

An Analytical Study on Covid-19 and Indian stock market

By

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Abstract

Purpose: The novel corona virus has led to unprecedented repercussions on daily life and the economy. This article analyses the effect of epidemic COVID 19 on investment behavior of investors while investing in stocks during this pandemic times. As during the pandemic market was volatile and investors were very skeptical about the market returns.

Research Design: This study uses analytical methods to evaluate the effect of pandemic on investor's behavior. The data was collected from various secondary sources to understand the effect of COVID 19 investment trends of investors.

Findings: The result shows that investors are now more inclined towards the options which can offer them liquidity with good significant returns as due to lockdown the economic activities had slowed down and impacted the pockets of the investors. Maximum investors were negatively affected due to the hit of the first wave with a return of the second wave as well as they were required to pay huge hospital bills. So this was one of the reasons that contributed towards change in behavior from moderate to risky.

Practical Implications: With this analytical study the investors will be able to formulate the strategies to invest in the market and also give them the outlook of the volatility and the dynamism of the share market along with an option of liquidity and hassle-free investment.

Social Implications: This study will encourage the new investors to understand the benefits of market returns and add on to the existing investors to analyze the market and have optimum returns from the market.

Keywords: Volatility, investment behavior, financial risk, investment strategies, a trade-off.

Introduction:

The rapid spread of the unprecedented COVID-19 pandemic has put the world in jeopardy and changed the global outlook unexpectedly. The SARS-CoV-2 virus was the proximate cause of outbreak of COVID – 19 in Wuhan city of China in December 2019, and swiftly spread around the globe. This contagious virus not only affected China but rapidly left entire world in mortify and outrage of health emergency. To lessen the proliferation of SARS-CoV-2 virus globally countries went for stern lockdown which resulted in slowdown of economy as well. Also many countries adopted stringent quarantine polices to fight with this invisible enemy. Transports was affected and restricted in many countries with a view to stop the spread of COVID 19, but this latching of countries slowed down the global economic activities.

The consumers and the corporate have changed their natural and regular consumption patterns due to the turmoil and the fearful situation which created market volatility and abnormality. Pandemic added to the uncertainty and risk of

investment causing economic impact globally to the developed and the emerging economies including India.

This economic slowdown affected the financial market sternly which includes share market, bonds and other wide range of financial investment products. This pandemic also contributed to the increase in the prices of oil and gold as well. Firzli (2020) cited this pandemic as "the greater financial crisis." Globally the business houses were shaken financially due to lockdown contributing to increase to corporate debt at a higher level. In response to pandemic financial market risk has increased extensively (Zhang et al., 2020). Due to pandemic investors faced significant losses resulted caused by fear and uncertainty. The researchers in their research on financial market have found that there was downfall in investment as investors were skeptical due to COVID-19 pandemic. Quarantine and lockdown adversely affected the revenue and the productivity of the companies contributed to the increase in operating cost and cash flows.

In March 20 Government of India announced Jaanta Curfew and imposed stringent lockdown with social distancing to slow down the outbreak of Nobel Corona Virus. Due to this lockdown various economic activities slowed down and some of them were totally stopped.

The Indian financial market was vulnerable due to the uncertainty of global market (Raja Ram, 2020). Due to uncertainty and risk factor associated with stock market Indian share market also tasted volatility. India is having two important stock exchanges namely Bombay Stock Exchange and National stock exchange. These stock exchanges seen the negative growth in March 2020 for almost about 13 and 29 percent as a result of lockdown. Few of the economists have named the impact of COVID 19 on Indian stock market as “Black Swan Event”. Due to the lockdown the corporate have gone for lay off, retrenchments and even downsizing to curtail down the losses. Also the retail investors reduced their consumption habits due to pandemic effect. This COVID-19 pandemic has a negative impact on demand supply mechanism which ultimately affected the investment preferences and attitude of the investors making them conservative and diverting them towards lesser risk profile investment options.

Research Questions

- Do any change in investment behavior witnesses during pandemic?
- Was volatility of Stock market may affected due to pandemic?
- What is different factors influence investment behavior?
- What is impact of retail investors on stock market volatility?

Pandemic Precedence of the Indian Investors

Due to the uneven impact of pandemic on different sectors and categories of the society lead to difference in consumer prospective, the optimistic trend have emerged both in terms of consumption and investment patterns during the pandemic.

The work from home culture resulted in transformation of the consumer behavior, coupled with prioritizing personal and family health which facilitated increase in elective spending and saving money among Indian consumers. Also work from home and lockdown gave the opportunity to investors to analyse their investments and track them which contributed to in-depth analysis of trading and exploring the new alternatives for creating liquid assets.

Many sectors were benefitted due to paradigm shift in consumer behavior such as pharmaceuticals, telecom, FMCG, Banking, financial services including insurance. This effected positively Indian indices which have recorded optimistic gains from the due to the negative corrections in market in March 2020.

Following the market sell-off, this broad-based equities rally drew in additional retail investors, who were attracted by favorable stock prices. Over the previous financial year, foreign portfolio investors (FPIs) invested Rs 2,74,034 crores in Indian stock markets, which, together with mutual fund inflows of Rs 96,000 crore, helped the Nifty and Sensex to trade well above their pre-pandemic levels and near all-time highs today. In fact, the Rs 9,182 crore SIP mutual fund inflows in March 2021 was the largest in the previous 12 months, indicating a decline in income uncertainty and restored investor optimism.

Apart from equities, a growing number of Indians are diversifying their portfolios to include real estate, debt, insurance products, and gold due to a variety of variables. A combination of decreased pricing in major markets, tax benefits granted by various state governments, and the follow-on effect of WFH culture, which has mandated separate quarters for both working members of a typical nuclear family, have encouraged real estate investments. Many first-time homebuyers are hurrying to close on their dream homes, as evidenced by the rise in sales. Housing loans are now available at rates as low as 6.75 percent, and some state governments are easing stamp duty for registrations.

Due to the cultural and social importance associated with the yellow metal, India has traditionally been a top consumer of actual gold. However, in the aftermath of the pandemic, Indian consumers are looking at alternative investments such as gold exchange traded funds, gold mutual funds, and sovereign gold bonds (SGBs) to take advantage of gold's relative price stability and long-term return potential. Due to the cultural and social importance associated with the yellow metal, India has traditionally been a top consumer of actual gold. However, in the aftermath of the pandemic, Indian consumers are looking at alternative investments such as gold exchange traded funds, gold mutual funds, and sovereign gold bonds (SGBs) to take advantage of gold's relative price stability and long-term return potential.

According to surveys, more than 70% of Indians are now putting more attention on raising their debt and insurance allocations in order to protect themselves in the event of another pandemic or tragedy in the future. As a result, traditional instruments such as fixed deposits and Public Provident Fund (PPF) have seen an increase in capital allocation, while knowledgeable investors are actively investing in mutual fund debt schemes, which provide a larger return potential than an FD or PPF. Because of increased consumer awareness of the importance of insurance in the post-pandemic era, the general and life insurance sectors have benefited the most. In addition to traditional life and medical insurance products, consumers are also buying home insurance to protect their real estate investments. Both life and general insurance businesses appear to be prepared to benefit from this trend, and their insured bases are expected to grow significantly in the coming years.

Furthermore, as outlined in the Union Budget for 2021, the foreign investment limit in Indian insurance companies has been raised from 49% to 74%, allowing foreign insurance firms to bring in international best practises, technology, processes, and long-term resources to help make insurance more accessible to the masses.

Despite the crushing effects of the first statewide lockdown in March 2020, the Indian economy has recovered stronger than ever, with most high-frequency lead indicators of consumption and investment demand strengthening through the third quarter of fiscal year 2020-21. The low-interest environment has acted as a further stimulant for both private consumption and investment, encouraging more Indians to spend their excess cash in a variety of financial products and asset classes. India presents a potential structural development storey for the next few decades, with a wide representation of attractive and high-return sectors such as technology, healthcare, consumer, and banking on its indices. Long-term prospects for the Indian economy remain bright if inflationary pressures are contained and the low-interest rate environment is maintained, and investors would do well to remain involved across the many financial markets accessible today

Objective of the study

- (1) Capture the behavior of NSE before and after impact of Covid 19
- (2) Analyse the co-movement of NSE during before and after Covid 19.
- (3) Examine both symmetric and asymmetric volatility of before and during and select the best suitable model to define this volatility

Stock market Volatility

Stock market volatility refers to risk and uncertainty associated with movement of stock market indexes such as Nifty or Sensex. In finance volatility denoted as σ , when rapid change in price of stock in either positive or negative, is volatility. Volatility can measure in specific time frame with reference to historic prices of stock. Volatility of stock market can be accessed on the basis of past data and other is market price of traded security. There are various models of volatility models i.e. traditional estimators, extreme value estimators and conditional models. With advancement of research that the financial market volatility is time varying and having volatility clustering effect, conditional models came into picture, as unconditional models lost its relevance as compare to conditional models.

One of the model that has the ability to model conditional volatility or variance after incorporating these characteristics is Generalized Autoregressive Conditional Heteroskedasticity (GARCH) which was proposed by Bollerslev (1986). heteroscedasticity (ARCH) that was given by Engle in 1982, it provides us more flexible approach to understand dynamic structure of conditional variance (Chou, 1988).

EGARCH was promulgated by Nelson in 1991, TGARCH was brought out by Zakoian in 1994, GJR-GARCH by Glosten, Jagannathan and Runkle in 1993. The GARCH processes are generalized ARCH processes in the sense that the squared volatility is allowed to depend on previous squared volatilities, as well as previous squared values of the process.

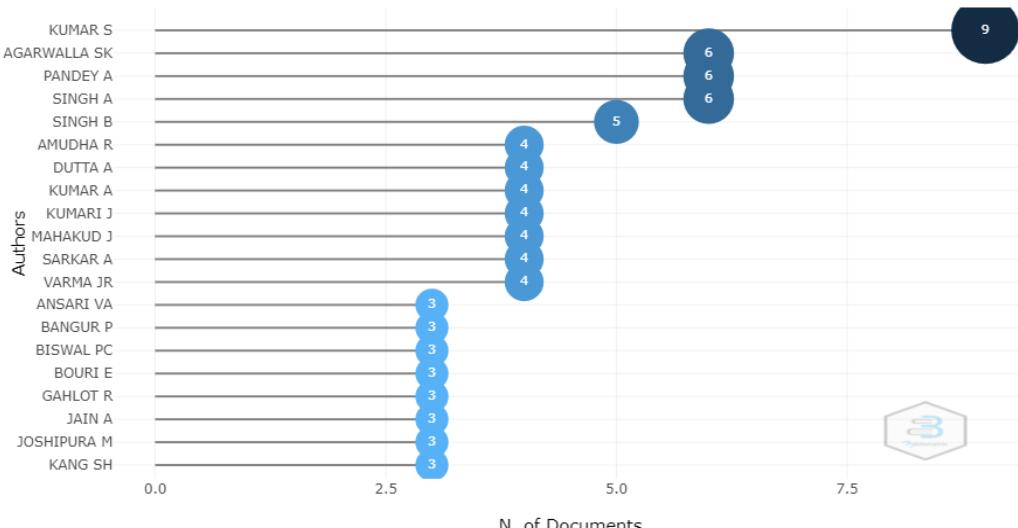
Systematic Literature Review

Table 1: Main Information

Time span	2003-2021
Sources (Journals, Books, etc)	136
Documents	297
Average years from publication	4.89
Average citations per documents	6.067

Table 1 showing study conducted on stock market volatility, it showing most of study conducted during 2003 to 2021, in total 433 works done at the rate of 4.89 publications per year.

Image 1: Most relevant Author worked for stock market volatility



Chou (1988), a study conducted in the US market for the period 1962 to 1985 for determination of volatility and risk aversion scenario with help of GARCH model. Uncertainty was there in 1974, that causes the markets to plunge causing increase in volatility by 26%. Lamoureux and Lastrapes (1990) in their study contributed to the empirical evidence in usage of ARCH to capture the heteroskedasticity in stock returns. Conclusions found to be valid in

the cases of analyzed stocks and this study further paved the way for the employment of ARCH and GARCH models in studying behavior of asset prices. Blair et al. (2002) made comparative study of the S & P 100 index and all its elementary stocks by estimating ARCH and TARCH Model, with conclusion that a majority of stocks have larger volatility response for negative returns compare to positive returns. Deb et al. (2003) did predictive

analysis for the monthly responses of market indices and its volatility for BSE and NSE volatility Indian capital markets using eight different univariate models. Out-of-sample forecasting performance of these models shows that GARCH (1, 1) model outperforms the other models.

Ng and McAleer (2004) used simple GARCH (1, 1) and TARCH (1, 1) models for testing, estimation and forecasting the volatility of daily returns in S&P 500 Index and the Nikkei 225 Index. Their empirical results indicate that the forecasting performance of both models depends on the data set used. Karmakar (2005) used conditional volatility models to estimate the volatility of 50 individual stocks of Indian stock exchange and observed that the GARCH (1, 1) model gives fairly good forecast. Pandey (2005) showed that extreme value estimators perform better than the conditional volatility models in the case of Indian stock market. Banerjee and Sarkar (2006) for Indian stock market, observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. Magnus and Fosu (2006) estimated GARCH type models for daily returns of the Ghana Stock Exchange Market and found that the GARCH (1, 1) model outperforms.

Trilochan Tripathy & Luis Gil-Alana (2010) has examined the suitability of various volatility forecasting model for National Stock Exchange of India. The data included in the study were the daily closing, high, low and open values of the NSE returns from 2005 to 2008. The study consist five models which were Historical/Rolling Window Moving Average Estimator, Exponentially Weighted Moving Average (EWMA), GARCH models, Extreme Value Indicators (EVI) and Volatility Index (VIX). The model comparison was

done on the basis of which models were explained the ex-post volatility well. The study was revealed that the GARCH and VIX models to be the best methods for volatility forecasting based on Wald's constant test. The study concluded that due to low frequency data extreme value models fail to forecast.

Emenike, Kalu O (2010), investigated the volatility of stock market returns in Nigeria using GARCH (1,1) and the GJR-GARCH (1,1) models. Volatility clustering, leptokurtosis and leverage effects were examined for the NSE returns series from January 1985, to December 2008. The results from GARCH (1,1) model show that volatility of stock returns is persistent in Nigeria. The result of GJR-GARCH (1,1) model shows the existence of leverage effects in Nigeria stock returns. Also, the shape parameter estimated from GED reveals evidence of leptokurtosis in the NSE returns distribution. Finally, volatility.

Aastha KHERA & Dr. Miklesh Prasad YADAV (2020), studied to examine and forecast the volatility of the stock exchanges of emerging countries. It is found that the volatility of every stock return can be forecasted. Both ARCH and GARCH terms are significant in all the cases. Their sum of the coefficients are large enough to denote the persistence of the volatility. The overall persistency of shock is largest in China's stock return and lowest in case of Chile's stock exchange as their parameters sum is highest and lowest respectively. The sum of α_1 & α_2 is less than one ($\alpha_1 + \alpha_2 < 1$) implies the mean reverting GARCH model. Comparing the result of short run and long run shock persistency, it is found that long run shock is more persistent than short run as their α_2 is larger than α_1 .

Table 2: Most Relevant Country's Contribution

Country	No of documents published	Country	No of documents published
INDIA	404	AUSTRALIA	8
USA	24	MALAYSIA	6
FRANCE	14	BANGLADESH	5
UK	14	SAUDI ARABIA	5
TUNISIA	11	BAHRAIN	4

Table 2 showing number of publication on the topic, India is contributed 404 document with maximum 939 citations. University of Delhi and Indian Institute of Management contributed most.

Data Collection and Research Method

Data Collection: To study the effect of Covid-19 on market Volatility and its impact on NSE and BSE market, we taken data from website of National Stock Exchange and data taken from March 1 2019 to September 03, 2021, in total 618 observations. Data of Nifty and Sensex taken for trading days i.e Monday to Friday, effect of Saturday and Sunday seen on Monday when market open for trading.

Research Methods: To understand the effect of

Covid-19 news and its reaction on Market Volatility, we taken data from March 1 2019, when everything was normal and market volatility can be seen due to others factors.

1. Volatility Clustering- Volatility cluster was checked by plotting graph of log value of Nifty value

2. Arch Effect in Data set – Arch Test conducted on data set

3. To stationary on data set Augmented Dickey-Fuller Test conducted and outcome is shown in data analysis section.

Augmented Dickey fuller test conducted to check the stationary of data set.

Pre Testing on Data Set

1. Volatility Clustering

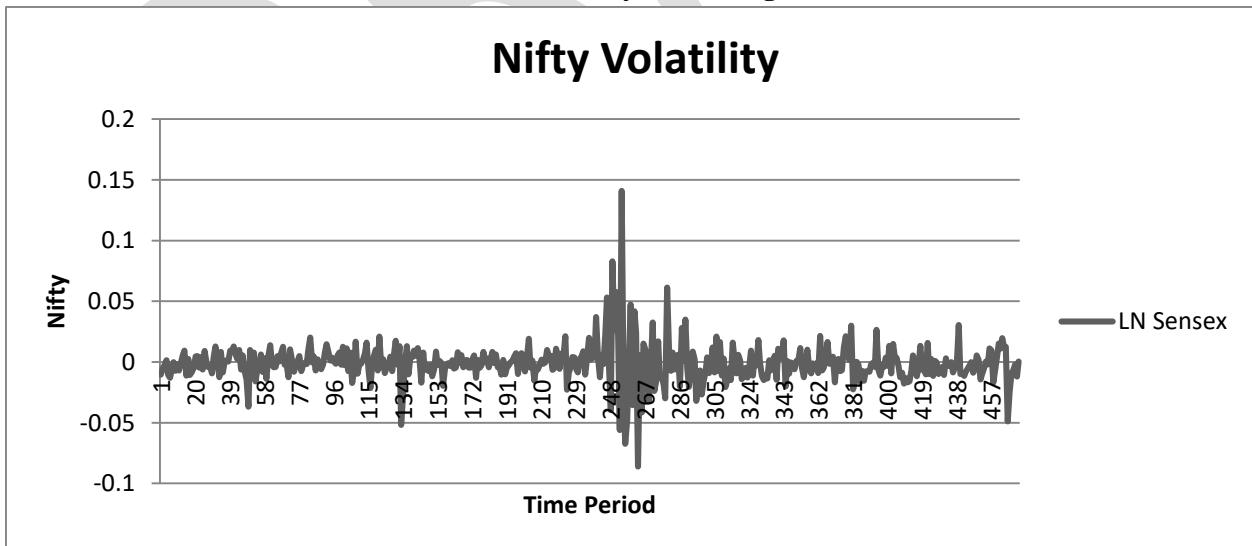


Chart 1: Time period Taken from March 1, 2019 – September 3, 2021

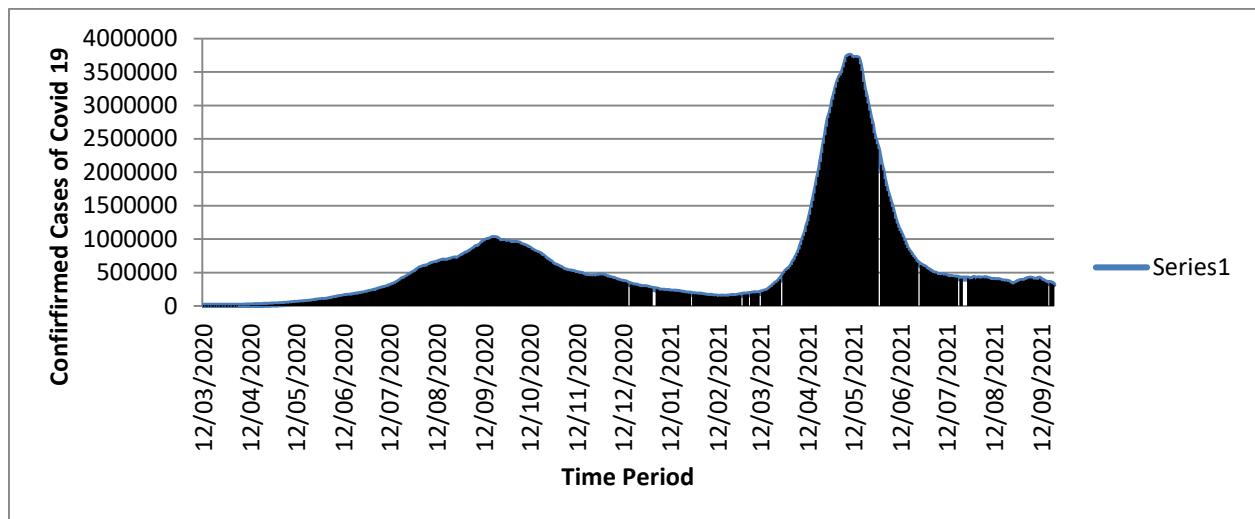


Chart 2: Time period Taken from March 1, 2020 – September 3, 2021

Hypothesis of Study

H₀₁: Nifty has a unit root(Non-Stationary)

H₁₁: Nifty has not unit root(Stationary)

Augmented Dickey-Fuller Test

data: rNifty=diff(log(Nifty))

Dickey-Fuller = -7.628, Lag order = 8, p-value = 0.01

alternative hypothesis: stationary

H₀₂: Nifty has no Arch effect

H₁₂: Nifty has Arch effect

ARCH LM-test; Null hypothesis: no ARCH effects

Chi-squared = 208.12, df = 12, p-value < 2.2e-16

GARCH Model - Conditional Variance Dynamics

Coefficient(s):	a0	a1	b1
	5.276e-06	1.712e-01	8.054e-01

Research Findings

GARCH Model : sGARCH(1,1)

Mean Model : ARFIMA(0,0,0) Distribution : normal

LogLikelihood : 1906.626 Information Criteria

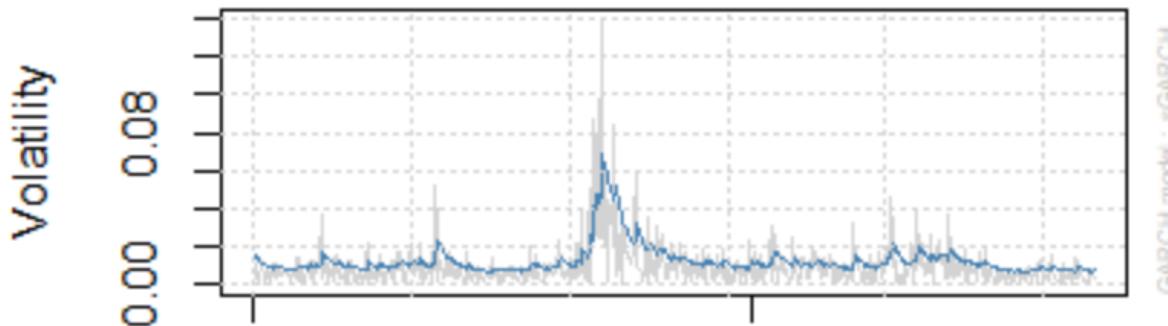
Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 1.07 1.24 1.6 Individual Statistic: 0.35 0.47 0.75

Optimal Parameters				Robust Standard Errors			
Estimate	Std. Error	t value	Pr(> t)	Estimate	Std. Error	t value	Pr(> t)
mu	0.001039	0.000323	3.2204	0.001039	0.001110	0.93568	0.349438
omega	0.000005	0.000006	0.8057	0.42041	0.000005	0.000034	0.14615
alpha1	0.157673	0.029787	5.2933	0.00000	0.157673	0.051647	3.05288
beta1	0.817882	0.032386	25.2538	0.00000	0.817882	0.247889	3.29939
Mu- Overall Mean of series				0.000969			
Omega - is Constant							
Weighted Ljung-Box Test on Standardized Residuals				Weighted Ljung-Box Test on Standardized Squared Residuals			
statistic p-value				statistic p-value			
				Lag[1] 0.2152 0.6427			

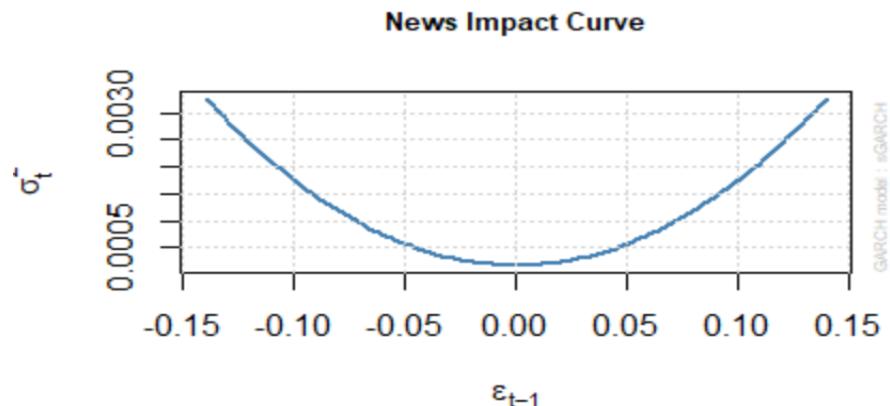
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Conditional SD (vs |returns|)



Standard Conditional Standard deviation Curve is time varying and its showing the variation in Nifty data Cleary visible.

News Impact Curve – It showing Symmetrical GARCH model



To check the Covid-19 effect Taken Covid-19 as Dummy Variable and regression analysis taken Nifty as dependent variable

Null Hypothesis: LN_NIFTY has a unit root				
Lag Length: 0 (Automatic - based on SIC, maxlag=17)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-23.31299	0.0000
Test critical values:	1% level		-3.444009	
	5% level		-2.867457	
	10% level		-2.569984	

.Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(LN_NIFTY)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LN_NIFTY(-1)	-1.073102	0.046030	-23.31299	0.0000
C	-0.000925	0.000717	-1.289794	0.1978

*MacKinnon (1996) one-sided p-values.
 Source: Collected from www.nseindia.com and computed using E Views

It is found from the analysis that the selected sample index has obtained high volatility -1.074027 (-1.073102 0.000925) during the study period. That is 106 percent of volatility exist in the selected

sample index during the study period. Hence the hypothesis “The Index price returns of sample indices are not volatile” is rejected.

Heteroskedasticity Test: ARCH				
F-statistic	83.83623	Prob. F(1,469)	0.0000	
Obs*R-squared	71.42597	Prob. Chi-Square(1)	0.0000	
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Included observations: 471 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.97E-07	2.12E-07	3.757102	0.0002
RESID^2(-1)	0.389450	0.042534	9.156212	0.0000
R-squared	0.151647	Mean dependent var		1.31E-06
Adjusted R-squared	0.149839	S.D. dependent var		4.82E-06
S.E. of regression	4.44E-06	Akaike info criterion		-21.80754
Sum squared resid	9.25E-09	Schwarz criterion		-21.78990
Log likelihood	5137.677	Hannan-Quinn criter.		-21.80060
F-statistic	83.83623	Durbin-Watson stat		1.909313
Prob(F-statistic)	0.000000			

P value is less than 5% of value thus Covid 19 significantly affected volatility of trading in NSE and this impact was reflected in Nifty index.

Findings

Graph chart of log return series of Nifty showing volatility clustering having fat tail with highly leptokurtic.

Augment dicker fuller test was applied to test stationary or presence of unit root p value is less 0.05, null hypothesis was not accepted means series is stationary. Arch Test results showing p value is less than 0.05 thus null hypothesis was not accepted, means Nifty series had Arch effect.

To knowing the order of GARCH Model, its result shown that GARCH model of order (1,1) and symmetrical GARCH or standard GARCH estimated.

In GARCH Model- Alpha 1 and Beta 1 is positive, its showing that if any news was in market is significant, means this news had significantly affected volatility.

Standard Conditional Standard deviation Curve is showing time varying and the variation in Nifty data Cleary visible.

It is found from the analysis that the selected sample index has obtained high volatility -1.074027 (-1.073102 0.000925) during the study period

Conclusion

The main aim and purpose of the study is to analyze the impact of COVID - 19 on Stock Market National Stock Exchange. Result from the GARCH (1,1). the impact of COVID – 19 and higher amount of equities been sold significant impact on index in India. Hence with the results of all the analysis it can be understood that the COVID-19 in India made an adverse impact in automobile sector during the study period. The sudden fall of stock values affect the industry manufacturing process and it has been influenced the stock market for a period and it may recover soon with optimum potential

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