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Stock Market Volatility during COVID-19: Empirical Analysis of NIFTY Index

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Abstract: COVID-19 has brought a disruptive change, is one of its kind scenarios, analysing it separately has special relevance to bring out movement of stock market index NIFTY and how its relationship with other variables changes and impact of derivatives on NIFTY and market volatility. The data sample has been collected from January 30, 2020, till October 1, 2020. The analysis has been divided into four periods. Total COVID-19 period, pre-lockdown period, during COVID lockdown and unlockdown period. During Lockdown the long term past return and role of the derivatives market in reducing the market volatility was found to be insignificant. Whereas past day or past two days lagged returns were found to have a significant impact on the market return.

Keywords: COVID, unlockdown, insignificant, derivatives, NIFTY

Introduction

The COVID pandemic has brought a high level of uncertainty in the financial and human world. Extraordinary volatility is seen in all financial markets of the world. COVID-19 pandemic has affected the whole world and analysing the changes in Indian stock market volatility during COVID becomes an area of interest.

Financial volatility is affected by macro-economic factors, political and economic conditions of a nation, corporate issues and market uncertainty (Hartwell, 2018). Announcements relating to macroeconomic issues also cause financial volatility. Onan et al. (2014) relate that both bad and good announcements cause volatility in the market. Zhu et al. (2019) also analyse the influence of fear on U.S market volatility.

Baret et al. (2020) found a fall in share prices and oil prices. Igwe (2020) opined that most developing and developed nations' financial markets have been impacted by the COVID-19 pandemic. The UK's index FTSE has fallen more than 10 per cent in March 2020 (Zhang et al., 2020). Japan's index has fallen more than 20 per cent in December 2019. Vishnoi and Mookerjee (2020). Georgieva (2020) believes that the pandemic crisis is more dangerous than the Global financial crisis of 2008. Raja Ram (2020) quotes that Indian financial markets have seen large volatility during the pandemic.

The present study attempts to understand the behaviour of stock market volatility during the COVID-19 period. The old evidence suggests that when a crisis emerges the market volatility and its dynamics change. Derivatives have been playing an important role in reducing the market volatility in the Indian economy since its introduction in 2000. This motivates to analyse the relationship of derivatives with stock market volatility during the pandemic. Thus, for this study, the data has been divided into four time periods i.e., before the national Lockdown, during the lockdown and post COVID-19 unlock down period. This will make it evident that what is the impact of COVID-19 on stock market volatility.

This paper is organized as follows after the introduction, section two reviews the related literature, section three provides the methodology of the study, section four analyses the results and section five concludes the study.

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Review of Literature

The impact of derivatives on the stock market volatility in India has been extensively studied during the year 2002 to 2020, implying that as there was a lot of curiosity of researchers to evaluate the relevance of the introduction of derivatives in India. Some of the significant studies include Hussain and Atif (2020), Pal and Chattopadhyay (2019), Singh and Tripathi (2016), Kalenteis and Milonas (2013), Kabir and Ikram (2012), Sahu, D. (2012), Girish, G.P. (2012), Singla, R. (2012), Otswal, Priyanka (2011), Kaur, Gurpreet (2011), Sakhtivel, P. and Kamaiah, B. (2011), Ray, K. and Panda, A.K. (2011), Singh, G. and Kansal, S. (2010), Gahlot, R., Datta, K. and Kapil, S. (2010), Pati, P.C. and Rajib, P. (2010), Manier, M. (2007), Gupta, K. and Singh, B. (2009), Gaurishankar S. Hiremath, (2009), Mallikarjunappa, T. and Afsal, E.M. (2008), Debasish, S.S. (2008), Bhaumik, Karanasos and Kartsaklas (2008), Sarangi, S.P. and Patnaik, U.S. (2006), Sah, A.N. and Omkarnath, G. (2005), Raju, M.T. and Karande, Kiran (2003), Ghosh, G. and Bandivadekar, S. (2003), Shenbagaraman, P. (2003), and Thenmozhi, M. (2002). These studies analysed the impact of futures and options on underlying spot market volatility in India. It is evident from these studies that analyse of impact on volatility have majorly been done on Index derivatives.

Various researchers have analysed the impact of the pandemic on market volatility including Baker et al. (2020), who established that government restrictions during pandemic have been a major cause of volatility. Zaremba et al. (2020) suggest that governments need to bring policy measures to reduce the volatility of the market. Onali (2020) found that U.S. market volatility moves with the increase in COVID positive cases and deaths. Pavlyshenko, (2020), Mirza, et al., (2021), Topcu & Gulal, (2020) have analysed the impact of a pandemic on the stock market. Albulescu, (2021); Cheng & Yao,(2021); Su, et al., (2021) specifically focused on the volatility of the market. Haroon & Rizvi, (2020) and Zaremba et al., (2020) studied market liquidity during the pandemic. Bretscher et al. (2020) analysed forecasting values after the pandemic.

Methodology

The study analyses the stock market volatility during the COVID-19 period. How has volatility been impacted due to the COVID-19 pandemic? The paper attempts to analyse that how the relationship between different variables has changed during this period. The study analyses the relationship of Nifty (Nifty 50) returns with past day news, Nifty next 50 index (also referred to as Nifty Junior), S&P500 Index and volatility. Data has been collected from the National Stock Exchange of India (NSE) website for closing prices of CNX Nifty Index, Nifty Next 50 Index and Nifty Index Futures. Data for the S&P 500 Index has been collected from the Yahoo finance database.

For the detailed analysis of data, a sample has been taken to study volatility patterns during the COVID-19 pandemic period. India went into lockdown on March 24, 2020, but the first case of COVID was reported in India on January 30, 2020. The nationwide lockdown was over on June 8, 2020, and the economy started opening up in a phased manner. The final data sample has been collected till October 1, 2020.

Market Volatility during COVID-19 Period

COVID-19 has brought a disruptive change, is one of its kind scenarios, is an abnormal situation so, analysing it separately has special relevance to bring out the movement of stock market index NIFTY and how its relationship with other variables changes and impact of derivatives on NIFTY and market volatility. Thus, for COVID-19 analysis, this section has been divided into five sub-sections i.e. sub-section one discusses analyses market volatility of total COVID-19 sample period, sub-section two relates to Pre-COVID-19 Lockdown period analysis, sub-section three covers COVID-19 Lockdown period analysis, sub-section four analyses Post-COVID-19 Lockdown period and sub-section five compares forecasted returns of all COVID-19 subsamples with actual returns of NIFTY during that period. Table 1 shows sub-sample details used in this analysis.

Table 1: Sub-Sample Details		
Period	**Dates**	**Observations**
Total COVID-19 Period Sample	January 30, 2020 to October 01, 2020	169
Pre-COVID-19 Lockdown Period	January 30, 2020 to March 24, 2020	38
COVID-19 Lockdown Period	March 25, 2020 to June 7, 2020	47
Post COVID-19 Lockdown Period	June 8, 2020 to October 01, 2020	83

The various sub-sections are discussed hereunder.

Market Volatility of Total COVID-19 Period

NIFTY is the benchmark index of the National Stock Exchange of India and is also a barometer of the health of the financial market. COVID-19 Pandemic has affected humanity not only in health but in all other aspects of life and livelihood. So, this analysis has picked up the COVID-19 period for analysing the impact of COVID-19 on financial markets and specifically analysing that whether the relationship of the impact of derivatives on market volatility (NIFTY returns) have remained the same or changed. The total period for COVID-19 analysis has been taken from January 30, 2020, to October 01, 2020. Figure 1, shows NIFTY Index movement during the total COVID-19 sample period. The figure depicts that there is a sharp fall in NIFTY Index value during March-April, 2020 and afterwards market picked up gradually and is improving since then. A similar trend is visible in Index values of NIFTY Next 50 Index, S&P 500 Index and Near-month Futures value. The reason is that as soon as Government declared a nationwide lockdown which was one of its kind and very strict in India, there was a situation of panic and loss of trust and negative emotions all around in public. Many people lost their livelihood, businesses, jobs and many were suffering on the health front. With relief packages both monetary, non-monetary and financial schemes, the Government was able to bring back confidence, trust, reduce the fear and brought some positive sentiments in the market. Although the economic activities and production cycle in businesses have not opened at 100 per cent capacity level till now, still the trust has been instilled by the Indian financial system.

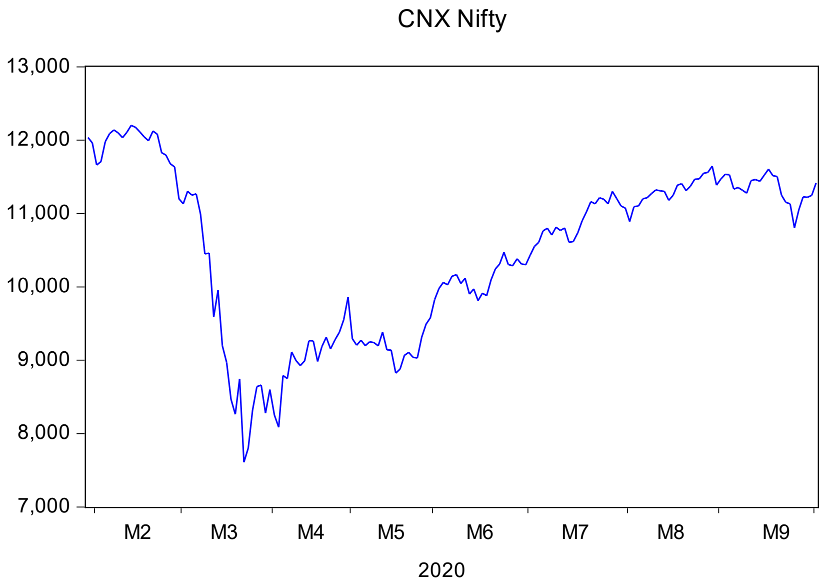

Figure 1: NIFTY Index Movement during COVID-19 Period (January 30, 2020 to October 01, 2020)

The results in Table 2 reveal descriptive statistics of Index values of all four Indexes used in the sample for COVID-19 total period and sub-sample period analysis. The NIFTY Index average value during the total COVID-19 sample period is 10474.30, similar NIFTY Next 50 has an average value of 25,467.71 and S&P500 Index has average value as 3099.10, whereas near-month futures has average going on as 10473.11. During the COVID-19 Lockdown period, these index values went down drastically such that the mean value of NIFTY was 9155.94, NIFTY Next 50 was 22868.34 and it again improved after the first phase of unlockdown in June 2020, where we can see the average NIFTY Index value of 10972.44 and S&P500 Index rose to 26588.10 levels. The standard deviation of the NIFTY index was highest in pre COVID-19 lockdown period 1401.57 and which was reduced to 461.38 during lockdown and is 500.10 in post COVID-19 lockdown period. The global index S&P 500 Index standard deviation was also more in pre lockdown period as compared to the lockdown period. The returns of all four indexes were also calculated and results are shown in Table 2.

Table 2: Descriptive Statistics of Index Prices During COVID-19 Period

	Total COVID-19 Period				Pre COVID-19 Lockdown Period				COVID-19 Lockdown Period				Post COVID-19 Lockdown Period			
	CNX NIFTY	NIFTY Next 50	S&P 500 Index	Near Month Futures	CNX NIFTY	NIFTY Next 50	S&P 500 Index	Near Month Futures	CNX NIFTY	NIFTY Next 50	S&P 500 Index	Near Month Futures	CNX NIFTY	NIFTY Next 50	S&P 500 Index	Near Month Futures
Mean	10474.30	25462.71	3099.13	10473.11	11003.72	26161.55	3017.32	10995.83	9155.94	22886.34	2850.01	9157.25	10972.44	26588.10	3275.52	10972.89
Median	10799.65	26264.85	3152.05	10766.65	11670.18	27437.23	3129.17	11675.28	9187.30	23088.50	2863.70	9188.30	11157.95	26606.95	3278.54	11166.15
Maximum	12201.20	29046.45	3580.84	12228.45	12201.20	29046.45	3386.15	12228.45	10142.15	25324.80	3193.93	10145.50	11647.60	28018.75	3580.84	11675.25
Minimum	7610.25	18524.65	2237.40	7581.55	7610.25	18524.65	2237.40	7581.55	8083.80	19393.00	2470.50	8084.50	9813.70	24768.80	3002.10	9813.75
Std. Dev.	1134.99	2355.40	286.01	1139.62	1401.57	3130.30	374.34	1416.31	461.38	1258.06	169.74	454.33	500.10	848.60	132.08	511.63
Skewness	-0.45	-0.76	-0.87	-0.43	-1.17	-1.16	-0.78	-1.15	-0.02	-0.90	-0.47	-0.01	-0.79	-0.38	-0.07	-0.77
	2.0	2.8	3.1	2.0	3.0	3.0	2.1	2.9	3.2	3.7	2.9	3.2	2.4	2.3	2.2	2.3

Kurtosis	8	8	5	6	0	4	6	3	1	6	9	9	3	4	8	8
Jarque-Bera	11.65	16.52	21.23	11.53	8.70	8.53	4.94	8.39	0.09	7.41	1.75	0.16	9.77	3.49	1.86	9.68
Probability	0.00	0.00	0.00	0.00	0.01	0.01	0.08	0.02	0.96	0.02	0.42	0.92	0.01	0.17	0.39	0.01
Observations	169	169	169	169	38	38	38	38	47	47	47	47	84	84	84	84

Table 3: Descriptive Statistics of Returns During COVID-19 Period																
	Total COVID-19 Period				**Pre-COVID-19 Lockdown Period**				**COVID-19 Lockdown Period**				**Post COVID-19 Lockdown Period**			
	CNX NIFTY	**NIFTY Next 50**	**S&P 500 Index**	**Near Month Futures**	**CNX NIFTY**	**NIFTY Next 50**	**S & P 500 Index**	**Near Month Futures**	**CNX NIFTY**	**NIFTY Next 50**	**S & P 500 Index**	**Near Month Futures**	**CNX NIFTY**	**NIFTY Next 50**	**S & P 500 Index**	**Near Month Futures**
Mean	-0.04	-0.04	0.02	-0.03	-1.16	-1.16	-0.77	-1.14	0.56	0.64	0.57	0.55	0.14	0.09	0.07	0.14
Median	0.10	0.13	0.30	0.09	-0.45	-0.56	-0.18	-0.43	0.63	0.65	0.73	0.35	0.19	0.17	0.31	0.17
Maximum	8.40	6.19	8.97	9.34	5.67	3.52	8.97	6.11	8.40	6.19	6.64	9.34	2.24	2.69	1.99	2.18
Minimum	-13.90	-12.37	-12.77	-14.03	-13.90	-12.37	-12.77	-14.03	-5.92	-4.21	-4.51	-6.00	-2.98	-4.36	-6.08	-3.12
Std.	2.3	2.0	2.5	2.4	3.4	3.0	4.2	3.5	2.6	1.9	2.1	2.7	1.0	1.0	1.2	1.1

Dev.	6	3	1	2	8	9	7	9	5	6	5	2	7	5	9	0
Skewness	-1.46	-1.85	-0.82	-1.33	-1.55	-1.66	-0.27	-1.46	0.20	0.37	0.31	0.37	-0.57	-1.11	-1.82	-0.53
Kurtosis	11.66	12.89	9.58	11.57	6.70	6.60	4.41	6.48	4.08	4.02	3.96	4.53	3.11	6.83	8.41	3.16
Jarque-Bera	588.20	785.07	323.60	566.92	36.78	38.08	3.62	32.64	2.59	3.08	2.56	5.69	4.54	68.52	148.73	4.01
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.27	0.21	0.28	0.06	0.10	0.00	0.00	0.13
Sum	-6.05	-6.38	3.23	-5.83	-44.14	-43.93	-29.08	-43.45	26.24	30.22	26.63	25.65	11.84	7.33	5.69	11.97
Sum Sq. Dev.	933.90	694.29	1061.96	982.16	449.06	354.24	673.42	475.59	322.23	177.54	213.13	340.33	95.24	91.90	137.73	101.06
Observations	169	169	169	169	38	38	38	38	47	47	47	47	84	84	84	84

Figure 2 shows high volatility in returns of the NIFTY index during March-April, 2020 and volatility in Index returns is less spiked in post lockdown period.

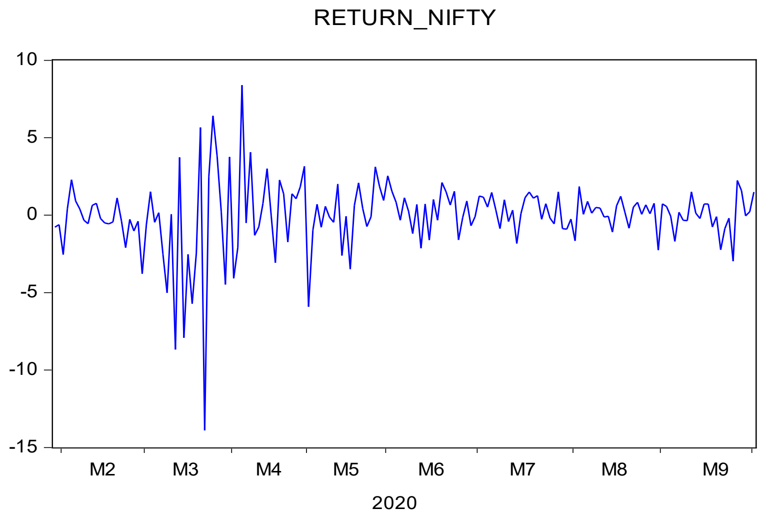

Figure 2: NIFTY Index Returns Movement during COVID-19 Period (January 30, 2020 to October 01, 2020)

The descriptive statistics of returns as shown in Table 3, reveals that average returns on the NIFTY index during the COVID-19 period has been negative (-0.04), but S&P 500 Index has slight positive returns of 0.02 during this period. During pre COVID-19 lockdown period all indexes have given negative returns and during lockdown, NIFTY has given positive average returns of 0.56 per cent and post lockdown returns of NIFTY and other indices have improved significantly and NIFTY average returns are 0.14 during post COVID-19 lockdown period.

The returns data for all the series has to be tested for stationarity. For this Unit root hypothesis testing has been done using Augmented Dickey-Fuller Test. Augmented Dickey-Fuller test where unit root hypothesis is that the return series is non-stationary. ADF unit root test is sensitive towards the lag length included in the regression equation.

So, lag length is chosen on the Schwarz Information Criterion (SIC) and ADF is applied with intercept and trend. The return series of Nifty, Nifty Junior, S&P 500 Index, Nifty futures have been analyzed for unit root for Total COVID-19 period, pre COVID-19 Lockdown period, COVID-19 Lockdown period and post COVID-19 Lockdown period. All the returns series are stationary at its level and they are significant at 1 per cent level. These results are also confirmed with Sahu, D. (2012), Girish, G.P. (2012) and Gahlot, R., Datta, K. and Kapil, S. (2010).

The Lagrange multiplier (LM) test (Pati, P.C. and Rajib, P. (2010) has been used to check for the ARCH/GARCH effect in the series. There was a significant ARCH effect found in the returns series so, data is found to be suitable to apply the GARCH test.

Table 4: GARCH (1,1) Estimates of COVID-19 Period

	Variable	Coefficient	Std. Error	z-Statistic	Prob.
	C	0.288756	0.104152	2.772457	0.0056
	Variance Equation				
α_0	**Constant**	0.104352	0.018414	5.666915	0
α_1	**ARCH (1)**	0.01879	0.024418	0.769539	0.4416
β_1	**GARCH(1) (R_{t-1})**	0.947872	0.028787	32.92695	0
δ_1	**Lagged Nifty Next 50 Returns (Rt-1,Nifty Next50)**	-0.262726	0.138941	-1.89092	0.0586
δ_2	**Lagged S&P 500 Index Returns (Rt-1, S&P500)**	-0.178106	0.067653	-2.632636	0.0085
Γ	**Near Futures Returns (D_f)**	-0.021374	0.155254	-0.137671	0.8905
	R-squared	-0.019065	**Mean dependent var**		-0.035823
	Adjusted R-squared	-0.019065	**S.D. dependent var**		2.357739
	S.E. of regression	2.380107	**Akaike info criterion**		3.738527
	Sum squared resid	951.7051	**Schwarz criterion**		3.868167
	Log likelihood	-308.9055	**Hannan-Quinn criter.**		3.791137
	Durbin-Watson stat	2.261661			
Dependent Variable: RETURN_NIFTY					

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Method: ML - ARCH (Marquardt) - Student's t distribution
Sample: 1/30/2020 10/01/2020
Included observations: 169
Convergence achieved after 36 iterations
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)*RETURN_NIFTYNEXT50 + C(7)*RETURN_SP500 + C(8)*Near Futures Returns

Estimation Command:

=========================

ARCH(BACKCAST=0.7,DERIV=AA) RETURN_NIFTY C @ RETURN_NIFTYNEXT50 RETURN_SP500 RETURN_NEARFUTURES

Estimation Equation:

=========================

RETURN_NIFTY = C(1)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1) + C(5)*RETURN_NIFTYNEXT50 + C(6)*RETURN_SP500 + C(7)*RETURN_NEARFUTURES

Substituted Coefficients:

=========================

RETURN_NIFTY = 0.288755763732

GARCH = 0.104351629616 + 0.0187903863929*RESID(-1)^2 + 0.947871643382*GARCH(-1) - 0.26272632897*RETURN_NIFTYNEXT50 - 0.178105956592*RETURN_SP500 - 0.0213739587278*RETURN_NEARFUTURES

After seeing the presence of ARCH effects in the residuals, we must use a suitable GARCH process to model volatility. The evidence from the previous studies [Sahu D. (2012), Girish, G.P. (2012), Otswal, Priyanka (2011), Sakhtivel, P. and Kamaiah, B. (2011), Gupta, K. and Singh, B. (2009), Gaurishankar S. Hiremath, (2009), Sah, A.N. and Omkarnath, G. (2005) and Shenbagaraman, P. (2003)] in Indian scenario suggests that we shall use GARCH (1,1) model in this study as we are not concerned with asymmetric effects in our study. To measure the impact of the introduction of derivatives on the market volatility, we have introduced the near future returns variable in the conditional variance equations.

A highly significant positive (negative) coefficient is an indication of an increase (decrease) in volatility after the introduction of derivatives contract. To nullify the effect of other market-wide factors, we have also introduced Nifty Next 50 Index (Sarangi, S.P. and Patnaik, U.S. (2006) and Sah, A.N. and Omkarnath, G. (2006)) as a proxy variable for explaining the behaviour of returns of Nifty Index. Worldwide factors are captured by S&P 500 Index return, which has been introduced as another proxy variable in the equation. To measure the impact of the introduction of derivatives, near month futures returns has been used.

Table 4 shows results of GARCH (1,1) estimation of the Total COVID-19 Period. It can be seen that the coefficient of near month futures γ is -0.021374 with a z ratio of -0.137671 which is insignificant this shows that derivatives are not playing any role in reducing the spot market volatility during the COVID-19 period.

The negative coefficient of futures dummy (γ) also suggests that after the introduction of futures, spot market volatility has reduced but the value is insignificant during the COVID-19 period. The mean equation of the model does not even have an AR term. These results are similar to those of (Yu, Shang-Wu. (2001)), the coefficient of ARCH (1) (1 lagged residual returns) $\propto_1$ is insignificant, GARCH (1) (lagged returns) β_1 and $\propto_0$ (Constant) are highly significant, which implies a great impact of news (shocks) on volatility. An insignificant ARCH coefficient $\propto_1$ indicates that a large shock on the t-1 day does not affect returns on 't' day. The $\propto_1$ or ARCH coefficient which has 0.01879 value explains that recent news has an impact on price changes in stocks, but this value is insignificant. The GARCH (1) coefficient β_1 measures the impact of old news and a higher value of β_1 implies a large memory of shocks in this model. The β_1 is 0.947872 which is very high and significant at 1 per cent level of significance indicate that old news has a lasting impact on price fluctuations in the Indian market. The Nifty Next 50 returns ($R_{Niftynext}$) has a coefficient δ_1 of -0.262726 which implies that there is an inverse relationship between Nifty Next 50 return and Nifty return. The coefficient of lagged S&P 500 Index returns (δ_2) is -0.178106 is also highly significant in the model and shows that Nifty and S&P500 Index are negatively related to each other. The conditional volatility of the Nifty Index as predicted by the model equation along with residual and returns for the period from January 2020 to October, 2020. The model has captured volatility clustering, which has occurred at different intervals as shown in the graph.

Pre COVID-19 Lockdown Period

The pre COVID-19 Lockdown period in India has been taken after the first case of COVID was reported in India on January 30, 2020, to March 24, 2020, after which nationwide lockdown was imposed in India. This pre-COVID-19 phase was full of uncertainties as other countries were undergoing lockdown and lots of negative news was coming from around the world. The markets also had started showing a downward trend. The uncertainties were also high because the death rate and health impact of COVID-19 were unknown and unpredictable, also corporates were unaware of the response of the Government to handle the pandemic. Figure 3 shows the movement of NIFTY returns and other indices during pre COVID-19 Lockdown period in India. Since the beginning of March return volatility is more spiked as compared to February, 2020. The Global Index of S&P 500 Index has higher extreme values of up and down as compared to other indices.

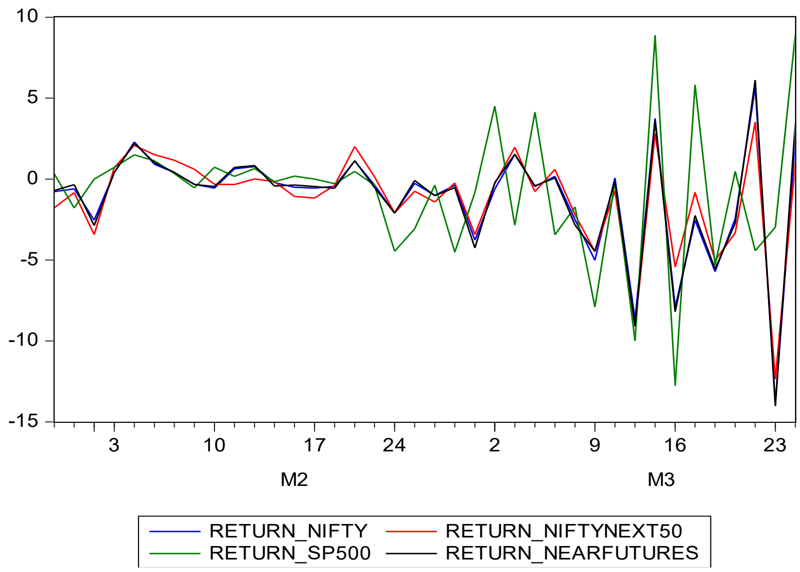

Figure 3: Index Movement during Pre COVID-19 Lockdown Period (January 30, 2020 to March 24, 2020)

The total number of observations in this sample period is just 38 so due to the small sample size and behaviour of returns, no ARCH effect was found in the return series and so the GARCH model could not be applied.

Table 5: ARCH _LM and ARMA Least Square Results of Pre-COVID-19 Period				
Heteroskedasticity Test: ARCH (no ARCH Effect found)				
F-statistic	1.397437	**Prob. F(1,35)**		0.2451
Obs*R-squared	1.420571	**Prob. Chi-Square(1)**		0.2333
ARMA Least Square Results				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-1.17553	0.376582	-3.12158	0.0035
AR(1)	-0.398474	0.154958	-2.571493	0.0144
R-squared	0.155179	**Schwarz criterion**		5.330263
Adjusted R-squared	0.131712	**Durbin-Watson stat**		1.843311
Sample: 1/30/2020 3/24/2020				
Included observations: 38				
Convergence achieved after 3 iterations				

Estimation Command:

=========================

LS RETURN_NIFTY C AR(1)

Estimation Equation:

=========================

RETURN_NIFTY = C(1) + [AR(1)=C(2)]

Substituted Coefficients:

=========================

RETURN_NIFTY = -1.1755295699 + [AR(1)=-0.398473996547]

Table 5 reports the results of the ARCH-LM test. The Lagrange multiplier (LM) test (Pati, P.C. and Rajib, P. (2010) is used to check for the ARCH/GARCH effect in the series. We start with the residual term in the mean equation for five lags using the following model.

$$\varepsilon_t^2 = \propto_0 + \sum_{i=1}^{5} \propto_i \varepsilon_{t-1}^2$$

The regression result reveals that the coefficient for none of the lags was significant. The F statistics value F (35) is 1.397437 which is not significant. Thus the null hypothesis cannot be rejected and we can conclude that there are no ARCH effects. So, the GARCH model cannot be applied to the sample series.

Table 5 further reveal the result of ARMA and the least square model which has been applied for analysis. NIFTY returns follow AR(1) process, which shows that NIFTY returns are based on past one day lagged returns.

It can be concluded that during pre COVID-19 Lockdown period, NIFTY returns are falling and market volatility is high, but the return volatility is influenced by previous day returns.

During COVID-19 Lockdown

In this sub-section, returns and volatility of NIFTY and other indices are analysed during the period of COVID-19 pandemic lockdown. This nationwide lockdown started on March 25, 2020, to June 7, 2020. The Index movement of NIFTY, NIFTY Next 50 and S&P 500 Index shows less volatility in index value between March to June, 2020. The return series shows low levels of volatility with specific breakpoints of high and low spikes. These breakpoints have an association with the specific dates where the Government came up with specific relief measures for financial and economic support to the public.

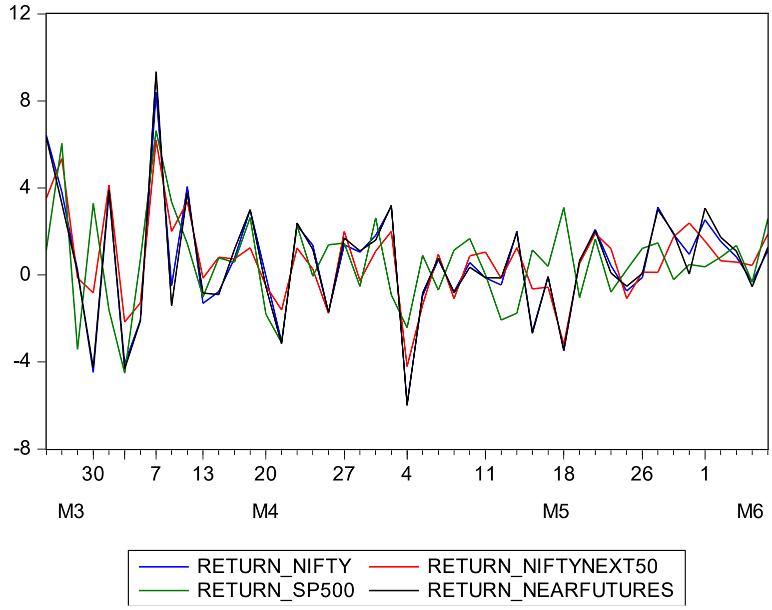

Figure 4: Index Movement during COVID-19 Lockdown Period (March 24, 2020, to June 7, 2020)

The total number of observations in this sample period is only 47 so due to the small sample size and behaviour of returns, no ARCH effect was found in the return series and so the GARCH model could not be applied.

Table 6 reports the results of the ARCH-LM test. The Lagrange multiplier (LM) test has been used to check for the ARCH/GARCH effect in the series. The regression result reveals that the coefficient for none of the lags was significant. The F statistics value F (45) is 1.392058 which is not significant. Thus the null hypothesis cannot be rejected and we can conclude that there are no ARCH effects. So, the GARCH model cannot be applied to the sample series. Table 6 further reveal the result of ARMA and the least square model which has been applied for analysis. NIFTY returns follow AR(1) and MA(1) processes, which shows that NIFTY returns are based on past one day lagged returns as well as past day error forecasts.

Table 6: ARCH _LM and ARMA Least Square Results of COVID-19 Lockdown Period				
Heteroskedasticity Test: ARCH (no ARCH Effect found)				
F-statistic	1.392058	**Prob. F(1,45)**		0.2443
Obs*R-squared	1.4103	**Prob. Chi-Square(1)**		0.235
ARMA Least Square Results				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.264095	0.084635	3.120417	0.0031
AR(1)	0.686728	0.101717	6.751338	0
MA(1)	-0.97539	0.024498	-39.81526	0
R-squared	0.172591	**Schwarz criterion**		4.794736
Adjusted R-squared	0.135817	**Durbin-Watson stat**		1.913101
Inverted AR Roots	0.69	**Inverted MA Roots**		0.98
Sample: 3/25/2020 6/07/2020				
Included observations: 47				
Convergence achieved after 18 iterations				

Estimation Command:

=========================

LS(DERIV=AA) RETURN_NIFTY C AR(1) MA(1)

Estimation Equation:

=========================

RETURN_NIFTY = C(1) + [AR(1)=C(2),MA(1)=C(3),BACKCAST=3/25/2020,ESTSMPL="3/25/2020 6/08/2020"]

Substituted Coefficients:

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RETURN_NIFTY = 0.26409527893 + [AR(1)=0.686727719268,MA(1)=-0.975387449026,BACKCAST=3/25/2020,ESTSMPL="3/25/2020 6/08/2020"]

The forecasted return series is generated by AR(1) MA(1) least square model for NIFTY Index.

It can be summarized that during the COVID-19 pandemic lockdown period, the returns had less volatility as compared to pre lockdown period. The result of the AR(1) MA(1) model shows that returns are affected by previous day lagged returns as well as errors of forecasted of the previous day.

Post COVID-19 Lockdown

The period of post COVID-19 Lockdown begins from June 8, 2020, to October 01, 2020, which includes unlockdown in a phased manner. The price series of the four indices shows an increase in index values as well as less volatility.

A comparison of returns series of four indices shows that all series offer returns in a similar range. The volatility in returns of the S&P500 Index is more spiked than returns of NIFTY.

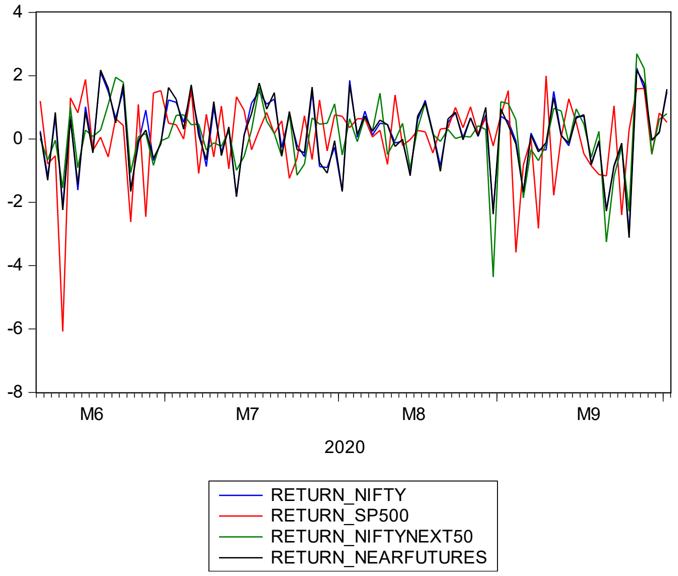

Figure 5: Nifty Index Values during Post COVID-19 Lockdown Period (June 8, 2020, to October 01, 2020)

After seeing the presence of ARCH effects in the residuals, we have used a suitable GARCH process to model volatility. The final model after comparing SIC of various model fits selected has been the GARCH (1,0) model.

Table 7: GARCH (1,0) Estimates of COVID-19 Period					
	Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
	C	0.279385	0.061054	4.576027	0
	AR(1)	0.815267	0.1524	5.349501	0
	AR(2)	-0.168129	0.069095	-2.433291	0.015
	MA(1)	-0.839697	0.09411	-8.922462	0
Variance Equation					
α_0	**Constant**	7.314973	4.236467	1.726668	0.0842
α_1	**ARCH (1)**	0.084622	0.217211	0.389585	0.6968
δ_1	**Lagged Nifty Next 50 Returns (Rt-1,Niftynext50)**	-0.361931	0.156736	-2.309176	0.0209
δ_2	**Lagged S&P 500 Index Returns (Rt-1, S&P500)**	-0.044392	0.208914	-0.212487	0.8317

Γ	**Near month futures (D_f)**	-0.000581	0.000376	-1.546612	0.122
	R-squared	-0.064336	**Mean dependent var**		0.139648
	Adjusted R-squared	-0.104753	**S.D. dependent var**		1.077621
	S.E. of regression	1.132658	**Akaike info criterion**		2.949483
	Sum squared resid	101.3502	**Schwarz criterion**		3.240909
	Log likelihood	-112.4035	**Hannan-Quinn criter.**		3.066561
	Durbin-Watson stat	2.054918			
Dependent Variable: RETURN_NIFTY					
Method: ML - ARCH (Marquardt) - Student's t distribution					
Sample: 6/09/2020 10/01/2020					
Included observations: 83					
Convergence achieved after 33 iterations					
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*RETURN_NIFTYNEXT50 + C(8)*RETURN_SP500 + C(9)*NEAR_MONTH_FUTURES					

The series follows AR(2) MA(1) mean equation and the GARCH (1,0) model has been applied to analyse volatility in the return series. The results show that AR 1 and AR 2 are highly significant so the past two days return has an impact on current day NIFTY returns and the past day error term also influences NIFTY returns. The variance regressors used in GARCH (1,0) model shows that the ARCH (1) term is insignificant and S&P 500 Index and near month futures are also insignificant at 5 per cent level of significance. This conveys that the previous day return and Nifty next 50 one day lagged return impact NIFTY return volatility.

Overall, it can be summarised that the post lockdown market has improved in returns and volatility has come down from pre-lockdown period. During post lockdown period previous two day returns and forecasted errors of the previous day also influences returns of NIFTY.

Comparison of Forecasted Returns with actual returns

In this sub-section, a comparison of all four volatility GARCH AND ARMA models of four time periods has been done. Table 8 shows a comparison of forecasted returns generated by four models using ARMA and GARCH process with actual returns. The comparison of returns forecasted by the model for the total COVID-19 period studied using GARCH (1,1) mode on 169 observations shows that the mean forecasted returns are positive (0.021) but actual NIFTY returns are negative (-0.036). The volatility as shown by the standard deviation of forecasted and actual returns are similar to each other.

During the pre COVID-19 lockdown the forecasted model mean returns and actual returns are the same (-1.162) but the standard deviation of actual returns is higher (3.484) as compared to the forecasted model standard deviation (1.372).

The Lockdown period forecasted returns of AR(2) MA(1) model shows little lower returns (0.529) as compared to actual returns of (0.552). The standard deduction of the forecasted model is also slightly higher than actual returns.

In the post COVID scenario, the GARCH (1,0) model forecasted returns (0.189) are higher than actual returns of the market (0.140). The standard deviation of the forecasted model (0.905) is lower than actual returns (1.078).

Table 8: Comparison of NIFTY Returns During COVID-19 Period (Forecasted and Actual Returns)

	NIFTY Returns of Total COVID-19 Period		NIFTY Returns of Pre-COVID-19 Period		NIFTY Returns of COVID-19 Lockdown Period		NIFTY Returns of Post-COVID-19 Period	
	Forecasted Returns	Actual Returns	Forecasted Returns	Actual Returns	Forecasted Returns	Actual Returns	Forecasted Returns	Actual Returns
Mean	0.021	-0.036	-1.162	-1.162	0.529	0.552	0.189	0.140
Median	0.289	0.102	-1.463	-0.454	0.600	0.600	0.228	0.187
Maximum	8.400	8.400	3.896	5.669	8.400	8.400	2.108	2.239
Minimum	-13.904	-13.904	-3.903	-13.904	-5.916	-5.916	-2.258	-2.975
Std. Dev.	2.298	2.358	1.372	3.484	2.626	2.619	0.905	1.078
Skewness	-1.641	-1.460	1.585	-1.545	0.235	0.214	-0.643	-0.560
Kurtosis	13.044	11.660	6.887	6.698	4.124	4.162	3.375	3.071
Jarque-Bera	786.253	588.198	39.827	36.776	2.970	3.066	6.204	4.350
Probability	0.000	0.000	0.000	0.000	0.226	0.216	0.045	0.114
Sum	3.596	-6.054	-44.138	-44.138	25.395	26.493	15.679	11.591
Observations	169	169	38	38	48	48	83	83

Conclusion

The results of the GARCH (1,1) estimation of Total COVID-19 Period shows that the coefficient of near month futures γ is -0.021374 with a z ratio of -0.137671 which is insignificant shows that derivatives are not playing any role in reducing the spot market volatility during the COVID-19 period. The negative coefficient of futures dummy (γ) also suggests that spot market volatility has reduced after the introduction of futures, but the value is insignificant during the COVID-19 period. It can be concluded that COVID-19 is a special scenario, where even the previous relationship between various indices and market variables has seen a change. During the COVID-19, market volatility is not affected by previous day news and shock but is influenced by long term shock and news. Also, the derivatives market's role in reducing the market volatility of Nifty has not been significant during the COVID period. But Nifty Next 50 and S&P 500 Index inversely influences Nifty return volatility. Thus, we can say that the COVID-19 period has seen high levels of volatility and negative mean returns in the pre-COVID-19 period, Medium positive returns during the lockdown and improved positive returns post COVID-19 lockdown period. In the total COVID-19 period, previous day news and derivatives' role is insignificant in explaining the returns and volatility the next day.

During the pre-COVID-19 Lockdown period, Nifty returns are falling and market volatility is high, but previous day returns influence the return volatility. Returns and volatility of Nifty and other indices are analysed during the period of COVID-19 pandemic lockdown. This nationwide lockdown started on March 25, 2020, to June 7, 2020. The Index movement of Nifty, Nifty Next 50 and S&P 500 Index shows less volatility in index value between March to June, 2020. The return series shows low levels of volatility with specific breakpoints of high and low spikes. These breakpoints are associated with the specific dates where the Government came up with specific relief measures for financial and economic support to the public. It can be summarized that during the COVID-19 pandemic lockdown period, the returns had less volatility than the pre lockdown period. The result of the AR(1) MA(1) model shows that returns are affected by previous day lagged returns and errors of the forecast of the previous day. Post COVID-19 Lockdown period begins from June 8, 2020, to October 01, 2020, which includes unlockdown in a phased manner. The price series of the four indices shows an increase in index values as well as less volatility. This conveys that the previous day return and Nifty next 50 one day lagged return impact Nifty return volatility.

The overall analysis concludes that since the COVID-19 pandemic is an abnormal situation thus, the returns of the market have also shown diverse behaviour during different phases of the pandemic lockdown. This period must always be studied separately for the specific analysis of market behaviour. During Lockdown the long term past return and role of the derivatives market in reducing the market volatility was found to be insignificant. Whereas past day or past two days lagged returns were found to have a significant impact on the market return.

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