VIDYASAGAR UNIVERSITY

The competing analysis of stock market dynamic in Indian Perspective: Before, During and After COVID-19

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1. INTRODUCTION ~

The novel coronavirus (COVID-19), which is a human-transmitted disease, was first detected in December 2019 in Wuhan, China, and then spread at an exploratory rate in the rest of the world (Wuhan Municipal Health Commission, 2019) to the public health, the World Health Organization (WHO) has confirmed this pandemic as an international emergency on March 11, 2020.

The COVID-19 pandemic has profoundly impacted global economies, causing upheavals in financial markets around the world. As the pandemic unfolded, countries implemented strict lockdown measures and faced disruptions in supply chains, consumer demand, and overall economic activities. India, being one of the largest and fastest-growing economies, experienced significant fluctuation in its stock market during this period.

This project will specifically focus on understanding how different sectors within the Indian stock market adapted their distribution approaches to navigate through the pandemic's challenges. We will examine the Before COVID-19 period, the impact of the pandemic, and the After COVID-19 recovery to gain comprehensive insights into the stock market's behaviour during these phases.

The primary objective of this study is to provide investors, financial analysts, and policymakers with valuable information and strategic recommendations to better understand the changing dynamics of the Indian stock market. By analyzing the distribution approach of various sectors, we aim to identify trends, patterns, and potential investment opportunities that emerged as a result of the pandemic.

Many researchers have suggested that volatility in the stock market is highly associated with uncertainty in the market, which is the main element in any stock market investment decision. The findings have suggested that volatility is one of the most reliable risk predictors (Green & Figlewski, 1999). Higher volatility relates to a greater chance of a bear market, whereas lower volatility relates to greater chances of a bull market (Ang & Liu, 2007).

The most commonly used measure of volatility is the standard deviation, but the challenge with standard deviation is its limitation, based on the assumption that returns are normally distributed. Another measure is skewness, which is not based on the normal distribution assumption, so skewness works on the data set's extremes rather than concentrating on the average return. Short-term and medium-term investors should focus more on extremes as their investment objective is not long-term to average out (Chang et al., 2013). Kurtosis, like skewness, is another measure to be used when the tails have extreme values. A large kurtosis indicates a high degree of investment risk, so there are high chances of either high returns or small returns (Mei, Liu, Ma, & Chen, 2017).

We will divide the timeline into three distinct periods: pre, during and post COVID-19. To begin, we will consider the pre COVID-19 period, which spans from January 29, 2020 to January 28, 2021, covering a duration of one year. The preceding year will be designated as the before COVID-19 period, while the subsequent year will be referred to as the post COVID-19 period. It is noteworthy that India detected its first COVID-19 case on January 29, 2020, in the state of Kerala. Subsequently, on January 16, 2021, India initiated its CIVID-19 vaccination program, commencing with the administration of the first does to the administration of the first dose to workers. And also shift the time point of the during COVID-19 we show their distribution.

2. **OBJECTIVE ~**

- To compare differential distribution aspects such as volatility, symmetric, and kurtosis among the period that is before during and after post covid-19 period.
- To test the goodness of fit to the data from these three periods.
- To fit an appropriate theoretical distribution to the data from these three periods.
- To compare the performance of different sectors during the three periods and determine the sector with the best performance.

3. **DATA DESCRIPTION ~**

We collect the data from the NSE Web–site(https://www.niftyindices.com/reports/historical-data) of daily price data for one composite index (Nifty 50) and four sectorial indices (Nifty Bank, Nifty IT, Nifty Pharma and Nifty FMCG) from 01st January 2019 to 31th January 2021.

- **Nifty 50**: Nifty 50 Index is a broad-based index consisting of 50 blue chip large and liquid stocks listed on the National Stock Exchange of India. Nifty 50 constituents captured 33.7% of full market capitalization and 62.2% of the turnover of active traded equities on NSE. Some of the major companies included in the Nifty 50 index are Reliance Industries Limited, Tata Consultancy Services Limited, HDFC Bank Limited, Infosys Limited, Housing Development Finance Corporation Limited (HDFC), Hindustan Unilever Limited, ICICI Bank Limited, Kotak Mahindra Bank Limited, Larsen & Toubro Limited, State Bank of India etc.

- **Nifty Bank:** Nifty Bank Index is an index comprised of the most liquid and large capitalised Indian Banking stocks. Some of the major companies included in the Nifty Bank index are State Bank of India, HDFC Bank Limited, ICICI Bank Limited, Axis Bank Limited Kotak Mahindra Bank Limited, IndusInd Bank Limited, Punjab National Bank, Bank of Baroda, Federal Bank Limited, IDFC First Bank Limited etc.

- **Nifty IT:** The Nifty IT index is a stock market index in India that represents the performance of the Information Technology (IT) sector. The Nifty IT index consists of the top 10 IT companies listed on the NSE based on market capitalization and liquidity. Some of the major companies included in the Nifty IT index are Tata Consultancy Services Limited, Infosys Limited, Wipro Limited, HCL Technologies Limited, Tech Mahindra Limited etc.

- **Nifty Pharma:** Nifty Pharma is a stock market index in India that represents the performance of the pharmaceutical sector. The Nifty Pharma index consists of companies engaged in pharmaceutical manufacturing, research and development, and related activities. some of the major companies included in the Nifty Pharma index are Sun Pharmaceutical Industries Limited, Dr Reddy's Laboratories Limited, Divi's Laboratories Limited, Cipla Limited, Lupin Limited etc.

- **Nifty FMCG:** Nifty FMCG is a stock market index in India that represents the performance of the fast-moving consumer goods (FMCG) sector. The Nifty FMCG index consists of companies engaged in the manufacturing and distribution of consumer goods such as food and beverages, personal care products, household products, tobacco, and more. some of the major companies included in the Nifty FMCG index are Hindustan Unilever Limited, ITC Limited, Nestle India Limited, Britannia Industries Limited, Godrej Consumer Products Limited, Marico Limited etc.

4. METHODOLOGY ~

In our study, we utilized the daily closing prices of Nifty 50, along with sectorial indices such as Nifty Bank, Nifty IT, Nifty Pharma and Nifty FMCG. These indices were analyzed using specific tools to gain insights and draw conclusions form the data.

✧ Descriptive statistics :

Descriptive statistics are used to measure the central tendency (mean and median) and variation (standard deviation, skewness, kurtosis). The descriptive statistics have been disclosed for three periods before the crisis, During the crisis and after the crisis. The following formula was used for computation :

❖ Log Return :

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Here r_t is the log return on the index P_t is the closing price on the index on the tth day, P_{t-1} is the closing price on the index on the (t-1)th day.

❖ Standard deviation :

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(r_i - \bar{r})^2}$$

Here n is the number of returns, r_i is the i return $\bar{r}$ is the mean return, and σ standard deviation of return.

❖ Skewness :

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(r_i - \bar{r})^3}{\sigma^3}$$

Here S is the measure of skewness, n is the number of returns, r_i is the i return, $\bar{r}$ is the mean return, and σ standard deviation of return. The interpretation of skewness is as follows:

- If $S = 0$, the distribution is considered symmetric.
- If $S > 0$, the distribution is considered positively skewed, indicating a tail on the right side of the distribution.
- If $S < 0$, the distribution is considered negatively skewed, indicating a tail on the left side of the distribution.

❖ **Kurtosis :**

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(r_i - \bar{r})^4}{\sigma^4}$$

Here K is the kurtosis measure, n is the number of returns, r_i is the i return, $\bar{r}$ is the mean return, and σ is the standard deviation of returns. we measure kurtosis $K' = K - 3$
The interpretation of Kurtosis is as follows:

- If $K' = 0$, the distribution is mesokurtic, including a normal distribution with a standard peak.
- If $K' > 0$, the distribution is leptokurtic, indicating a higher peak and heavier tails compared to a normal distribution.
- If $K' < 0$, the distribution is platykurtic, indicating a flatter peak and lighter tails compared to a normal distribution.

✧ **Q-Q plot:** A Q-Q plot, short for the quantile-quantile plot, is a graphical tool used in statistics to compare the quantiles of a dataset to those of a theoretical distribution. It helps determine if a dataset follows a specific distribution. It helps determine if a dataset follows a specific distribution or deviates from it. The plot displays quantiles of the dataset on the vertical axis and quantiles of the theoretical distribution on the theoretical distribution on the theoretical distribution on horizontal axis. If the points roughly align along a straight line, the dataset and theoretical distribution have similar shapes. Departures from the line indicate deviations from the expected distribution. Q-Q plots are useful for assessing distributional models and identifying skewness, tails, and outliers in data distribution.

✧ **Test of Symmetry (Cabilio – Masaro Test)**: The Cabilio and Masaro Test (1996) analyze symmetry in a dataset. It compares the mean and median of the distribution to assess whether they significantly differ from each other. If the differences are statistically significant, it suggests a departure from symmetry.

Test statistics : $\boldsymbol{S_1 = \sqrt{n}\,\frac{\bar{X}-\tilde{\theta}}{s}}$

where $\bar{X}$ and $\tilde{\theta}$ are the sample mean and sample median, respectively, and s is the sample standard deviation.
H_0 = The distribution is symmetric.
H_1 = The distribution is asymmetric.

- **Kolmogorov Goodness of Fit test:** The Kolmogorov test is used to decide if a sample came from a population with a specific distribution.

  H_0 : *The data follow a specified distribution.*

  H_1 : *The data does not follow the specified distribution.*

  Test Statistics : $D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right)$

- **Kolmogorov test for student-t distribution:** The Kolmogorov test is used to decide of a sample came from Student-t distribution.

  $\boldsymbol{H_0}$: $X \sim t_v$ *with c, scale c, and degrees of freedom* v

- **Kolmogorov test for Normal distribution:** The Kolmogor test is used to decide of a sample came from Normal distribution.

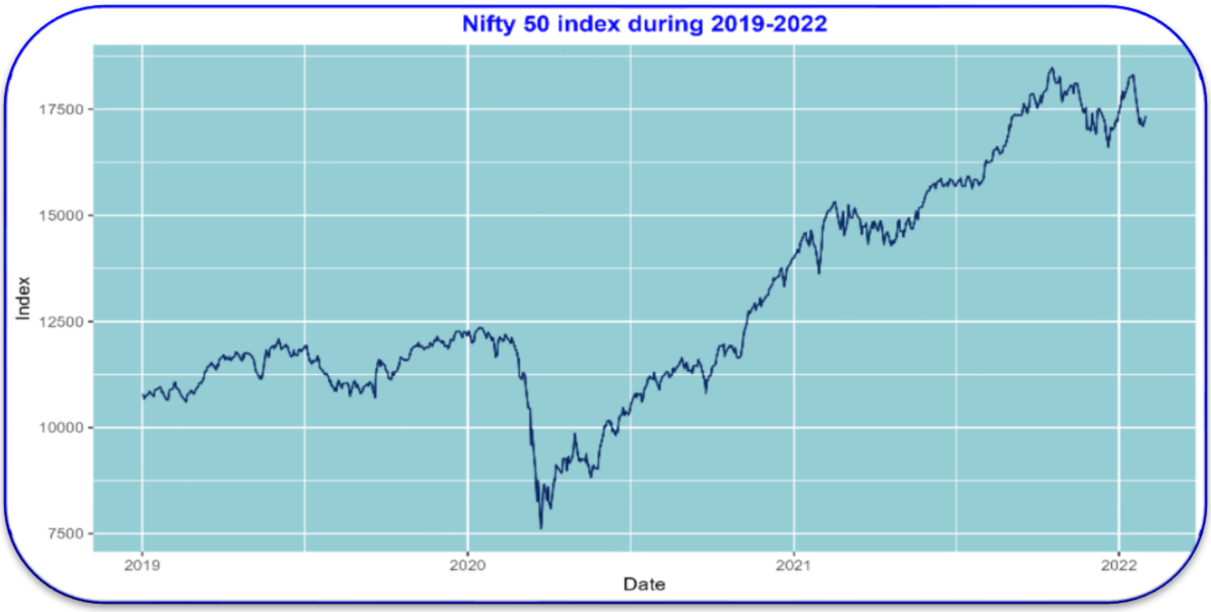
  $\boldsymbol{H_0}$: $X \sim N(\bar{X}, S_x)$ *where* $\bar{X}$ *is sample mean and* S_X *is sample variance.*

5. Result And Discussion ~

The descriptive analysis used the daily return for each index, including one composite index (Nifty 50) and four sectorial indexes (Nifty Bank, Nifty FMCG, Nifty IT, Nifty Pharma) of the Indian stock market.

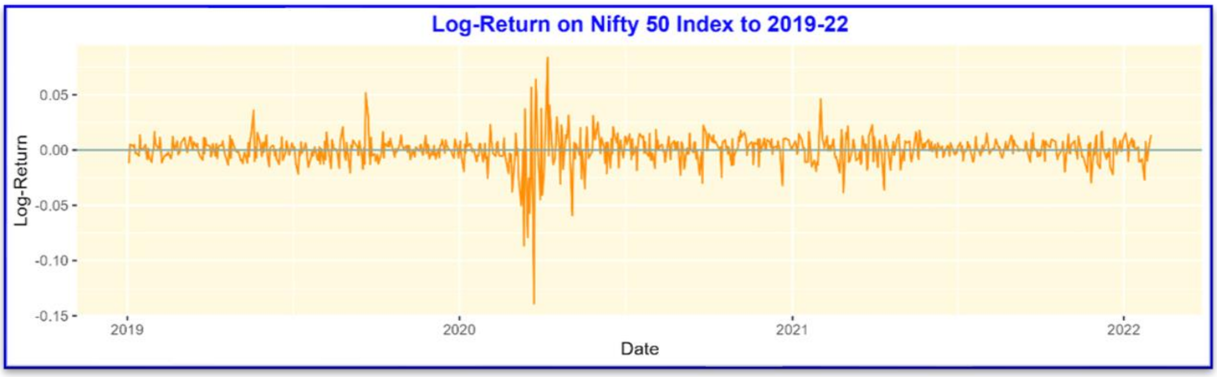
Graphical Representation:

- **Nifty 50:** To begin, we plot the Nifty 50 Index on a graph. Initially, we observe that the curve is going up, indicating a positive trend over time. However, when we look at the period affected by Covid-19 (or mid-February to the end of March), we see a



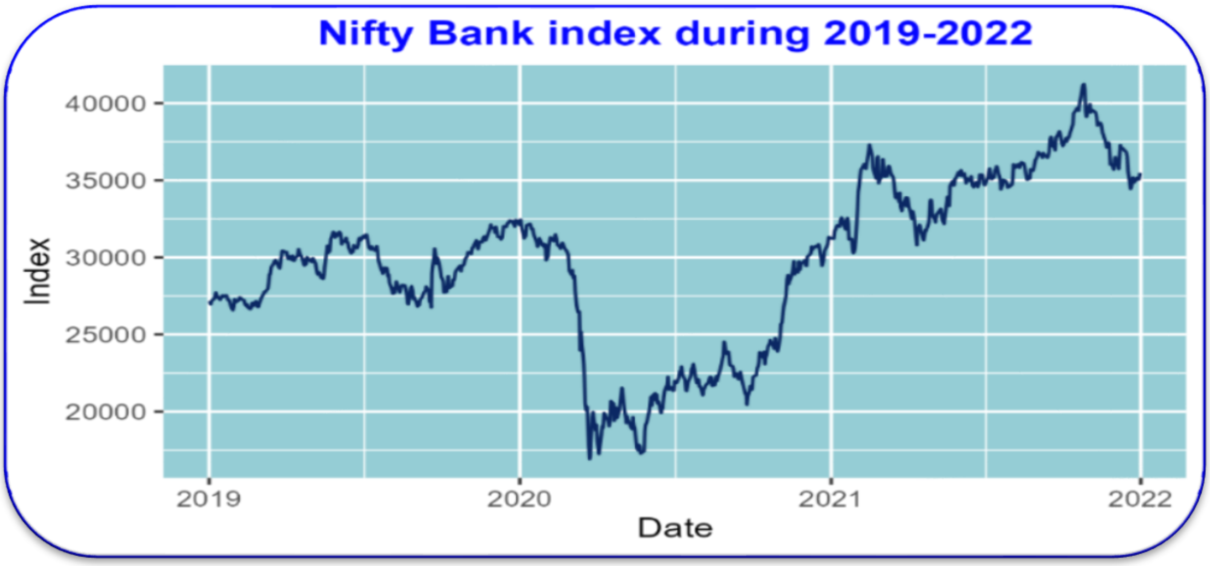
sudden and significant drop in the curve.

This decline is much steeper compared to the previous upward movement. This shows

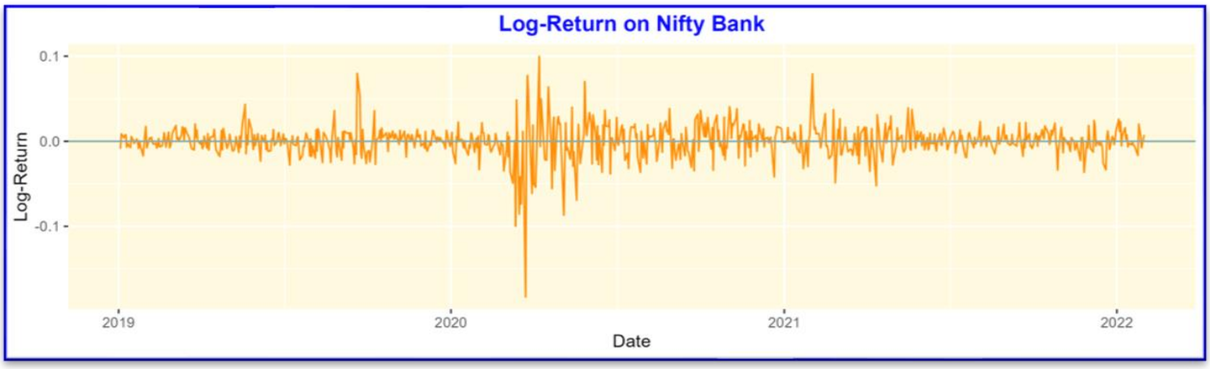


how the Covid-19 situation had a strong negative impact on the Nifty 50 Index, causing it to fall sharply. After this, the Nifty 50 Index gradually resumed an upward trend. And also we see the log return curve for the nifty 50. This time Nifty 50 was a sharp fall (or significant decline) in this time log return of Nifty 50 become more volatile.

- **Nifty Bank:** During the Covid-19 pandemic, the Nifty Bank sectorial index experienced a sharp decline, but its recovery was slower compared to the broader Nifty

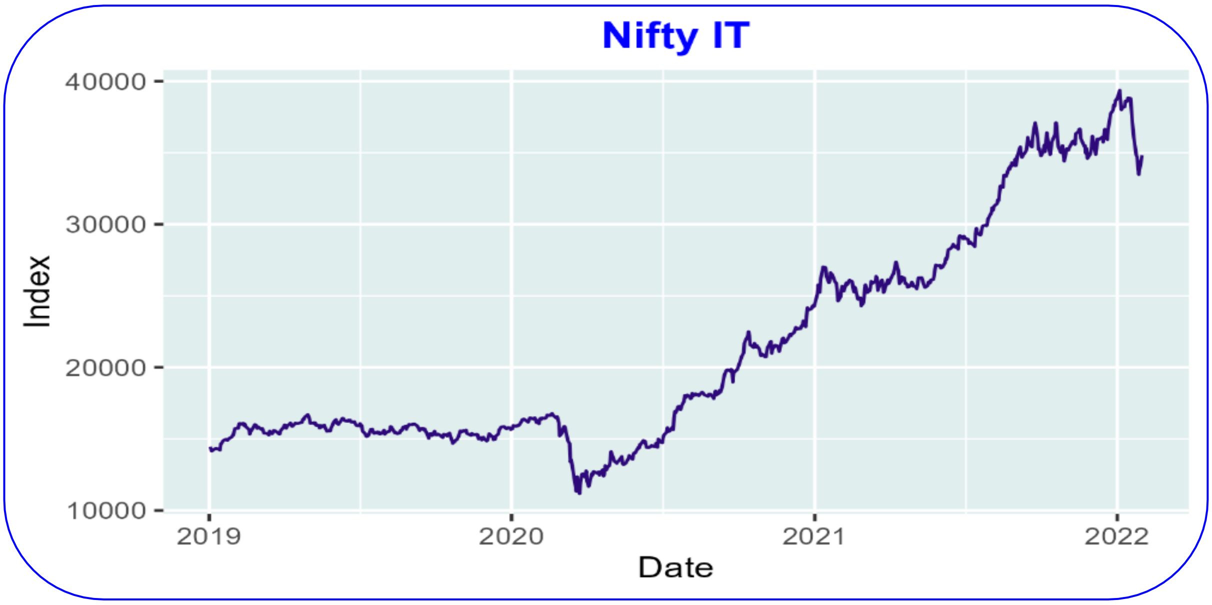


50 composite index. This slower recovery can be attributed to factors such as increased

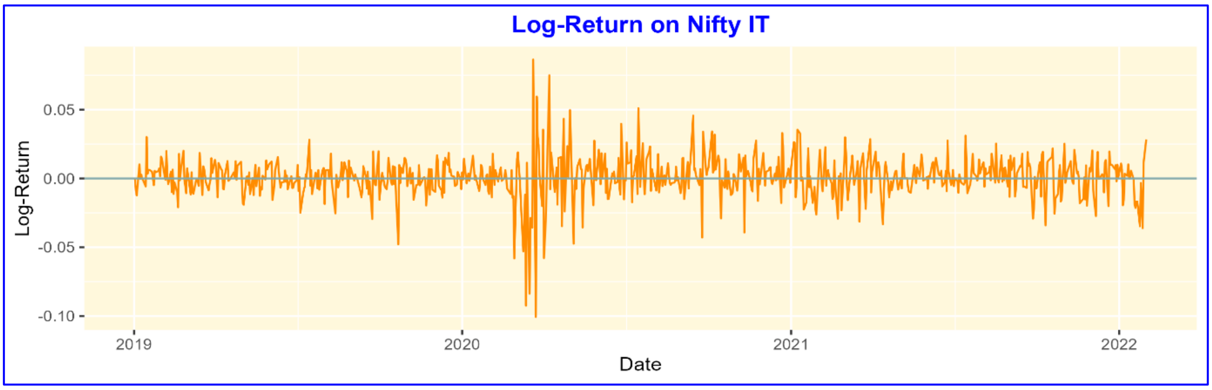


non-performing assets (NPAs) due to reduced economic activity, concerns about asset quality, and provisioning requirements for banks. The lockdown measure and disruptions in business operations further affected the performance of the banking sector. And we see the Log-Return of Nifty Bank is more volatile than Nifty 50, we can conclude that the price movements of the index is more unpredictable during that time.

- **Nifty IT:** The curve of the Nifty It index in 2019 showed a gradual increase,

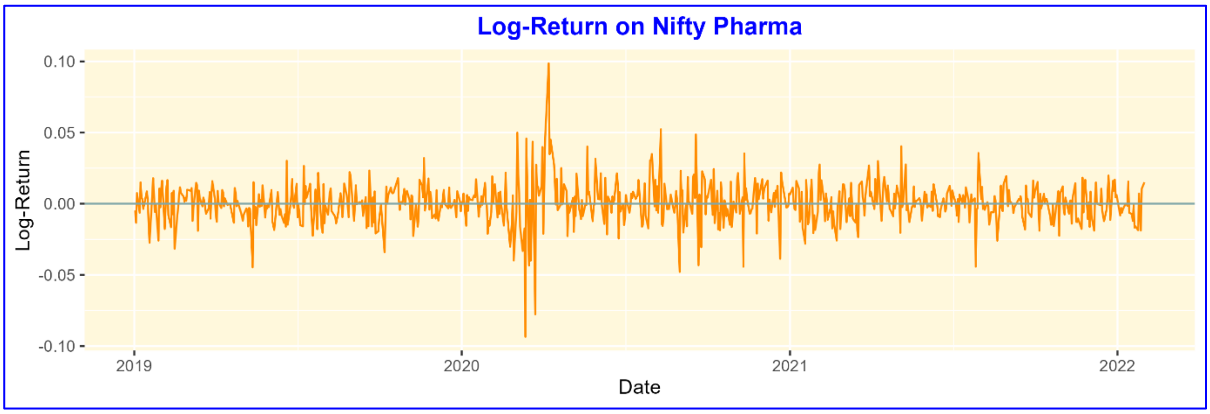


indicating a positive trend in the performance of the IT sector. With the arrival of the COVID-19 pandemic, the Nifty IT index experienced a sharp fall, because of the overall market turbulence and uncertainty during that period. But post COVID-19 Nifty IT index has a strong rapid growth Because of the accelerated shift towards online platforms, e-commerce, telecommunication, and digital services a significant demand for IT products and government initiatives and policies aimed at promoting digitalization and technology adoption further contributed to the growth of the IT sector. Then the Log-return of the Nifty IT index is volatile than the Nifty 50 index but the price movements of the index are more increasing during that time.



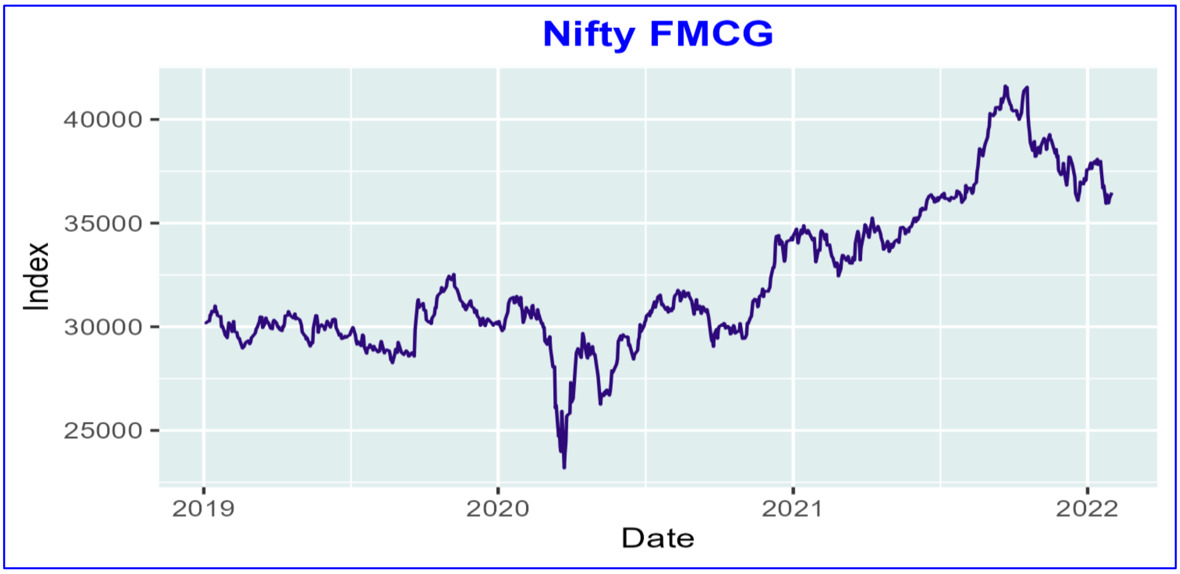
- **Nifty Pharma:** The curve of the Nifty Pharma index in 2019 exhibited a gradual decrease, indicating a downward trend. With the arrival of the COVID-19 pandemic, the Nifty Pharma index experienced a sharp fall because of the overall market turbulence and uncertainty during that period. But post COVID-19 Nifty Pharma

index has a strong rapid growth Because of increasing demand for pharmaceutical products and services and the race for COVID-19 treatments. Then the Log-return of

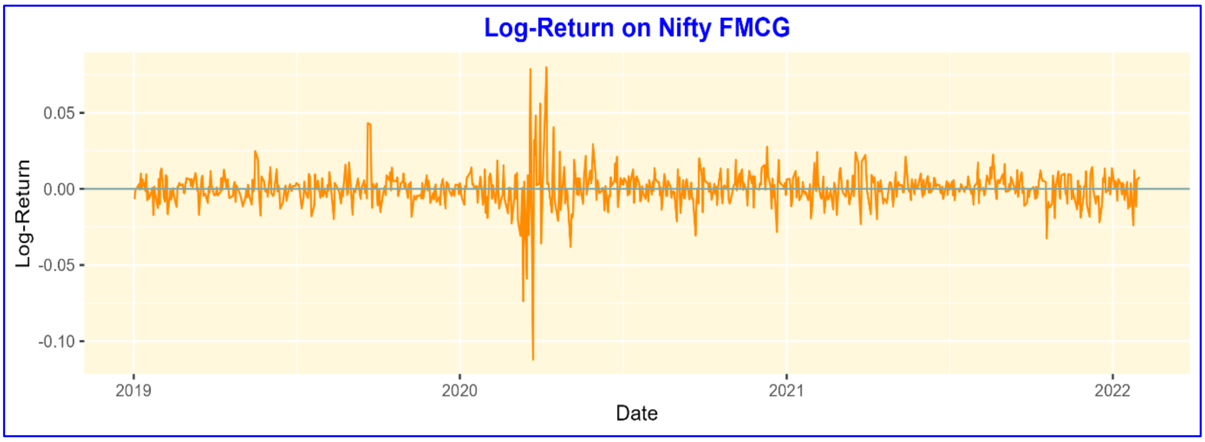


the Nifty IT index is less volatile than the Nifty 50 index so we conclude that the price movements of the index are more predictable during that time.

- **Nifty FMCG:** The curve of the Nifty FMCG (Fast Moving Consumer Goods) index in 2019 exhibited a constant or a very slowly increasing. With the arrival of the



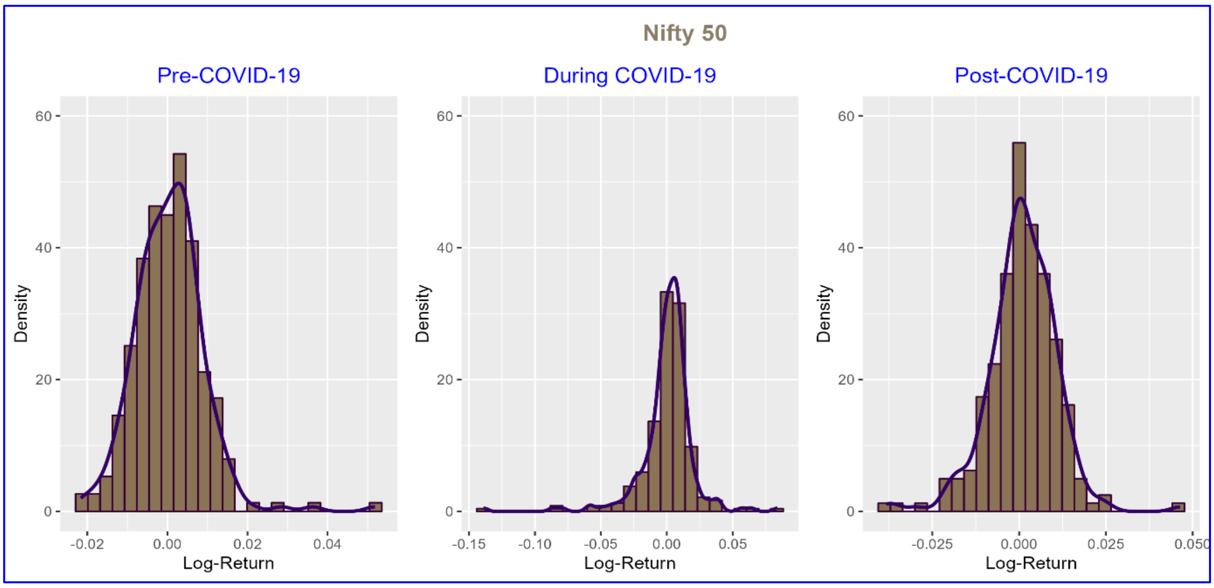
COVID-19 pandemic, the index experienced a sharp fall because of disruptions in supply chains, manufacturing and distribution challenges, and reduced consumer spending due to economic uncertainties. But post-COVID-19, it is also slowly



increasing. Then the Log-return of the Nifty FMCG index is less volatile than the Nifty 50 index so we conclude that the price movements of the index are more predictable during that time.

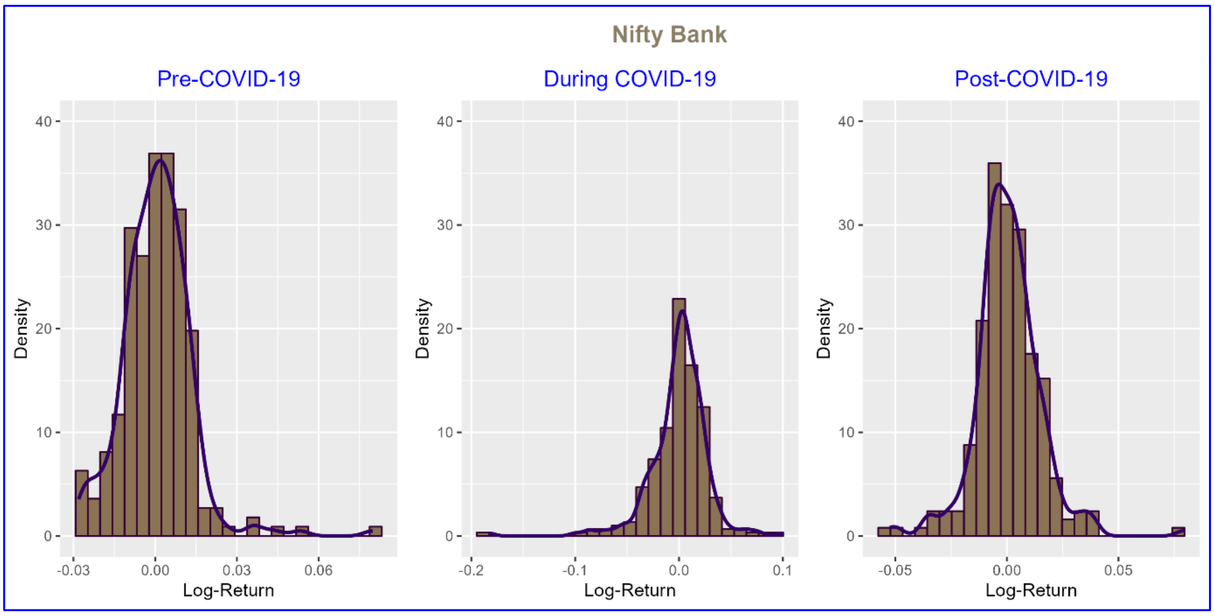
The analysis of the Nifty 50 index throughout the COVID-19 pandemic reveals a sharp initial decline, marked by increased volatility as reflected in higher log returns. This heightened volatility signifies substantial market instability driven by pandemic-related uncertainty. Similar trends were noted in sectorial indices like Nifty Bank, Nifty IT, Nifty Pharma, and Nifty FMCG, suggesting a widespread economic impact. Notably, the Nifty Bank index displayed greater volatility compared to sectors like IT, FMCG, and Pharma, which can be attributed to its regulatory role in the financial sector. The uncertainties regarding economic conditions and loan defaults influenced the pronounced fluctuations within the Nifty Bank index.

- ✧ **Histogram Plot of the three-time zone:** Here we plot the nifty 50, Nifty Bank, Nifty IT, Nifty Pharma and Nifty FMCG and three time periods pre, during and post COVID Histogram Plot.
  - ◆ **Nifty 50:** Before COVID 19, the histogram displayed a slight positive skewness and a high degree of kurtosis. During COVID 19, the histogram shifted to a slight negative



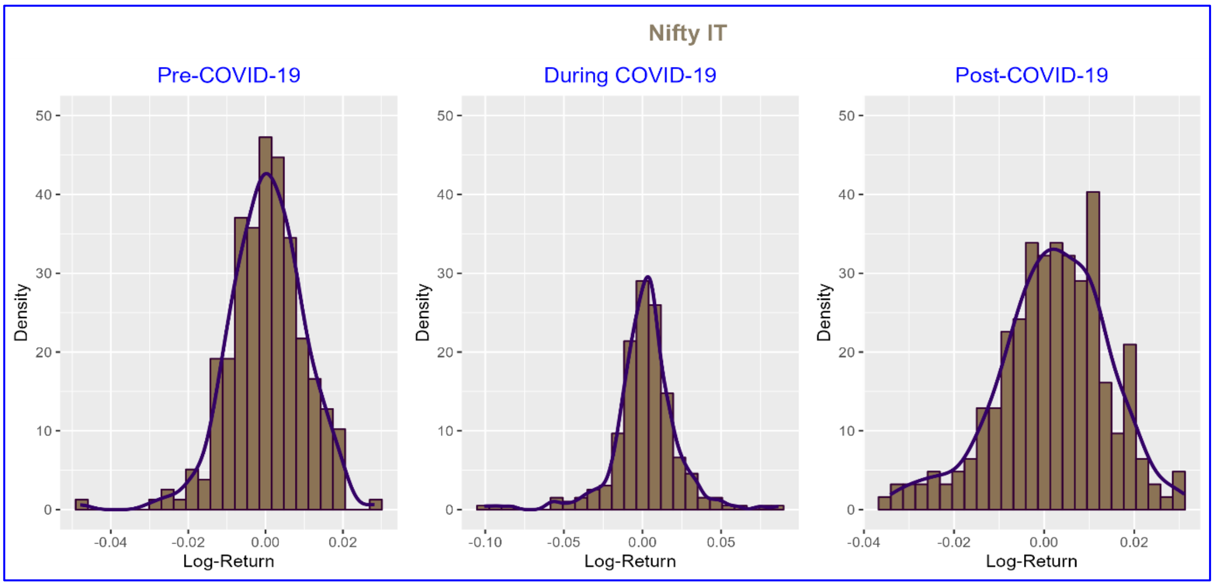
skewness while maintaining a high kurtosis. Post-COVID-19, the histogram become more symmetric, suggesting a more balanced distribution, yet it still retained a high kurtosis. These changes in skewness and kurtosis reflect the shifting patterns and impacts experienced during and after the COVID 19 pandemic.

  - ◆ **Nifty Bank:** Before COVID 19, the histogram displayed a slight positive skewness and a high degree of kurtosis During COVID 19, the histogram shifted to a slight negative skewness while maintaining a high kurtosis. Post COVID 19, the histogram become more symmetric, suggesting a more balanced distribution, yet it still retained



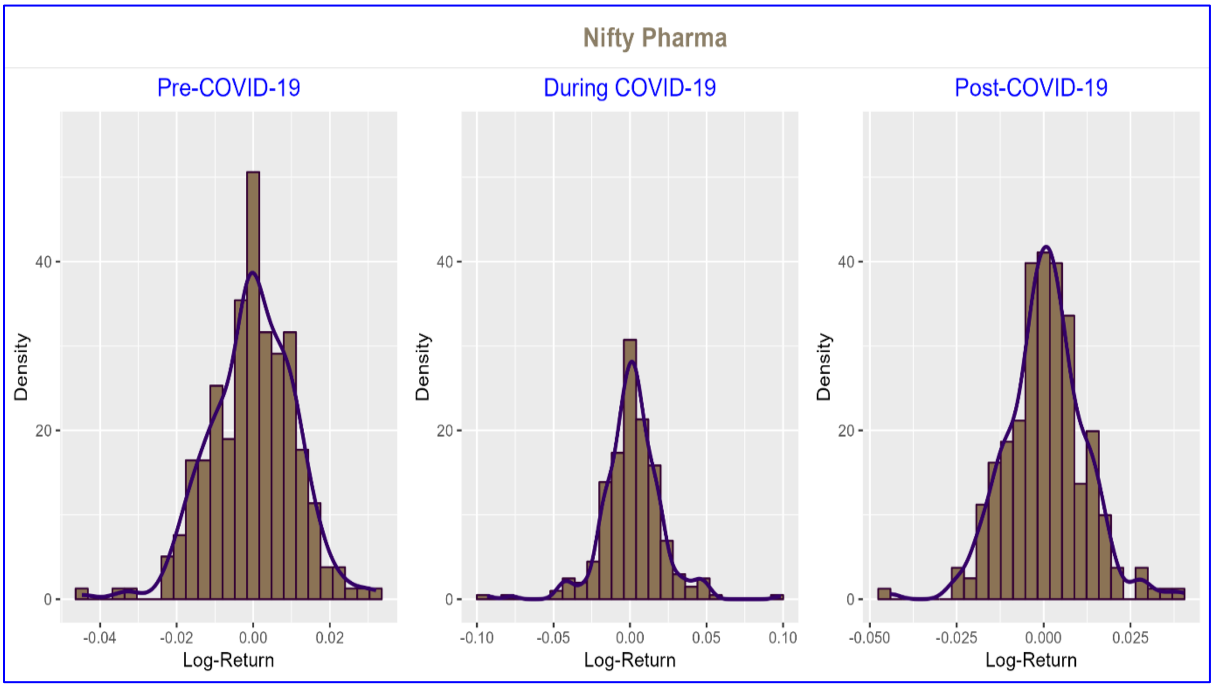
a high kurtosis. These changes in skewness and kurtosis reflect the shifting patterns and impacts experienced during and after the COVID 19 pandemic.

- **Nifty IT:** Before COVID 19, the histogram displayed a slight negative skewness and high degree of kurtosis. During COVID 19 and Post COVID 19, the histogram become



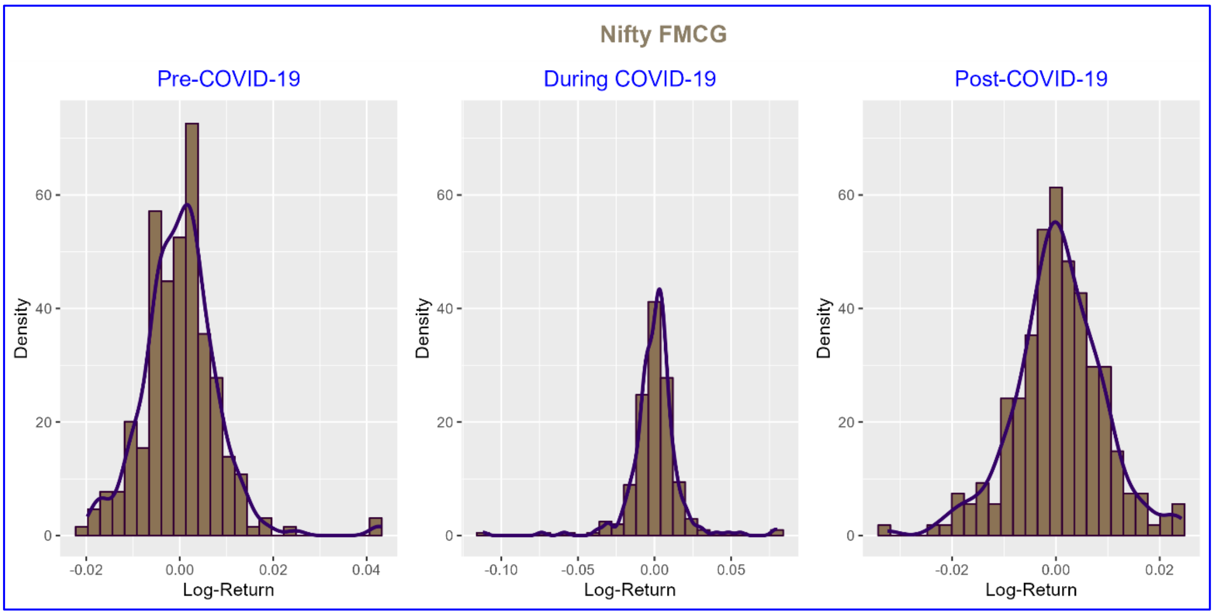
more symmetric, suggesting a more balanced distribution, yet it still retained a high kurtosis. These changes in skewness and kurtosis reflect the shifting patterns and impacts experienced during and after the COVID 19 pandemic.

- **Nifty Pharma:** The histogram of Nifty Pharma before, during and after COVID-19 displayed a symmetrical distribution. The high kurtosis in each period indicates a concentration of values around the centre with notable variability. These consistent



characteristics suggest a balanced distribution of values throughout the different phases, despite the impact of the pandemic.

- **Nifty FMCG**: Before COVID 19, the histogram displayed a slight positive skewness and a high degree of kurtosis. During COVID 19, the histogram shifted to a symmetric one while maintaining a high kurtosis. Post COVID 19, the histogram become more symmetric, suggesting a more balanced distribution, yet it still retained a high kurtosis. These changes in skewness and kurtosis reflect the shifting patterns and impacts experienced during and after the COVID 19 pandemic.



Based on our observation of the histograms for various indices (Nifty 50, Nifty Bank, Nifty IT, Nifty pharma, Nifty FMCG) during three different periods, we have concluded that all the histograms exhibit a more or less symmetric, distribution with high kurtosis. Symmetric in the histograms suggests a balanced distribution of values. High kurtosis indicates a concentration of values around the centre with significant variability. Based on these characteristics, we propose that the data may potentially follow normal or t-distribution. Both of these distributions can exhibit symmetry distribution. And t-distribution has higher kurtosis.

✧ Descriptive Analysis:

We see the descriptive statistics of the three-time zone before, during and after COVID-19 and also compare them. Standard Deviation says that this time period volatility. It is also associated with risk. A large kurtosis indicates a high degree of investment risk, so there are high chances of either high returns or small returns.

Nifty 50			
	Pre-COVID19	During-COVID19	Post-COVID19
Mean	0.00049086	0.00048835	0.00096140
Median	0.00047035	0.00239322	0.00122246
Maximum	0.05182469	0.08400291	0.04633331
Minimum	-0.02161425	-0.13903750	-0.03836226
Standard Deviation	0.00870340	0.02006500	0.00986154
Skewness	1.04469500	-1.72243600	-0.25176970
Kurtosis	8.22911800	15.18839000	6.08564800
Observation	247	252	228

During COVID, we noted that the standard deviation of Nifty 50 was high, indicating greater variability in the data than before and after COVID. So during COVID, investing risk is high. Additionally, the kurtosis during was high, indicating high investment risk in the data compared to before and post COVID. Based on the definition, the distribution of Nifty 50 was positively skewed before COVID, negatively skewed during COVID, and either negatively skewed or close to symmetry post COVID.

Nifty Bank			
	Pre-COVID19	During-COVID19	Post-COVID19
0Mean	0.00056536	-0.00002535	0.00063199
Median	0.00020543	0.00252783	-0.00000072
Maximum	0.07983901	0.09995149	0.07933049
Minimum	-0.02809318	-0.18313000	-0.05238543
Standard Deviation	0.01266587	0.02765849	0.01458764
Skewness	1.26935200	-1.40340300	0.42693010
Kurtosis	9.92752100	11.58263000	7.43203700
Observation	247	252	228

During COVID, we noted that the standard deviation of Nifty Bank was high, indicating greater variability in the data compare to the before and post COVID.So during COVID, investing risk is high. Based on the definition, the distribution of Nifty Bank was positively skewed before COVID, negatively skewed during COVID, and either negatively skewed or close to symmetry post COVID. All three-time kurtosis is high indicates a high degree of investment risk, so there are high chances of either high returns or small returns.

Nifty IT			
	Pre-COVID19	During-COVID19	Post-COVID19
Mean	0.00031113	0.00160917	0.00185930
Median	0.00035731	0.00229113	0.00237391
Maximum	0.02814415	0.08640420	0.03115885
Minimum	-0.04794805	-0.10064981	-0.03414740
Standard Deviation	0.00972663	0.02123672	0.01222483
Skewness	-0.54465620	-0.70241295	-0.41758041
Kurtosis	5.09657800	8.39770940	3.33957443
Observation	247	252	228

During COVID, the standard deviation of Nifty IT was high, indicating greater variability in the data than before and after COVID. So during COVID, investing risk is high. We observed a negatively skewed throughout all three periods. The skewness values were small, indicating a relatively mid-departure from symmetry. Regarding kurtosis, we noted that during COVID, the kurtosis was high compared to the before and post COVID periods.

Nifty Pharma			
	Pre-COVID19	During-COVID19	Post-COVID19
Mean	-0.00020455	0.00146173	0.00057596
Median	-0.00021690	0.00121730	0.00079962
Maximum	0.03210367	0.09864997	0.04035055
Minimum	-0.04470944	-0.09350741	-0.04422580
Standard Deviation	0.01101399	0.01966089	0.01125724
Skewness	-0.29158410	-0.10942332	0.04648471
Kurtosis	3.91181700	7.85114873	4.36259800
Observation	247	252	228

During COVID, the standard deviation of Nifty Pharma was high, indicating greater variability in the data compare to the before and post COVID.So during COVID, investing risk is high. We observed that negatively skewed before and during and the post was positively skewed but the skewness are very small so we noted that they are symmetric. Kurtosis during was high indicating investment risk is high, in the data compare to the before and post COVID.

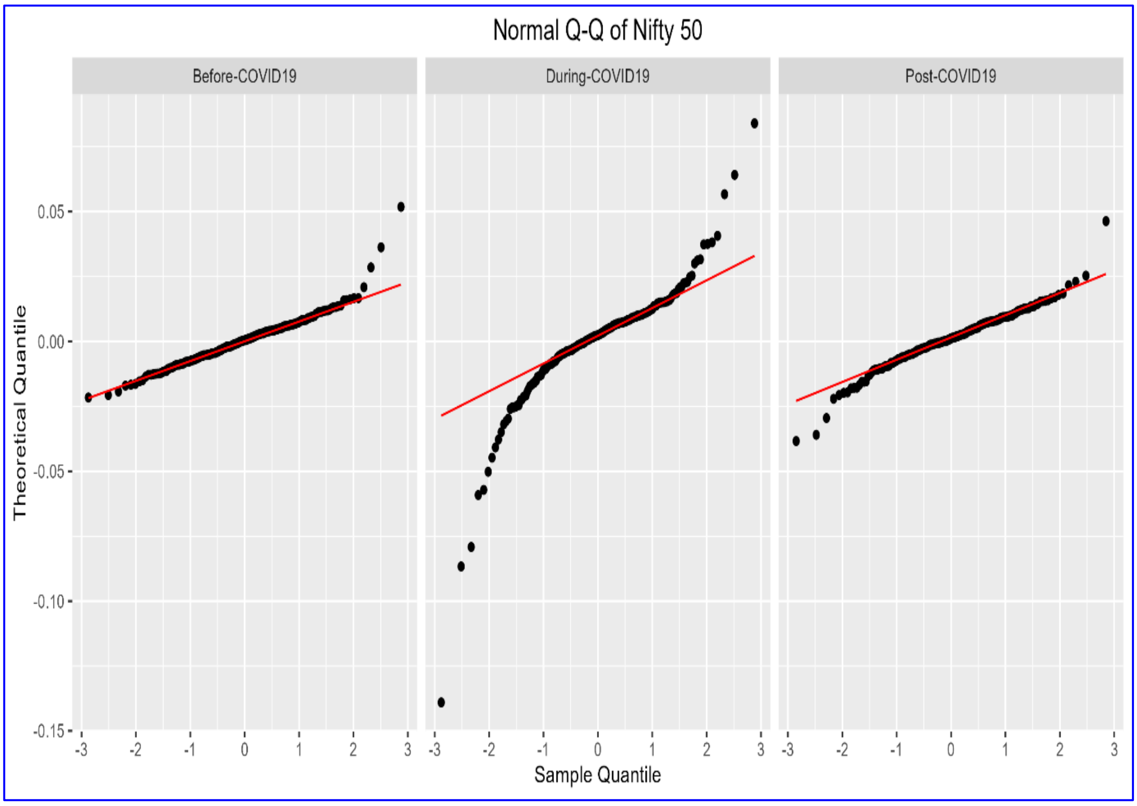
Nifty FMCG			
	Pre-COVID19	During-COVID19	Post-COVID19
Mean	0.00018350	0.00025917	0.00042836
Median	0.00015718	0.00114388	0.00035972
Maximum	0.04314073	0.07990603	0.02420708
Minimum	-0.01977294	-0.11199780	-0.03244359
Standard Deviation	0.00811928	0.01660987	0.00859764
Skewness	1.05660300	-0.72296920	-0.18503910
Kurtosis	8.24879100	16.32729000	4.09195300
Observation	247	252	228

During COVID, the standard deviation of Nifty FMCG was high, indicating greater variability in the data than before and after COVID.So during COVID, investing risk is high. We observed negatively skewed during and post but before COVID, was positively skewed but skewness are small so we noted that they are symmetric. Kurtosis during was very high indicating investment risk is high, in the data compare to the before and post COVID.

Based on the analysis of log returns for the Nifty index and sectorial indices, it is evident that the standard deviation during the COVID-19 period was higher compared to before and after the pandemic. This indicates an increased level of risk and market uncertainty during that time. The skewness of the distributions was generally close to zero, suggesting symmetric distributions across the board. And also observed the kurtosis values were consistently higher than the normal distribution. Therefore, to accurately capture the data's characteristics, it is advisable to assess both the t-distribution and normal distribution and choose the distribution that provides the best fit for our specific dataset. Notably, during the COVID-19 period, the kurtosis was significantly higher, indicating the returns were small or high return.

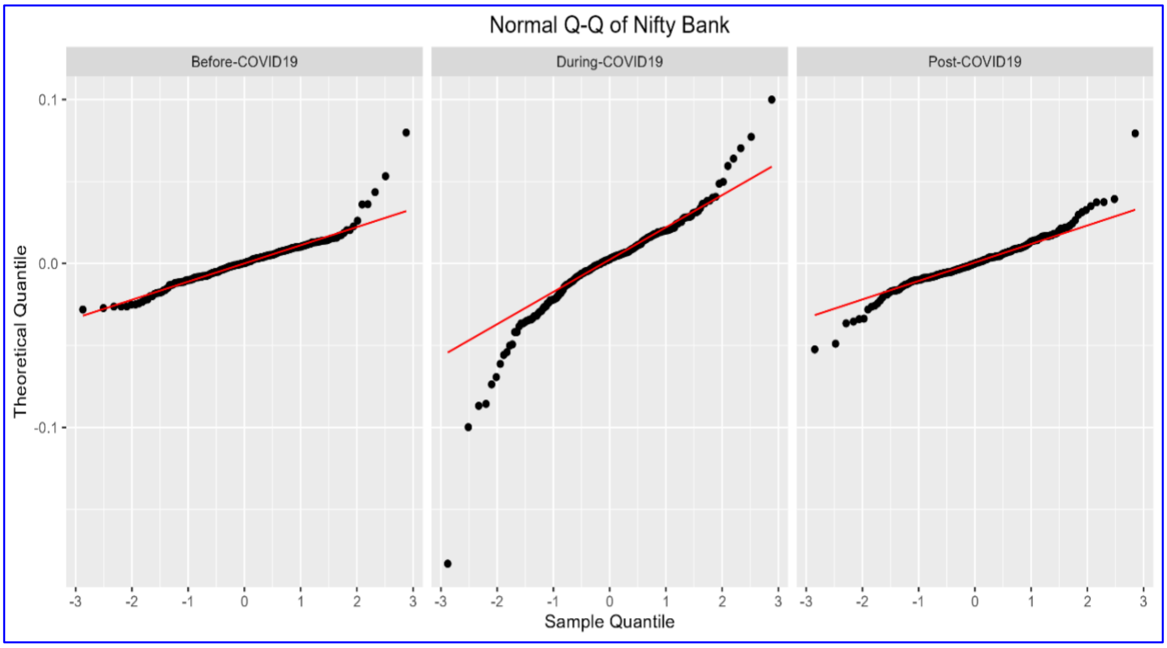
✧ Q-Q Plot of Normal Distribution:

- **Nifty 50:** Before COVID, we observed that the right-side tail of the QQ plot did not fit properly, suggesting a departure from a perfect normal distribution. During the COVID period, we observed that the data points were far away from the line on the QQ plot, indicating a significant deviation from a normal distribution. Post COVID, we noticed that both the right and left tails were not set properly, indicating a lack of proper fit to a normal distribution. Based on these observations, it can be concluded that the data for Nifty 50 does not fit a normal distribution well, with varying degrees

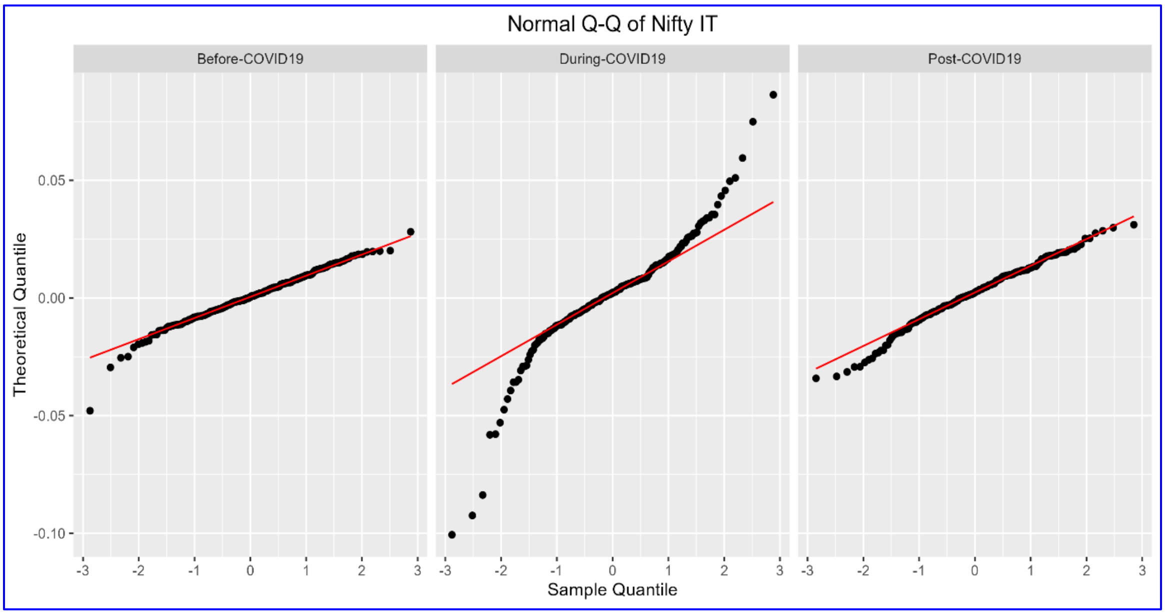


of deviation in different time periods.

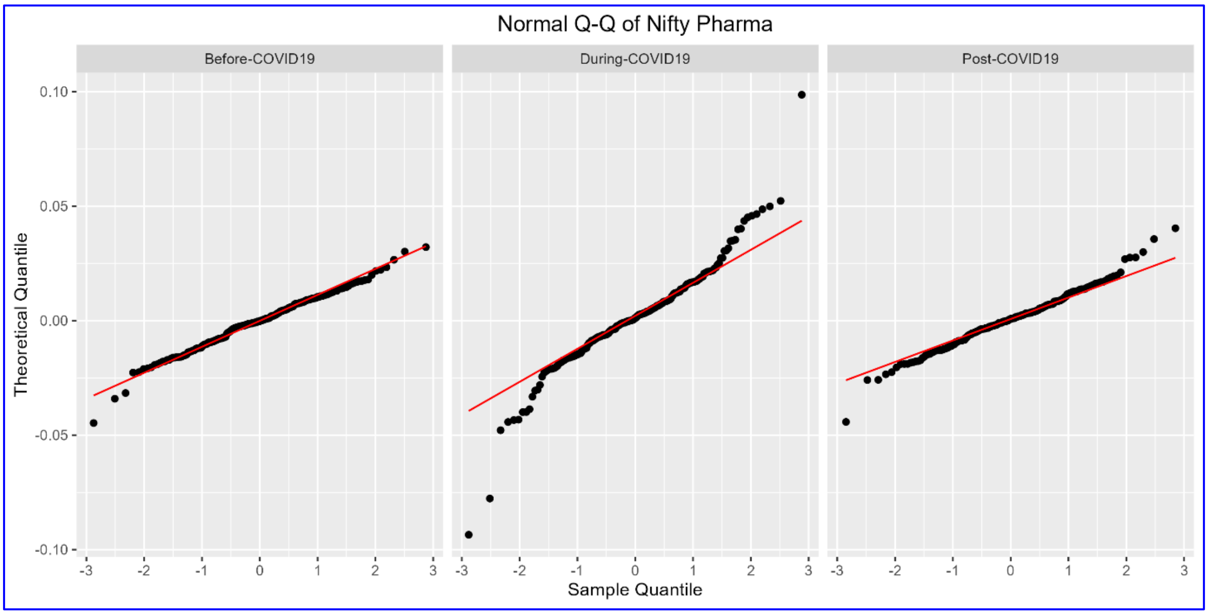
- **Nifty Bank:** Before COVID, we observed that the right-side tail of the QQ plot did not fit properly, suggesting a departure from a perfect normal distribution. And same as Nifty Bank QQ plot so concluded that the data for Nifty Bank does not fit a normal distribution well, with varying degrees of deviation in different time periods.



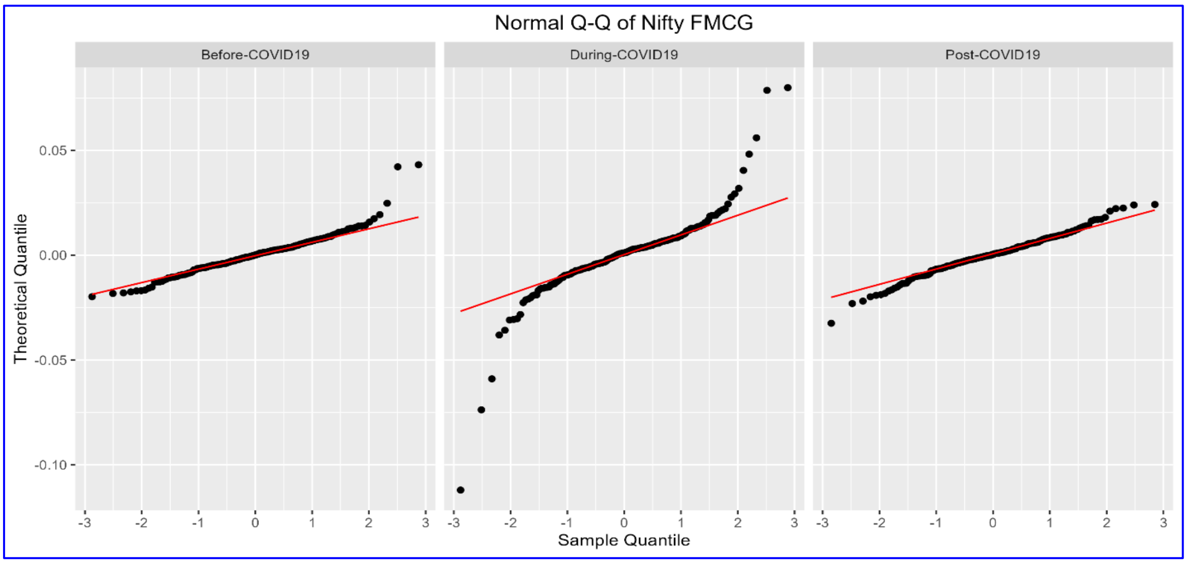
- **Nifty IT:** Before COVID, there were one of four points in the left tail that did not fit properly, the overall fit of the QQ plot was good. This suggests that a normal distribution can reasonably approximate the data distribution before the pandemic. Post COVID, we observed a similar pattern where overall fit is a good, indicating that a normal distribution can be considered a reasonable approximation for the post COVID data. During the COVID period, we observed that the data points were far away from the line on the QQ plot, indicating a significant deviation from a normal distribution.



- **Nifty Pharma:** Before and after COVID, there were one of three points in the left tail that did not fit properly, the overall fit of the QQ plot was good. This suggests that a normal distribution can reasonably approximate the data distribution before the pandemic. During the COVID period, we observed that the data points were far away from the line on the QQ plot, indicating a significant deviation from a normal distribution.



- **Nifty FMCG:** Before COVID, we observed that the right-side tail of the QQ plot did not fit properly, suggesting a departure from a perfect normal distribution. During the COVID period, we observed that the data points were far away from the line on the QQ plot, indicating a significant deviation from a normal distribution. Post COVID, we noticed that overall fit is good. This suggests that a normal distribution can reasonably approximate the data distribution post the pandemic.



The QQ plots of the Nifty 50 index and sectorial indices revealed that before and after COVID-19, the data closely followed a Normal distribution. However, during the COVID-19 period, the data deviated from the Normal distribution, indicating increased volatility and potential extreme events.

✧ Test of Symmetry (Cabilio – Masaro Test):

- Nifty 50: Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty 50 data for three different time periods. Here are the results and conclusions:

Nifty 50			
Cabilio and Masaro Test	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.049015	0.98	Accept the H_0
During COVID-19	-1.9947	0.034*	Reject the H_0
After COVID-19	-0.52907	0.59	Accept the H_0

1. Before COVID-19: The test resulted in a p-value of 0.98, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the data is symmetric. Therefore, we conclude that the Nifty 50 data before COVID-19 exhibits symmetry.
2. During COVID-19: The test yielded a p-value of 0.34, considering a 1% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis of symmetry for the Nifty 50 data during the COVID-19 period. Therefore, we conclude that the data maintains its symmetry during this time.
3. After COVID-19: The test resulted in a p-value of 0.59, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the data is symmetric after COVID-19. Consequently, we conclude that the Nifty 50 data remains symmetric during this period.

In summary, based on the Cabilio Masaro test, we find that the distribution of the Nifty 50 data is symmetric across all three time periods: before COVID-19, during COVID-19, and after COVID-19. This indicates that the data exhibits a balanced distribution around its central tendency.

- **Nifty Bank:** Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty Bank data for three different time periods. Here are the results and conclusions:

Nifty Bank			
Cabilio and Masaro Test	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.59114	0.552	Accept the H_0
During COVID-19	-1.9396	0.046*	Reject the H_0
After COVID-19	0.86686	0.408	Accept the H_0

In summary, based on the Cabilio Masaro test, we find that the distribution of the Nifty Bank data is symmetric across all three time periods: before COVID-19, during COVID-19, and after COVID-19. This indicates that the data exhibits a balanced distribution around its central tendency.

- **Nifty IT:** Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty IT data for three different time periods. Here are the results and conclusions:

Nifty IT			
Cabilio and Masaro Test	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	-0.098758	0.912	Accept the H_0
During COVID-19	-0.67473	0.476	Accept the H_0
After COVID-19	-0.84132	0.412	Accept the H_0

In summary, based on the Cabilio Masaro test, we find that the distribution of the Nifty IT data is symmetric across all three time periods: before COVID-19, during COVID-19, and after COVID-19. This indicates that the data exhibits a balanced distribution around its central tendency.

- **Nifty Pharma:** Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty Pharma data for three different time periods. Here are the results and conclusions:

Nifty Pharma			
Cabilio and Masaro Test	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.023342	0.974	Accept the H_0
During COVID-19	0.26121	0.772	Accept the H_0
After COVID-19	-0.39708	0.69	Accept the H_0

In summary, based on the Cabilio Masaro test, we find that the distribution of the Nifty Pharma data is symmetric across all three time periods: before COVID-19, during COVID-19, and after COVID-19. This indicates that the data exhibits a balanced distribution around its central tendency.

- **Nifty FMCG:** Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty Pharma data for three different time periods. Here are the results and conclusions:

Nifty FMCG			
Cabilio and Masaro Test	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.06743	0.948	Accept the H_0
During COVID-19	-1.1192	0.286	Accept the H_0
After COVID-19	0.15956	0.87	Accept the H_0

In summary, based on the Cabilio Masaro test, we find that the distribution of the Nifty FMCG data is symmetric across all three time periods: before COVID-19, during COVID-19, and after COVID-19. This indicates that the data exhibits a balanced distribution around its central tendency.

In our analysis of the Nifty 50, Nifty Bank, Nifty IT, Nifty Pharma, and Nifty FMCG indices, we employed the Cabilio-Masaro test to examine the symmetry of log returns. For all the datasets, including the periods after, during, and post-COVID, the test results supported the null hypothesis of symmetric distribution at a significance level of 5%. However, during the COVID-19 period, the Nifty 50 and Nifty Bank indices exhibited a slight departure from symmetry, although they still upheld the null hypothesis at a higher significance level of 1%. Therefore, we conclude that the log return distributions of these indices, overall, can be considered symmetric. Based on these findings, we approached the analysis by considering both the t-distribution and normal distribution to evaluate the best fit for the data.

✧ Kolmogorov-Smirnov test for Normal Distribution:

- **Nifty 50**: Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty 50 data for three different time periods. Here are the results and conclusions:

Nifty 50					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.000490857	0.008703398	0.059374	0.3486	Accept the H_0
During COVID-19	0.000488352	0.020065	0.14665	3.93E-05	Reject the H_0
After COVID-19	0.000961401	0.009861536	0.06296	0.3267	Accept the H_0

1. Before COVID-19: The KS test resulted in a p-value of 0.34, considering a 5% level of significance. This p-value is higher than the significance level, leading us to accept the null hypothesis. Therefore, we conclude that the Nifty 50 data before COVID-19 approximately follows a normal distribution.
2. During COVID-19: The KS test yielded a p-value of <0.001, which is lower than the 1% level of significance. Thus, we reject the null hypothesis, indicating that the Nifty 50 data during COVID-19 does not adhere to a normal distribution.
3. After COVID-19: The KS test resulted in a p-value of 0.32, considering a 5% level of significance. This p-value is higher than the significance level, leading us to accept the null hypothesis. Therefore, we conclude that the Nifty 50 data before COVID-19 approximately follows a normal distribution.

Based on these findings, we conclude that during the COVID-19 period, the Nifty 50 data did not adhere to a normal distribution. Although the p-value was accepted, it was relatively small, indicating that the fit to the normal distribution was not very good.

- **Nifty Bank:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty Bank data for three different time periods. Here are the results and conclusions:

Nifty Bank					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.000565361	0.01266587	0.072385	0.1502	Accept the H_0
During COVID-19	-2.53521E-05	0.02765849	0.1069	0.006305	Reject the H_0
After COVID-19	0.00063199	0.01458764	0.087467	0.06109	Accept the H_0

Based on these findings, we conclude that during the COVID-19 period, the Nifty Bank data did not adhere to a normal distribution. Although the p-value was accepted, it was relatively small, indicating that the fit to the normal distribution was not very good.

- **Nifty IT:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty IT data for three different periods. Here are the results and conclusions:

Nifty IT					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.000311135	0.009726632	0.036519	0.8968	Accept the H_0
During COVID-19	0.00160917	0.021236716	0.10992	0.004534	Reject the H_0
After COVID-19	0.001859301	0.012224827	0.045332	0.7369	Accept the H_0

Based on these findings, we conclude that during the COVID-19 period, the Nifty IT data did not adhere to a normal distribution. Although the p-value was accepted, it was good, indicating that the fit to the normal distribution was good.

- **Nifty Pharma:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty Pharma data for three different time periods. Here are the results and conclusions:

Nifty Pharma					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	-0.000204545	0.01101399	0.060737	0.3219	Accept the H_0
During COVID-19	0.001461726	0.019660888	0.07883	0.08726	Accept the H_0
After COVID-19	0.000575963	0.01125724	0.049696	0.6265	Accept the H_0

Based on these findings, we conclude that here the p-value was accepted, it was relatively small, indicating that the fit to the normal distribution was not very good.

- **Nifty FMCG:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty FMCG data for three different time periods. Here are the results and conclusions:

Nifty FMCG					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	0.000183503	0.008119282	0.06939	0.1852	Accept the H_0
During COVID-19	0.000259165	0.01660987	0.13945	0.0001109	Reject the H_0
After COVID-19	0.000428357	0.008597639	0.052592	0.5537	Accept the H_0

Based on these findings, we conclude that during the COVID-19 period, the Nifty 50 data did not adhere to a normal distribution. Although the p-value was accepted, it was relatively small, indicating that the fit to the normal distribution was not very good.

The Kolmogorov-Smirnov test for normal distribution was conducted for the Nifty 50 index and sectorial indices. The results indicated that before and after COVID-19, the null hypothesis of symmetric distribution was accepted, supported by small p-values (close to or less than 0.5). Specifically, the Nifty Pharma index followed the Normal distribution in all three time periods, with low probabilities. This suggests that the data exhibited symmetric distribution characteristics before and after COVID-19, while the Nifty IT index consistently adhered to the Normal distribution.

✧ Kolmogorov-Smirnov test for student-t distribution (KS Test student-t):

- **Nifty 50:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty 50 data for three different time periods. Here are the results and conclusions:

Nifty 50					
KS test for t-distribution	DF	Scale	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	7.41	0.01	0.031696	0.9651	Accept the H_0
During COVID-19	2.06	0.01	0.049762	0.5606	Accept the H_0
After COVID-19	4.61	0.01	0.030034	0.9863	Accept the H_0

1. Before COVID-19: We fit a t-distribution with a degree of freedom (df) of 7.41 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.96, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the Nifty 50 data during this period follows a t-distribution.
2. During COVID-19: We fit a t-distribution with a degree of freedom (df) of 2.06 and a scale parameter of 0.01 to the data. The KS test yielded a p-value of 0.56, also considering a 5% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis that the Nifty 50 data during this period can be approximated by a t-distribution.
3. After COVID-19: We fit a t-distribution with a degree of freedom (df) of 4.61 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.98, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the Nifty 50 data after COVID-19 follows a t-distribution.

In summary, based on the KS test and fitting t-distributions with appropriate degrees of freedom, we conclude that a t-distribution provides the best fit to the Nifty 50 data across all three time periods. This suggests that the data exhibits heavier tails compared to a normal distribution, which is expected as the t-distribution accommodates more extreme values.

- **Nifty Bank:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty Bank data for three different time periods. Here are the results and conclusions:

Nifty Bank					
KS test for t-distribution	DF	Scale	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	4.71	0.01	0.034658	0.928	Accept the H_0
During COVID-19	2.92	0.02	0.0466	0.6444	Accept the H_0
After COVID-19	3.63	0.01	0.040251	0.8538	Accept the H_0

1. Before COVID-19: We fit a t-distribution with a degree of freedom (df) of 4.71 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.92, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the Nifty Bank data during this period follows a t-distribution.

2. During COVID-19: We fit a t-distribution with a degree of freedom (df) of 2.92 and a scale parameter of 0.02 to the data. The KS test yielded a p-value of 0.64, also considering a 5% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis that the Nifty Bank data during this period can be approximated by a t-distribution.
3. After COVID-19: We fit a t-distribution with a degree of freedom (df) of 3.68 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.85, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the Nifty Bank data after COVID-19 follows a t-distribution.

In summary, based on the KS test and fitting t-distributions with appropriate degrees of freedom, we conclude that a t-distribution provides the best fit to the Nifty Bank data across all three time periods. This suggests that the data exhibits heavier tails compared to a normal distribution, which is expected as the t-distribution accommodates more extreme values.

- **Nifty IT:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty IT data for three different time periods. Here are the results and conclusions:

Nifty IT					
KS test for t-distribution	DF	Scale	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	9.85	0.01	0.019589	1	Accept the H_0
During COVID-19	2.39	0.01	0.040933	0.7923	Accept the H_0
After COVID-19	10.29	0.01	0.037718	0.9019	Accept the H_0

1. Before COVID-19: We fit a t-distribution with a degree of freedom (df) of 9.85 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 1, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the Nifty IT data during this period follows a t-distribution.
2. During COVID-19: We fit a t-distribution with a degree of freedom (df) of 2.39 and a scale parameter of 0.02 to the data. The KS test yielded a p-value of 0.79, also considering a 5% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis that the Nifty IT data during this period can be approximated by a t-distribution.
3. After COVID-19: We fit a t-distribution with a degree of freedom (df) of 10.29 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.90, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the Nifty IT data after COVID-19 follows a t-distribution.

In summary, based on the KS test and fitting t-distributions with appropriate degrees of freedom, we conclude that a t-distribution provides the best fit to the Nifty IT data across all three time periods. This suggests that the data exhibits heavier tails compared to a normal distribution, which is expected as the t-distribution accommodates more extreme values.

- **Nifty Pharma:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty Pharma data for three different time periods. Here are the results and conclusions:

Nifty Pharma					
KS test for t-distribution	DF	Scale	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	10.19	0.01	0.045649	0.6821	Accept the H_0
During COVID-19	3.19	0.01	0.022366	0.9996	Accept the H_0
After COVID-19	7.79	0.01	0.034104	0.9536	Accept the H_0

1. Before COVID-19: We fit a t-distribution with a degree of freedom (df) of 10.19 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.68, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the Nifty Pharma data during this period follows a t-distribution.
2. During COVID-19: We fit a t-distribution with a degree of freedom (df) of 3.19 and a scale parameter of 0.01 to the data. The KS test yielded a p-value of 0.99, also considering a 5% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis that the Nifty Pharma data during this period can be approximated by a t-distribution.
3. After COVID-19: We fit a t-distribution with a degree of freedom (df) of 7.79 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.95, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the Nifty Pharma data after COVID-19 follows a t-distribution.

In summary, based on the KS test and fitting t-distributions with appropriate degrees of freedom, we conclude that a t-distribution provides the best fit to the Nifty Pharma data across all three time periods. This suggests that the data exhibits heavier tails compared to a normal distribution, which is expected as the t-distribution accommodates more extreme values.

- **Nifty FMCG:** Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty FMCG data for three different time periods. Here are the results and conclusions:

Nifty FMCG					
KS test for t-distribution	DF	Scale	Test Statistic	p-value	Decision (5% level of significance)
Before COVID-19	4.89	0.01	0.032463	0.957	Accept the H_0
During COVID-19	2.34	0.01	0.038138	0.857	Accept the H_0
After COVID-19	9.05	0.01	0.03138	0.9783	Accept the H_0

1. Before COVID-19: We fit a t-distribution with a degree of freedom (df) of 4.89 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.95, considering a 5% level of significance. Since the p-value is higher than the significance level, we accept the null hypothesis that the Nifty FMCG data during this period follows a t-distribution.

2. During COVID-19: We fit a t-distribution with a degree of freedom (df) of 2.34 and a scale parameter of 0.01 to the data. The KS test yielded a p-value of 0.85, also considering a 5% level of significance. Given that the p-value is higher than the significance level, we accept the null hypothesis that the Nifty FMCG data during this period can be approximated by a t-distribution.

3. After COVID-19: We fit a t-distribution with a degree of freedom (df) of 9.05 and a scale parameter of 0.01 to the data. The KS test resulted in a p-value of 0.97, considering a 5% level of significance. Since the p-value is higher than the significance level, we again accept the null hypothesis that the Nifty FMCG data after COVID-19 follows a t-distribution.

In summary, based on the KS test and fitting t-distributions with appropriate degrees of freedom, we conclude that a t-distribution provides the best fit to the Nifty FMCG data across all three time periods. This suggests that the data exhibits heavier tails compared to a normal distribution, which is expected as the t-distribution accommodates more extreme values.

6. During COVID Time point Shift analysis:~

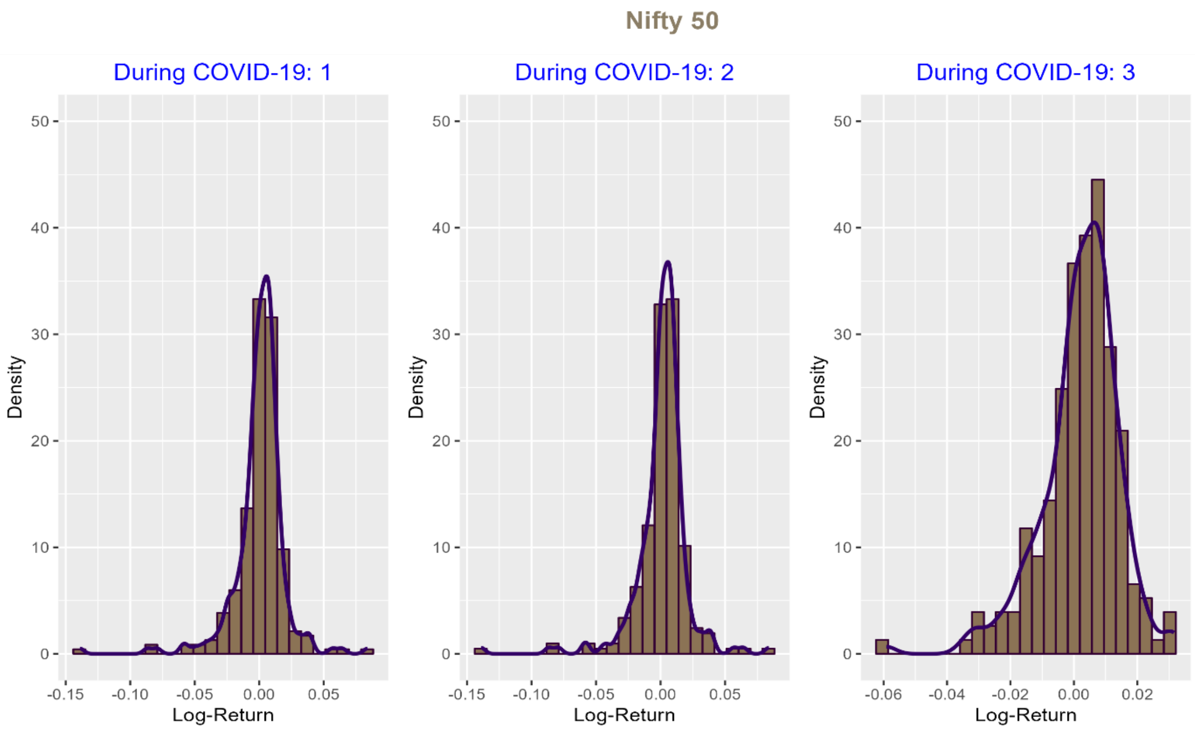
During our analysis of the during COVID time period, which spanned from January 29, 2020, to January 30, 2021, we observed a significant event on March 11, 2020, when the World Health Organization (WHO) declared COVID-19 as a pandemic. Additionally, we noticed a sharp fall in the Nifty 50 curve during this time. To further investigate the impact of this event and subsequent market behaviour, we decided to shift the first time point of our analysis to April 15, 2020. By doing so, we can focus specifically on the period after the sharp fall in the Nifty 50 curve and assess any trends or patterns that emerged during that time.

By adjusting the starting point of our analysis to March 11, 2020, and April 15, 2020 we can focus on the effects of the pandemic declaration and the initiation of the lockdown on the data. This modified analysis will enable us to gain insights into the specific changes and patterns in the data surrounding these key events.

1. Descriptive Analysis: During the three phases of the COVID-19 pandemic, namely COVID-1, COVID-2, and COVID-3, distinct patterns emerge when analyzing various statistical measures. Notably, in COVID-3, a significant reduction in the standard deviation becomes evident when compared to the previous two phases. This decrease can be attributed to the mitigation of sharp falls and extreme fluctuations that characterized the earlier periods. Additionally, a consistent negative skewness persists across all three phases, indicating a distribution skewed towards the higher values. Interestingly, during COVID-3, a noteworthy decrease in kurtosis is observed, suggesting a flatter and less risky distribution compared to the preceding phases. This reduction in kurtosis implies a decrease in the likelihood of extreme events, reflecting a potentially more stable and controlled situation.

Nifty 50			
	During Covid 1	During Covid 2	During Covid 3
Time	29/01/2020-30/01/2021	11/03/2020-30/01/2021	15/04/2020-30/01/2021
Mean	0.000488352	0.001192242	0.002059751
Median	0.002393217	0.00305787	0.003305883
Maximum	0.08400291	0.084002906	0.031584148
Minimum	-0.1390375	-0.139037542	-0.059160796
Standard Deviation	0.020065	0.020530779	0.012256318
Skewness	-1.722436	-1.80837137	-1.027891322
Kurtosis	15.18839	15.65630172	6.044609287
Observation	252	223	202

2. Histogram Plot: The histograms across all phases exhibit a consistent negative skewness, indicating a bias towards higher values. Notably, in the context of COVID-3, the observed low kurtosis distinguishes it from the preceding two phases, suggesting a distribution with less pronounced tails and lower likelihood of extreme outcomes.



3. Test of Symmetry (Cabilio – Masaro Test): Based on the Cabilio Masaro test for symmetry, we conducted an analysis of the Nifty 50 data for three different time periods. Here are the results and conclusions:

Nifty 50				
	Time	Test Statistic	p-value	Decision (5% level of significance)
During Covid 1	29/01/2020-30/01/2021	-1.9947	0.044*	**Reject the H_0**
During Covid 2	11/03/2020-30/01/2021	-1.7961	0.048*	**Reject the H_0**
During Covid 3	15/04/2020-30/01/2021	-1.9127	0.024*	**Reject the H_0**

Utilizing the Cabilio-Masaro test, we rejected all symmetric tests at a 5% significance level. However, at a more stringent 1% significance level, the null hypothesis is accepted, indicating symmetry in the distribution

4. Kolmogorov test for Normal Distribuiton: Based on the Kolmogorov-Smirnov (KS) test, we conducted a normality analysis of the Nifty data for three different periods. Here are the results and conclusions:

Nifty 50					
TS Test for Normal Distribution	Mean	Standard Deviation	Test Statistic	p-value	Decision (5% level of significance)
During COVID-19: 1	0.000488352	0.020065	0.14665	3.93E-05	Reject the H_0
During COVID-19: 2	0.001192242	0.020531	0.15354	5.43E-05	Reject the H_0
During COVID-19: 3	0.002059751	0.012256	0.094623	0.05371	Accept the H_0

Based on these findings, we conclude that during the COVID-19 period, the Nifty data did not adhere to a normal distribution. Although the p-value was rejected and During COVID 19:3 we accepted the null hypothesis. So we conclude that Nifty 50 during COVID 19 was not fit Normal Distribution but that sharp fall we removed then some time Normal Distribution follows.

5. Kolmogorov test for t - Distribution: Based on the Kolmogorov-Smirnov (KS) test, we conducted a t-distribution analysis of the Nifty 50 data for three different time periods. Here are the results and conclusions:

Nifty 50				
Kolmogorov test for t-distribution	DF	Test Statistic	p-value	Decision (5% level of significance)
During COVID-19: 1	2.06	0.49762	0.5606	**Accept the H_0**
During COVID-19 : 2	<2			
During COVID-19: 3	4.14	0.045046	0.807	**Accept the H_0**

In COVID-1 and COVID-3 periods, the null hypothesis was accepted, implying a suitable fit to the t-distribution. However, during COVID-2, due to the maximum likelihood estimation constraints where the degrees of freedom (df) are less than 2, the t-distribution does not provide a suitable fit.

In summary, the distribution during the COVID-19 period occasionally conforms to the t-distribution, provided we select appropriate time points. This underscores the significance of choosing the right time frame, as it strongly influences the distribution's behavior and statistical properties.

7. CONCLUSION:~

The analysis of the Nifty 50 index during COVID-19 indicates a pronounced initial decline, accompanied by increased volatility in log returns, reflecting market instability due to the pandemic. This trend aligns with similar fluctuations observed in sectorial indices like Nifty Bank, Nifty IT, Nifty Pharma, and Nifty FMCG, signifying a widespread economic impact. Specifically, the Nifty Bank's higher volatility can be attributed to the banking sector's nature, linked to government-regulated services and lending activities, resulting in increased fluctuations driven by economic uncertainties..

The shape of histograms, displaying high peaks and symmetric distributions, suggests that the data could follow either a normal or t-distribution, both capable of exhibiting such characteristics. In our examination of Nifty 50, Nifty Bank, Nifty IT, Nifty Pharma, and Nifty FMCG indices, the Cabilio-Masaro test affirmed symmetric distribution across all time periods. Although slight deviations were noted during COVID-19, they still upheld symmetry at a higher significance level. These findings guided us to consider both t-distribution and normal distribution for the best fit. The QQ plots showed that data closely adhered to Normal distribution before and after COVID-19, deviating during the pandemic, indicating increased volatility and potential extreme events.

The Kolmogorov-Smirnov test assessed normal distribution for Nifty 50 index and sectorial indices, confirming acceptance of the null hypothesis before and after COVID-19, backed by small p-values (around or below 0.5). Notably, Nifty Pharma consistently adhered to Normal distribution throughout all three periods, implying symmetry characteristics pre and post-COVID-19. Similarly, the Nifty IT index consistently followed Normal distribution.

Fitting the t-distribution and using the Kolmogorov-Smirnov test, we found that the t-distribution's degrees of freedom (df) were lower during COVID-19 compared to before and after. Test results, with high p-values (near 1), favored the null hypothesis, signifying the t-distribution as the optimal fit during the pandemic. The reduced df in the t-distribution indicates heavier tails, capturing heightened volatility and potential outliers observed in this period. Thus, we conclude that the t-distribution is the most suitable fit for COVID-19 data.

The distribution during the COVID-19 period exhibits alignment with the t-distribution on certain occasions, contingent upon judicious time point selection. This underscores the critical importance of accurately choosing the timeframe, as it significantly shapes the distribution's characteristics and statistical attributes.

8. REFERENCE:~

- R. Chaudhary, P. Bakhshi & H. Gupta (2020). The performance of the Indian stock market during COVID-19. *The Journal of Investing Management and Financial Innovations*. Retriveved from https://dx.doi.org/10.21511/imfi.17(3).2020.11 .
- https://www.niftyindices.com/reports/historical-data
- Rahul Kumar, Prince Bhatia and Deeksha Gupta (2021). The impact of the COVID-19 outbreak on the Indian stock market – A sectoral analysis. *The Journal of Investment Management and Financial Innovations.* Retriveved from http://dx.doi.org/10.21511/imfi.18(3).2021.28
- https://www.niftyindices.com/

9. APPENDIX:

 # Including All Library __

```
library(ggplot2)
library(moments)
library(cowplot)
library(LambertW)
library(tidyverse)
library(ggpubr)
library(lawstat)
library(devtools)
```

 # Input All Data __

```
nifty <- read.csv("NIFTY_50_Data.csv",header = TRUE)
nbank <- read.csv("C:/Users//hp//Desktop//Project//SECTORIAL INDEX//NIFTY BANK_Data.csv")
nit <- read.csv("C:/Users//hp//Desktop//Project//SECTORIAL INDEX//NIFTY IT_Data.csv")
npharma <- read.csv("C:/Users//hp//Desktop//Project//SECTORIAL INDEX//NIFTY PHARMA_Data.csv")
nfmcg <- read.csv("C:/Users//hp//Desktop//Project//SECTORIAL INDEX//NIFTY FMCG_Data.csv")
```

 # Graphical Representation of Nifty Index to 2019-2021 __

```
ggplot(data = nifty)+geom_line(aes(x=Date,y=Close), col = "#05235f")+
  labs(title = "Nifty 50 index during 2019-2022",x = "Date",y = "Index")+
  theme(panel.background = element_rect(fill = "#91cad2"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))

ggplot(data = nbank)+geom_line(aes(x=Date,y=Close), col = "#05235f")+
  labs(title = "Nifty Bank index during 2019-2022",x = "Date",y = "Index")+
  theme(panel.background = element_rect(fill = "#91cad2"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
```

```
ggplot(data = nit)+geom_line(aes(x=Date,y=Close), col = "#2d097a")+
  labs(title = "Nifty IT",x = "Date",y = "Index")+
  theme(panel.background = element_rect(fill = "azure2"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
ggplot(data = npharma)+geom_line(aes(x=Date,y=Close), col = "#2d097a")+
  labs(title = "Nifty Pharma",x = "Date",y = "Index")+
  theme(panel.background = element_rect(fill = "azure2"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
ggplot(data = nfmcg)+geom_line(aes(x=Date,y=Close), col = "#2d097a")+
  labs(title = "Nifty FMCG",x = "Date",y = "Index")+
  theme(panel.background = element_rect(fill = "azure2"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
#Graphical Representation of Log-Return on Nifty 50 Index to 2019-2021
ggplot(data = nifty)+geom_line(aes(x=Date,y=log_re_nifty), col = "darkorange")+
  labs(title = "Log-Return on Nifty 50 Index to 2019-22",x = "Date",y = "Log-Return")+
  geom_hline(yintercept = 0,col = "#82a8a8")+
  theme(panel.background = element_rect(fill = "cornsilk1"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
g_bank <- ggplot(data = nbank)+geom_line(aes(x=Date,y=log_re_nbank), col =
"darkorange")+
  labs(title = "Log-Return on Nifty Bank",x = "Date",y = "Log-Return")+
  ylim(-0.15,0.1)+
  geom_hline(yintercept = 0,col = "#82a8a8")+
  theme(panel.background = element_rect(fill = "cornsilk1"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))

g_it <- ggplot(data = nit)+geom_line(aes(x=Date,y=log_re_nit), col = "darkorange")+
  labs(title = "Log-Return on Nifty IT",x = "Date",y = "Log-Return")+
  ylim(-0.15,0.1)+
  geom_hline(yintercept = 0,col = "#82a8a8")+
  theme(panel.background = element_rect(fill = "cornsilk1"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))

g_pharma <- ggplot(data = npharma)+geom_line(aes(x=Date,y=log_re_npharma), col =
"darkorange")+
  labs(title = "Log-Return on Nifty Pharma",x = "Date",y = "Log-Return")+
  ylim(-0.15,0.1)+
  geom_hline(yintercept = 0,col = "#82a8a8")+
  theme(panel.background = element_rect(fill = "cornsilk1"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
g_fmcg <- ggplot(data = nfmcg)+geom_line(aes(x=Date,y=log_re_nfmcg), col =
"darkorange")+
  labs(title = "Log-Return on Nifty FMCG",x = "Date",y = "Log-Return")+
  ylim(-0.15,0.1)+
  geom_hline(yintercept = 0,col = "#82a8a8")+
  theme(panel.background = element_rect(fill = "cornsilk1"))+
  theme(plot.title = element_text(hjust = 0.5,face = "bold",colour = "blue"))
#Data Set __
nifty_pre_c <- subset(nifty,Date <= "2020-01-30" & Date >= "2019-01-29" )
nifty_dur_c <- subset(nifty,Date <= "2021-01-30" & Date >= "2020-01-29")
```

```
nifty_pos_c <- subset(nifty,Date <="2021-12-30" & Date >= "2021-01-29")
nit_pre_c <- subset(nit,Date <= "2020-01-30" & Date >= "2019-01-29" )
nit_dur_c <- subset(nit,Date <= "2021-01-30" & Date >= "2020-01-29")
nit_pos_c <- subset(nit,Date <="2021-12-30" & Date >= "2021-01-29")
nbank_pre_c <- subset(nbank,Date <= "2020-01-30" & Date >= "2019-01-29" )
nbank_dur_c <- subset(nbank,Date <= "2021-01-30" & Date >= "2020-01-29")
nbank_pos_c <- subset(nbank,Date <="2021-12-30" & Date >= "2021-01-29")
npharma_pre_c <- subset(npharma,Date <= "2020-01-30" & Date >= "2019-01-29" )
npharma_dur_c <- subset(npharma,Date <= "2021-01-30" & Date >= "2020-01-29")
npharma_pos_c <- subset(npharma,Date <="2021-12-30" & Date >= "2021-01-29")
nfmcg_pre_c <- subset(nfmcg,Date<= "2020-01-30" & Date >= "2019-01-29" )
nfmcg_dur_c <- subset(nfmcg,Date<= "2021-01-30" & Date >= "2020-01-29")
nfmcg_pos_c <- subset(nfmcg,Date<="2021-12-30" & Date >= "2021-01-29")
```
 # plot Histogram of Log-Return on Nifty 50 Index __
```
hist_dur_c <- ggplot(data = nifty_dur_c,aes(x=log_re_nifty,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+ylim(0,60)+
  labs(title = "During COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pre_c <- ggplot(data = nifty_pre_c,aes(x=log_re_nifty,y=after_stat(density)))+
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+ylim(0,60)+
  labs(title = "Pre-COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pos_c <-ggplot(data = nifty_pos_c,aes(x=log_re_nifty,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col= "#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  labs(title = "Post-COVID-19",x= "Log-Return",y ="Density")+
  ylim(0,60)+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
  title <- ggdraw()+draw_label("Nifty 50",fontface = "bold",x=0.6,hjust = 1,color ="wheat4" )
  hist_plot <-plot_grid(hist_pre_c,hist_dur_c,hist_pos_c, ncol = 3)
  plot_grid(title,hist_plot,ncol=1,rel_heights = (c(0.1,1)))
```
 # plot Histogram of Log-Return on Nifty Bank Index __
```
hist_dur_c <- ggplot(data = nbank_dur_c,aes(x=log_re_nbank,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  ylim(0,40)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  labs(title = "During COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pre_c <- ggplot(data = nbank_pre_c,aes(x=log_re_nbank,y=after_stat(density)))+
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+  ylim(0,40)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  labs(title = "Pre-COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pos_c <-ggplot(data = nbank_pos_c,aes(x=log_re_nbank,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col= "#330033",bins = 25)+ ylim(0,40)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  labs(title = "Post-COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
```

```
  title <- ggdraw()+draw_label("Nifty Bank",fontface = "bold",x=0.6,hjust = 1,color
="wheat4" )
  hist_plot <-plot_grid(hist_pre_c,hist_dur_c,hist_pos_c, ncol = 3)
  plot_grid(title,hist_plot,ncol=1,rel_heights = (c(0.1,1)))
```

 # plot Histogram of Log-Return on Nifty IT Index __

```
hist_dur_c <- ggplot(data = nit_dur_c,aes(x=log_re_nit,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+  ylim(0,50)+
  labs(title = "During COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pre_c <- ggplot(data = nit_pre_c,aes(x=log_re_nit,y=after_stat(density)))+
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+  ylim(0,50)+
  labs(title = "Pre-COVID-19",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
hist_pos_c <-ggplot(data = nit_pos_c,aes(x=log_re_nit,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col= "#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  labs(title = "Post-COVID-19",x= "Log-Return",y ="Density")+  ylim(0,50)+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))
  title <- ggdraw()+draw_label("Nifty IT",fontface = "bold",x=0.6,hjust = 1,color ="wheat4" )
  hist_plot <-plot_grid(hist_pre_c,hist_dur_c,hist_pos_c, ncol = 3)
  plot_grid(title,hist_plot,ncol=1,rel_heights = (c(0.1,1)))
```

#Define a function

```
MySummary <- function(x) {
  c(mean(x),median(x),max(x),min(x),sd(x),skewness(x),kurtosis(x),length(x))}
```

#Calculated Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis of of Log-Return on Nifty 50 Index __

```
summ_dur_c <- MySummary(nifty_dur_c$log_re_nifty)
summ_pre_c <- MySummary(nifty_pre_c$log_re_nifty)
summ_pos_c <- MySummary(nifty_pos_c$log_re_nifty)
nifty_ma <-matrix(c(summ_pre_c, summ_dur_c, summ_pos_c), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard
Deviation","Skewness" ,"Kurtosis","Observation"), c("Pre-COVID19","During-
COVID19","Post-COVID19")))
nifty_ma

summ_dur_c <- MySummary(nbank_dur_c$log_re_nbank)
summ_pre_c <- MySummary(nbank_pre_c$log_re_nbank)
summ_pos_c <- MySummary(nbank_pos_c$log_re_nbank)
nbank_ma <-matrix(c(summ_pre_c, summ_dur_c, summ_pos_c), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard
Deviation","Skewness" ,"Kurtosis","Observation"), c("Pre-COVID19","During-
COVID19","Post-COVID19")))
nbank_ma

summ_dur_c <- MySummary(nit_dur_c$log_re_nit)
summ_pre_c <- MySummary(nit_pre_c$log_re_nit)
summ_pos_c <- MySummary(nit_pos_c$log_re_nit)
```

```
nit_ma <-matrix(c(summ_pre_c, summ_dur_c, summ_pos_c), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard
Deviation","Skewness" ,"Kurtosis","Observation"), c("Pre-COVID19","During-
COVID19","Post-COVID19")))
nit_ma

summ_dur_c <- MySummary(npharma_dur_c$log_re_npharma)
summ_pre_c <- MySummary(npharma_pre_c$log_re_npharma)
summ_pos_c <- MySummary(npharma_pos_c$log_re_npharma)
npharma_ma <-matrix(c(summ_pre_c, summ_dur_c, summ_pos_c), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard
Deviation","Skewness" ,"Kurtosis","Observation"), c("Pre-COVID19","During-
COVID19","Post-COVID19")))
npharma_ma

summ_dur_c <- MySummary(nfmcg_dur_c$log_re_nfmcg)
summ_pre_c <- MySummary(nfmcg_pre_c$log_re_nfmcg)
summ_pos_c <- MySummary(nfmcg_pos_c$log_re_nfmcg)
nfmcg_ma <-matrix(c(summ_pre_c, summ_dur_c, summ_pos_c), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard
Deviation","Skewness" ,"Kurtosis","Observation"), c("Pre-COVID19","During-
COVID19","Post-COVID19")))
nfmcg_ma
# Test of symmetry about Nifty 50
symmetry.test(nifty_pre_c$log_re_nifty, option ="CM")
symmetry.test(nifty_dur_c$log_re_nifty,option ="CM")
symmetry.test(nifty_pos_c$log_re_nifty,option ="CM")
# Test of symmetry about Nifty Bank
symmetry.test(nbank_pre_c$log_re_nbank, option ="CM")
symmetry.test(nbank_dur_c$log_re_nbank, option ="CM")
symmetry.test(nbank_pos_c$log_re_nbank, option ="CM")
# Test of symmetry about Nifty IT
symmetry.test(nit_pre_c$log_re_nit, option ="CM")
symmetry.test(nit_dur_c$log_re_nit, option ="CM")
symmetry.test(nit_pos_c$log_re_nit, option ="CM")
# Test of symmetry about Nifty Pharma
symmetry.test(npharma_pre_c$log_re_npharma, option ="CM")
symmetry.test(npharma_dur_c$log_re_npharma, option ="CM")
symmetry.test(npharma_pos_c$log_re_npharma, option ="CM")
# Test of symmetry about Nifty  FMCG
symmetry.test(nfmcg_pre_c$log_re_nfmcg, option ="CM")
symmetry.test(nfmcg_dur_c$log_re_nfmcg, option ="CM")
symmetry.test(nfmcg_pos_c$log_re_nfmcg, option ="CM")
# Kolmogorov Smirnov test for Normal Distribution about Nifty 50 __
ks.test(nifty_pre_c$log_re_nifty,"pnorm",mean
=mean(nifty_pre_c$log_re_nifty),sd=sd(nifty_pre_c$log_re_nifty))
ks.test(nifty_dur_c$log_re_nifty,"pnorm",mean =
mean(nifty_dur_c$log_re_nifty),sd=sd(nifty_dur_c$log_re_nifty))
ks.test(nifty_pos_c$log_re_nifty,"pnorm",mean =
mean(nifty_pos_c$log_re_nifty),sd=sd(nifty_pos_c$log_re_nifty))
```

```
# Kolmogorov Smirnov test for Normal Distribution about Nifty Bank __
ks.test(nbank_pre_c$log_re_nbank,"pnorm",mean =
mean(nbank_pre_c$log_re_nbank),sd=sd(nbank_pre_c$log_re_nbank))
ks.test(nbank_dur_c$log_re_nbank,"pnorm",mean =
mean(nbank_dur_c$log_re_nbank),sd=sd(nbank_dur_c$log_re_nbank))
ks.test(nbank_pos_c$log_re_nbank,"pnorm",mean =
mean(nbank_pos_c$log_re_nbank),sd=sd(nbank_pos_c$log_re_nbank))
# Kolmogorov Smirnov test for Normal Distribution about Nifty IT __
ks.test(nit_pre_c$log_re_nit,"pnorm",mean =
mean(nit_pre_c$log_re_nit),sd=sd(nit_pre_c$log_re_nit))
ks.test(nit_dur_c$log_re_nit,"pnorm",mean =
mean(nit_dur_c$log_re_nit),sd=sd(nit_dur_c$log_re_nit))
ks.test(nit_pos_c$log_re_nit,"pnorm",mean =
mean(nit_pos_c$log_re_nit),sd=sd(nit_pos_c$log_re_nit))
# Kolmogorov Smirnov test for Normal Distribution about Nifty Pharma __
ks.test(npharma_pre_c$log_re_npharma,"pnorm",mean =
mean(npharma_pre_c$log_re_npharma),sd =sd(npharma_pre_c$log_re_npharma))
ks.test(npharma_dur_c$log_re_npharma,"pnorm",mean =
mean(npharma_dur_c$log_re_npharma),sd =sd(npharma_dur_c$log_re_npharma))
ks.test(npharma_pos_c$log_re_npharma,"pnorm",mean =
mean(npharma_pos_c$log_re_npharma),sd =sd(npharma_pos_c$log_re_npharma))
# Kolmogorov Smirnov test for Normal Distribution about Nifty FMCG __
ks.test(nfmcg_pre_c$log_re_nfmcg,"pnorm",mean = mean(nfmcg_pre_c$log_re_nfmcg), sd
= sd(nfmcg_pre_c$log_re_nfmcg))
ks.test(nfmcg_dur_c$log_re_nfmcg,"pnorm",mean = mean(nfmcg_dur_c$log_re_nfmcg), sd
= sd(nfmcg_dur_c$log_re_nfmcg))
ks.test(nfmcg_pos_c$log_re_nfmcg,"pnorm",mean = mean(nfmcg_pos_c$log_re_nfmcg), sd
= sd(nfmcg_pos_c$log_re_nfmcg))
# Kolmogorov Smirnov test for t-Distribution about Nifty 50 __
ks_test_t(nifty_pre_c$log_re_nifty)
ks_test_t(nifty_dur_c$log_re_nifty)
ks_test_t(nifty_pos_c$log_re_nifty)
# Kolmogorov Smirnov test for t-Distribution about Nifty Bank __
ks_test_t(nbank_pre_c$log_re_nbank)
ks_test_t(nbank_dur_c$log_re_nbank)
ks_test_t(nbank_pos_c$log_re_nbank)
# Kolmogorov Smirnov test for t-Distribution about Nifty IT __
ks_test_t(nit_pre_c$log_re_nit)
ks_test_t(nit_dur_c$log_re_nit)
ks_test_t(nit_pos_c$log_re_nit)
# Kolmogorov Smirnov test for t-Distribution about Nifty Pharma __
ks_test_t(npharma_pre_c$log_re_npharma)
ks_test_t(npharma_dur_c$log_re_npharma)
ks_test_t(npharma_pos_c$log_re_npharma)
# Kolmogorov Smirnov test for t-Distribution about Nifty FMCG __
ks_test_t(nfmcg_pre_c$log_re_nfmcg)
ks_test_t(nfmcg_dur_c$log_re_nfmcg)
ks_test_t(nfmcg_pos_c$log_re_nfmcg)
# Q-Q plot of Nifty 50
df <- data.frame(
```

```
  group = c(rep("Before-COVID19", length(nifty_pre_c$log_re_nifty)),rep("During-COVID19", length(nifty_dur_c$log_re_nifty)),rep("Post-COVID19", length(nifty_pos_c$log_re_nifty))),
  log_returns = c(nifty_pre_c$log_re_nifty,nifty_dur_c$log_re_nifty, nifty_pos_c$log_re_nifty))
ggplot(df, aes(sample = log_returns)) +geom_qq(show.legend = TRUE) +geom_qq_line(color = "red") + facet_wrap(~group, nrow = 1) + labs(title = "Normal Q-Q of Nifty 50",x="Sample Quantile",y="Theoretical Quantile") + theme(plot.title = element_text(hjust = 0.5))
```

 # During COVID Time

```
nifty_dur_c_1 <- subset(nifty,Date <= "2021-01-30" & Date >= "2020-01-29")
nifty_dur_c_2 <- subset(nifty,Date <= "2021-01-30" & Date >= "2020-03-11")
nifty_dur_c_3 <- subset(nifty,Date <= "2021-01-30" & Date >= "2020-04-15")

summ_dur_c_1 <- MySummary(nifty_dur_c_1$log_re_nifty)
summ_dur_c_2 <- MySummary(nifty_dur_c_2$log_re_nifty)
summ_dur_c_3 <- MySummary(nifty_dur_c_3$log_re_nifty)
nifty_ma <-matrix(c(summ_dur_c_1, summ_dur_c_2, summ_dur_c_3), ncol = 3,
        dimnames=list(c("Mean","Median","Maximum","Minimum","Standard Deviation","Skewness" ,"Kurtosis","Observation"), c("1","2","3")))
nifty_ma
```

 # Histogram

```
hist_dur_c_1 <- ggplot(data = nifty_dur_c_1,aes(x=log_re_nifty,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  ylim(0,50)+
  labs(title = "During COVID-19: 1",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))

hist_dur_c_2 <- ggplot(data = nifty_dur_c_2,aes(x=log_re_nifty,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  ylim(0,50)+
  labs(title = "During COVID-19: 2",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))

hist_dur_c_3 <- ggplot(data = nifty_dur_c_3,aes(x=log_re_nifty,y = after_stat(density))) +
  geom_histogram(fill = "burlywood4",col="#330033",bins = 25)+
  geom_density(col = "#330066",lwd=1,alpha = 0.2)+
  ylim(0,50)+
  labs(title = "During COVID-19: 3",x= "Log-Return",y ="Density")+
  theme(plot.title = element_text(hjust = 0.5,colour = "blue"))

  title <- ggdraw()+draw_label("Nifty 50",fontface = "bold",x=0.6,hjust = 1,color ="wheat4" )

  hist_plot <-plot_grid(hist_dur_c_1,hist_dur_c_2,hist_dur_c_3, ncol = 3)
  plot_grid(title,hist_plot,ncol=1,rel_heights = (c(0.1,1)))
```

 # Test of symmetry about Nifty 50

```
symmetry.test(nifty_dur_c_1$log_re_nifty, option ="CM")
symmetry.test(nifty_dur_c_2$log_re_nifty,option ="CM")
symmetry.test(nifty_dur_c_3$log_re_nifty,option ="CM")
```

 # KS Test for Normal Distribution

```
ks.test(nifty_dur_c_1$log_re_nifty,"pnorm",mean = mean(nifty_dur_c_1$log_re_nifty),sd
=sd(nifty_dur_c_1$log_re_nifty)) mean(nifty_dur_c_1$log_re_nifty)
sd(nifty_dur_c_1$log_re_nifty)
ks.test(nifty_dur_c_2$log_re_nifty,"pnorm",mean = mean(nifty_dur_c_2$log_re_nifty),sd
=sd(nifty_dur_c_2$log_re_nifty)) mean(nifty_dur_c_2$log_re_nifty)
sd(nifty_dur_c_2$log_re_nifty)
ks.test(nifty_dur_c_3$log_re_nifty,"pnorm",mean = mean(nifty_dur_c_3$log_re_nifty),sd
=sd(nifty_dur_c_3$log_re_nifty)) mean(nifty_dur_c_3$log_re_nifty)
sd(nifty_dur_c_3$log_re_nifty)
```

#KS test for t distribution

```
ks_test_t(nifty_dur_c_1$log_re_nifty)
ks_test_t(nifty_dur_c_3$log_re_nifty)
ks_test_t(nifty_dur_c_2$log_re_nifty)
```