The Impact of COVID-19 on Financial Volatility: A Pre & Post Analysis Using the EGARCH Model

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Abstract

Purpose: *This study aimed to critically evaluate the effects of the COVID-19 pandemic on financial market volatility in India, with a special focus on the changes in volatility behaviour of the Nifty 50 index during the pre-COVID and post-COVID periods.*

Methodology: *To accomplish this goal, we used the daily closing values of the Nifty 50 index as provided by the National Stock Exchange of India between 06 February 2020 and 11 May 2020. The sample was split into a pre-COVID segment (06 February 2020 -20 March 2020) and a post-COVID segment (24 March 2020 -11 May 2020), with 23 March 2020 as the date of the pivotal event. An econometric toolkit was used, such as descriptive statistics, Chow breakpoint test, t-tests, Augmented Dickey-Fuller (ADF) test, and Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model, to question volatility dynamics, heteroskedasticity, and clustering behaviour.*

Key Results: *The Chow breakpoint test revealed beyond any doubt that there was a substantive structural discontinuity in the Nifty index on the epidemiological event date. In line with this, the t-test showed a statistically significant reduction in the index in the post-COVID period. The ADF test showed that the series of returns was stationary. The EGARCH estimates indicated that volatility clustering and antecedent shock dependence were strong in the pre-COVID period; in the post-COVID period, historical returns and shock dependence diminished, indicating that the market was highly sensitive to new information. Together, the volatility in the market increased significantly after the outbreak.*

Conclusion: *The empirical findings demonstrate that the COVID 19 pandemic sharply reorganised volatility patterns within the Indian equity market. Although the pre-pandemic environment was dominated by volatility clustering, the post-pandemic environment changed dramatically, with a reduced reliance on historic volatility and increased sensitivity to current shocks. Under crisis conditions, the EGARCH framework is useful for capturing asymmetric volatility behaviour.*

Future Research Directions: *Further questions can be posed to extend this study to the post-pandemic recovery phase to evaluate the continuity of volatility effects. Further studies would also benefit from questioning the implications of pandemic-induced volatility on asset prices, portfolio diversification, and risk management strategies in new financial markets.*

Keywords: Volatility Dynamics, EGARCH Model, Heteroskedasticity, Volatility Clustering, COVID-19, Financial Markets.

JEL Codes: C22, G10, G15, E32

The global financial environment in present-day academic work has achieved greater complexity, especially with emerging economies such as India, expressing unique risks and opportunities. The stock market has been the centre of the financial market in India and has been characterised by a high degree of volatility which has been attributed to a combination of both domestic and foreign forces. Conventional macroeconomic models have strived to explain market processes; however, recent events, such as the rise of digital payment systems, macroeconomic refocusing, and widespread crises around the globe, have complicated the analysis (Vevek et al., 2022). Although a considerable amount of literature has been dedicated to the subject of market volatility, the long-term processes and triggering factors which influence the dynamics of major Indian indices, namely, the Nifty 50, have not been fully explained. Advanced knowledge of these sources and paths is needed by investors, regulatory authorities, and policymakers.

The current investigation attempts to fill this gap by strictly analysing the factors that lead to volatility in the Indian financial market and a narrower scope of the Nifty 50 index. The analysis questions the interdependence between global and domestic macroeconomic factors, such as foreign exchange movement, energy price trends, and automotive industrial performance, in an attempt to explain their synergic effect on market behaviour (Muthusamy & Vevek, 2016; Vevek et al., 2021). Additionally, the study will assess the implications of changing financial technologies, especially digital payment platforms such as UPI, on market dynamics under the exigencies of global conditions such as the COVID-19 pandemic (Gopinath et al., 2022). The final goal is to provide a holistic framework that explains market volatility and provides practical information to investors facing economic uncertainty.

The following research questions are addressed: What are the major factors that influence volatility in the Nifty 50 index, and how does it alter with time? To what extent do macroeconomic factors, namely foreign exchange rates and changes in oil prices, influence the volatility of the Indian stock market? With the introduction of digital financial systems, such as the Unified Payments Interface (UPI) and Immediate Payment Service (IMPS), Indian financial markets have significantly transformed the volatility and stability environment. The answers to these questions are expected to significantly improve scholarly language and guide real investment practices.

This research is important because it is likely to increase the understanding of how the Indian financial market behaves, particularly during a crisis. The study is a good source of advice for investors involved in risk management and policymakers mandated to stabilise an economy during high uncertainty, as they can understand the underlying factors that have led to volatility. In addition, it will contribute to the academic knowledge of financial volatility in the context of developing economies and will add to the understanding of the impact of technological progress on the market (Baker et al., 2021).

Despite extensive research on financial market volatility, existing studies have largely focused on developed economies or short-term market reactions during crises. Limited empirical evidence is available on how extreme exogenous shocks, such as the COVID-19 pandemic, alter volatility persistence, asymmetry, and clustering behaviour in emerging markets such as India. Moreover, few studies have adopted a comparative pre- and post-event framework using asymmetric volatility models, such as EGARCH, to identify structural changes in market dynamics. Consequently, the nature of volatility transformation in the Indian stock market during the COVID-19 crisis remains insufficiently explored in the literature. This study addresses this gap by examining the pre- and post-COVID volatility behaviour of the Nifty 50 index using the EGARCH model.

This study examines the impact of COVID-19 on the financial volatility of the Nifty 50 index by comparing pre- and post-pandemic market behaviour, analysing return patterns, and modelling volatility dynamics using the EGARCH framework.

Review of Literature

The analytical question of financial volatility is one of the pillars in the field of financial economics, which has received a lot of academic interest, especially in the field of time-series models that explain and forecast market changes. The authors of the seminal work by Box et al. (2015) emphasized the central importance of autoregressive structures in the modeling of asset returns, thus establishing the foundation of advanced econometric models that can address the dynamic behaviour of financial markets. Campbell et al. (1998) took this investigation a step further by incorporating macroeconomic variables into volatility models to elaborate on how exchange rates, interest rates, and monetary conditions influence asset returns and, consequently, market dynamics in general.

The advent of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982) and its extension, the GARCH framework, developed by Bollerslev (1986) and subsequently enhanced by Nelson (1991), marked a significant advancement in volatility modelling. These models greatly enhance our comprehension of the temporal variability of financial volatility, notably including the idea of volatility clustering, which posits that times of heightened volatility are likely to be followed by similar events. GARCH-family models have become invaluable instruments of analysis in the study of financial markets, especially at times of increased uncertainty and economic hardship, owing to their empirical strength.

Emerging markets, especially India, have gained increasing academic attention because of their greater susceptibility to both domestic and external shocks. Muthusamy and Vevek (2016) and Vevek and Selvam (2021) studied how macroeconomic factors, such as foreign exchange movements and international oil prices, affect Indian equity indices, particularly Nifty 50. Their results shed light on the unique structural features of developing economies, where global shocks and national policy reactions have a strong impact on market volatility.

With the emergence of the COVID-19 pandemic, world markets faced a new wave of financial destabilisation never seen before. Baker et al. (2020) reported unprecedented volatility in the stock-market triggered by increased uncertainty and investor panic in the face of this unprecedented crisis. In the Indian context, Gopinath et al. (2022) highlighted the stabilising function of digital payment systems, such as UPI and IMPS, underscoring the need for technological adaptation to financial operations during crises. These studies indicate that volatility caused by crises differs significantly from traditional market volatility.

More recent empirical studies also support the applicability of event based volatility analysis. Gayathri and Sophia (2025) studied the stock-market volatility during the elections of the prime-minister of India and found that there had been substantial volatility changes caused by political shocks and thus confirmed the vulnerability of Indian markets to major events in the country. On the same note, Cadena-Silva et al. (2025) examined the effects of oil-price shocks on stock-market volatility in the G7 economies, and found strong transmission channels between macroeconomic shocks and stock-market shocks. Kaur and Chavali (2025) used a GARCH-M framework to uncover distinctive risk-return connections across pharmaceutical businesses, therefore illustrating the significance of volatility modeling in assessing firm-specific and industry-specific risk under volatile economic conditions. These modern results confirm the further relevance of GARCH type models in explaining volatility behaviour in a variety of shock settings.

Financial crises, systemic risk and market contagion are some of the persistent issues in the field of financial economics especially after the global financial crisis of 2008. Kaufman (2000) offered a conceptual basis of the interpretation of bank- and currency-crises and their systemic consequences. Kaminsky and Schmukler (1999) also demonstrated the role played by exogenous shocks in the sudden change in the sentiment of investors, which leads to a sudden instability in the emerging markets. In line with this view, Dua and Tuteja (2016) and Duenas et al. (2011) have shown that the volatility in major economies can spread through international financial networks, increasing the volatility in the world.

Historical occurrences, such as the Asian financial crisis of the late 1990s, provide compelling evidence of the impact of contagion on developing countries. Kaminsky and Schmukler (1999) explained the intensity of the crisis by the increased fear of investors and sudden changes in capital. Caporale et al. (2017) took this knowledge a step further to show that macroeconomic news has more pronounced effects on commodity and financial markets during crisis times, which exacerbates volatility-transmission processes.

Alongside the conventional econometric methods, the past few decades have seen an explosion of interest in computational and machine-learning-based forecasting methods. Zhang et al. (2010) used fuzzy frequent-pattern trees to make predictions in the short-term stock-market whereas Qian and Rasheed (2007) evaluated several classifiers to enhance the accuracy of forecasting. The complex-systems viewpoint was introduced by Farmer et al. (2012), who asserted that nonlinear feedback effects intrinsic to financial markets may not be captured by linear econometric models. Bond et al. (2012) and Calida and Katina (2015) emphasized the macroeconomic consequences of financial instability, including its enduring effects on growth, employment, the income inequality. Further, the works of classical authors such as Alexander (1961) and Kaeppel (2008) have remained in the mind of the volatility research by highlighting the significance of historical trends and seasonality in the financial markets.

Although there is much literature on market volatility, there are still significant research gaps. Although developed markets have been widely studied, little empirical data are available on the persistence and structural change of volatility in the Indian stock market, especially in the case of the Nifty 50 index during extreme crisis events. Moreover, despite the fact that technological innovations and digital financial systems have been linked to enhanced market efficiency, the indirect relationship between them and volatility dynamics during systemic shocks has not been thoroughly studied. To fill these gaps, the current study adopts an event-based approach and uses the EGARCH model to compare the pre- and post-COVID volatility behaviour, thus contributing to both theoretical and policy-relevant knowledge on the emergent financial markets.

Research Methodology

The information to support this investigation was obtained from the National Stock Exchange of India (NSE India), and more specifically, the Nifty 50 index which summarises the performance of the 50 largest and most liquid stocks listed on the exchange. This study takes advantage of daily closing index observations (NCOVID) and the respective return sequence (RNCOVID). The time frame of the study is divided into three time intervals: a pre-event period between 06 February 2020 and 20 March 2020; the day of the event, to which the market perturbation caused by COVID-19 is synchronised (23 March 2020); and a post-event phase between 24 March 2020 and 11 May 2020. Under this model, NCOVID[t] is the closing price of the Nifty index on day t, and RNCOVID[t] is the daily return on the index.

The empirical evaluation utilises a set of statistical and econometric techniques that are aimed at providing a holistic evaluation of market processes before and after the pandemic shock. Descriptive statistics are used to summarise the distributional properties of index values and returns, thus enabling the determination of changes in central tendency, dispersion, and tail behaviour across delineated study periods. Visual inspection is enhanced by the use of line plots and histograms that allow the study of price changes and volatility switches in a subtle manner (Tsay, 2010). The Chow break point test is called to identify structural discontinuities that are concurrent with the date of the COVID-19 event (Chow, 1960). T-tests are used to question the mean differences between the pre- and post-event index values to support statistically significant market changes (Campbell et al., 1997). The patterns of autocorrelation are investigated using correlograms and Ljung Box Q-statistics (Box & Jenkins, 1976), whereas the Augmented Dickey Fuller (ADF) test is used to verify the stationarity of the return sequence, which is a prerequisite for volatility modelling (Dickey & Fuller, 1979).

To question volatility dynamics, the present study uses the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model suggested by Nelson (1991). The choice of EGARCH is well-founded on several methodological and empirical points. First, the traditional ARCH and GARCH models place non-negativity restrictions on variance parameters, which may limit the accurate modelling of extreme market movements that are characteristic of crisis periods. On the other hand, EGARCH models the logarithm of the conditional variance, thus ensuring positivity without the restriction of parameters and more flexibility in turbulent market conditions. Second, financial markets tend to exhibit asymmetric volatility, also known as the leverage effect, where bad shocks have a disproportionately larger effect on volatility than good shocks. Classical GARCH specifications do not have the capability to model such asymmetries, and EGARCH explicitly models the sign and magnitude of shocks, making it especially appropriate for analysing crisis-driven volatility. Third, extraordinary exogenous events, such as the COVID-19 pandemic, are characterised by a sudden influx of information, investor panic, and nonlinear behaviour in the market. EGARCH is well-suited to these dynamics, allowing volatility to respond to positive and negative innovations differently and deal with rapid changes in the regime. Since the aim of the research is to compare the pre- and post-pandemic volatility trends and identify the structural changes in the volatility persistence, an asymmetric volatility model such as EGARCH is more methodologically appropriate than symmetric models such as GARCH(1,1).

Therefore, the EGARCH provides a strong econometric framework that can be used to analyse volatility clustering, persistence, and asymmetry in the Indian equity market when faced with extreme levels of uncertainty. The insights created with the help of this model help to understand how the COVID-19 pandemic redefined market behaviour and the mechanisms of investor response.

Hypothesis

H_0 (Null Hypothesis): There is no significant difference in the volatility and returns of the Nifty index before and after the event (COVID-19 impact).

Analysis and Discussion

Table 1 Descriptive Statistics for NCOVID and RNCOVID

	NCOVID	RNCOVID
Mean	10003.29	-0.168
Median	9287.9	-0.296
Maximum	12201.2	8.763
Minimum	7801.05	-8.302
Std. Dev.	1407.796	3.108
Skewness	0.400	0.005
Kurtosis	1.623	4.046
Jarque-Bera	6.346	2.737
Probability	0.042	0.255
Sum	600197.4	-10.108
Sum Sq. Dev.	1.17E+08	570.005
Observations	60	60

Source: https://www.nseindia.com/

Table 1 shows the performance of the Nifty index over the 60 days period, using descriptive statistics of Nifty closing values (NCOVID) and returns (RNCOVID). The average closing value of NCOVID (that is, Nifty) over the entire period was 10,003.29. The median of 9,287.9 indicates a skewed distribution toward the lower end. The index showed significant volatility during the research period, with the highest point of 12,201.2 and the lowest point of 7,801.05. A standard deviation of 1,407.8 indicates a high range of variation in the index closing values. The skewness of 0.400 indicates a slight positive skew, and the values are high. The kurtosis of 1.623 indicates a flatter shape and reduced frequency of extreme values, which is a platykurtic rather than a normal distribution. The p-value of 0.042 combined with a Jarque-Bra test value of 6.346 shows that there is a significant non-normality in the NCOVID distribution.

RNCOVID (Nifty returns) had a marginal average negative value of -0.168 during the research period. The median return of -0.296 shows that most returns were negative. The highest Nifty index value was 8.763, and the lowest was -8.302 which highlights high volatility. The standard deviation of 3.108 indicates a significant variation in the data. The skewness of the distribution was 0.005, indicating that it was almost symmetric about zero. A kurtosis of 4.046, which is not equal to the normal distribution, indicates more tail events and more extreme return fluctuations. The Jarque-Bra statistic is 2.737, and the probability is 0.255, which means that the distribution of returns is approximately normal, as the p-value is greater than 0.05.

Table 2 Result of Chow Breakpoint Test

Test Statistics	Value	Degrees of Freedom	Prob.
F-statistic	72.283	(1,58)	0.00
Loglikelihood ratio	48.556	(1)	0.00
Wald Statistic	72.283	(1)	0.00

Source: https://www.nseindia.com/

As shown in Table 2, the Chow breakpoint test was conducted to examine the existence of a structural break in the behaviour of the Nifty index around the COVID-19 event, that is, on 23 March 2020. The null hypothesis states that there is no break at the specified breakpoint. The test outcome shows that the F -statistic of 72.283 is significantly high with a p -value of 0.00, which is a strong indication to reject the null hypothesis; therefore, there was actually a structural break on the specified date (23 -Mar -2020). The chi-square value and p-value of the log-likelihood ratio test are 48.556 and 0.00, respectively, thus supporting the conclusion that a significant change occurred at this point. Similarly, the Wald statistic of 72.283 and p-value of 0.00 also support this conclusion. Therefore, the data show that the COVID-19 event had a significant impact on the Nifty index, which created a significant change in its behaviour before and after the event.

Table 3 Result of t' test Nifty index values before and after the COVID-19 event

Method		df	Value	Probability
t-test		58	-8.502	0.00
Satterthwaite-Welch t-test*		36.750	-8.502	0.00
Anova F-test		(1, 58)	72.283	0.00
Welch F-test*		(1, 36.75)	72.283	0.00
Category	**Count**	**Mean**	**Std. Dev.**	**Std. Err. of Mean**
Before (1)	30	11043.13	1256.984	229.4928
After (0)	30	8963.457	463.7146	84.66231
All	60	10003.29	1407.796	181.7457

Source: https://www.nseindia.com/

The results of the two-sample t-test in Table 3 indicate that there is a statistically significant difference in the levels of the Nifty index before and after the COVID-19 shock, which is why we can conclude that the market dynamics have a structural discontinuity. The calculated t-statistic of -8.502, with a p-value of virtually zero, is a clear rejection of the null hypothesis which states that period means are equal. This is a significantly negative figure that indicates that the average Nifty in the post-pandemic period (24 March–11 May 2020) is significantly lower than the average in the pre-pandemic period (6 February–20 March 2020). Specifically, the average index value of the antecedent stage was 11,043.13, which fell to 8,963.46 subsequently, highlighting the strong market shrinkage triggered by the COVID-19 crisis.

Moreover, the use of the Satterthwaite–Welch correction of heteroscedasticity between the two samples gives the same results as the standard t-test, thus supporting the strength of our inference. The consistency of the mean discrepancy is confirmed by the agreement between these two procedures. The strong negative t -statistic is indicative of the swift decline in the Nifty index after COVID -19 - a trend that is consistent with the recent global market behaviour, where the pervasive uncertainty and increased volatility caused massive equity sell-offs. Other omnibus tests, namely the one-way ANOVA and the Welch-adjusted test, both resulted in an F-statistic of 72.283 and a p-value of 0.00, which further supports the null hypothesis being invalid. These procedures support the statistical significance found above by interrogating the aggregated inter-group variances. The coincidence of results in the approaches that support equal and unequal variances supports the conclusion that the COVID-19 event had a substantive structural shock on the Nifty index's behaviour.

Combined, the results of the t-tests support the claim that the COVID-19 pandemic produced a significant and statistically significant effect on the Nifty index, which is expressed in a significant decrease in the mean levels and a corresponding decrease in the dispersion in the post-pandemic period. These findings show the need to include shocks in financial studies because they can trigger long-lasting changes in the market.

Table 4 Results of the Augmented Dickey-Fuller

	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic	-7.87	0
Test critical values:	1% level	-3.55
	5% level	-2.91
	10% level	-2.59

Source: https://www.nseindia.com/

As shown in Table 4, the Augmented Dickey-Fuller (ADF) test does not accept the null hypothesis of a unit root of RNCOVID, meaning that the series is stationary. The ADF test value of -7.86825 is much less than the critical values at the 1, 5, and 10 percent levels (-3.5461, -2.91173, and -2.59355, respectively) which again confirms the rejection of the unit-root null hypothesis. The associated p-value of zero is far below the traditional significance levels (0.01 and 0.05), thus supporting the time-series stationary nature. As a result, the RNCOVID series does not have a unit root, deterministic trend, or random-walk characteristics and is therefore applicable to rigorous time-series analysis, such as econometric modelling and forecasting.

Table 5 EGARCH Model Results (Pre and Post-COVID Periods)

Parameter	Pre-COVID Period(2/10/2020 - 3/20/2020)	Post-COVID Period 3/24/2020 - 5/11/2020)
Mean Equation		
Constant (C)	-1.57102**	0.63814***
RNCOVID(-1)	-0.41453***	-0.18821
AR(1)	0.36895	0.04451
MA(4)	0.42058**	-0.89534***
Variance Equation		
Constant (C5)	1.57213***	3.44575***
C6	-1.49389***	-2.36187***
C7	-1.08417	0.42747
C8	0.74431**	0.03981
Goodness-of-Fit		
R-squ	-0.02441	0.08294
Adjd R-squ	-0.15247	-0.02288
S.E. of Regre	3.20004	3.1573
Log Likelihood	-54.4593	-65.5773
Durbin-Watson Stat	2.27341	1.8846
ARCH Effect Test		
F-statistic (ARCH Test)	0.09375	1.7745
Chi-Square (ARCH Test)	0.10087	1.7884

Level of significance 10% (*), 5% (**), 1% (***); Source: https://www.nseindia.com/

The EGARCH formulation indicates that the dynamics of the index returns related to the coronavirus (RNCOVID) significantly differ between the pre- and post-pandemic periods, particularly in the mean and variance sub-models. During the pre-COVID period (10 February 2020 -20 March 2020), the intercept term (C) is significantly negative (-1.571, p -0.05), which indicates a systematic decrease in returns. A statistically significant change in market sentiment (0.638, p 0.01) appeared in the post-COVID window (24 March 202011 May 2020). The lag-one coefficient of RNCOVID, denoted RNCOVID(-1), is very negative during the pre-pandemic period (-0.415, $p < 0.01$), which means that past returns have a negative impact on current returns. Conversely, this autocorrelation disappears ($p > 0.05$) after the beginning of COVID-19, indicating that the impact of delayed returns is significantly reduced during the pandemic. The autoregressive AR(1) has an insignificant effect on the return series in both periods, with coefficients of 0.369 and 0.045, respectively. On the other hand, the moving-average component MA(4) is significantly positive before COVID (0.421, $p < 0.05$) and significantly negative after it (-0.895, $p < 0.01$), which shows that before the pandemic, the market was more susceptible to preceding shocks, whereas after it became more responsive and countervailing.

The intercept term C5 of the variance equation is statistically significant in both the pre- and post-COVID epochs, with estimated coefficients of 1.572 (p 0.01) and 3.446 (p 0.01), respectively, indicating a significant increase in market volatility after the pandemic. This empirical observation supports the hypothesis that the pandemic triggered an increase in return volatility. The parameter C6, which measures the impact of previous squared innovations on current volatility, is very important in both periods. C6 in the pre-pandemic window is negative (-1.494) (p 0.01) and indicates that past volatility had a dampening effect on future volatility, thus suppressing future volatility changes. The adverse effect worsened to a negative value of -2.362 ($p<0.01$) post-pandemic, indicating a greater vulnerability to volatility shocks in the market. The coefficient of C7, which is a proxy for market shocks, is not statistically significant in either period (-1.084 and 0.427), which highlights the insignificance of previous shocks on current volatility dynamics. The C8 parameter, which captures the impact of absolute residuals on volatility, is positive and significant during the pre-COVID period (0.744, $p < 0.05$), suggesting that larger shocks are more likely to increase future volatility. However, in the post-pandemic regime, this effect reduces to an almost negligible value (0.0398, $p > 0.05$), which means that the connection between the shock size and volatility is weaker.

The model has very limited explanatory power before the outbreak of COVID-19, which can be seen in the negative coefficient of determination (R 2 = -0.024). The R 2 increases to 0.083 in the post-pandemic period, indicating a slight increase in the share of returns explained by the specification. The adjusted R 2 also shows a slight increase, with the value decreasing to -0.152 before COVID and -0.022 after COVID, indicating a minor increase in the overall fit when the number of parameters is considered. The standard error of the residual is practically the same, with 3.20 and 3.16 before and after the pandemic, respectively, which means that the error terms are dispersed equally in both the regimes. However, the log-likelihood is worse in the post-pandemic period (-65.5773 compared to -54.4593), indicating a reduced level of model adequacy. The value of the Durbin-Watson decreases between 2.273 and 1.885 in the post-COVID period, suggesting a slight yet significant trend of approaching positive autocorrelation between the residuals. In the post-COVID period, the ARCHLM diagnostic provides insignificant F- and Chi-square values (F = 1.7745, 2 = 1.7884, p = 0.1940 and 0.1811, respectively). The EGARCH model effectively accommodated volatility clustering, and no residual heteroskedasticity was observed.

The EGARCH specification shows that market volatility differs significantly between the pre- and post-pandemic periods. The dependence between historical returns, volatility, and shock components became significantly less significant in the post-COVID era. To this end, there has been a sharp change in market dynamics, with increased volatility and reactivity compared to historic trends, and the impact of past returns and shocks has significantly diminished.

Discussion and Conclusion

The current study uses the EGARCH model to address the issue of heteroskedasticity and volatility clustering to examine the volatility dynamics of RNCOVID prior to and following the COVID -19 pandemic. The observed variability in the two periods of time sheds light on the substantive impact of COVID -19 on market dynamics. The EGARCH specification indicates a high level of volatility clustering within the pre-COVID period (2/10/20203-20/2020) which is due to the ARCH effects, and both the F-statistic and the Chi-square statistic are significant at the 10% level. The implication of these findings is that volatility shocks were already present and concentrated before the outburst, indicating market uncertainty and erratic behaviour. The AR(1) and MA(4) factors were statistically significant, supporting the effect of antecedent values and residuals on the volatility of RNCOVID.

On the other hand, during the post-COVID window (3/24/20205-11/2020), the F-statistics and Chi-square values have p-values of more than 0.05, which means that the EGARCH specification was effective in reducing volatility clustering; ARCH effects were insignificant after the pandemic. The volatility dynamics at this stage were less dependent on past shocks, and the residuals were homoskedastic. The uncertainty created by the pandemic and the market responses to it apparently created a more stable, or at least more predictable, volatility pattern after the adjustments to the model. In the post-COVID environment, historical shocks have a stronger impact on RNCOVID volatility, which proves the importance of the MA(4) term. Following the pandemic, market participants became more adaptive and assimilated more information, thus aligning with the changing economic and financial environment. The EGARCH model eventually manages to identifies volatility dynamics before and after the COVID-19 pandemic. Even though volatility clustering before COVID was also present, the heteroskedasticity decreased after COVID, which is a sign of a visible change in market dynamics. These findings shed light on the effects of key events, such as COVID-19, on market behaviour and demonstrate how advanced econometric tools, such as EGARCH, can model and predict financial volatility during times of increased uncertainty.

Further examination of financial markets in the post-epidemic environment can define the survival of similar tendencies. Therefore, this study underscores the need for sophisticated econometric modelling to investigate complex financial phenomena, particularly during crises when volatility dynamics can change.

Limitations of the Study

Despite its contributions, this study has some limitations. The study is limited to a short period of observation around the COVID-19 outbreak, which may not be enough to identify long-term volatility persistence and the market's adaptive behaviour. The Nifty-50 index is the only index that has been interrogated, thus limiting the generalisability of the findings to other sectors, asset classes, or international markets. The use of daily statistics might miss intraday volatility dynamics that can provide more information during times of crisis.

Future Research Directions

Future studies should further this investigation by looking at longer post-COVID periods to determine whether the volatility patterns in question are sustained throughout the different stages of market recovery. Furthermore, cross-market or cross-jurisdictional comparative frameworks may shed light on the volatility transmission and contagion processes between the Indian and global financial markets. The addition of sectoral indices, high-frequency data, or other volatility modelling strategies would probably help gain a better insight into the market dynamics that crises create.

Suggestion

Policy Implications: The implications of this study are far-reaching for policymakers and market stakeholders. The identification of a pronounced structural discontinuity and heightened volatility during the COVID-19 phase underscores the need for improved real-time market surveillance and the establishment of crisis-responsive measures, such as volatility-based circuit-breakers and timely policy communication. Early warning systems can be further improved by incorporating sophisticated volatility-monitoring tools during periods of significant uncertainty.

Investor Implication

The changed volatility patterns witnessed during the pandemic indicate that the use of past risk patterns might not be adequate during times of crisis. Investors and portfolio managers should use dynamic risk-management strategies, focus on diversification, and use the right hedging instruments to absorb abrupt volatility shocks. These findings underscore the need for flexible regulatory frameworks and adaptive investment methods to enhance market resilience to future systemic disturbances.

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