	15065.35	15097.35	15097.35	803900
1267	2021-02-26	14888.60	14919.45	14467.75	14529.15	14529.15	1103600

summary(nifty)

Date	Open	High	Low	Close
Min. :2016-01-04	Min. : 7024	Min. : 7034	Min. : 6826	Min. : 6971
1st Qu.:2017-04-19	1st Qu.: 9085	1st Qu.: 9128	1st Qu.: 8957	1st Qu.: 9056
Median :2018-07-26	Median :10527	Median :10572	Median :10469	Median :10526
Mean :2018-08-01	Mean :10350	Mean :10399	Mean :10280	Mean :10340
3rd Qu.:2019-11-20	3rd Qu.:11394	3rd Qu.:11452	3rd Qu.:11341	3rd Qu.:11385
Max. :2021-02-26	Max. :15371	Max. :15432	Max. :15243	Max. :15315

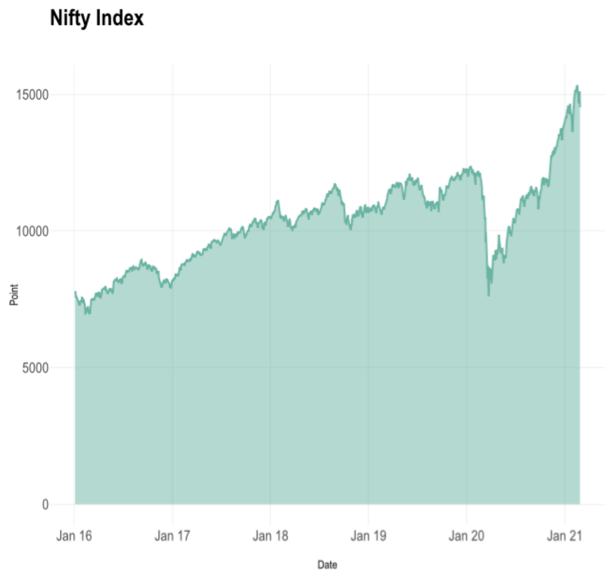
Adj.Close	Volume
Min. : 6971	Min. : 0
1st Qu.: 9056	1st Qu.: 188950
Median :10526	Median : 277700
Mean :10340	Mean : 368118
3rd Qu.:11385	3rd Qu.: 527550
Max. :15315	Max. :1811000

4 Graph and Visual Analysis

After visualizing the Graph below, I found that there is a sharp dip in the market, in the month of march'20, which is clearly seen in the graphs. This dip gives a clear idea that there is a partition in the graph.

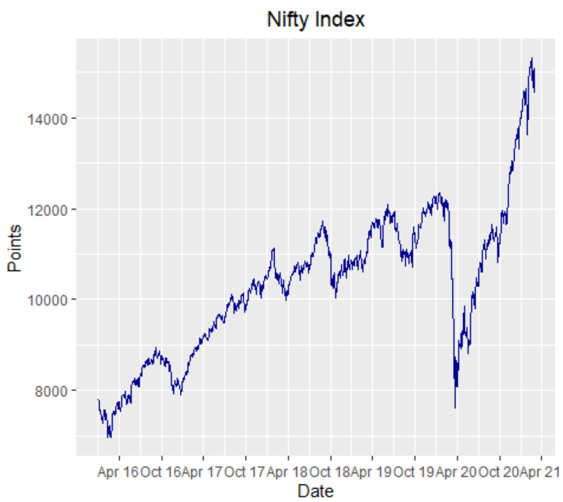
4.1 Area Graph

```
library(ggplot2)
library(plotly)
library(hrbrthemes)

p <- nifty %>%
  ggplot( aes(x=Date, y= nifty[,6])) +
  geom_area(fill="#69b3a2", alpha=0.5) +
  geom_line(color="#69b3a2") +ggtitle("Nifty Index") +
  ylab("Point") + scale_x_date(date_labels = "%b %y",
  date_breaks = "1 year")+
  theme_ipsum()

# Turn it interactive with ggplotly
p <- ggplotly(p)
p
```



4.2 Normal Graph with 6 month interval

```
ggplot(nifty, aes(x = Date, y = nifty[,6])) + geom_line(color
= "darkblue") + ggtitle("Nifty Index") + xlab("Date") +
ylab("Points") + theme(plot.title = element_text(hjust = 0.5))
+ scale_x_date(date_labels = "%b %y", date_breaks = "6
months")
```



5 Structural Break Test

I am using 2 structural break test name **Chow Test** and **Bai- Perron Test**. Both of this test help us to find the break point of the data.

5.1 Chow Test - (F-statistics)

The Chow test tells if the regression coefficients are different for split data sets. It tests whether one regression line or two separate regression lines best fit a split set of data.

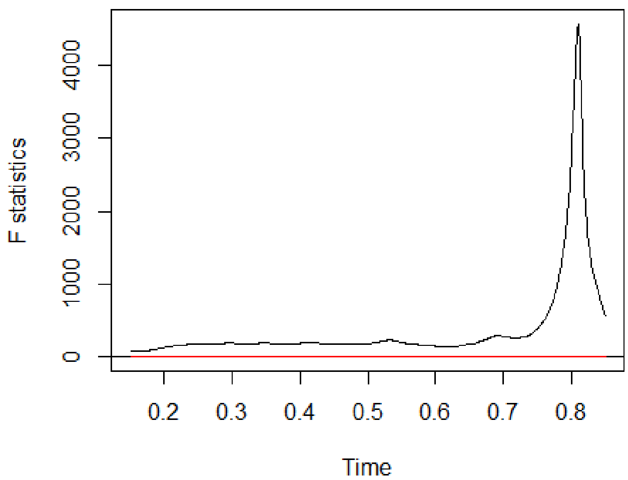
The null hypothesis for the test is that there is no break point (i.e. that the data set can be represented with a single regression model).

The formula used is $Chow = \frac{(RSS_p-(RSS_1+RSS_2))/k}{(RSS_1+RSS_2)/(N_1+N_2-2k)}$, where

- RSS_p = pooled (combined) regression line.
- RSS_1 = regression line before break.
- RSS_2 = regression line after break.

Reject the null hypothesis if the calculated F-value falls into the rejection region (i.e. if the calculated F-value is greater than the F-critical value).

```
fndp <- Fstats(nifty$Adj.Close ~ nifty$Date)
plot(fndp)
```



```
fndp$breakpoint #breakpoint 1027
nifty[,1][1027] # "2020-03-11"
```

1027
"2020-03-11"

From this the result is clear that there is break point which is 2020-03-11.

5.2 Bai-Perron Test

Bai and Perron (1998, 2003) provide the foundation for estimating structural break models based on least squares principles. Bai and Perron start with following multiple linear regression with m breaks

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + u_t$$

$$t = T_{j-1} + 1, ..., T,$$

where $j = 1, ..., m+1$. The dependent variable y_t is modeled as a linear combination of regressors with both time-invariant coefficients, x_t, and time variant coefficient, z_t. This model is rewritten in matrix form as

$$Y = X\beta + \bar{Z}\delta + U$$

where $Y = (y_1, ..., y_T)^{'}$, $X = (x_1, ..., x_T)^{'}$, $U = (u_1, ..., u_T)^{'}$, $\delta = (\delta_1^{'}, ..., \delta_{m+1}^{'})^{'}$ and $\bar{Z}$ is a matrix which diagonally partitions Z at $T_1, ..., T_m$ such that $\bar{Z} = diag(Z_1, ..., Z_{m+1})$.
For each time partition, the least squares estimates of β and δ_j are those that minimize

$$(Y - X\beta - \bar{Z}\delta)^{'}(Y - X\beta - \bar{Z}\delta) = \sum_{n=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} [y_t - x_t^{'}\beta - x_t^{'}\delta_i]^2$$

Given the m partitions the estimates become $\beta(T_j)$ and $\hat{\delta}(T_j)$. These coefficients and the m partitions are chosen as the global minimizers of the sum of the squared residuals across all partitions

$$(\hat{T_1}, ..., \hat{T_m}) = argmin_{T_1,....T_m} S_T(T_1, ...T_m)$$

where $S_T(T_1, ..., T_m)$ are the sum of squared residuals given $\hat{\beta}(T_j)$ and $\hat{\delta}(T_j)$.
Below is the method, I have used only for one break point as there is major change in index before Covid and after Covid crisis

```
Niftybpt <- breakpoints(nifty$Adj.Close ~ nifty$Date, h = 7,
breaks = 1)
Niftybpt
```

Optimal 2-segment partition:
Call:
breakpoints.formula(formula = nifty$Adj.Close   nifty$Date, h = 7, breaks = 1)
Breakpoints at observation number:
1027
Corresponding to breakdates:
0.8105762

```
nifty[,1][1027] # "2020-03-11"
```

"2020-03-11"

Now, I found that the break date for both the test is same which is "2020-03-11". This break date is correct as it was the time were Covid was begin in India. It means the stock market got the panic attack at the start of Covid and it is reflecting in the graph of nifty 50. Hence, we are beginning with our analysis of pre-Covid which is from **2016-01-04** to **2020-03-11** and during Covid which from **2020-03-11** to **2021-02-26** of Nifty 50 index.

6 Time-Series Analysis of data

Our Analysis begin in 3 part: **Whole Period**, **Pre-Covid** and **During Covid Crisis**. So, first we will take the log of returns and shows that why log of return is important for further analysis.

Here, I have separate the data set of log of return in 2 parts of pre-Covid and during Covid. Also, I have exclude the break-point, as it act as an outlier.

```
library(rugarch)
library(tseries)
library(fBasics)
library(zoo)
library(lmtest)
library(forecast)

nifty_index <- zoo(nifty$Adj.Close,
as.Date(as.character(nifty$Date), format = c("%Y-%m-%d")))

nifty_whole <- log(nifty_index/lag(nifty_index, -1))
#strip off the dates and create numeric object
```

```
#Data into two parts
nifty_pre <- nifty_whole[1:1025]
nifty_during <- nifty_whole[1027:1266]

basicStats(nifty_index)
```

	x
nobs	1.267000e+03
NAs	0.000000e+00
Minimum	6.970600e+03
Maximum	1.531470e+04
1. Quartile	9.055875e+03
3. Quartile	1.138520e+04
Mean	1.034019e+04
Median	1.052620e+04
Sum	1.310102e+07
SE Mean	4.558591e+01
LCL Mean	1.025076e+04
UCL Mean	1.042962e+04
Variance	2.632921e+06
Stdev	1.622628e+03
Skewness	2.477230e-01
Kurtosis	1.366620e-01

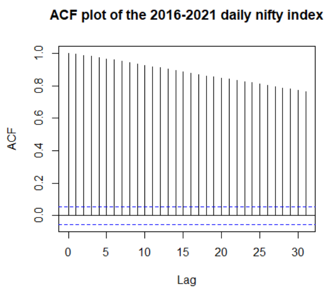
6.1 ACF and PACF

An ACF measures and plots the average correlation between data points in a time series and previous values of the series measured for different lag lengths.
A PACF is similar to an ACF except that each partial correlation controls for any correlation between observations of a shorter lag length.

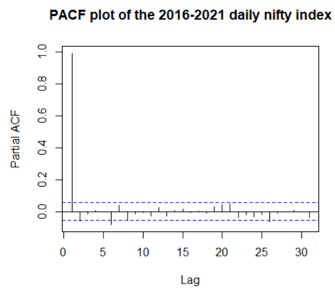
ACF and **PACF** for nifty index.

```
acf(coredata(nifty_index), main="ACF plot of the 2016-2021
daily nifty index")
pacf(coredata(nifty_index), main="PACF plot of the 2016-2021
daily nifty index")
```

From the ACF plot, we observe that the plot decays to zero slowly, meaning the shock affects the process permanently. We can conclude that we need to perform time series analysis on the daily return (log return) of the Nifty Index.



(a) ACF



(b) PACF

Figure 1: ACF and PACF of nifty index

6.2 Time Series analysis on Log return of Whole period, Pre crisis and During crisis

First we will look at the basic stats.

```
basicStats(nifty_whole)
basicStats(nifty_pre)
basicStats(nifty_during)
```

basicStats(nifty_whole)	
	x
nobs	1266.000000
NAs	0.000000
Minimum	-0.139038
Maximum	0.084003
1. Quartile	-0.004381
3. Quartile	0.006094
Mean	0.000492
Median	0.000782
Sum	0.623149
SE Mean	0.000328
LCL Mean	-0.000151
UCL Mean	0.001135
Variance	0.000136
Stdev	0.011666
Skewness	-1.659568
Kurtosis	24.601879

basicStats(nifty_pre)	x
nobs	1025.000000
NAs	0.000000
Minimum	-0.050195
Maximum	0.051825
1. Quartile	-0.004386
3. Quartile	0.005163
Mean	0.000287
Median	0.000470
Sum	0.293733
SE Mean	0.000263
LCL Mean	-0.000230
UCL Mean	0.000803
Variance	0.000071
Stdev	0.008425
Skewness	-0.121730
Kurtosis	3.638487

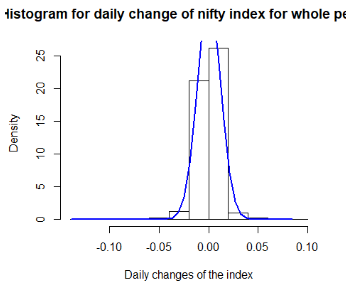
basicStats(nifty_during)	x
nobs	240.000000
NAs	0.000000
Minimum	-0.139038
Maximum	0.084003
1. Quartile	-0.004302
3. Quartile	0.009973
Mean	0.001370
Median	0.002952
Sum	0.328751
SE Mean	0.001315
LCL Mean	-0.001221
UCL Mean	0.003961
Variance	0.000415
Stdev	0.020377
Skewness	-1.712436
Kurtosis	12.092931

From the basic statistics of the log return of the whole period, pre crisis and during crisis, I observe that the mean is 0 and the distribution of log returns has large kurtosis(fat tails). Although, the whole period has the largest kurtosis and pre is smallest. We observe this further using histogram and Q-Q plot.

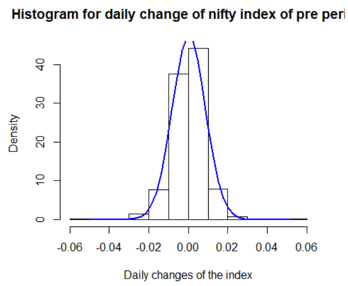
6.2.1 Histogram Plots and Q-Q Plots

Histogram Plots

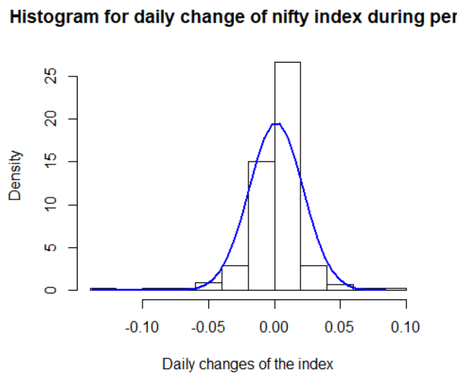
```
hist(nifty_whole, xlab="Daily changes of the index",
prob=TRUE, main="Histogram for daily change of nifty index for
whole period")
xfit<-seq(min(nifty_whole),max(nifty_whole),length=40)
yfit<-dnorm(xfit,mean=mean(nifty_whole),sd=sd(nifty_whole))
lines(xfit, yfit, col="blue", lwd=2)

hist(nifty_pre, xlab="Daily changes of the index", prob=TRUE,
main="Histogram for daily change of nifty index of pre
period")
xfit<-seq(min(nifty_pre),max(nifty_pre),length=40)
yfit<-dnorm(xfit,mean=mean(nifty_pre),sd=sd(nifty_pre))
lines(xfit, yfit, col="blue", lwd=2)

hist(nifty_during, xlab="Daily changes of the index",
prob=TRUE, main="Histogram for daily change of nifty index
during period")
```



(a) Histogram Plot for whole period



(b) Histogram Plot for pre period



(c) Histogram Plot for during period

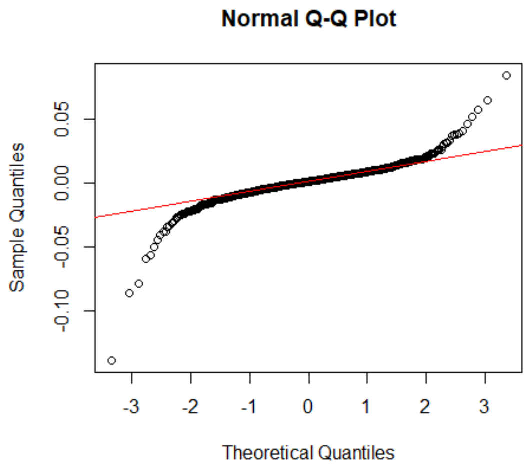
Figure 2: Histogram Plots

```
xfit<-seq(min(nifty_during),max(nifty_during),length=40)
yfit<-dnorm(xfit,mean=mean(nifty_during),sd=sd(nifty_during))
lines(xfit, yfit, col="blue", lwd=2)
```

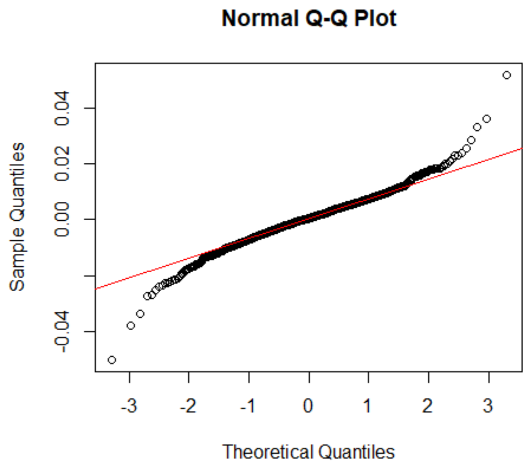
Q-Q Plots

```
qqnorm(nifty_whole)
qqline(nifty_whole, col = 2)

qqnorm(nifty_pre)
qqline(nifty_pre, col = 2)

qqnorm(nifty_during)
qqline(nifty_during, col = 2)
```

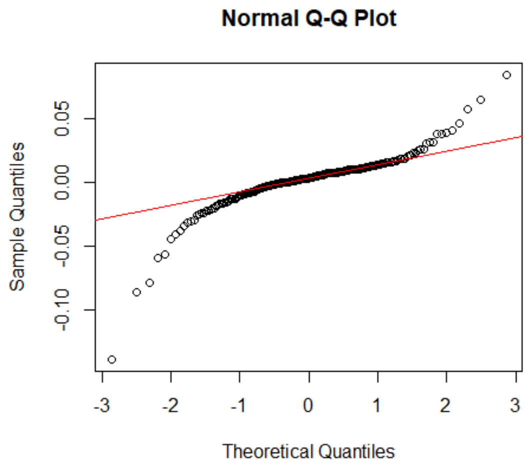
As seen from the histogram **in Figure 2** and the QQ-plot **in Figure 3**, the series has a somewhat normal distribution with fat tails at both ends.



(a) Q-Q Plot for whole period

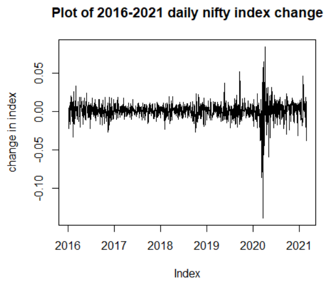


(b) Q-Q Plot for pre period

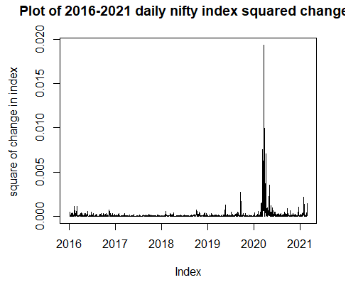


(c) Q-Q Plot for during period

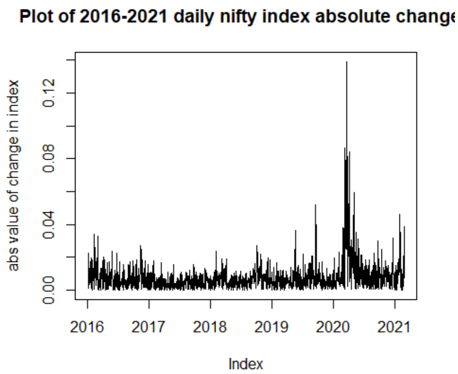
Figure 3: Q-Q Plots



(a) Time plot of log return of whole period



(b) Time plot of square of log return of whole period



(c) Time plot of absolute value of log return of whole period

Figure 4: Time plots for whole period

6.2.2 Time Plots

```
#Time plot of log return of whole_period
plot(nifty_whole, type='l', ylab = "change in index",
main="Plot of 2016-2021 daily nifty index change")

#Time plot of square of log return of whole_period
plot(nifty_whole^2,type='l', ylab = "square of change in index
", main="Plot of 2016-2021 daily nifty index squared changed")

#Time plot of absolute value of log return of whole_period
plot(abs(nifty_whole),type='l', ylab = "abs value of change in
index", main="Plot of 2016-2021 daily nifty index absolute
changed")
```

From the time plot **in Figure 4**, I observe that the returns vary along the zero line with the largest log return of the index observed around 2020 having a value above -0.10. The period after shows signs of volatility. During the years 2020, there

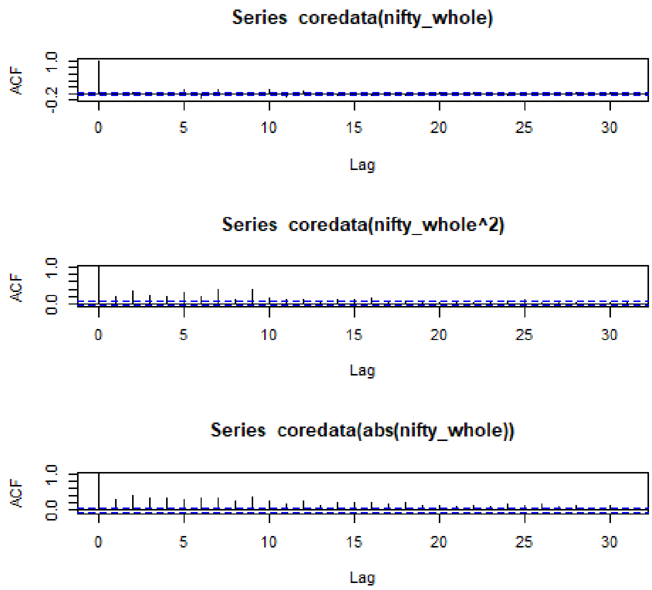


Figure 5: ACF plot of **whole period** for log change, square of log change and absolute of log change of index respectively

is spike in volatility indicating non-constant conditional volatility.

6.2.3 ACF Plots

a. **Whole Period**

```
par(mfrow=c(3,1))
#ACF plot of log change of index
acf(coredata(nifty_whole))

#ACF plot of square of log change of index
acf(coredata(nifty_whole^2))

#ACF plot of absolute value of log change of index
acf(coredata(abs(nifty_whole)))
```

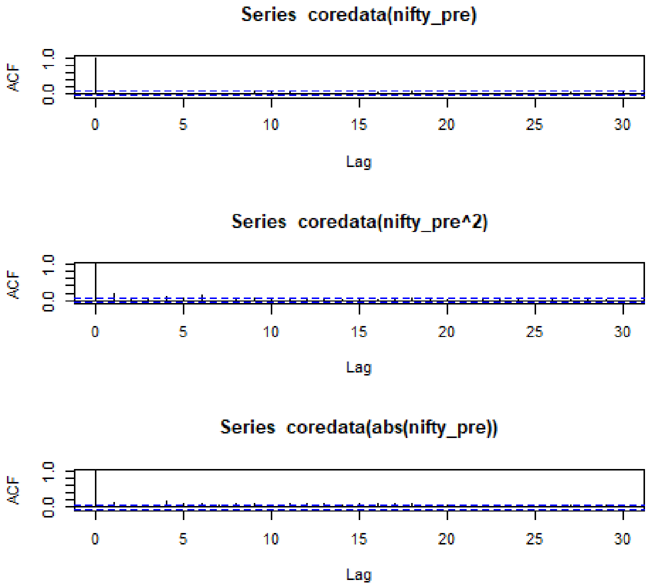


Figure 6: ACF plot of **pre crisis** for log change, square of log change and absolute of log change of index respectively

b. **Pre Crisis**

```
par(mfrow=c(3,1))
#ACF plot of log change of index
acf(coredata(nifty_pre))

#ACF plot of square of log change of index
acf(coredata(nifty_pre^2))

#ACF plot of absolute value of log change of index
acf(coredata(abs(nifty_pre)))
```

c. **During Crisis**

```
par(mfrow=c(3,1))
#ACF plot of log change of index
acf(coredata(nifty_during))

#ACF plot of square of log change of index
acf(coredata(nifty_during^2))

#ACF plot of absolute value of log change of index
acf(coredata(abs(nifty_during)))
```

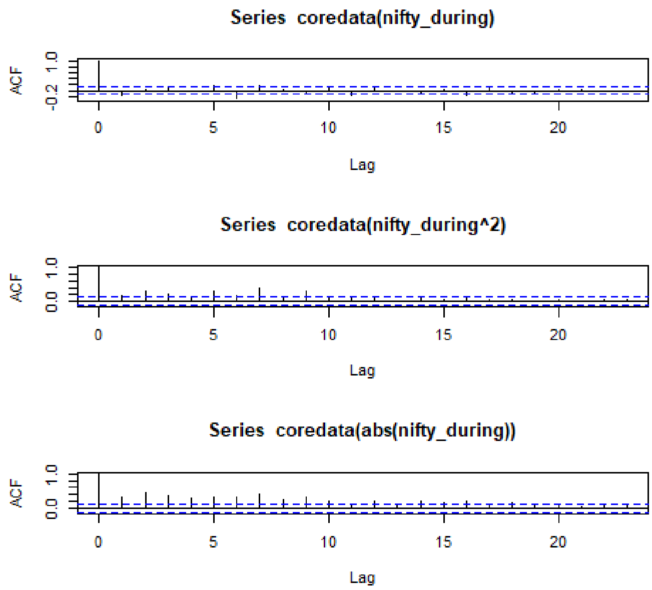


Figure 7: ACF plot of **during crisis** for log change, square of log change and absolute of log change of index respectively

The statistics revealed that the mean was nearly 0 and constant. The time series plot further confirms this. The ACF plot also shows that the mean for the time series is constant since the log stock price returns are not correlated. The squared and absolute stock price return values, on the other hand, have a high correlation, implying that the log returns method has a significant non-linear dependency.

6.3 Test of independence: Ljung Box Test

The Ljung Box test (sometimes called the modified Box-Pierce, or just the Box test) is a way to test for the absence of serial autocorrelation, up to a specified lag k.

The test determines whether or not errors are iid (i.e. white noise) or whether there is something more behind them; whether or not the autocorrelations for the errors or residuals are non zero. Essentially, it is a test of lack of fit: if the autocorrelations of the residuals are very small than the model doesn't show 'significant lack of fit'.

The null hypothesis of the Box Ljung Test, H_0, is that our model does not show lack of fit. The alternate hypothesis, H_a, is just that the model does show a lack of fit. A significant p-value in this test rejects the null hypothesis that the time series isn't autocorrelated.

For a time series Y of length n:

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j}$$

where,

- r_j = the accumulated sample auto correlations,
- m = the time lag.

The null hypothesis get rejected if $Q > \chi^2_{1-\alpha,h}$.

Below is the method,

```
Box.test(nifty_whole, lag=2, type="Ljung")
Box.test(nifty_whole, lag=4, type="Ljung")
Box.test(nifty_whole, lag=6, type="Ljung")
```

> Box.test(nifty_whole, lag=2, type="Ljung")

Box-Ljung test

data: nifty_whole
X-squared = 1.3182, df = 2, p-value = 0.5173

> Box.test(nifty_whole, lag=4, type="Ljung")

Box-Ljung test

data: nifty_whole
X-squared = 5.7003, df = 4, p-value = 0.2227

> Box.test(nifty_whole, lag=6, type="Ljung")

Box-Ljung test

data: nifty_whole
X-squared = 12.108, df = 6, p-value = 0.05961

```
Box.test(nifty_whole^2, lag=2, type="Ljung")
Box.test(nifty_whole^2, lag=4, type="Ljung")
Box.test(nifty_whole^2, lag=6, type="Ljung")
```

> Box.test(nifty_whole^2, lag=2, type="Ljung")

Box-Ljung test

data: nifty_whole^2
X-squared = 163.54, df = 2, p-value < 2.2e-16

> Box.test(nifty_whole^2, lag=4, type="Ljung")

Box-Ljung test

data: nifty_whole^2
X-squared = 402.02, df = 4, p-value < 2.2e-16

> Box.test(nifty_whole^2, lag=6, type="Ljung")

Box-Ljung test

data: nifty_whole^2
X-squared = 519.24, df = 6, p-value < 2.2e-16

```
Box.test(abs(nifty_whole), lag=2, type="Ljung")
Box.test(abs(nifty_whole), lag=4, type="Ljung")
Box.test(abs(nifty_whole), lag=4, type="Ljung")
```

> Box.test(abs(nifty_whole), lag=2, type="Ljung")

Box-Ljung test

data: abs(nifty_whole)
X-squared = 233.42, df = 2, p-value < 2.2e-16

> Box.test(abs(nifty_whole), lag=4, type="Ljung")

Box-Ljung test

data: abs(nifty_whole)
X-squared = 602.22, df = 4, p-value < 2.2e-16

> Box.test(abs(nifty_whole), lag=6, type="Ljung")

Box-Ljung test

data: abs(nifty_whole)
X-squared = 869.82, df = 6, p-value < 2.2e-16

To test the independence of stock return values, I use the Ljung Box test. I note that the log returns are not correlated as the p-values>0.05 in all of the Ljung Box Tests above, so we can't reject the null hypothesis of no autocorrelation. However, it shows signs of ARCH impact on nifty index log returns, as the Ljung Box test on both the squared and absolute values of nifty index log returns are significant.

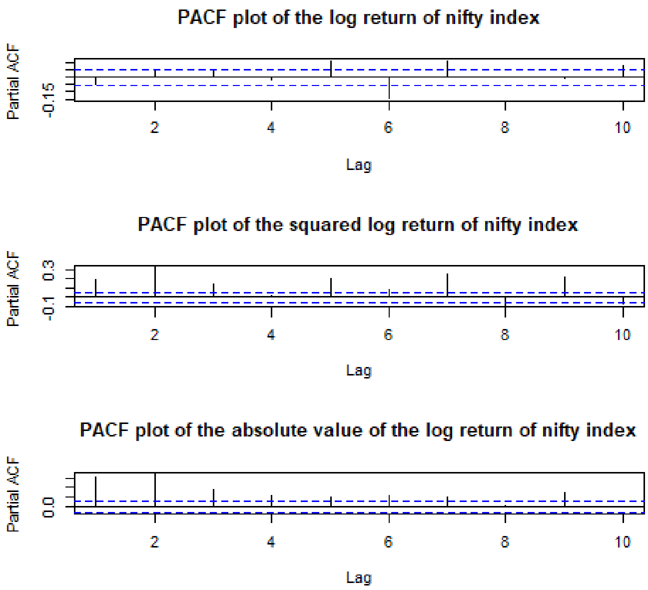


Figure 8: PACF plot of **whole period** for log change, square of log change and absolute of log change of nifty index respectively

6.3.1 PACF plots

a. **Whole Period**

```
#Determine the order of the model
#PACF plot on the log return of the nifty index
pacf(coredata(nifty_whole), lag=10, main="PACF plot of the log
return of nifty index")

#PACF plot on the squared return of the nifty index
pacf(coredata(nifty_whole)^2, lag=10, main="PACF plot of the
squared log return of nifty index")

#PACF plot on the absolute value of the return on the nifty
index
pacf(abs(coredata(nifty_whole)), lag=10, main="PACF plot of
the absolute value of the log return of nifty index")
```

b. **Pre Crisis**

```
pacf(coredata(nifty_pre), lag=10, main="PACF plot of the log
return of nifty index")
pacf(coredata(nifty_pre)^2, lag=10, main="PACF plot of the
```

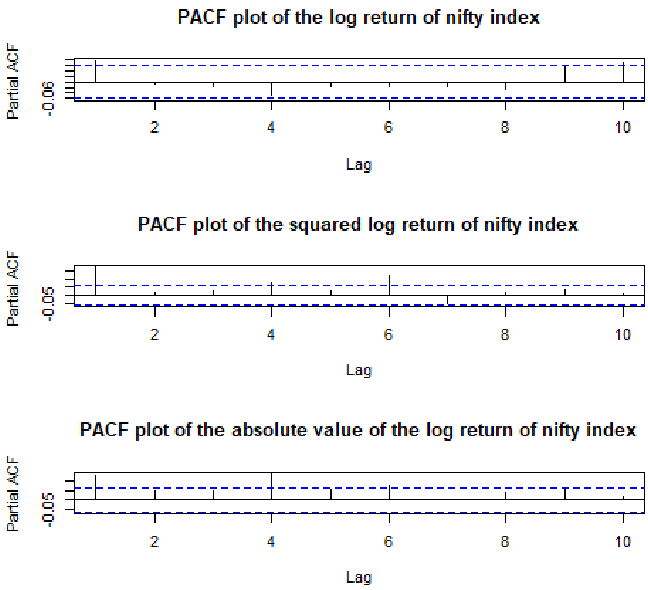


Figure 9: PACF plot of **pre crisis** for log change, square of log change and absolute of log change of nifty index respectively

```
squared log return of nifty index")
pacf(abs(coredata(nifty_pre)), lag=10, main="PACF plot of the
absolute value of the log return of nifty index")
```

c. **During Crisis**

```
pacf(coredata(nifty_during), lag=10, main="PACF plot of the
log return of nifty index")

pacf(coredata(nifty_during^2), lag=10, main="PACF plot of the
squared log return of nifty index")

pacf(abs(coredata(nifty_during)), lag=10, main="PACF plot of
the absolute value of the log return of nifty index")
```

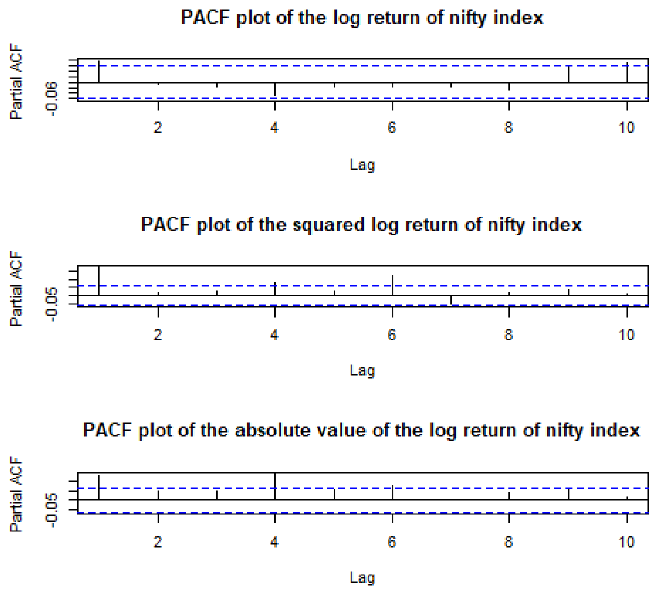


Figure 10: PACF plot of **during crisis** for log change, square of log change and absolute of log change of nifty index respectively

7 Modelling

For modelling, I have used 2 models, first is GARCH(1,1) model and second one is EGarch(1,1) model. In both this model, I have take t-distribution as an error assumption.

7.1 GARCH Model

The GARCH processes are generalized ARCH processes in the sense that the squared volatility σ_t^2 is allowed to depend on previous squared volatilities, as well as previous squared values of the process.

Let Z_t be N(0,1). The process X_t is a GARCH(p, q) process if it is stationary and if it satisfies, for all t and some strictly positive-valued process σ_t, the equations

$$X_t = \sigma_t Z_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i X_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

Where $\omega > 0$ and $\alpha_i \geq 0$, i = 1, . . . , q, $\beta_j \geq 0$, j = 1, . . . , p.

The GARCH(1, 1) process is a covariance-stationary white noise process if and only if $\alpha_1 + \beta < 1$. The variance of the covariance-stationary process is given by $\frac{\omega}{1-\alpha_1-\beta}$

Below is the modelling for all 3 events:

a. **For whole period**

```
garch11.t.spec=ugarchspec(variance.model=list(garchOrder=c(1,
1)), mean.model=list(armaOrder=c(0,0)), distribution.model =
"std")

#estimate model
garch11.t.fit=ugarchfit(spec=garch11.t.spec, data=nifty_whole)
garch11.t.fit
```

----
* GARCH Model Fit *

Conditional Variance Dynamics

GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
mu	0.000897	0.000215	4.1619	0.000032
omega	0.000002	0.000002	1.3808	0.167350
alpha1	0.086631	0.020480	4.2301	0.000023
beta1	0.888341	0.022484	39.5099	0.000000
shape	6.509087	1.133379	5.7431	0.000000

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
mu	0.000897	0.000200	4.48299	0.000007
omega	0.000002	0.000006	0.42607	0.670061
alpha1	0.086631	0.048368	1.79110	0.073277
beta1	0.888341	0.059620	14.89998	0.000000
shape	6.509087	1.435656	4.53388	0.000006

LogLikelihood : 4200.575

Information Criteria

Akaike	-6.6281
Bayes	-6.6078
Shibata	-6.6281
Hannan-Quinn	-6.6204

Weighted Ljung-Box Test on Standardized Residuals

	statistic	p-value
Lag[1]	3.692	0.05469
Lag[2*(p+q)+(p+q)-1][2]	3.973	0.07668
Lag[4*(p+q)+(p+q)-1][5]	4.432	0.20492
d.o.f=0		
H_0 : No serial correlation		

Weighted Ljung-Box Test on Standardized Squared Residuals

	statistic	p-value
Lag[1]	0.1575	0.6914
Lag[2*(p+q)+(p+q)-1][5]	3.4395	0.3326
Lag[4*(p+q)+(p+q)-1][9]	4.9039	0.4437
d.o.f=2		

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.3342	0.500	2.000	0.5632
ARCH Lag[5]	1.2116	1.440	1.667	0.6713
ARCH Lag[7]	1.4094	2.315	1.543	0.8393

Nyblom stability test

Joint Statistic: 40.0834

Individual Statistics:

mu	0.1314
omega	8.0335
alpha1	0.4180
beta1	0.2988
shape	0.1196

Asymptotic Critical	Values (10%	5%	1%)
Joint Statistic:	1.28	1.47	1.88
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

	t-value	prob	sig
Sign Bias	3.5859	0.0003488	***
Negative Sign Bias	0.3275	0.7433090	
Positive Sign Bias	1.6538	0.0984247	*
Joint Effect	14.6716	0.0021199	***

Adjusted Pearson Goodness-of-Fit Test:

	group	statistic	p-value(g-1)
1	20	24.68	0.1714
2	30	34.28	0.2290
3	40	37.19	0.5526
4	50	41.66	0.7623

Elapsed time : 0.9325011

Conclusion:The Fitted model: $\boldsymbol{r_t = 0.000897 + a_t}$**, where** $\boldsymbol{a_t =}$ **stet** $\boldsymbol{\sigma_t^2 = 0.00 + 0.086631 * a_{t-1} + 0.888341 * \sigma_{t-1}^2}$ with t-distribution.
The shape has p-value = $\mathbf{0 < 0.05}$ and hence, is significant. Thus, this model is a good choice.
AIC value = **-6.6281** and BIC value = **-6.6078**.
Further, there is no evidence of serial correlation in the weighted Ljung-Box test on squared residuals, as the p-values are >0.05, and thus the null hypothesis of serial correlation can be rejected, and I can conclude that the residuals act as a white noise process.
Looking at the Goodness-of-fit test, I observe that for all the group, the p-value>0.05 and hence I cannot reject the null hypothesis that this model is adequate for this process.

b. **For Pre Crisis**

```
garch11.t.spec=ugarchspec(variance.model=list(garchOrder=c(1,
1)), mean.model=list(armaOrder=c(0,0)), distribution.model =
"std")

#estimate model
garch11.t.fit=ugarchfit(spec=garch11.t.spec, data=nifty_pre)
garch11.t.fit
```

————————————

* GARCH Model Fit *

————————————

Conditional Variance Dynamics

GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
mu	0.000682	0.000226	3.0153	0.002567
omega	0.000002	0.000002	1.2478	0.212119
alpha1	0.073944	0.020271	3.6478	0.000264
beta1	0.895693	0.023980	37.3521	0.000000
shape	7.561660	1.664626	4.5426	0.000006

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(> $\|t\|$)
mu	0.000682	0.000201	3.39901	0.000676
omega	0.000002	0.000006	0.34689	0.728672
alpha1	0.073944	0.038814	1.90507	0.056771
beta1	0.895693	0.064007	13.99358	0.000000
shape	7.561660	1.942793	3.89216	0.000099

LogLikelihood : 3517.431 Information Criteria

Akaike	-6.8535
Bayes	-6.8295
Shibata	-6.8536
Hannan-Quinn	-6.8444

Weighted Ljung-Box Test on Standardized Residuals

---

	statistic	p-value
Lag[1]	5.680	0.01716
Lag[2*(p+q)+(p+q)-1][2]	5.699	0.02646
Lag[4*(p+q)+(p+q)-1][5]	6.546	0.06674
d.o.f=0		
$\boldsymbol{H_0}$: No serial correlation		

Weighted Ljung-Box Test on Standardized Squared Residuals

---

	statistic	p-value
Lag[1]	1.367	0.2423
Lag[2*(p+q)+(p+q)-1][5]	2.018	0.6143
Lag[4*(p+q)+(p+q)-1][9]	2.800	0.7914
d.o.f=2		

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.06468	0.500	2.000	0.7992
ARCH Lag[5]	0.63128	1.440	1.667	0.8443
ARCH Lag[7]	1.23678	2.315	1.543	0.8723

Nyblom stability test

Joint Statistic: 63.7102

Individual Statistics:

mu	0.1070
omega	6.4957
alpha1	0.2329
beta1	0.1885
shape	0.1653

Asymptotic Critical	Values (10%	5%	1%)
Joint Statistic:	1.28	1.47	1.88
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

---

	t-value	prob	sig
Sign Bias	1.5888	0.1124112	
Negative Sign Bias	2.0252	0.0431069	**
Positive Sign Bias	0.1191	0.9052162	
Joint Effect	18.9949	0.0002741	***

Adjusted Pearson Goodness-of-Fit Test:

	group	statistic	p-value(g-1)
1	20	12.56	0.8603
2	30	20.26	0.8847
3	40	24.17	0.9698
4	50	30.56	0.9820

Elapsed time : 0.191541

Conclusion: The Fitted model: $\boldsymbol{r_t = 0.000682 + a_t}$, **where** $\boldsymbol{a_t}$ **=stet** $\boldsymbol{\sigma_t^2 = 0.00 + 0.073944 * a_{t-1} + 0.895693 * \sigma_{t-1}^2}$ with t-distribution.
The shape has p-value = $\mathbf{0 < 0.05}$ and hence, is significant. Thus, this model is a good choice.
AIC value =**-6.8535** and BIC value = **-6.8295**.
Further, there is no evidence of serial correlation in the weighted Ljung-Box test on squared residuals, as the p-values are >0.05, and thus the null hypothesis of serial correlation can be rejected, and I can conclude that the residuals act as a white noise process.
Looking at the Goodness-of-fit test, I observe that for all the group, the p-value>0.05 and hence I cannot reject the null hypothesis i.e this model is adequate for this process.

c. **During Crisis**

```
garch11.t.spec=ugarchspec(variance.model=list(garchOrder=c(1,
1)), mean.model=list(armaOrder=c(0,0)), distribution.model =
"std")

#estimate model
garch11.t.fit=ugarchfit(spec=garch11.t.spec,
data=nifty_during)
garch11.t.fit
```

----
* GARCH Model Fit *

——————————————

Conditional Variance Dynamics

GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	Pr(>—t—)
mu	0.003126	0.000700	4.4636	0.000008
omega	0.000008	0.000007	1.1421	0.253431
alpha1	0.101695	0.037598	2.7048	0.006835
beta1	0.861771	0.033231	25.9326	0.000000
shape	4.097944	0.497984	8.2291	0.000000

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(>—t—)
mu	0.003126	0.000765	4.08432	0.000044
omega	0.000008	0.000018	0.46394	0.642693
alpha1	0.101695	0.106738	0.95275	0.340715
beta1	0.861771	0.059808	14.40894	0.000000
shape	4.097944	1.926386	2.12727	0.033398

LogLikelihood : 687.1724

Information Criteria

Akaike	-5.6848
Bayes	-5.6123
Shibata	-5.6856
Hannan-Quinn	-5.6556

Weighted Ljung-Box Test on Standardized Residuals

---

	statistic	p-value
Lag[1]	0.1845	0.6675
Lag[2*(p+q)+(p+q)-1][2]	0.5182	0.6851
Lag[4*(p+q)+(p+q)-1][5]	0.7585	0.9115
d.o.f=0		
H0 : No serial correlation		

Weighted Ljung-Box Test on Standardized Squared Residuals

---

	statistic	p-value
Lag[1]	0.2133	0.6442
Lag[2*(p+q)+(p+q)-1][5]	1.2227	0.8076
Lag[4*(p+q)+(p+q)-1][9]	3.4919	0.6758
d.o.f=2		

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.001186	0.500	2.000	0.9725
ARCH Lag[5]	0.107235	1.440	1.667	0.9855
ARCH Lag[7]	2.659456	2.315	1.543	0.5800

Nyblom stability test

Joint Statistic: 1.1078

Individual Statistics:

mu	0.05539
omega	0.10353
alpha1	0.17566
beta1	0.05420
shape	0.18867

Asymptotic Critical Values	(10%	5%	1%)
Joint Statistic:	1.28	1.47	1.88
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

---

	t-value	prob	sig
Sign Bias	2.279	0.02357	**
Negative Sign Bias	1.206	0.22908	
Positive Sign Bias	2.351	0.01956	**
Joint Effect	7.705	0.05252	*

Adjusted Pearson Goodness-of-Fit Test:

	group	statistic	p-value(g-1)
1	20	27.17	0.10083
2	30	48.50	0.01304
3	40	50.00	0.11152
4	50	61.25	0.11251

Elapsed time : 0.3486021

Conclusion: Fitted model: $\boldsymbol{r_t = 0.0003126 + a_t}$**, where** $\boldsymbol{a_t =}$ **stet** $\boldsymbol{\sigma_t^2 = 0.00 + 0.101695 * a_{t-1} + 0.861771 * \sigma_{t-1}^2}$ with t-distribution.
The shape has p-value = $\mathbf{0 < 0.05}$ and hence, is significant. Thus, this model is a good choice.
AIC value = **-5.6848** and BIC value = **-5.6123**.
Further, there is no evidence of serial correlation in the weighted Ljung-Box test on squared residuals, as the p-values are >0.05, and thus the null hypothesis of serial correlation can be rejected, and we can conclude that the residuals act as a white noise process.

7.2 EGARCH Model

The EGARCH model was proposed by Nelson (1991). Nelson and Cao (1992) argue that the nonnegativity constraints in the linear GARCH model are too restrictive. The GARCH model imposes the nonnegative constraints on the parameters, α_i and γ_j, while there are no restrictions on these parameters in the EGARCH model. In the EGARCH model, the conditional variance, h_t, is an asymmetric function of lagged disturbances ϵ_{t-i}:

$$ln(h_t) = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_j ln(h_{t-j})$$

where,

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$$
$$z_t = \frac{\epsilon_t}{\sqrt{h_t}}$$

The properties of the EGARCH model are summarized as follows:

- The function g(z_t) is linear in z_t with slope coefficient $\theta + 1$ if z_t is positive while g(z_t) is linear in z_t with slope coefficient $\theta - 1$ if z_t is negative.
- Suppose that $\theta = 0$. Large innovations increase the conditional variance if $|z_t| - E|z_t| > 0$ and decrease the conditional variance if $|z_t| - E|z_t| < 0$

a. **Whole Period**

```
egarch11.t.spec=ugarchspec(variance.model=list(model =
"eGARCH", garchOrder=c(1,1)),
mean.model=list(armaOrder=c(0,0)), distribution.model = "std")
#estimate model
egarch11.t.fit=ugarchfit(spec=egarch11.t.spec, data=
nifty_whole)
egarch11.t.fit
```

———————————
* GARCH Model Fit *
———————————

Conditional Variance Dynamics

GARCH Model : eGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	Pr(>—t—)
mu	0.000669	0.000244	2.7435	0.006078
omega	-0.206721	0.012096	-17.0896	0.000000
alpha1	-0.127012	0.020415	-6.2215	0.000000
beta1	0.978474	0.001382	707.8750	0.000000
gamma1	0.131325	0.027944	4.6996	0.000003
shape	7.520821	1.760669	4.2716	0.000019

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(>—t—)
mu	0.000669	0.000314	2.1315	0.033046
omega	-0.206721	0.016363	-12.6338	0.000000
alpha1	-0.127012	0.034515	-3.6800	0.000233
beta1	0.978474	0.002041	479.3097	0.000000
gamma1	0.131325	0.044418	2.9566	0.003111
shape	7.520821	2.753115	2.7317	0.006300

LogLikelihood : 4224.908

Information Criteria

Akaike	-6.6649
Bayes	-6.6406
Shibata	-6.6650
Hannan-Quinn	-6.6558

Weighted Ljung-Box Test on Standardized Residuals

	statistic	p-value
Lag[1]	3.967	0.04640
Lag[2*(p+q)+(p+q)-1][2]	3.995	0.07565
Lag[4*(p+q)+(p+q)-1][5]	4.375	0.21080
d.o.f=0		
H_0 : No serial correlation		

Weighted Ljung-Box Test on Standardized Squared Residuals

	statistic	p-value
Lag[1]	0.1920	0.6613
Lag[2*(p+q)+(p+q)-1][5]	0.6852	0.9257
Lag[4*(p+q)+(p+q)-1][9]	1.8167	0.9257
d.o.f=2		

Weighted ARCH LM

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.03149	0.500	2.000	0.8592
ARCH Lag[5]	0.88505	1.440	1.667	0.7673
ARCH Lag[7]	1.72920	2.315	1.543	0.7744

Nyblom stability test

Joint Statistic: 2.204

Individual Statistics:

mu	0.61011
omega	0.80712
alpha1	0.06815
beta1	0.75335
gamma1	0.73760
shape	0.10018

Asymptotic Critical Values	(10	5	1)
Joint Statistic:	1.49	1.68	2.12
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

---

	t-value	prob	sig
Sign Bias	2.141	0.03246	**
Negative Sign Bias	1.136	0.25633	
Positive Sign Bias	1.789	0.07391	*
Joint Effect	5.550	0.13570	

Adjusted Pearson Goodness-of-Fit Test:

---

	group	statistic	p-value(g-1)
1	20	23.42	0.2195
2	30	36.23	0.1670
3	40	48.57	0.1402
4	50	59.67	0.1413

Elapsed time : 0.3794799

Conclusion: The fitted model: $\boldsymbol{r_t = 0.000669 + a_t, a_t = \text{stet } ln(h_t) = -0.206721 + (-0.127012 z_{t-1} + 0.131325(|z_{t-1}| - E(|z_{t-1}|)) + 0.978474 ln(h_{t-1}))}$ with t-dsitribution.
The shape parameter is significant as the p-value ¡ 0.05, indicating that the t-distibution is a good choice.
AIC value = **-6.6649** and BIC value = **-6.6406**
Residual diagnostics: All the p-values for the Ljung Box Test of squared residuals

are > 0.05, thus indicating that there is no evidence of serial correlation in the squared residuals and hence, they behave as white noise process.
Looking at the test for goodness-of-fit, since all the p-values > 0.05, I cant reject the null hypothesis, and hence I may conclude that the Egarch model with the t-distribution is also a good choice.

b. **Pre Crisis**

```
egarch11.t.spec=ugarchspec(variance.model=list(model =
"eGARCH", garchOrder=c(1,1)),mean.model=list(armaOrder=c(0,0)
), distribution.model = "std")
#estimate model
egarch11.t.fit=ugarchfit(spec=egarch11.t.spec, data=
nifty_pre)
egarch11.t.fit
```

—————————————
* GARCH Model Fit *
—————————————

Conditional Variance Dynamics

GARCH Model : eGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	$Pr(> \|t\|)$
mu	0.000427	0.000185	2.3061	0.021103
omega	-0.457066	0.006206	-73.6502	0.000000
alpha1	-0.167211	0.018973	-8.8130	0.000000
beta1	0.953192	0.000296	3218.4469	0.000000
gamma1	0.068979	0.018824	3.6645	0.000248
shape	9.644974	2.420920	3.9840	0.000068

Robust Standard Errors:

	Estimate	Std. Error	t value	$\Pr(>\lvert t \rvert)$
mu	0.000427	0.000176	2.4285	0.015163
omega	-0.457066	0.006775	-67.4596	0.000000
alpha1	-0.167211	0.016450	-10.1650	0.000000
beta1	0.953192	0.000262	3634.4314	0.000000
gamma1	0.068979	0.016292	4.2339	0.000023
shape	9.644974	2.392459	4.0314	0.000055

LogLikelihood : 3547.703

Information Criteria

Akaike	-6.9106
Bayes	-6.8818
Shibata	-6.9107
Hannan-Quinn	-6.8997

Weighted Ljung-Box Test on Standardized Residuals

	statistic	p-value
Lag[1]	6.616	0.01011
Lag[2*(p+q)+(p+q)-1][2]	6.841	0.01314
Lag[4*(p+q)+(p+q)-1][5]	8.535	0.02168
d.o.f=0		

$\boldsymbol{H_0}$: No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

	statistic	p-value
Lag[1]	1.576	0.2094
Lag[2*(p+q)+(p+q)-1][5]	4.282	0.2209
Lag[4*(p+q)+(p+q)-1][9]	6.087	0.2883
d.o.f=2		

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.005859	0.500	2.000	0.9390
ARCH Lag[5]	4.311006	1.440	1.667	0.1479
ARCH Lag[7]	4.726388	2.315	1.543	0.2537

Nyblom stability test

Joint Statistic: 1.1936

Individual Statistics:

mu	0.10005
omega	0.24279
alpha1	0.10551
beta1	0.23090
gamma1	0.10450
shape	0.09693

Asymptotic Critical Values	(10	5	1)
Joint Statistic:	1.49	1.68	2.12
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

	t-value	prob	sig
Sign Bias	3.0688	0.002206	***
Negative Sign Bias	0.4353	0.663463	
Positive Sign Bias	2.2455	0.024947	**
Joint Effect	11.4643	0.009463	***

Adjusted Pearson Goodness-of-Fit Test:

	group	statistic	p-value(g-1)
1	20	19.23	0.4419
2	30	33.14	0.2723
3	40	37.05	0.5592
4	50	41.68	0.7615

Elapsed time : 0.495127

Conclusion: The fitted model: $\boldsymbol{r_t = 0.000427 + a_t, a_t = \text{stet } ln(h_t) = -0.457066 + (-0.167211 z_{t-1} + 0.068979(|z_{t-1}| - E(|z_{t-1}|)) + 0.953192 ln(h_{t-1}))}$ with t-dsitribution.
The shape parameter is significant as the p-value $<$ 0.05, indicating that the t-distibution is a good choice.
AIC value = **-6.9106** and BIC value = **-6.8818**
Residual diagnostics: All the p-values for the Ljung Box Test of squared residuals are $>$ 0.05, thus indicating that there is no evidence of serial correlation in the squared residuals and hence, they behave as white noise process.
Looking at the test for goodness-of-fit, since all the p-values $>$ 0.05, I cant reject the null hypothesis, and hence I may conclude that the Egarch model with the t-distribution is also a good choice.

c. **During Crisis**

```
egarch11.t.spec=ugarchspec(variance.model=list(model =
"eGARCH", garchOrder=c(1,1)),mean.model=list(armaOrder=c(0,0))
, distribution.model = "std")
#estimate model
egarch11.t.fit=ugarchfit(spec=egarch11.t.spec, data=
nifty_during)
egarch11.t.fit
```

----
* GARCH Model Fit *

Conditional Variance Dynamics

GARCH Model : eGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : std

Optimal Parameters

	Estimate	Std. Error	t value	Pr(> |t|)
mu	0.002838	0.000603	4.7048	0.000003
omega	-0.195050	0.009772	-19.9600	0.000000
alpha1	-0.196656	0.056178	-3.5006	0.000464
beta1	0.980188	0.001174	835.0082	0.000000
gamma1	0.058647	0.035541	1.6501	0.098919
shape	4.550080	0.939586	4.8426	0.000001

Robust Standard Errors:

	Estimate	Std. Error	t value	Pr(> |t|)
mu	0.002838	0.000692	4.1003	0.000041
omega	-0.195050	0.015713	-12.4134	0.000000
alpha1	-0.196656	0.059152	-3.3246	0.000886
beta1	0.980188	0.001517	646.2759	0.000000
gamma1	0.058647	0.052263	1.1221	0.261799
shape	4.550080	1.027811	4.4270	0.000010

LogLikelihood : 691.6382

Information Criteria

Akaike	-5.7137
Bayes	-5.6266
Shibata	-5.7149
Hannan-Quinn	-5.6786

Weighted Ljung-Box Test on Standardized Residuals

	statistic	p-value
Lag[1]	0.2072	0.6490
Lag[2*(p+q)+(p+q)-1][2]	0.3927	0.7462
Lag[4*(p+q)+(p+q)-1][5]	0.5792	0.9448
d.o.f=0		
$\boldsymbol{H_0}$: No serial correlation		

Weighted Ljung-Box Test on Standardized Squared Residuals

	statistic	p-value
Lag[1]	0.3251	0.5685
Lag[2*(p+q)+(p+q)-1][5]	1.0121	0.8569
Lag[4*(p+q)+(p+q)-1][9]	2.3339	0.8616
d.o.f=2		

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.2464	0.500	2.000	0.6196
ARCH Lag[5]	0.2636	1.440	1.667	0.9498
ARCH Lag[7]	1.7384	2.315	1.543	0.7725

Nyblom stability test

Joint Statistic: 0.8981

Individual Statistics:

mu	0.11209
omega	0.07133
alpha1	0.39077
beta1	0.07840
gamma1	0.20097
shape	0.12381

Asymptotic Critical Values	(10%	5%	1%)
Joint Statistic:	1.49	1.68	2.12
Individual Statistic:	0.35	0.47	0.75

Sign Bias Test

	t-value	prob	sig
Sign Bias	1.261	0.20856	
Negative Sign Bias	1.075	0.28332	
Positive Sign Bias	2.017	0.04483	**
Joint Effect	5.258	0.15384	

Adjusted Pearson Goodness-of-Fit Test:

	group	statistic	p-value(g-1)
1	20	39.83	0.003441
2	30	56.50	0.001649
3	40	58.67	0.022354
4	50	63.33	0.081857

Elapsed time : 0.1506329

Conclusion: The fitted model: $\boldsymbol{r_t = 0.002838 + a_t, a_t =}$ **stet** $\boldsymbol{ln(h_t) = -0.195050 + (-0.196656 z_{t-1} + 0.058647(|z_{t-1}| - E(|z_{t-1}|)) + 0.980188 ln(h_{t-1}))}$ with t-dsitribution.
The shape parameter is significant as the p-value $<$ 0.05, indicating that the t-distibution is a good choice.
AIC value = **-5.7137** and BIC value = **-5.6266**
Residual diagnostics: All the p-values for the Ljung Box Test of squared residuals are $>$ 0.05, thus indicating that there is no evidence of serial correlation in the squared residuals and hence, they behave as white noise process.

8 Comparision between Events

Below two table comprimises of the parameters that are involved in the model above used. The parameters are ω, $\alpha 1$ and $\beta 1$ for the GARCH Model and ω, $\alpha 1$, $\beta 1$ and $\gamma 1$ for EGARCH model.Now, the table content the values of this parameters of all the 3 events that we have calculated above and also the number in bracket is there of significance.

For GARCH Model, the result show that the volatility for whole period and pre-crisis is almost same but it is seen that during the crisis there are high volatility spike. The coefficients $\alpha1$ and $\beta1$ are staticsally significant at the 5 percent level in the case of all model but ω is not significant for the model.

GARCH MODEL			
Parameters	**Whole Period**	**Pre-crisis**	**During-crisis**
$\boldsymbol{\omega}$	0.000002	0.000002	0.000008
	(0.167350)	(0.212119)	(0.253431)
$\boldsymbol{\alpha 1}$	0.086631	0.073944	0.101695
	(0.000023)	(0.000264)	(0.006835)
$\boldsymbol{\beta 1}$	0.888341	0.895693	0.861771
	(0.000000)	(0.000000)	(0.000000)

For EGARCH Model, the coeffient of conditional volatity is positive and significant in all three cases, it does imply that there is positive and significant relationship between say nifty index return and conditional volatility. The relevant coefficients ω, $\alpha1$,$\beta1$ and $\gamma1$ are statistically significant at the 5 per cent level in the case of all models. In addition, all of the $\gamma1$ coefficients are positive. For positive $\gamma1$, if $\delta1 = \frac{\alpha1}{\gamma1} < 0$ which is in our case, then negative innovations have a higher impact on volatility than positive innovations. It is clearly note that assymetric effect is more during the crisis ($\delta_d = -3.35$) rather than whole $\delta_w = -0.96$ or the pre crisis time ($\delta_p = -2.42$). So, it will be conclude that the nifty index or the stock market of NSE is more sensitive to bad than good news.

EGARCH MODEL			
Parameters	**Whole Period**	**Pre-crisis**	**During-crisis**
$\boldsymbol{\omega}$	-0.206721	-0.457066	-0.195050
	(0.000000)	(0.000000)	(0.000000)
$\boldsymbol{\alpha 1}$	-0.127012	-0.167211	-0.196656
	(0.000233)	(0.000000)	(0.000464)
$\boldsymbol{\beta 1}$	0.978474	0.953192	0.980188
	(0.000000)	(0.000000)	(0.000000)
$\boldsymbol{\gamma 1}$	0.131325	0.068979	0.058647
	(0.000003)	(0.000248)	(0.000001)

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