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An empirical study to estimate volatility of Indian stock market during pre and post covid times

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Abstract
In the present study, researchers tried to measure the volatility of Indian stock exchange before and after COVID- outbreak and also to compare the volatility pattern in both groups. To conduct the study, the researchers has collected 30 months daily closing price of NIFTY 50 prior to the COVID outbreak [From 9th September 2017- 9th march 2020] and 30 months after outbreak [From 10th march 2020 – 10th September 2022]. The researcher has used various statistical tools such as descriptive statistics, Augmented Dickey fuller test and Phillips Perron test for stationarity. The researcher used ARCH model, GARCH model and GARCH-M model. The study revealed that, the daily return calculated for both categories are stationary at level, found from both ADF and PP test. From the ARCH – LM test they got that there was an arch effect in both the categories. The found that for pre-covid time and also for post-covid time GARCH [1,1] model was the best fitted model. From the study, they have concluded that in both categories' volatility clustering was there but the shocks during the Post-pandemic time was more persistent as compared to pre pandemic. As the sum of ARCH & GARCH coefficient model was near to unity during the pre-pandemic time, indicating that the stock prices will revert back to the historical value after a certain time period.
Keywords: Indian stock market, Nifty 50, Volatility, ARCH model, GARCH (1,1) model.

1. Introduction

In earlier times to measure the risk, researchers were used to use variance or the standard deviation in order to estimate the risk. Later on, many researchers started using autoregressive integrated moving average [ARMA] to assist the risk which was developed by box and Jenkins (1976). After this the researchers started focusing on the effect of heteroscedasticity and volatility modelling.

In simple terms the volatility refers to the risk or uncertainty related to changes in the price of stocks or it denotes the fluctuation in price of the stocks near the mean value. A higher volatility denotes higher risk and lower volatility denotes low risk. There are various methods to measure the volatility in time series data.

Volatility can be of two types one is symmetrical and the another one is asymmetrical. Symmetrical volatility mainly is conditional variance that depends on the lag value of squared error and on the past conditional volatility but error term does not have any effect on it while in case of asymmetrical volatility it depends on both [lag value and squared error term along with the sign of error term. For appropriate investment decision it is important to measure the volatility. In order to estimate the volatility of any stock or any index, most of the people such as corporate treasurers, risk arbitragers and managers closely observe the volatility trends because a certain changes in price has an effect on risk management decision.

During March 2020 the economy has faced a shift due to the global pandemic COVID-19. Almost all the economies of the world faced serious challenges to survive, India is not an exception to that. Due to the pandemic the stock market has faced a lot of challenges. In this study, an attempt has been made by the researchers to compare market before and after the outbreak of COVID Pandemic.

1.1 Overview of Indian stock market

Stock market is a platform for purchasing and selling of shares are taken place. Indian stock market is a very wide and developed stock market under which mainly there are two stock exchanges namely Bombay Stock Exchange [BSE] and National Stock Exchange [NSE]. Among these two, BSE is the oldest Stock Exchange and National Stock Exchange is the busiest Stock Exchange of India. The national Stock Exchange has an index namely NIFTY 50 which is a group of top 50 companies based on their market capitalization. In this particular study, the researchers have collected the secondary data of and calculated the log return to conduct the further study.

2. Literature review

Various studies were reviewed by the researchers on this particular topic. Among these, few are mentioned below.

Sarkar (2022) in his research article titled "Indian stock market volatility estimation using symmetric GARCH family models during pre and post pandemic periods" tried to compare the volatility of stock market before and after the outbreak of covid pandemic. The researcher collected the daily closing price of S&P BSE Sensex for 8 months for both categories. To capture the systematic volatility the researcher, use ARCH, GARCH (1,1) and M-GARCH models and beyond this he also used Augmented Dickey Fuller and Phillips Perron Test to test the stationary. His study revealed that the daily mean return was negative during pre-covid times while it was positive after the COVID outbreak.

Engle (1982) was the first one to come up with a very new model of the heteroscedasticity in time series data. He tried to develop a new model of heteroscedasticity in which the variance is dependent upon past squared error. With the help of this model, it was easy to address the problem of variance but still the coefficient was difficult to estimate.

Bollerslev (1986) also conducted a study to model the heteroscedasticity problem. He developed a new model that was quite similar to the auto regressive conditional heteroscedasticity model but an advanced version of it. He did the generalization of ARCH model in which the variance was not only dependent on the past squared error but also on its own past value.

Engle, Lilien and Robins (1987) conducted a study to develop advance heteroscedasticity Model. They further improve the Bollerslev's GARCH model and accommodated the variance in the mean equation of asset return. They tried to establish risk return relationship in their new model which is popularly known as GARCH – M model.

Susruth (2017) has made an attempt to forecast the volatility in Indian stock market, for this he used daily stock return of S&P BSE 500 index for 10 years from 2007 till 2016. He used GARCH, GARCH – M and EGARCH models to measure leverage effect, risk premium and the volatility clustering of Indian stock market. His study revealed that market had a leverage effect as well as volatility clustering but no risk premium was found.

Adesina (2013) tried to measure the return volatility of Nigerian stock exchange. The researcher used both symmetric as well as asymmetric GARCH models to estimate the persistency of shock to the volatility. He Collected secondary data of Nigerians stock exchange for 324 months from 1985 till 2011, he collected the data for all the share indexes. His study revealed that there was a high persistency of volatility in the Nigerian Stock Exchange although no asymmetric shock phenomena was found.

Zakaria, Abdalla and winker (2012) in their study tried to compare the volatility of two African stock exchanges that is Khartoum stock exchange [KSE] and Cairo and Alexandria Stock Exchange [CASE]. They have used both asymmetric as well as symmetric GARCH models to estimate the volatility of stock exchanges. To conduct the study, they have collected daily closing prices of both the index from January 2016 till November 2010. Their study revealed that there was a conditional variance which was explosive in nature in KSE index return while it was persistent in CASE index return. Beyond this their study also revealed the presence of risk premium for both the stock exchanges.

Banumathy and Azhagaiah (2015) empirically investigated Indian stock market volatility, for which they have collected the secondary data related to closing price of S&P and CNX nifty index from January 2003 till December 2012. They used both symmetrical as well as asymmetrical models to estimate the Indian stock market volatility. From Akaike information criterion and Schwarz information criterion, they found that TGARCH [1,1] and GARCH [1,1] were the most appropriate models for the study. Their study revealed that insignificant risk premium was there in the stock market as well as they found a significant effect of negative shocks on the volatility.

Prasad, Singh and Gautam (2019) tried to estimate the volatility stock market for which they have collected the daily stock return of NIFTY 50 from July 2018 till July 2018. They have used the GARCH models to estimate the volatility and they also have used ADF & KPSS test to check the stationarity of the data series. Their study revealed that the behaviour of NIFTY 50 index was highly volatile which gave very good opportunity for the long-term investors of Indian stock market.

2.1 Research Gap

Based on the above reviews it is clear that the modern volatility estimating models are used by the researchers to measure the volatility. The researchers found various studies where the researchers have used GARCH family models for modelling volatility but no paper was found in which a comparison was made between the volatility clustering before and after the outbreak of covid pandemic. This gap encouraged the researcher to probe into this area and to conduct a study in this respect.

3. Research methodology

The study is based on the secondary data. The researchers has collected the daily closing price of NSE [NIFTY 50] which is considered the proxy of India stock market. The data related to daily closing price of NIFTY 50 is collected for 60 months. Among which 30 months closing price were related to pre-pandemic period (from 9th September 2017 till 9th march 2020) and 30 months for post-pandemic period (from 10th march 2020 till 10th September 2022). For collecting reliable data the official website of National stock exchange is used by the researcher. Besides this, in order to get other information related to Indian stock market various other websites such as money control, Chittorgarh and capital line database are used by the researchers.

The researcher has used various statistical tools in order to fulfil the above-mentioned objectives. This include descriptive statistics [mean, standard deviation, skewness, kurtosis etc.]. To measure the stationarity of data Augmented Dickie Fuller Test and Philips Perron Test were used. Beyond this, in order to estimate the volatility ARCH – LM test and symmetric GARCH family models GARCH (1,1) and GARCH-M(1,1) models were used. Since the volatility of daily return series is estimated in the present study for this the researchers have calculated the log return using the closing value as log first difference. The formula for the same is mentioned below:

$R_t = \log p_t / p_{t-1}$

In order to measure the volatility of the stock price, usually ARCH & GARCH family models are applied. To model the conditional volatility usually GARCH and GARCH – M models are used while to model the unconditional volatility the advance GARCH family models are used. Since the researchers tried to measure only the conditional volatility they have used ARCH model and GARCH [1, 1] and GARCH – M model. In the present study, the researchers have collected the daily closing price of Nifty 50 and also calculated the daily return as the log of first difference.

Auto regressive conditional heteroscedasticity Open racket [ARCH] model: This model was developed by Engle [1982]. This model is considered as the first model to measure the heteroscedasticity problem. The ARCH model analyses the volatility of time series data based on the past sample variances. The mean and variance equations of ARCH model are mentioned below:

Mean equation: $r_t = \mu + \Theta r_{t-1} + \varepsilon_t$

Variance equation: $\sigma^2_{t}= \acute{\omega} + \alpha\varepsilon^2_{t-1}$

3.1 Generalized auto regressive conditional heteroscedasticity [GARCH] model

This model was first introduced by Bollerslev [1986] to estimate the volatility. This model not only take into consideration the past distributions but also it considers its own lagged values to estimate the volatility. The mean and variance equation of GARCH [1,1] model is as follows

Mean equation: $r_t = \mu + \Theta r_{t-1} + \lambda\sigma^2_t + \varepsilon_t$
Variance equation: $\sigma^2_{t} = \acute{\omega} + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

Generalized auto regressive conditional heteroskedasticity in mean [GARCH – M] model

This model is an advance version of GARCH [1,1] model developed by Engle, Lilien and Robins [1987] which considers the mean return along with the above mention values. The mean and variance equation of GARCHM [1,1] model are as follows
Mean equation: $r_t = \mu + \Theta r_{t-1} + \lambda\sigma^2_t + \varepsilon_t$
Variance equation: $\sigma^2_{t} = \acute{\omega} + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

4. Result and discussion

Table [1] represents the descriptive statistics as well as the normality test of daily return calculated for NIFTY 50.

Table 1. Descriptive statistics and Normality test of pre and post covid daily return

	Pre pandemic	Post pandemic
Mean	7.07	0.000859
Maximum	0.051825	0.084003
Minimum	-0.05019	-0.13904
Std. deviation	0.008606	0.015024
Skewness	-0.14992	-1.71405
Kurtosis	4.748202	17.38704
Kolmogorov-Smirnov	0.051062	0.090122
Shapiro-Wilk	0.955413	0.861584
Observation	617	622

Source: author’s computation with SPSS 15

Above Table states that the average daily return during the pre-covid period was way more higher than post covid period. As seen from the standard deviation, the deviation of return is quite higher during the post pandemic period and for both categories the kurtosis value is higher than 3 indicating a leptokurtic curve. The skewness value for both categories is negative. The result of Kolmogorov Smirnov test and Shapiro wilk test that showed that the data selected for both categories follows normal distribution curve.

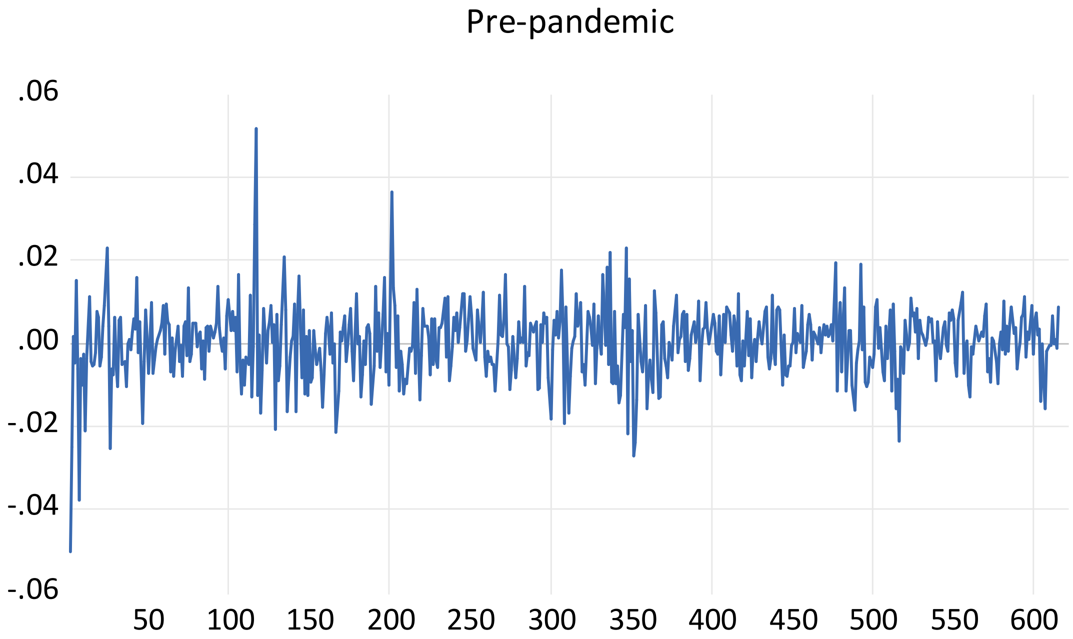

Figure 1: volatility clustering of pre-covid daily return of NIFTY 50 for 30 months

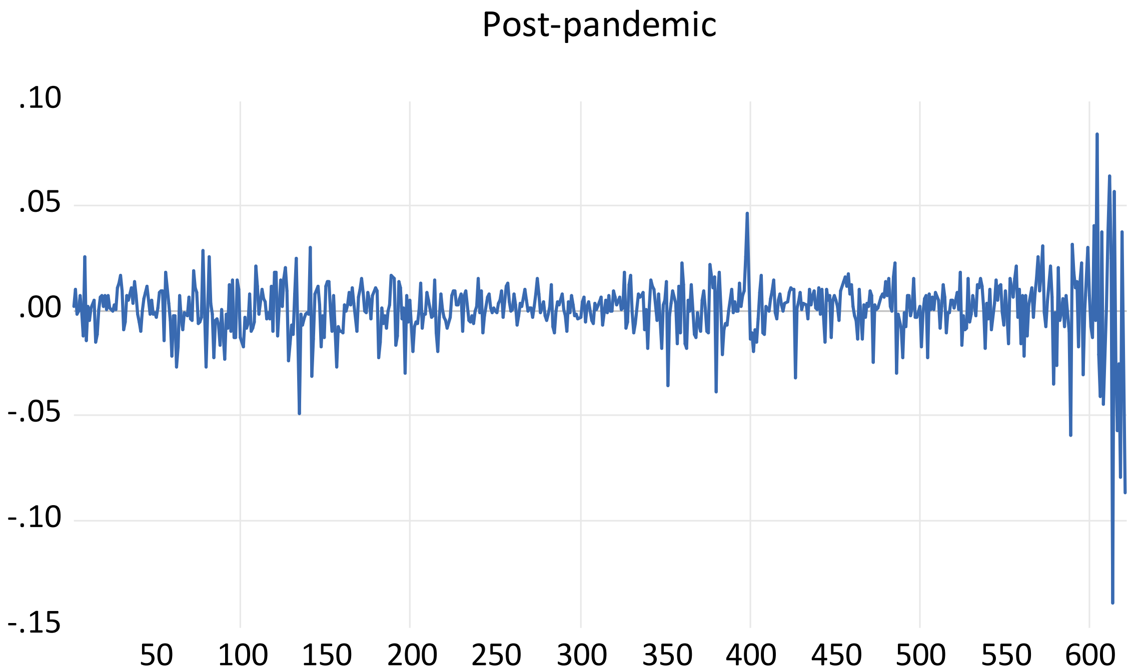

Figure 2. Volatility clustering of post-covid daily return of NIFTY 50 for 30 months

From the above two figures it is visible that the variability of return during the pre-pandemic period was quite higher as compared to post pandemic. Although a huge volatility was found towards the end of post pandemic period. From both the figures it is very evident that for a prolonged period the high volatility tends to follow high, and the lower volatility tends to follow low. From this we can infer that volatility clustering is present in both return series.

Table 2. Result of Unit-root test

	Pre-covid		Post-covid	
	ADF	PP	ADF	PP
t-statistics	-23.12434	-23.1078	-7.435041	-26.67299
Probability (P-value)	0.00000	0.00000	0.000000	0.00000
Test critical value at 1% Level	-3.44075	-3.44075	-3.440771	-3.44067
Test critical value at 5% Level	-2.86602	-2.86602	-2.866029	-2.86598
Test critical value at 10% Level	-2.56921	-2.56921	-2.569219	-2.56920

Source: Author's computation using EViews 12

The above-mentioned table states result of unit root test. The researchers have used Augmented Dickey fuller test and Philip Perron test to check the stationery of selected data. Since the probability value for both test at level is less than 0.05 indicating that the time series data is stationery for both categories.

Table 3. Heteroskedasticity Test- ARCH effect

	Pre pandemic	Post pandemic
F-statistics	1.724844	1.36156
Prob.	0.1896	0.2437
Obs R-squared	1.725616	1.362964
Prob. Chi Square (1)	0.189	0.243

Source: Author's computation using EViews 12

The above-mentioned table shows the result of heteroskedasticity. The researchers have used ARCH-LM test to detect the presence of ARCH effect. The result shows that the p-value for both the categories is greater than 0.05 which indicates that there is an ARCH effect in the selected model.

After the descriptive statistics, confirmation of volatility clustering through volatility graphs, stationery of data of both categories from the ADF and PP tests and the ARCH effect from ARCH-LM test, the next step is to test the conditional volatility using the GARCH family model. Since the researchers are interested to capture the impact of conditional volatility, they are using GARCH [1,1] and GARCH-M [1,1] models for modelling volatility.

Below mention 2 tables [Table 4 and Table 5] shows the result of GARCH [1,1] and GARCH-M [1,1] models for both categories.

Table 4. Estimated result of GARCH (1,1) & GARCH-M (1,1) Models for pre-covid period

Coefficient	GARCH (1,1)	GARCH-M(1,1)
Mean		
μ (constant)	0.000565	0.003133
ϴ(coefficient of own log)	0.944	0.067443
Variance		

ώ(Constant)	3.92	4.49
α(ARCH effect)	0.100976	0.110024
β(GARCH effect)	0.838648	0.819539
α + β	0.939624	0.929563
Log likelihood	2105.311	2114.886
Akaike info criterion (AIC)	-6.83028	-6.85817
Schwarz info criterion (SIC)	-6.79433	-6.81503

Source: Author's computation using EViews 12

In the above mention table, it is found that in GARCH [1,1] model the ARCH term and the GARCH term are statistically significant. The table also shows that the beta [β] value is higher than the alpha [α] value which simply implies that the market volatility is very sensitive towards its own lagged volatility than the other disturbance or surprises taking place in the market. The sum of alpha and beta is 0.9396 which is closer to one indicates that the impact of recent shocks will be higher as compared to distant shocks.

In GARCH – M [1,1] model It is found that ARCH and GARCH coefficients are statistically significant as their value is greater than 0.05. In GARCH – M model the beta value is again higher than the alpha value which indicates the pre-covid daily return is sensitive towards its own lagged value than any other disturbance from market. The sum of alpha and beta values is again close to unity, showing that the recent shocks may bring more changes in the stock price.

The Akaike information model is an indicator to the best fitted model for the selected data. During the pre-pandemic. The AIC value for GARCH [1,1] model is-6.83028 while it is -6.85 8174 for GARCH-M [1,1] model which is slight lower indicating that GARCH [1,1] model is the best fitted model for estimating the stock market volatility during the pre-covid times.

Table 5. Estimated result of GARCH (1,1) & GARCH-M (1,1) Models for post-covid period

Coefficient	GARCH (1,1)	GARCH-M (1,1)
Mean		
μ (constant)	0.001151	0.002588
Θ(coefficient of own log)	0.026546	0.002594
Variance		
ώ(Constant)	7.09	8.52
α(ARCH effect)	0.103506	0.104563
β(GARCH effect)	0.903065	0.904745
α + β	1.006571	1.009308
Log likelihood	1894.169	1900.361
Akaike info criterion (AIC)	-6.09409	-6.11084
Schwarz info criterion (SIC)	-6.05836	-6.06797

Source: Author's computation using EViews 12

In the above mention table, it is found that In GARCH [1,1] model the ARCH term and the GARCH term are statistically significant. The table also shows that the beta value is higher than the alpha value which simply implies that the market volatility is very sensitive towards its own lagged volatility than the other disturbance or surprises taking place in the market. The sum of alpha and beta is unity indicates that any shock whether good or bad would bring a permanent change in the stock prices.

In GARCH – M [1,1] model It is found that GARCH and ARCH terms are statistically significant as their value is greater than 0.05. In GARCH – M model the beta value is again higher than the alpha value which indicates the pre-covid daily return is sensitive towards its own lagged value than any other disturbance from market. The sum of alpha and beta values is again unity, showing that the good or bad shocks may bring more changes in the stock price and that would be permanent in nature.

The Akaike information model is an indicator to the best fitted model for the selected data. During the pre-pandemic. The AIC value for GARCH [1,1] model is-6.09409 while it is -6.11084 for GARCH-M [1,1] model which is slight lower indicating that GARCH [1,1] model is the best fitted model for estimating the stock market volatility during the pre-covid times.

5. Conclusion

Present study was done by the researcher to check which GARCH family model is known for capturing the conditional volatility for the selected data. In this paper, the researchers have also tried to compare the volatility pattern of the daily stock return before and after the COVID outbreak. The researchers from the study conclude that the selected variables are stationary in nature and volatility clustering is there in both categories of return. The return also shows arch effect, proved from ARCH – LM test. The researchers have applied two symmetrical models, one is GARCH [1,1] model and GARCH – M [1,1] model. Based on the AIC criteria they found that for both the categories GARCH [1,1] model is found to be the best to capture the conditional volatility. The sum of ARCH & GARCH terms were near to unity during the pre-pandemic period indicating that the stock price is more sensitive towards the recent shocks than the distant shocks while its value is exactly unity during the post-pandemic period which gives evidence that during the post pandemic period the stock prices were sensitive towards any kind of shocks whether good or bad in nature and the changes were permanent in nature.

Limitations:

1. In the present study the daily time series data for 30 months prior to the outbreak of COVID-19 Pandemic and also 30 months after outbreak is taken into consideration which includes 617 and 622 data points before and after the COVID outbreak.
2. In the present study only the symmetric GARCH models are used to model the volatility of Indian stock market while the asymmetric models are not used which is the drawback of the study.
3. The present study only measured the daily return volatility of stock market while the other volatility that takes place during a day is not taken into consideration which is further a limitation of the study.

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