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COVID-19 Pandemic and Indices Volatility: Evidence from GARCH Models

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Abstract: This study examines the impact of volatility on the returns of nine National Stock Exchange (NSE) indices before, during, and after the COVID-19 pandemic. The study employed generalized autoregressive conditional heteroskedasticity (GARCH) modelling to analyse investor risk and the impact of volatility on returns. The study makes several contributions to the existing literature. First, it uses advanced volatility forecasting models, such as ARCH and GARCH, to improve volatility estimates and anticipate future volatility. Second, it enhances the analysis of index return volatility. The study found that the COVID-19 period outperformed the pre-COVID-19 and overall periods. Since the Nifty Realty Index is the most volatile, Nifty Bank, Metal, and Information Technology (IT) investors reaped greater returns during COVID-19 than before. The study provides a comprehensive review of the volatility and risk of nine NSE indices. Volatility forecasting techniques can help investors to understand index volatility and mitigate risk while navigating these dynamic indices.

Keywords: COVID-19; GARCH; NSE index; returns; risk; volatility

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1. Introduction

Capital markets are crucial to economic development and expansion because they foster investment and relocate funds from savers to investors (Bello et al. 2022). Excessive volatility would lead to runaway booms followed by collapses, depleting millions of investors' funds and bankrupting traders (Jebabli et al. 2022). Volatility is neither unusual nor undesirable. On the other hand, if volatility keeps increasing, it could negatively affect investors and policymakers (Uddin et al. 2021). Investors may associate higher risk with greater uncertainty, and, hence, their investment decisions may change. The stock market's potential to harm the economy may worry policymakers (Rehman et al. 2021). Volatility is typically expressed as the standard deviation or variance of returns from a single security or market index (Muguto and Muzindutsi 2022). This study examined volatility over two periods, namely the pre-COVID-19 and COVID-19 periods. A comprehensive examination was designed to determine how volatility could affect investor returns and which period would offer better returns. The daily results of each index were collected over 10 years. The Government announced the first case of the pandemic in India on 11 March 2020 and it helped to determine pre-COVID-19 and COVID-19 timeframes.

Different tools and methodologies were employed to assess which index had reported the highest volatility based on the standard deviation and which had yielded the highest return throughout the three periods to better comprehend the objective of the study. Previous research studies had analysed the risk and return characteristics and assessments of various companies of different sectors or the same sector, with inconsistent various results

(Lobo and Bhat 2021). Hence, this study attempts to analyse the volatility of eight different indices by analysing the returns pre-COVID-19, during COVID-19, and post-COVID-19 (Dutta et al. 2021). This research is significant since more people are concentrating on stock market investing or trading, and they must comprehend how stock returns, risk, and volatility affect decision making abilities. The study also focuses on how the volatility of various NSE indexes could affect companies. It offers a broader discussion on how one may make informed investment decisions and how these volatility swings could impact their investment. The study's scope is quite broad and significant in terms of its understanding of stock market volatility, how the volatility of the Nifty Index could affect investors' decision making regarding investments, and the risks that investors should be aware of when they trade in the stock market. A descriptive study was conducted to better understand which index yielded higher or lower returns, with the corresponding risk. The correlation was also conducted on each index to understand whether they had recorded positive or negative correlations. The GARCH linear model was employed because it is most suited for studying volatility under all periods, including pre- and post-COVID-19. The layout of the paper is as follows.

The literature is introduced in Section 2. The data and procedures are detailed in Section 3. Section 4 contains the findings and discussion, while Section 5 includes the conclusion and policy implications.

2. Review of Literature

Numerous studies have been conducted on stock market volatility and developing solid portfolio systems based on predicting volatility and future stock prices using highly complex predictive models (Guha et al. 2016; Lv et al. 2018; Chronopoulos et al. 2018; Mehtab and Sen 2020; Mehtab et al. 2021). Based on an evaluation of predicting performance, using two different error statistics, the Root Mean Square Error and Means Absolute Error, the GARCH model performs better, and, hence, is the best-fitted model (Kannan and Balamurugan 2022). The results reveal that the estimated volatility of all the indices instantaneously increased during the pandemic phase, followed by a steady decline (Lakshmi 2013; Priya and Sharma 2023). Volatility of Metal, Oil, and Gas was found to be more susceptible to market volatility (Mishra et al. 2023; Verma and Rathore 2023). Following COVID-19, fluctuations by different indices substantially impacted India (Rajamohan et al. 2020). A substantial number of models based on the GARCH (1, 1) framework were employed, and it has been noted that the generalized distribution of the residuals of these models was more reliable in measuring the volatility of the series than other residual modelling (Arumugam and Soundararajan 2013; Shankar and Ramulu 2014; Kim and Lee 2019). The receptivity of entropy-based predictions is higher, whereas the GARCH-based volatility model generates more consistent and reliable forecasts (Islam and Mahkota 2013; Krishnaprabha and Vijayakumar 2015; Pele et al. 2017). The study revealed that asymmetrical GARCH models produce more precise projections of stock volatility (Sen et al. 2021). Researchers demonstrated that GARCH is the best model to employ while analysing the unpredictable nature of stock returns, with a large number of observations (Engle 1982; Bollerslev 1986; Leung et al. 2000). The purpose of this study is to compare stock market prices before and after the COVID-19 pandemic. The study addresses the important question of whether stock market prices and trading volumes differed before and after the pandemic. Hence, the study would be relevant because it fills a research gap by providing a comparative analysis of the impact of COVID-19 on stock prices and stock market psychology in the Asian region. The results of the study would provide practitioners in the financial markets with valuable insights.

In some aspects, this research adds something new to the body of extant literature. Firstly, this study investigated the volatility in the stock price returns of all nine major stock indices returns (NSE 100 ESG, NSE 50, NSE Bank, NSE Commodities, NSE IT, NSE Metal, NSE Realty, NSE FMCG, and NSE Auto) during the periods of pre-COVID-19, during COVID-19, and post-COVID-19 by using the three most effective GARCH models, namely

GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1). Second, during the COVID-19 pandemic, the returns of all indices showed indications of volatility clustering. Since the COVID-19 pandemic, foreign investors have invested in the Indian stock markets using a range of tools and approaches. The findings of the research may be used by international investors to meet their strategic requirements for investing in the Indian stock markets.

3. Data and Methodology

This study employed the event study methodology, developed by Fama et al. (1969), Binder (1998), and MacKinlay (1997), to analyse the market reaction to the arrival of COVID-19 in India. The data used in this study included stock prices registered in the National Stock Exchange. The event study methodology helped to measure the impact of news or information on stock prices (Fama 1991). This study employed the event study methodology to analyse how different industries responded to the outbreak of a virus and to test the efficiency of markets during such an event. Some studies have confirmed the efficient market hypothesis, while others have questioned the rationality of market participants (Malkiel 2003). There are only a few studies that analysed the change in the spillover effect in the Indian stock market (Maital and Barzani 2020; Ali et al. 2023) as a result of the COVID-19 pandemic, even though many research papers concentrated on capturing financial market spillover effects, downside risk–return spillovers, and their effects on market volatility. Thus, the purpose of this study is to assess the impact of the COVID-19 epidemic on the National Stock Exchange of India.

3.1. Data

The data used in this study were obtained from the National Stock Exchange's online database (https://www.nseindia.com/reports-indices-historical-index-data, accessed on 1 March 2023) which provides information on prices and trading volumes for all the markets integrated into it. The data on daily prices for stocks included in the National Stock Exchange covered the period from 1 January 2018 to 31 December 2022. Further, the analysis was divided into three parts: pre-COVID-19 analysis, during-COVID-19 analysis, and post-COVID-19 analysis. The sample size was collected from the National Stock Exchange (NSE) and included data from a variety of indices, such as the Nifty 100 ESG, Nifty 50, Nifty Bank, Nifty Auto, Nifty IT, Nifty Metal, Nifty FMCG, Nifty Commodities, and Nifty Realty. The following equation was used to determine daily returns:

$$R_t = ln(P_t/P_{t-1}) \tag{1}$$

3.2. Tools Used for Analysis

The following tools were used to analyse the data for this study

- Descriptive Statistics (to ascertain the normal distribution of sample indices' returns)
- Unit Root Test (to examine the stationarity of indices)
- GARCH Model: The financial time series indicate a period of low volatility, followed by a period of high volatility, and this phenomenon is known as volatility clustering. The most frequent models used to model the volatility of economic and financial time series are ARCH and GARCH (Bollerslev 1986).

3.2.1. GARCH Model

The GARCH (p, q) model is represented as

$$\sigma_t^2 = \omega + \sum_{t-1}^{p} \alpha i \mu_t^2 + \sum_{j=1}^{q} \beta J \sigma_{t-1}^2 \tag{2}$$

where the model's parameters are indicated by i and j. In the modelling of financial returns volatility, the GARCH family can account for dynamic volatility phenomena and volatility clustering. As a result, one of the models selected is known as the GARCH (1, 1) model.

Karmakar (2005) suggests using GARCH (1, 1) to simulate market return conditional volatility. Thus, the GARCH (1, 1) is given in Equation (2):

$$\sigma_t^2 = \omega + \propto \mu_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

3.2.2. GJR-GARCH Model

The GJR-GARCH model was used to investigate the asymmetric behaviour of financial market returns. The model posits that investor anxiety about negative returns is greater than concern about good financial returns, resulting in the leverage effect. The following is how to solve the GJR-GARCH (1, 1) model equation:

$$\sigma_t^2 = \omega + \alpha_1\mu_{t-1}^2 + \beta i\sigma_{t-1}^2 + \gamma i I_{t-1}\, u_{t-1}^2 \quad (4)$$

$$I_{t-1} = \begin{cases} 1\ when\ \mu_{t-1} < 0\ shows\ postive\ shocks \\ 0\ when\ \mu_{t-1} > 0\ shows\ postive\ shocks \end{cases}$$

3.2.3. EGARCH Model

Nelson (1991) developed the exponential GARCH (EGARCH) model to account for the asymmetry in the fundamental GARCH model. The EGARCH (1, 1) is calculated as follows:

$$logh_t = (\omega - 1) + \propto n_{t-1} + \gamma n_{t-1} + \beta logh_{t-1} \quad (5)$$

where log ht = E ε 2 t, $_{t-1}$, α, β, and γ are the parameters.

4. Data Analysis and Interpretation

The analysis of normality, stationarity, and volatility is presented as follows:

1. Descriptive statistics for the sample indices under pre-, during-, and post-COVID-19 periods.
2. ADF test for the sample indices under pre-, during-, and post-COVID-19 periods.
3. Volatility test for the sample indices under pre-, during-, and post-COVID-19 periods.

4.1. Descriptive Statistics for the Sample Indices before, during, and after COVID-19

The results of descriptive statistics of the sample variables for the pre-COVID-19 period, from 1 January 2018 to 31 December 2019, are presented in Table 1. The standard deviation (SD), skewness, probability values, minimum, mean, maximum, kurtosis, and Jarque–Bera were used for the analysis. The NSE IT index had reported the highest mean return of 0.0482, while the NSE Realty index had recorded the lowest mean return of −0.0034. In other words, investments in NSE IT had yielded higher returns to investors than NSE Realty. NSE 100 ESG, NSE 50, NSE FMCG, NSE Bank, NSE commodities, and NSE Auto had recorded mean returns, between those of NSE IT and NSE Realty. In terms of standard deviation, NSE Realty was the most volatile index, with a value of 2.0819, while NSE 100 ESG was the least volatile, with a value of 1.0843. This indicates that the NSE Realty index was more likely to experience large swings in price than the NSE 100 ESG index. The return distributions of all the indices were negatively skewed, indicating that tails of the distributions were longer on the left side than on the right side. In other words, the probability of a negative return was higher than the probability of a positive return. The NSE Metal return distribution was the most skewed, with a value of −0.4903, while the NSE 50 was the most negatively skewed, with a value of −1.5101. The return distributions were also observed to be leptokurtic because they had more pronounced peaks than a normal distribution. The NSE 50 had reported the highest kurtosis value of 23.6725, which implies that its return distribution was more peaked than the other indices. Overall, investment in the NSE IT index had provided the highest returns to investors with a moderate risk, while the NSE Realty index had underperformed during the study period.

Table 1. Results of descriptive analysis for the returns of sample NSE indices during the pre-COVID-19 period of study.

Statistic/ Index	NSE 100 ESG	NSE 50	NSE Bank	NSE Commodities	NSE IT	NSE Metal	NSE Realty	NSE FMCG	NSE Auto
Mean	0.0417	0.0370	0.0345	0.0195	0.0482	0.0005	−0.0034	0.0408	0.030424
Median	0.0854	0.0651	0.0645	0.0829	0.0719	0.0551	0.1159	0.0844	0.079489
Maximum	8.3320	8.0571	9.5119	7.0652	8.5349	8.9603	7.9672	7.6797	9.425424
Minimum	−14.3932	−14.9167	−20.0971	−13.9581	−13.3031	−13.1244	−13.1279	−11.8510	−16.0737
Std Dev	1.0843	1.0901	1.5442	1.3057	1.3336	1.8100	2.0819	1.1074	1.40304
Skewness	−1.3949	−1.5101	−1.0758	−1.0138	−0.9770	−0.4903	−0.6190	−0.6058	−0.74332
Kurtosis	21.5504	23.6725	18.8630	12.2645	14.0327	6.3555	6.3769	13.1651	14.21112
Jarque-Ber	37,213.55	46,157.29	27,099.90	9511.33	13,275.59	1292.34	1368.044	11,082.30	13,525.34

Source: Compiled from http://finance.yahoo.com (accessed on 1 March 2023) and computed using E-views of 6 version.

Table 2 presents the descriptive statistics of sample stock indices in India during the COVID-19 period, from 1 January 2020 to 31 December 2021. The summary statistics include mean, minimum, maximum, median, standard deviation (SD), skewness, kurtosis, and the Jarque–Bera test. The NSE FMCG index had reported the highest mean return of 0.0403, while the NSE Metal index had registered the lowest mean return of −0.3401. In other words, investments in NSE FMCG had yielded higher returns to investors than NSE Metal, NSE 100 ESG, NSE 50, NSE Bank, NSE commodities, NSE Realty, and NSE Auto. In terms of standard deviation, NSE Realty was the most volatile index, with a value of 2.0033, while NSE 50 was the least volatile, with a value of 0.9057. As a result, the NSE Realty index was more likely to experience large swings in price than the NSE 50 index. The return distributions of all the indices were positively skewed, meaning that tails of distributions were longer on the right side than on the left side. This indicated that the probability of a positive return was higher than the probability of a negative return. The NSE Bank return distribution was the most positively skewed, with a value of 0.0612, while the NSE IT was the most negatively skewed, with a value of −1.0850. The return distributions were also observed to be leptokurtic, meaning that they had more pronounced peaks than a normal distribution. The NSE IT had reported the highest kurtosis value of 16.4444 because return distribution was more peaked than the other indices. Overall, the investment in the NSE FMCG index provided the highest returns to investors, with a moderate risk, while the NSE Metal index had underperformed during the study period.

Table 2. Results of descriptive analysis for the returns of sample NSE indices during the COVID-19 period of study.

Statistic/ Index	NSE 100 ESG	NSE 50	NSE Bank	NSE Commodities	NSE IT	NSE Metal	NSE Realty	NSE FMCG	NSE Auto
Mean	0.0349	0.0303	0.0395	−0.0002	0.0348	−0.0341	−0.0165	0.0403	0.0157
Median	0.0657	0.0482	0.0550	0.0455	0.0487	−0.0137	0.1053	0.0806	0.0676
Maximum	5.1145	5.0505	8.6415	5.4279	8.5349	8.9603	7.7741	5.1092	9.0095
Minimum	−6.5342	−6.2863	−7.4118	−8.1375	−13.3031	−8.1112	−13.1279	−7.2181	−7.8254
Std Dev	0.9234	0.9057	1.3043	1.1633	1.1811	1.6285	2.0033	1.0400	1.2147
Skewness	−0.3693	−0.3452	0.0612	−0.4158	−1.0850	−0.1526	−0.5723	−0.3179	−0.0685
Kurtosis	6.0332	6.3493	6.7074	5.7294	16.4444	4.6348	6.2129	6.3803	6.3997
Jarque-Ber	797.5625	957.0051	1125.9900	666.2061	15,176.7900	226.3398	951.9392	968.1190	947.3818

Source: Compiled from http://finance.yahoo.com and computed using E-views of 6 version.

Table 3 presents the descriptive statistics for sample indices in the NSE of India during the post-COVID-19 period from 1 January 2022 to 31 December 2022. The summary statistics included mean, minimum, maximum, median, standard deviation (SD), skewness, kurtosis, and the Jarque–Bera test. The NSE Metal index had reported the highest mean return of 0.1218, while the NSE Bank index had registered the lowest mean return of 0.0174. Hence, investments in NSE Metal have yielded higher returns to investors than NSE Bank. In terms of standard deviation, NSE Realty was the most volatile index, with a value of

2.3310, while NSE FMCG was the least volatile, with a value of 1.3129. Hence, NSE Realty index was more likely to experience large swings in price than the NSE FMCG index. The return distributions of all the indices were negatively skewed, meaning that the tails of the distributions were longer on the left side than on the right side. In other words, the probability of a negative return was higher than the probability of a positive return. The NSE Realty return distribution was the least negatively skewed, with a value of −0.7272, while the NSE 50 was the most negatively skewed, with a value of −2.0589. The return distributions were also observed to be leptokurtic because they had more pronounced peaks than a normal distribution. The NSE 100 ESG had reported the highest kurtosis value of 22.5600, which indicated that its return distribution was more peaked than the other indices. Overall, the investment in the NSE Metal index had provided the highest returns to investors, with a moderate risk, while the NSE Bank index had underperformed during the study period.

Table 3. Results of descriptive analysis for the returns of sample NSE indices during the post-COVID-19 period of study.

Statistic/ Index	NSE 100 ESG	NSE 50	NSE Bank	NSE Commodities	NSE IT	NSE Metal	NSE Realty	NSE FMCG	NSE Auto
Mean	0.0651	0.0596	0.0174	0.0883	0.0961	0.1218	0.0448	0.0426	0.0825
Median	0.1512	0.1504	0.1016	0.2526	0.1464	0.3298	0.2329	0.0902	0.1499
Maximum	8.3320	8.0571	9.5119	7.0652	8.2777	7.3176	7.9672	7.6797	9.4254
Minimum	−14.3932	−14.9167	−20.0971	−13.9581	−10.5889	−13.1244	−12.8087	−11.8510	−16.0737
Std Dev	1.5112	1.5654	2.1747	1.7042	1.7577	2.3228	2.3310	1.3129	1.9121
Skewness	−2.0234	−2.0589	−1.7365	−1.6326	−0.8079	−0.9284	−0.7272	−1.0701	−1.2906
Kurtosis	22.5600	22.3525	18.2284	14.7001	9.1636	6.7115	6.3943	20.9255	14.8243
Jarque-Ber	9542.0250	9362.7500	5834.8460	3528.9980	971.0386	411.9300	326.1435	7794.5000	3503.2330

Source: Compiled from http://finance.yahoo.com and computed using E-views of 6 version.

4.2. ADF Test for the Sample Indices before, during, and after COVID-19

Time series data were examined for the presence of unit roots. The assumption that statistical properties remain constant over time is behind the majority of statistical tests and techniques. A stationary time series should be used for modelling and predicting the relationship between variables. This study examined the indices in NSE of India returns, looking for a structural break in the series, to determine whether there was an increase or decrease in the transmission of information and volatility since COVID-19. Table 4 shows the results of the augmented Dickey–Fuller (ADF) test for daily closing price returns for sample indices during the period from 1 January 2018 to 31 December 2022. The ADF test was used to determine whether a time series is stationary. A stationary time series is one whose statistical properties do not change over time. The sample indices of national stock exchanges in India, taken for this study, included NSE 100 ESG, NSE 50, NSE Bank, NSE Commodities, NSE FMCG, NSE IT, NSE Metal, NSE Realty, and NSE Auto. The probability values of the nine sample indices were near zero during the study period. This indicated that all the indices' returns remained stationary during the study period. A unit root null hypothesis was rejected for all log-returns of stock indices because all underlying variables were stationary at the level.

4.3. Volatility Test for the Sample Indices before COVID-19, during COVID-19, and after COVID-19

The present study was based on modelling the daily indices returns behaviour because of similarities in the distribution of the return series for the daily, weekly, and monthly maintenance periods. The presence of ARCH effects on the median of daily returns was examined by using the Lagrange Multiplier (LM) Test. The results are displayed in Table 5.

Table 4. ADF test for the sample indices before, during, and post COVID-19.

Indexes	Pre-COVID-19 (2018–2019)		During COVID-19 (2020–2021)		Post-COVID-19 (2022)	
	t-Statistics	Prob	t-Statistics	Prob	t-Statistics	Prob
NSE 100 ESG	−49.8272	0.0001 ***	−40.3596	0.0000 ***	−27.1343	0.0000 ***
NSE 50	−17.6576	0.0000 ***	−40.5739	0.0000 ***	−27.2358	0.0000 ***
NSE Bank	−47.7710	0.0001 ***	−40.7010	0.0000 ***	−24.0624	0.0000 ***
NSE Commodities	−50.0823	0.0001 ***	−40.9087	0.0000 ***	−28.0294	0.0000 ***
NSE FMCG	−50.8216	0.0001 ***	−40.9087	0.0000 ***	−27.8529	0.0000 ***
NSE IT	−50.6876	0.0001 ***	−42.9772	0.0000 ***	−17.9500	0.0000 ***
NSE Metal	−50.5380	0.0001 ***	−42.7703	0.0000 ***	−26.4323	0.0000 ***
NSE Realty	−47.0132	0.0001 ***	−41.2715	0.0000 ***	−23.0745	0.0000 ***
NSE Auto	−48.5447	0.0001 ***	−40.6786	0.0000 ***	−25.2969	0.0000 ***

*** significant at 1 percent. Source: Compiled from http://finance.yahoo.com and computed using E-views of 6 version.

Table 5. Lagrange Multiplier Test for ARCH effects in NSE indices returns.

Lags	NSE 100 ESG	NSE 50	NSE Bank	NSE Commodities	NSE IT	NSE Metal	NSE Realty	NSE FMCG	NSE Auto
Pre-COVID-19 (2018–2019)									
1	222.26 (0.000)	189.52 (0.000)	571.66 (0.000)	549.76 (0.000)	330.97 (0.000)	222.26 (0.000)	136.23 (0.000)	549.76 (0.000)	361.35 (0.000)
5	1079.97 (0.000)	317.96 (0.000)	547.31 (0.000)	662.92 (0.000)	563.23 (0.000)	385.87 (0.000)	739.24 (0.000)	739.24 (0.000)	563.23 (0.000)
10	827.59 (0.000)	413.28 (0.000)	1167.28 (0.000)	463.03 (0.000)	413.28 (0.000)	1167.28 (0.000)	804.67 (0.000)	732.62 (0.000)	621.29 (0.000)
20	449.68 (0.000)	658.83 (0.000)	1235.45 (0.000)	639.78 (0.000)	639.78 (0.000)	235.45 (0.000)	498.62 (0.000)	871.65 (0.000)	910.10 (0.000)
During COVID-19 (2020–2021)									
1	136.23 (0.000)	330.97 (0.000)	222.26 (0.000)	361.33 (0.000)	136.23 (0.000)	289.60 (0.000)	183.34 (0.000)	189.52 (0.000)	183.34 (0.000)
5	317.96 (0.000)	736.58 (0.000)	641.59 (0.000)	739.24 (0.000)	317.96 (0.000)	662.92 (0.000)	638.81 (0.000)	1079.97 (0.000)	638.81 (0.000)
10	413.28 (0.000)	753.76 (0.000)	589.44 (0.000)	589.44 (0.000)	804.67 (0.000)	802.37 (0.000)	463.03 (0.000)	827.59 (0.000)	732.62 (0.000)
20	639.78 (0.000)	658.83 (0.000)	449.68 (0.000)	893.91 (0.000)	871.65 (0.000)	871.65 (0.000)	449.68 (0.000)	912.78 (0.000)	498.62 (0.000)
Post-COVID-19 (2022)									
1	549.76 (0.000)	289.60 (0.000)	361.33 (0.000)	222.26 (0.000)	571.66 (0.000)	330.97 (0.000)	361.35 (0.000)	571.66 (0.000)	289.60 (0.000)
5	736.58 (0.000)	1079.97 (0.000)	563.23 (0.000)	385.87 (0.000)	547.31 (0.000)	638.81 (0.000)	547.31 (0.000)	641.59 (0.000)	641.59 (0.000)
10	802.37 (0.000)	1167.28 (0.000)	413.28 (0.000)	753.76 (0.000)	827.59 (0.000)	802.37 (0.000)	713.76 (0.000)	732.62 (0.000)	1167.28 (0.000)
20	912.78 (0.000)	1235.45 (0.000)	498.62 (0.000)	658.83 (0.000)	893.91 (0.000)	893.91 (0.000)	910.10 (0.000)	978.58 (0.000)	988.58 (0.000)

Source: Compiled from http://finance.yahoo.com and computed using MATLAB lmtest.

According to Table 6, the values of Akaike Information Criteria (AIC) for the nine indices indicated that E-GARCH (1, 1) was the best-fitted model for simulating the return volatility of the NSE 100 ESG, NSE 50, NSE Bank, NSE Commodities, NSE FMCG, NSE IT, NSE Metal, NSE Realty, and NSE Auto before the COVID-19 pandemic period. The best model for modelling the volatilities of NSE IT, NSE Metal, and NSE Realty is GJR-GARCH (1, 1), while the best model for modelling the volatilities of NSE Bank and NSE Commodities was the E-GARCH (1, 1). These results are shown in Table 6 of the AIC. The GARCH (1, 1) was chosen as the best model for describing the volatilities of NSE 100 ESG and NSE 50. The results of the GARCH models, for examining the impact of COVID-19 on the returns of nine national stock exchanges indices, are presented in Tables 6–8. These tables show the results for the three COVID-19 periods: pre-COVID-19, during COVID-19, and post-COVID-19. According to the E-GARCH (1, 1) model, the majority of NSE indices reported asymmetric effects at different significance levels during the study period. With respect to the ARCH model, the findings of the study clearly confirmed that the sample indices returns reported significant asymmetric behaviour during the COVID-19 pandemic. Further, the NSE Realty index experienced the highest volatility (β = 0.999803), and the NSE Auto index registered the lowest (β = 0.519419) during the pre-COVID-19 period. It is to be noted that, during the COVID-19 period, the NSE IT index reported the highest volatility (β = 0.519419) and the NSE Metal index experienced the lowest volatility (β = 0.04606), which revealed that the COVID-19 pandemic exerted a strong impact on the NSE IT index. Concerning the E-GARCH (1, 1) results, under both the pre-COVID-19 and during-COVID-19 returns, the indices return series experienced high persistence behaviour due to the fact that the sum of the ARCH and GARCH parameters was close to 1. This high persistence was probably the result of the global financial instability.

Table 6. The results of the GARCH models for the returns of sample NSE indices during the pre-COVID-19 period of study (1 January 2018 to 31 December 2019).

Indices	Model	Log	AIC	α (ARCH)	β (GARCH)	α + β
NSE 100 ESG	GARCH (1, 1)	620.1043	−3.7778	0.124018 *	0.874682 ***	0.8747
	GJR-GARCH (1, 1)	1398.0760	−6.8506	0.143439 *	0.887596 ***	0.8876
	EGARCH (1, 1)	906.4832	−5.5653	0.036888	0.974107 ***	1.0110
NSE 50	GARCH (1, 1)	1104.3230	−8.5692	0.076241	0.79702 ***	0.8733
	GJR-GARCH (1, 1)	911.2845	−8.566	0.118079 **	0.676175 ***	0.6762
	EGARCH (1, 1)	619.8894	−5.5648	0.098288 **	0.89229 ***	0.8990
NSE Bank	GARCH (1, 1)	795.7955	−5.5414	0.247109 ***	0.974897 ***	0.9749
	GJR-GARCH (1, 1)	619.8894	−6.9935	0	0.919419 ***	0.9194
	EGARCH (1, 1)	1115.6770	−7.0108	−0.310019 ***	0.826323 ***	0.8263
NSE Commodities	GARCH (1, 1)	1399.5020	−6.8506	0.002481	0.594084 ***	0.5966
	GJR-GARCH (1, 1)	797.5716	−6.8226	0.009621	0.997803 ***	1.0074
	EGARCH (1, 1)	790.1403	−3.7778	−0.057158	0.995427 ***	0.9955
NSE FMCG	GARCH (1, 1)	1398.9700	−8.566	0.122254 *	0.940652 ***	0.9407
	GJR-GARCH (1, 1)	624.1617	−3.7778	0	0.76539 ***	0.7654
	EGARCH (1, 1)	911.3619	−7.0108	−0.14327 ***	0.92683 ***	0.7268
NSE IT	GARCH (1, 1)	1143.4380	−5.5653	0	0.908961 ***	0.9090
	GJR-GARCH (1, 1)	1143.2980	−3.7729	0	0.893921 ***	0.8939
	EGARCH (1, 1)	911.2845	−5.5414	−0.12458 *	0.845516 ***	0.8455
NSE Metal	GARCH (1, 1)	1120.2240	−3.7778	0.000062	0.972107 ***	0.9722
	GJR-GARCH (1, 1)	624.1617	−5.5653	0.000054	0.887696 ***	0.8878
	EGARCH (1, 1)	1143.4380	−5.5414	−0.174239 *	0.894982 ***	0.8750
NSE Realty	GARCH (1, 1)	1399.5020	−6.8506	0.000001	0.999803 ***	0.9998
	GJR-GARCH (1, 1)	1398.9700	−4.8651	0.000001	0.792084 ***	0.5921
	EGARCH (1, 1)	1120.2240	−7.0108	−1.058863 ***	0.927323 ***	0.8273
NSE Auto	GARCH (1, 1)	1146.2500	−5.5414	0.000004	0.519419 ***	0.9194
	GJR-GARCH (1, 1)	1146.2500	−7.0108	0.000004 ***	0.678175 ***	0.6782
	EGARCH (1, 1)	1115.6770	−6.9935	−0.575678 ***	0.89802 ***	0.7980

Note: *** refers to 1% significance level, ** refers to 5% significance level, and * refers to 10% significance level.

Table 7. The results of the GARCH models for the returns of sample NSE indices during the COVID-19 period of study (1 January 2020 to 31 December 2021).

Indices	Model	Log	AIC	α (ARCH)	β (GARCH)	α + β
NSE 100 ESG	GARCH (1, 1)	893.60050	−6.9988	0.086228 ***	0.6171 ***	0.617100
	GJR-GARCH (1, 1)	895.30240	−6.9935	0.21278 ***	0.21723 ***	0.217230
	EGARCH (1, 1)	893.26190	−7.0108	−0.104427 **	0.87867 ***	0.578670
NSE 50	GARCH (1, 1)	798.68120	−4.3271	0.000142	0.19222 ***	0.192360
	GJR-GARCH (1, 1)	798.87520	−4.3349	0.009999	0.70243 ***	0.712430
	EGARCH (1, 1)	798.99160	−4.3023	0.021306	0.92665 ***	0.247960
NSE Bank	GARCH (1, 1)	993.60050	−3.5098	0.086228 ***	0.20326 ***	0.203260
	GJR-GARCH (1, 1)	995.30240	−3.4996	0.117035	0.70026 ***	0.817300
	EGARCH (1, 1)	993.26190	−3.5044	0.086228 ***	0.90852 ***	0.408520
NSE Commodities	GARCH (1, 1)	1309.74400	−5.9925	0.040641	0.39244 ***	0.433080
	GJR-GARCH (1, 1)	1310.42000	−6.9784	0.117035	0.47424 ***	0.591280
	EGARCH (1, 1)	1311.02900	−5.0017	0.21278 ***	0.960941 ***	0.160940
NSE FMCG	GARCH (1, 1)	525.45890	−9.3271	0.009999	0.165211 ***	0.175210
	GJR-GARCH (1, 1)	525.67740	−9.3349	0.21892 ***	0.331058 ***	0.331060
	EGARCH (1, 1)	597.34270	−9.3023	0.002145	0.910388 ***	0.112530
NSE IT	GARCH (1, 1)	1209.74400	−6.1046	0.000002	0.395535 ***	0.395540
	GJR-GARCH (1, 1)	1210.42000	−6.1038	0.012131	0.814144 ***	0.126280
	EGARCH (1, 1)	1211.02900	−6.1088	0.035923	0.913997 ***	0.149920
NSE Metal	GARCH (1, 1)	619.88940	−3.0693	0.000002	0.110325 ***	0.110330
	GJR-GARCH (1, 1)	624.16170	−3.0819	−0.017036	0.046055 ***	0.046060
	EGARCH (1, 1)	619.88940	−3.0775	0.021306	0.903944 ***	0.125250
NSE Realty	GARCH (1, 1)	705.12720	−7.0248	−0.023663	0.50354 ***	0.503540
	GJR-GARCH (1, 1)	711.42220	−7.021	0.102173 *	0.65774 ***	0.657740
	EGARCH (1, 1)	710.15450	−7.023	0.021306	0.98373 ***	0.905040
NSE Auto	GARCH (1, 1)	567.34270	−2.5098	0.012131	0.121474 ***	0.133610
	GJR-GARCH (1, 1)	545.67740	−2.4996	−0.104427 **	0.142996 ***	0.143000
	EGARCH (1, 1)	535.45890	−2.5044	0.096668 **	0.94594 ***	0.545940

Note: *** refers to 1% significance level, ** refers to 5% significance level, and * refers to 10% significance level.

Table 8. The results of the GARCH models for the returns of sample NSE indices during the post-COVID-19 period of study (1 January 2022 to 31 December 2022).

Indices	Model	Log	AIC	α (ARCH)	β (GARCH)	α + β
NSE 100 ESG	GARCH (1, 1)	519.88940	−5.1117	0.056481	0.110325	0.16681
	GJR-GARCH (1, 1)	520.10430	−4.1284	0.163904 ***	0.46055	0.46055
	E-GARCH (1, 1)	524.16170	−4.3225	0.121029 ***	0.103944	0.10394
NSE 50	GARCH (1, 1)	1706.76100	−3.3044	0.000002	0.50354	0.50354
	GJR-GARCH (1, 1)	1707.98700	−3.8996	0.117035	0.65774	0.77478
	E-GARCH (1, 1)	1708.07900	−3.7298	0.000142	0.88373	0.88387
NSE Bank	GARCH (1, 1)	1193.30500	−6.9888	0.021306	0.121474	0.14278
	GJR-GARCH (1, 1)	1193.57600	−6.1238	−0.023663	0.142996	0.143
	E-GARCH (1, 1)	1198.77200	−6.1446	0.009999	0.54594	0.55594
NSE Commodities	GARCH (1, 1)	993.60050	−4.2341	0.040641	0.57307	0.61371
	GJR-GARCH (1, 1)	993.26190	−4.2302	0.000002	0.149947	0.14995
	E-GARCH (1, 1)	995.30240	−4.1257	0.117035	0.153381	0.27042
NSE FMCG	GARCH (1, 1)	819.78320	−8.61	−0.177449 ***	0.165211	0.16521
	GJR-GARCH (1, 1)	821.98880	−8.2390	0.000142	0.331058	0.3312
	E-GARCH (1, 1)	865.27760	−8.611	0.21892 ***	0.110388	0.11039
NSE IT	GARCH (1, 1)	721.14030	−6.3545	−0.017036	0.395535	0.39554
	GJR-GARCH (1, 1)	792.57160	−6.1214	0.012131	0.114144	0.12628
	E-GARCH (1, 1)	738.79550	−6.5605	0.021306	0.113997	0.1353
NSE Metal	GARCH (1, 1)	1311.02900	−4.2523	−0.104427 **	0.110325	0.11033
	GJR-GARCH (1, 1)	1310.42000	−4.2149	0.102173 *	0.46055	0.46055
	E-GARCH (1, 1)	1309.74400	−4.1271	0.21278 ***	0.65774	0.65774

Table 8. *Cont.*

Indices	Model	Log	AIC	α (ARCH)	β (GARCH)	α + β
NSE Realty	GARCH (1, 1)	1398.07600	−5.3653	−0.023663	0.88373	0.88373
	GJR-GARCH (1, 1)	1399.50200	−5.8748	0.002145	0.54594	0.54809
	E-GARCH (1, 1)	1398.97000	−5.5414	0.009999	0.57307	0.58307
NSE Auto	GARCH (1, 1)	576.45890	−3.3378	0.035923	0.149947	0.18587
	GJR-GARCH (1, 1)	574.67740	−3.2179	0.096668 **	0.153381	0.15338
	E-GARCH (1, 1)	572.34270	−3.7778	0.086228 ***	0.88373	0.88373

Note: *** refers to 1% significance level, ** refers to 5% significance level, and * refers to 10% significance level.

After analysing the volatility of NSE indices, under three different periods, the study found that no single model can be used to accurately model the volatility of all indices. Before the COVID-19 pandemic, the E-GARCH (1, 1) model provided the best fit for all indices. During the pandemic, the volatility of NSE 50 and NSE Bank was best modelled by the GARCH (1, 1) model, which showed persistent behaviour. The volatility of NSE Realty and NSE Auto was best modelled by the GJR-GARCH (1, 1) model, which exhibited a significant leverage effect and persistence phenomena. The volatility of NSE Commodities and NSE IT was best modelled by the E-GARCH (1, 1) model, which captured the leverage effect and persistent behaviour. The graphical expression for the impact of volatility on the returns of nine National Stock Exchange (NSE) indices before, during, and after the COVID-19 pandemic, during the study period from 2018 to 2022, is presented in Figures 1–3.

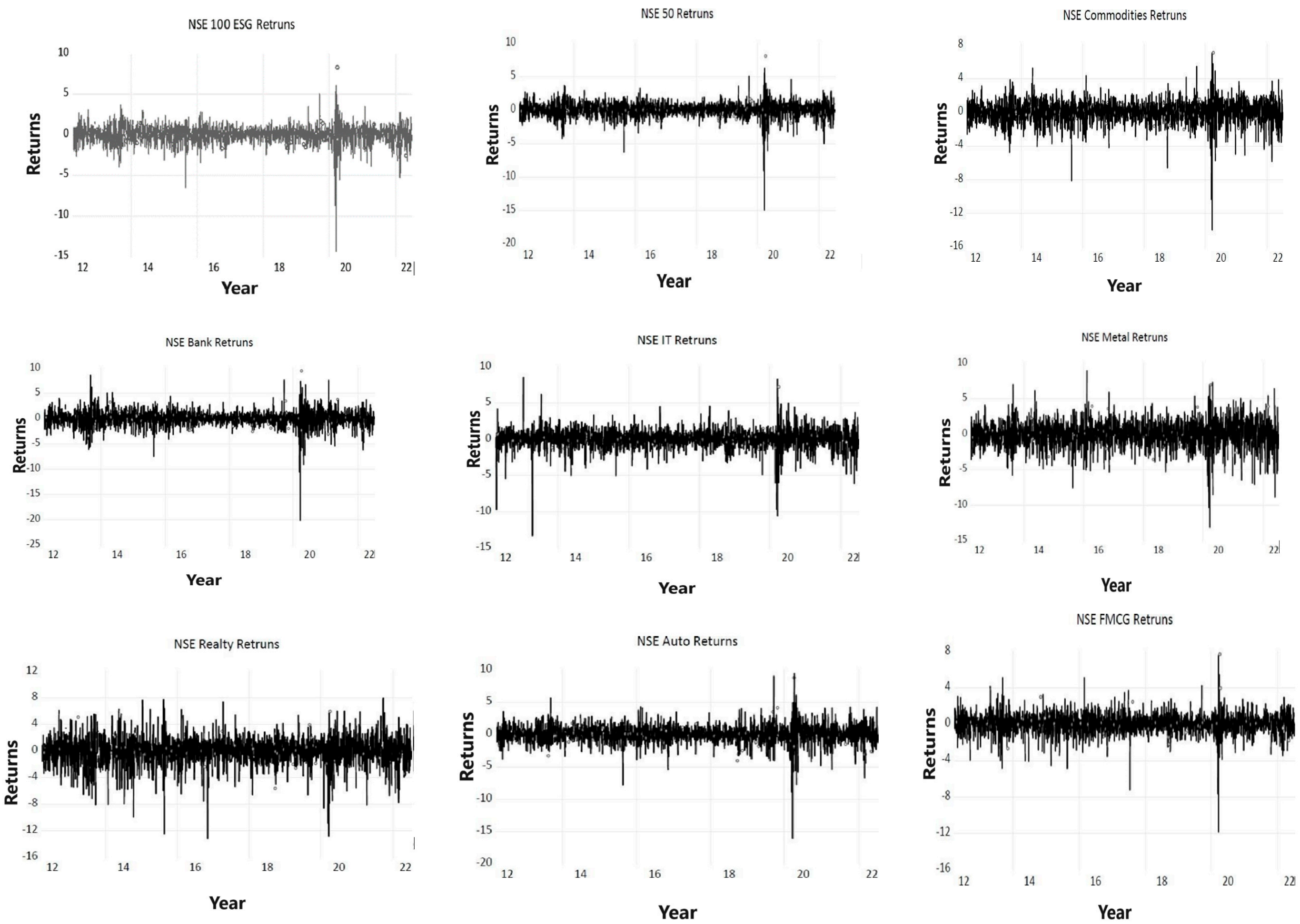

Figure 1. Graphical expression for the returns of sample indices in India during the pre-COVID-19 period from 1 January 2018 to 31 December 2019. Source: Compiled from http://finance.yahoo.com/ and computed using EViews.

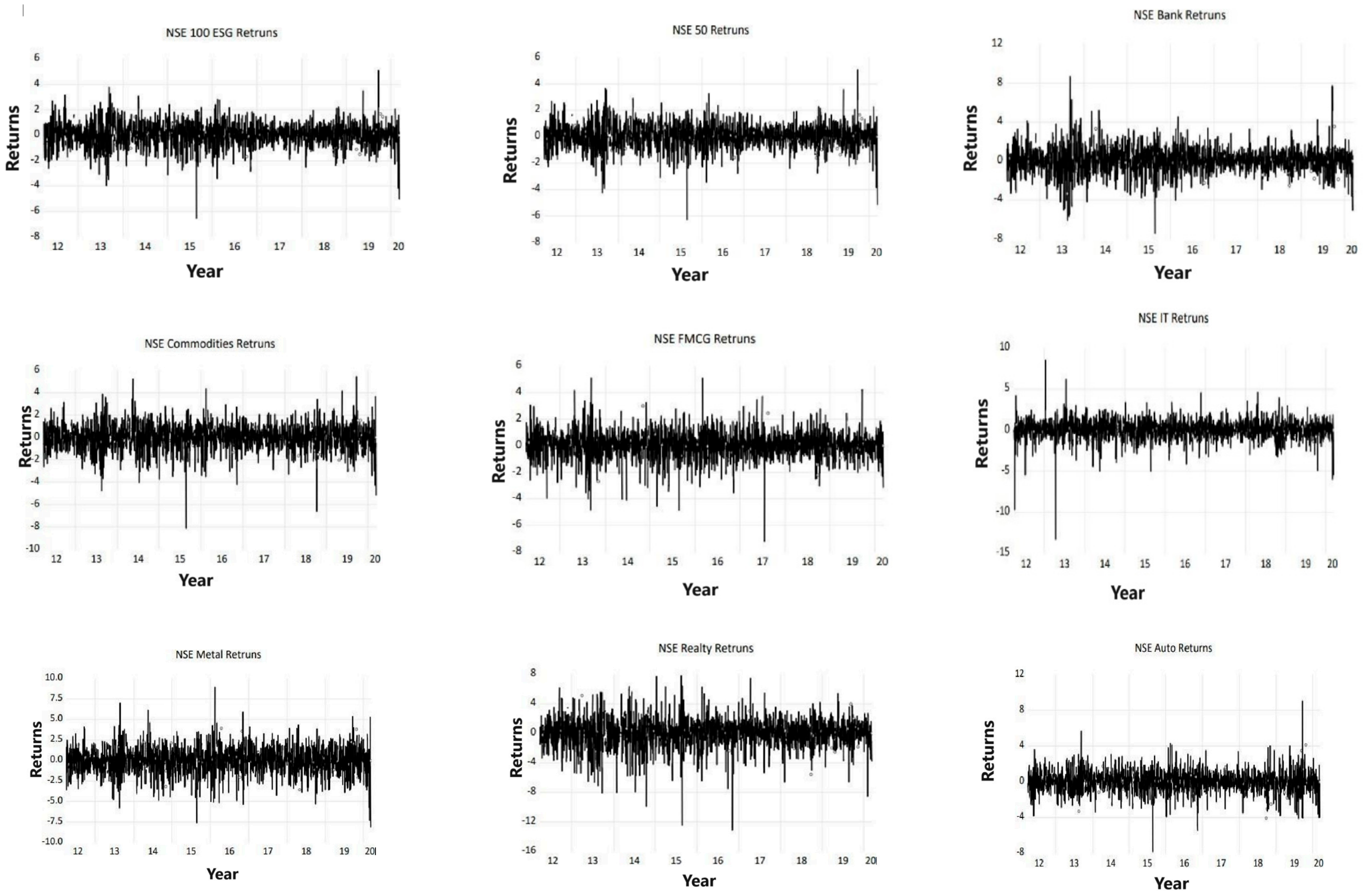

Figure 2. Graphical expression for the returns of sample indices in India during the COVID-19 period from 1 January 2020 to 31 December 2021. Source: Compiled from http://finance.yahoo.com/ and computed using EViews.

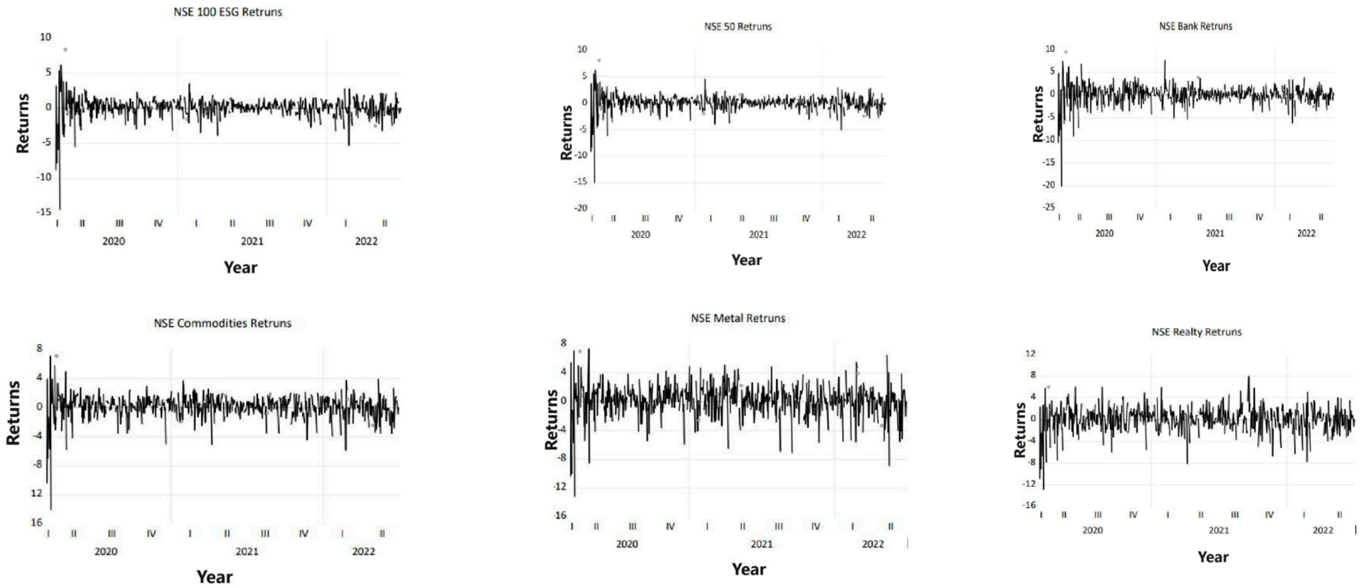

Figure 3. *Cont.*

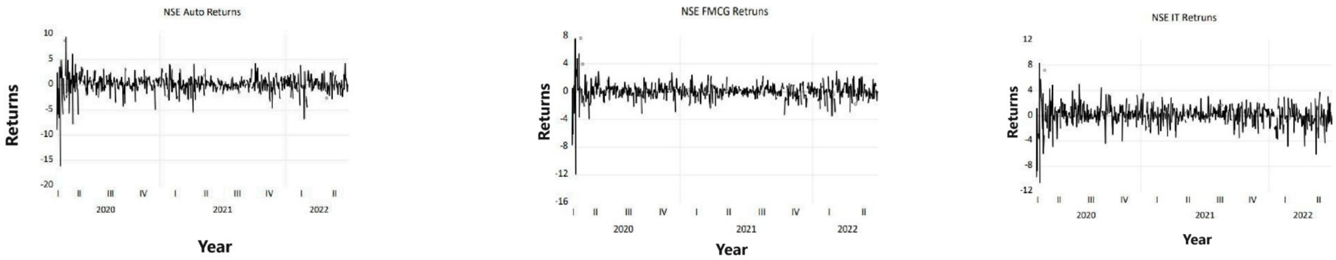

Figure 3. Graphical expression for the returns of sample indices in India during the post-COVID-19 period from 1 January 2022 to 31 December 2022. Source: Compiled from http://finance.yahoo.com/ and computed using EViews-10.

5. Discussion and Conclusions

The impact of stock price movement on the economic growth of different regions has been extensively studied in the literature. The stock indices' prices and volatility were severely impacted by the COVID-19 epidemic (Chaudhary et al. 2020; Sadiq et al. 2021). Further, the literature indicated that COVID-19 had an impact on stock price and return in some parts of the world. However, the volatility of stock indices returns in the pre-, during-, and post-COVID-19 periods remains unexplored. Hence, the present study aimed to explore the impact of the COVID-19 pandemic period on indices volatility in India. This study examined the indices volatility of nine national stock exchange indices returns (NSE 100 ESG, NSE 50, NSE Bank, NSE Commodities, NSE IT, NSE Metal, NSE Realty, NSE FMCG, and NSE Auto) during the COVID-19 pandemic period. For this purpose, the study utilized the daily data, covering the period from 1 January 2019 to 31 December 2022. This study adopted statistical tools like GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1). In nine major stock indices, the returns were normally distributed and also attained stationarity during the study period. Under the augmented Dickey–Fuller (ADF) test, the p-value was less than 0.05. Further, the results of GARCH (1, 1) revealed that Nifty IT had reported the greatest overall and pre-COVID-19 returns, whereas FMCG had registered the highest post-COVID-19 returns. The nifty metal performed better, both before and after COVID-19. Further, the bulk of the indices experienced positive skew, indicating that, if an investment was made, investors could expect a higher return. The Nifty Realty Index was identified as the most volatile of all the indices in this analysis. During the COVID-19 period, the Nifty Bank, Metal, and IT delivered investors larger returns than they did before the COVID-19 period. Overall, this study provides useful insights into the risk and volatility of NSE indices. These findings are supported by Iqbal et al. (2021), who demonstrated that, while simulating volatility, the EGARCH model beats the regular GARCH model. Shehzad et al. (2021) found that crises like COVID-19 had exerted immediate influence on stock markets. As a result of the COVID-19 pandemic, increased financial market volatility produced a fear of losing money among investors may use this information to make educated investing decisions and limit their risk. Based on the empirical results, this study suggests practical policy implications that require immediate attention and implementation to maintain economic performance and control the volatility of indices returns. First, empirical estimates show that the return volatility of nine stock indices did exert a significant impact on economic efficiency. Therefore, any policy change must take economic efficiency into account. This is because changes to policies relating to indices returns will significantly affect India's economic efficiency, particularly in the years following the COVID-19 pandemic. This study empirically analysed the indices' price return movements in the years before, after, and during the COVID-19 pandemic period. This study has limitations because it only looked at one country, namely India. The current research study employed the GARCH models from the GARCH family, which only analyse the volatility behaviour regarding indices returns, but other empirical methods are also available, and they could be employed in future research.

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