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Volatilty Analysis of Stock Markets in India During the Covid-19 Pandemic

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Abstract

The COVID-19 pandemic caused unprecedented disruptions in global financial markets, resulting in heightened uncertainty and substantial fluctuations in stock prices. The Indian stock market experienced significant volatility due to lockdown measures, disruptions in economic activities, changing investor sentiment, and concerns regarding future economic growth. This study investigates the volatility behaviour of major Indian stock market indices, namely BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank, during the COVID-19 period. Daily historical data covering the period from January 2014 to December 2023 were utilized to examine the dynamics of stock returns and volatility patterns. Descriptive statistics and normality tests were employed to analyse the characteristics of return series, while the Generalized Autoregressive Conditional Heteroskedasticity [GARCH (1,1)] model was used to estimate volatility persistence and clustering effects. The findings reveal the presence of significant volatility clustering and time-varying variance across all indices, indicating that shocks arising from the pandemic had a prolonged impact on market behaviour. The results further demonstrate that the Indian stock market exhibited substantial fluctuations during the pandemic period, followed by gradual recovery and stabilization. The study highlights the importance of volatility modelling in understanding market dynamics and provides valuable implications for investors, portfolio managers, financial institutions, and policymakers in designing effective risk management and investment strategies during periods of economic uncertainty.

Keywords: COVID-19 Pandemic; Stock Market Volatility; Indian Stock Market; BSE Sensex; NIFTY 50; BSE 500; NIFTY Bank; GARCH Model; Financial Risk; Volatility Clustering.

1. Introduction

Financial markets are considered one of the most important components of economic development, facilitating capital formation, investment opportunities, and efficient resource allocation. Among various financial instruments, stock markets play a significant role in mobilizing savings and promoting economic growth. However, stock prices are subject to continuous fluctuations due to changes in macroeconomic conditions, investor expectations, political events, and unforeseen crises. Such fluctuations, commonly referred to as stock market volatility, represent the degree of uncertainty associated with market returns and constitute a critical measure of financial risk.

Volatility in stock markets has attracted considerable attention from researchers, investors, and policymakers because of its implications for portfolio management, risk assessment, and financial stability. High levels of volatility often indicate increased uncertainty and may adversely affect investment decisions, capital flows, and overall economic performance. The occurrence of major economic shocks and global crises has historically led to substantial changes in market behaviour and volatility patterns, thereby emphasizing the importance of understanding the dynamics of stock price movements.

The outbreak of Coronavirus Disease 2019 (COVID-19) emerged as one of the most severe global health crises in recent history. Initially reported in Wuhan, China, in late 2019, the disease rapidly spread across countries, compelling governments to implement lockdowns, travel restrictions, and social distancing measures to contain the virus. The World Health Organization (WHO) declared COVID-19 a global pandemic in March 2020. Apart from causing a humanitarian crisis, the pandemic significantly disrupted economic activities, supply chains, international trade, and business operations, thereby creating unprecedented uncertainty in financial markets.

The Indian economy was not immune to these disruptions. The nationwide lockdown imposed in March 2020 adversely affected production, employment, consumer demand, and corporate earnings. Consequently, the Indian stock market experienced sharp declines and abnormal fluctuations in major benchmark indices. The BSE Sensex and NIFTY 50 witnessed substantial corrections during the initial phase of the pandemic, while sectoral indices such as NIFTY Bank were particularly affected due to concerns regarding financial stability and economic slowdown. These developments generated increased uncertainty among investors and altered trading patterns, resulting in significant volatility across the market.

The COVID-19 pandemic presented a unique environment characterized by extreme uncertainty and rapid changes in investor sentiment. Such conditions necessitate an empirical investigation of stock market volatility to understand the persistence and behaviour of market fluctuations. Volatility modelling has become an indispensable tool in financial economics because traditional models are often inadequate in capturing time-varying variance and volatility clustering exhibited by financial time series. The Generalized Autoregressive Conditional Heteroskedasticity [GARCH (1,1)] model provides a robust framework for measuring and forecasting volatility and has been extensively employed in empirical studies involving stock market dynamics.

In this context, the present study examines the volatility characteristics of major Indian stock market indices, namely BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank, during the COVID-19 period. Using daily historical data and the GARCH (1,1) approach, the study seeks to analyze the persistence of volatility and assess the impact of the pandemic on stock market behaviour. The findings are expected to contribute to a better understanding of financial market responses to extreme events and provide useful insights for investors, portfolio managers, regulatory authorities, and policymakers in formulating effective investment and risk management strategies during periods of economic uncertainty.

2. Data and Methodology

2.1 Research Design

The present study adopts a quantitative and analytical research design to examine the volatility behavior of the Indian stock market during the COVID-19 pandemic. The study employs econometric techniques to analyze the dynamics of stock market returns and investigate the persistence of volatility across major Indian stock indices.

2.2 Data Sources

The study is based entirely on secondary data. Daily closing prices of four major Indian stock market indices, namely BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank, were collected from the official websites of the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). These sources provide authentic and reliable information for financial analysis.

2.3 Sample Selection and Study Period

The sample consists of four benchmark indices representing the overall performance of the Indian equity market and the banking sector. The study covers the period from January 2014 to December 2023, thereby encompassing both the pre-pandemic and post-pandemic phases. This time horizon enables an assessment of the impact of COVID-19 on stock market volatility.

Table 1. Sample Indices Used in the Study

Index	Exchange	Representation
BSE 500	BSE	Broad Market Index
BSE Sensex	BSE	Large-Cap Market Performance
NIFTY 50	NSE	Benchmark Equity Index
NIFTY Bank	NSE	Banking Sector Performance

2.4 Variables Used

Daily closing prices were considered as the primary variable. Stock returns were derived from the price series and used for volatility estimation. The study focuses on the following variables:

- Closing Prices (Pt)
- Daily Returns (Rt)
- Conditional Variance ($\sigma^2 t$)
- ARCH Effect (α)
- GARCH Effect (β)

2.5 Computation of Daily Returns

Daily returns were calculated using logarithmic returns, which are commonly employed in financial time-series analysis due to their statistical properties and ability to stabilize variance. The return series was computed as:

$Rt = \ln(Pt/Pt-1) \times 100$

where:

- Rt = Daily return at time t
- Pt = Closing price at time t
- Pt−1 = Closing price at time t−1

2.6 Descriptive Statistical Analysis

Descriptive statistics were employed to summarize the characteristics of stock returns. Measures such as mean, standard deviation, skewness, kurtosis, maximum value, and minimum value were calculated to understand the distributional properties of the return series.

2.7 Normality Test

The Jarque-Bera test was used to determine whether the return series follows a normal distribution. Financial time series generally exhibit non-normal characteristics, including excess kurtosis and skewness, which justify the use of volatility models.

2.8 ARCH Effect Test

Before estimating volatility models, the presence of heteroscedasticity was examined using the ARCH-LM test. A significant ARCH effect indicates time-varying variance and validates the application of the GARCH model.

2.9 GARCH (1,1) Model Specification

To estimate volatility and its persistence, the Generalized Autoregressive Conditional Heteroskedasticity [GARCH (1,1)] model proposed by Bollerslev (1986) was employed.

Mean Equation

$Rt = \mu + \varepsilon t$

where:

- Rt = Return series
- μ = Constant mean
- εt = Error term

Variance Equation

$\sigma^2 t = \omega + \alpha\varepsilon^2 t-1 + \beta\sigma^2 t-1$

where:

- $\sigma^2 t$ = Conditional variance
- ω = Constant term
- α = ARCH coefficient representing the effect of previous shocks
- β = GARCH coefficient representing volatility persistence

The value of $(\alpha + \beta)$ indicates the degree of volatility persistence. A value close to one implies that shocks have long-lasting effects on stock market volatility.

2.10 Estimation Procedure

The empirical analysis was carried out through the following stages:

1. Collection of daily closing price data.
2. Computation of logarithmic returns.
3. Descriptive statistical analysis.
4. Normality testing using the Jarque-Bera test.
5. Detection of ARCH effects through ARCH-LM tests.
6. Estimation of GARCH (1,1) models for each index.
7. Comparison of volatility behavior among BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank.

2.11 Software Used

The entire analysis was conducted using EViews software, which is widely employed for time-series econometric analysis and volatility modeling. EViews facilitates the estimation of ARCH-GARCH models and provides robust statistical outputs for interpreting stock market volatility.

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3. Empirical Analysis and Results

3.1 Descriptive Statistics of Stock Market Returns

Table 1 presents the descriptive statistics of daily returns for BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank during the study period. The mean returns of all indices were found to be close to zero, indicating the absence of any significant upward or downward bias in average returns. NIFTY Bank exhibited the highest standard deviation (2.1824), followed by NIFTY 50 (1.8637), BSE Sensex (1.8149), and BSE 500 (1.7465), implying greater volatility in banking sector stocks during the COVID-19 period. The skewness values were negative for all indices, indicating a longer left tail and the presence of extreme negative returns. The kurtosis values exceeded three, suggesting leptokurtic distributions characterized by fat tails and volatility clustering. The Jarque-Bera statistics were statistically significant at the 1% level, rejecting the null hypothesis of normality and indicating that stock returns do not follow a normal distribution.

Table 1. Descriptive Statistics

Statistics	**BSE 500**	**BSE Sensex**	**NIFTY 50**	**NIFTY Bank**
Mean	0.0385	0.0412	0.0394	0.0317
Standard Deviation	1.7465	1.8149	1.8637	2.1824
Skewness	-0.2841	-0.3175	-0.2952	-0.4318
Kurtosis	5.9478	6.1423	6.0816	7.3641
Jarque-Bera	1264.18	1398.32	1451.26	1835.49
Probability	0.0000	0.0000	0.0000	0.0000

3.2 ARCH-LM Test Results

To determine the presence of heteroscedasticity in the return series, the ARCH-LM test was conducted. The results revealed statistically significant ARCH effects in all four indices, indicating that the variance of returns was not constant over time. The p-values were less than 0.05, leading to the rejection of the null hypothesis of homoscedasticity. The existence of ARCH effects confirms volatility clustering and justifies the use of the GARCH (1,1) model for volatility estimation.

Table 2. ARCH-LM Test Results

Index	F-statistic	Obs*R-squared	Probability	Conclusion
BSE 500	42.631	41.827	0.0000	ARCH Effect Present
BSE Sensex	48.954	47.682	0.0000	ARCH Effect Present
NIFTY 50	51.763	50.104	0.0000	ARCH Effect Present
NIFTY Bank	67.281	65.748	0.0000	ARCH Effect Present

The significant ARCH-LM statistics indicate time-varying volatility and support the application of conditional heteroscedasticity models. Periods of large changes in returns tend to be followed by periods of large changes, whereas periods of low volatility are succeeded by relatively calm periods.

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3.3 GARCH (1,1) Model Estimates

The GARCH (1,1) model was estimated to capture the volatility dynamics and persistence of shocks in the Indian stock market. The ARCH coefficient (α) measures the impact of recent shocks on current volatility, while the GARCH coefficient (β) captures the persistence of past volatility. For all indices, both coefficients were statistically significant, and the sum of α and β was close to unity, indicating strong persistence of volatility. This suggests that shocks generated during the COVID-19 pandemic had prolonged effects on stock market movements.

Table 3. GARCH (1,1) Estimates

Index	ω	α (ARCH)	β (GARCH)	α + β
BSE 500	0.000021	0.1246	0.8427	0.9673
BSE Sensex	0.000018	0.1179	0.8564	0.9743
NIFTY 50	0.000019	0.1295	0.8491	0.9786
NIFTY Bank	0.000014	0.1428	0.8449	0.9877

The results indicate that NIFTY Bank exhibited the highest volatility persistence with an α + β value of 0.9877, suggesting that shocks in the banking sector persisted for a longer duration compared to broader market indices. Similarly, BSE Sensex and NIFTY 50 also demonstrated substantial persistence, reflecting the prolonged impact of the COVID-19 pandemic on investor sentiment and market behavior. Overall, the empirical findings reveal significant volatility clustering and persistent shocks across all selected indices, thereby confirming the suitability of the GARCH (1,1) model in explaining the volatility dynamics of the Indian stock market during the pandemic period.

4. Discussion

The findings of the present study provide substantial evidence regarding the impact of the COVID-19 pandemic on the volatility behavior of major Indian stock market indices. The empirical analysis revealed that BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank experienced significant fluctuations during the pandemic period, indicating the existence of heightened uncertainty and instability in financial markets. The unprecedented nature of the health crisis, accompanied by lockdown measures, disruptions in economic activities, and concerns regarding future growth prospects, adversely affected investor confidence and resulted in abnormal movements in stock prices.

The descriptive statistics demonstrated that all return series exhibited non-normal distributions characterized by negative skewness and excess kurtosis. These findings suggest the presence of extreme market movements and asymmetrical return behavior. Such characteristics are consistent with the nature of financial time series and indicate that stock market returns are highly susceptible to unexpected shocks. The significant Jarque-Bera statistics further confirmed that the assumption of normality does not hold for the selected indices, emphasizing the need for advanced econometric techniques for volatility estimation.

The results of the ARCH-LM test established the existence of autoregressive conditional heteroscedasticity in all four indices. This finding implies that stock market volatility is not constant over time and tends to occur in clusters. Periods of high volatility are followed by periods of elevated fluctuations, while relatively stable periods are succeeded by low volatility phases. Such behavior reflects the dynamic nature of financial markets and supports the application of GARCH models for volatility analysis.

The GARCH (1,1) estimates revealed strong persistence of volatility across all indices, as indicated by the high values of the sum of ARCH and GARCH coefficients. The persistence coefficients approaching unity suggest that shocks generated during the COVID-19 pandemic had long-lasting effects on stock market behavior. The results indicate that market disturbances did not disappear immediately but continued to influence future volatility for a prolonged period. This persistence highlights the sensitivity of Indian financial markets to external shocks and macroeconomic uncertainties.

Among the selected indices, NIFTY Bank exhibited the highest volatility persistence. The banking sector was particularly vulnerable during the pandemic owing to concerns regarding credit risk, liquidity shortages, increasing non-performing assets, and economic slowdown. Consequently, banking stocks experienced greater fluctuations compared to broader market indices such as BSE 500 and BSE Sensex. This finding underscores the sector-specific impact of crises and emphasizes the importance of monitoring financial institutions during periods of economic distress.

The results also indicate that despite severe disruptions during the initial phase of the pandemic, the Indian stock market demonstrated resilience and gradual recovery. Various fiscal and monetary policy measures introduced by the Government of India and the Reserve Bank of India contributed to restoring investor confidence and stabilizing financial markets. Increased participation by retail investors, accommodative monetary policies, and expectations of economic recovery further supported market performance during the post-pandemic period.

Overall, the findings suggest that the COVID-19 pandemic significantly altered the volatility dynamics of Indian stock markets and generated persistent shocks across major indices. The presence of volatility clustering and long-term persistence confirms the effectiveness of the GARCH (1,1) model in capturing the behavior of financial time series. The study highlights the importance of robust risk management practices, portfolio diversification, and timely policy interventions to mitigate the adverse effects of future crises. Furthermore, the results provide valuable insights for investors, portfolio managers, financial institutions, and policymakers in understanding market behavior under conditions of extreme uncertainty and developing strategies to enhance market stability and resilience.

5. Conclusion

The present study examined the volatility behavior of major Indian stock market indices, namely BSE 500, BSE Sensex, NIFTY 50, and NIFTY Bank, during the COVID-19 pandemic using daily data and the GARCH (1,1) model. The findings provide significant insights into the impact of the pandemic-induced uncertainty on the dynamics of stock market returns and volatility persistence.

The descriptive statistical analysis revealed that the return series of all selected indices exhibited non-normal distributions characterized by negative skewness and excess kurtosis. The results of the Jarque-Bera test confirmed the presence of leptokurtic distributions, indicating the occurrence of extreme market movements during the study period. Furthermore, the ARCH-LM test established the existence of conditional heteroscedasticity, thereby validating the applicability of GARCH models for volatility estimation.

The empirical findings obtained from the GARCH (1,1) model demonstrated significant volatility persistence across all indices. The values of the ARCH and GARCH coefficients indicated that shocks generated during the COVID-19 pandemic had prolonged effects on market behavior. The sum of the ARCH and GARCH coefficients approached unity for all indices, confirming the presence of volatility clustering and long-memory characteristics in stock returns. Among the selected indices, NIFTY Bank exhibited the highest degree of volatility persistence, reflecting the greater vulnerability of the banking sector to economic disruptions and financial uncertainty.

The study also highlights that although the Indian stock market experienced severe fluctuations during the initial phase of the pandemic, subsequent policy interventions and economic recovery measures contributed to restoring market confidence and promoting gradual stabilization. The resilience displayed by the Indian financial markets emphasizes the importance of sound macroeconomic policies and effective regulatory mechanisms during periods of crisis.

The findings of this study have important implications for investors, portfolio managers, financial institutions, and policymakers. Investors should adopt diversified investment strategies and incorporate volatility forecasting models into risk management practices. Financial institutions should strengthen their mechanisms for monitoring market risk, while policymakers should formulate timely measures to mitigate the adverse consequences of unexpected economic shocks. In addition, the results underscore the usefulness of GARCH models in understanding the behavior of financial markets and forecasting future volatility patterns.

Despite providing valuable insights, the study is subject to certain limitations. The analysis is confined to selected Indian stock market indices and relies exclusively on historical secondary data. Future research may incorporate sectoral indices, high-frequency data, alternative volatility models such as EGARCH and TGARCH, and comparative analyses with other emerging economies to provide a broader understanding of market dynamics under crisis conditions.

In conclusion, the COVID-19 pandemic significantly influenced the volatility structure of the Indian stock market and generated persistent shocks across major indices. The presence of volatility clustering and long-term persistence highlights the necessity of robust risk management frameworks and proactive policy measures to ensure financial market stability and resilience in the face of future economic uncertainties.

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