Journal of Applied Economic Sciences
Volume XIX, Winter, Issue 4(86)

Nexus Between Stock Return and Market Volatility in Indian Perspective

Ravi Ranjan MISHRA
https://orcid.org/0009-0001-4991-6007
Department of Commerce
Mahatma Gandhi Central University, Bihar, India
rrmphd97@gmail.com

Shirish MISHRA
https://orcid.org/0009-0003-6647-3994
Department of Commerce
Mahatma Gandhi Central University, Bihar, India
shirishmishra@mgcub.ac.in

Article's history:

Received 1st of September, 2024; *Received in revised form* 27th of September, 2024; *Accepted* 19th of October, 2024; *Available online*: 21th of October, 2024. *Published* as article in the Volume XIX, Winter, Issue 4(86), 2024.

Suggested citation:

Mishra, R.R., & Mishra, S. (2024). Nexus between stock return and market volatility in Indian perspective. *Journal of Applied Economic Sciences*, Volume XIX, Winter, 4(86), 417 – 425. https://doi.org/10.57017/jaes.v19.4(86).05

Abstract:

This research seeks to explore the volatility patterns for the SENSEX index to figure out the characteristics of volatility in Indian stock trading and to investigate the relationship between returns and volatility of the Indian market for the last ten years. The research adds to the existing knowledge about stock market fluctuations, their implications for investors, and their impact on developing the country's economy. The study involves using daily returns data from BSE SENSEX from 01 Jan 2014 to 31 Dec 2023. Daily closing prices are obtained from the official website of BSE, and returns are calculated based on these prices. The Dickey-Fuller and Phillips-perron are taken to make the time series static. ARCH, GARCH, and GARCH-M tests are utilized to capture volatility clustering, return and volatility relationship. The results reveal that Fluctuations in the Indian stock market, particularly shown in the SENSEX index of the BSE, were highest in the year 2020. Findings suggest that GARCH-M does not show any relation between expected returns and market volatility. The risk-premium parameter is positive but statistically insignificant. If you want to hedge against risk, the risk premium is not very high. It means that taking risks does not give you more returns. Durbin Watson's value of 1.981401 further supports the model's suitability.

Keywords: volatility pattern, BSE Sensex; Indian stock market, risk-return, GARCH-M model.

JEL Classification: C22, G10, G12, G17.

Introduction

In the fields of economic and financial study, volatility is an issue of concern. It has a strong connection to market volatility and influences how both individuals and businesses make investments. One of the main challenges of contemporary financial research is the examination of the volatility of financial asset returns, which is frequently quantified and defined by the variance of the rate of return (Bhowmik & Wang, 2020). "The fluctuations in the stock market and trading volume are influenced by the flow of information. The higher the volume, the narrower the spreads, as a result, there is less slippage and less volatility. Traders keep a close eye on trading volume because it reflects the dynamic interplay between informed traders and uninformed traders who interact with each other in the marketplace in light of their trading strategies and, ultimately, set market clearing prices," (Mubarik & Javid, 2009, 2). For examples (Bekaert & Wu, 2000, 1) state that "it appears that volatility in equity markets is asymmetric: returns and conditional volatility are negatively correlated." While their work is critically driven by this assertion, there is conflicting empirical evidence in US stock markets for this negative association between volatility and expected returns, and this data has not yet been published in other foreign stock markets. Our research significantly enhances in this regard (Bekaert & Wu, 2000, 1).

International investors should consider volatility spillovers between stock markets since variations in indices might impact investing strategies and diversification (Habiba et al., 2019). The stock exchange is regarded as the "economic barometer" which reflects the state of the economy. It provides the readymade platforms for issuing, buying, and selling of securities. Volatility is an essence of the stock market which reflects the degree of variation of stock prices over time. Higher volatility implies higher risk associated with the security and Lower volatility implies lower risk associated with the security. During 2020, a high degree of volatility was seen not only in the Indian stock market but even in the global stock market because the dissemination of the virus elevated social isolation, resulting in the closing of corporate offices, financial markets, businesses, and events. Estimation of stock Volatility is essential due to increasing importance and awareness about the stock market. "Volatility of a stock may incur a risk premium, leading to a positive correlation between volatility and returns. On the other hand, the leverage effect or news effect, whereby negative returns increase volatility, acts in the opposite direction," (Macrosynergy, 2015, para. 2). Investments in the stock market might be highly turbulent, but they also contribute to the expansion and robustness of the economy. The exchange of securities and transactions involving securities is facilitated by the securities market (Agarwal, 2020). Anticipating the direction of fluctuations in the stock market is a difficult financial pursuit. Completely anticipating a stock's price trend in the future can boost investor earnings dramatically (Zhao & Chen, 2021). The risk-return connection is critical in finance and economics since it influences approaches to investing, allocation of assets, and regulation. The GARCH-M approach serves as crucial for correctly examining this link (Dwarika, 2022).

1. Literature Review

Fakhfekh et al. (2023) Applied the GARCH approach to figure out the variations of volatility in Tunisia's sectorial equity markets during 2020. It discovered this volatility persisted longer after the COVID-19. The findings demonstrated that the asymmetric effect of building construction materials, the construction industry, and the food and beverage sectors on return volatilities was negligible. On the other hand, the return volatility of the banking sector, basic materials, consumer service sector, financials and distribution, and basic materials had rather large positive asymmetric effects. Agarwal (2020) This study uses the GARCH model to analyze stock market volatility in the Indian stock markets (NSE and BSE) over the years 2015–2020. The findings show that both exchanges' volatility clusters, with BSE indices showing higher volatility than NSE, suggest a higher level of risk for investors. Both the BSE and NSE market indices are volatile; descriptive statistics show that the BSE indices and sectoral indices are more volatile than the NSE indices. The statistics clearly show persistent rising and negative tendencies, a phenomenon known as volatility clustering. The persistent downward trend that began in late January 2020 points to a possible upsurge followed by a prolonged downturn consistent with volatility clustering patterns.

Birau & Trivedi (2015) The work in this paper focuses on investigating the long-term volatility of the NSE of India based on GARCH models along with the volatility clustering, international portfolio diversification, globalization, financial integration, and asymmetric GARCH models. Using 1,698 daily observations from October 2007 to July 2014, this research empirically tests the CNX 100 index volatility clustering. Analysis has shown that the CNX 100 index revealed a usual pattern of market volatility between the year 2009 and the beginning of 2013. Investment profits have been maximized for investors due to a high degree of kurtosis, positive skewness, and consideration of reduced standard deviations. Because it permits the It encompasses 38 different industries and keeps an open market for liquidity ranging between 75% to 82%, the National Stock Exchange (NSE) index CNX100 can be a beneficial alternative for investors.

Ali (2016) This study focuses on the association between volatility and stock returns, as well as the clustering of volatility, leverage Effect, and persistence of volatility along with the GARCH and EGARCH model for the Indian stock markets, specifically NSE and BSE from 2006 to 2014. The correlation between returns and volatility, as well as the clustering and persistence of volatility, are all examined using the GARCH model. The asymmetric effect is captured by the EGARCH model. Recent and past news significantly impact volatility, with a notable leverage effect: negative shocks wield greater influence than positive ones.

Khan & Zia (2019) Examined study the impact of merger agreements by SBI and its associated banks on the return fluctuations of SBI equity during a 300-day news period. This study used the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) class model, which is regarded as a crucial tool for time series data analysis, to describe the volatility of the return series to accomplish the stated goal. According to the data, it was anticipated that the announcement of the merger would result in a reaction in the returns, which is linked to a larger abnormal return for investors in a shorter amount of time.

Umar et al. (2023) This paper assesses the volatility structure of equities returns on the Pakistan Stock Exchange (PSX) from 2006 to 2020, with an emphasis on persistence and asymmetry. The study uses a variety of GARCH models to measure daily, weekly, and monthly returns. The findings reveal that volatility persists only in daily returns, indicating that ongoing news influences investor behavior. However, this impact fades over time, suggesting that the PSX performs well in a semi-strong construct. These insights have major consequences for handling price assets, expense allocation, and strategy optimization.

Dimitriou & Simos (2011) This study looks at the relationship between projected stock returns and volatility in twelve EMU nations and five major non-EMU foreign stock markets between December 1992 and December 2007. Previous research has yielded varied results on the mean-variance trade-off. Using parametric the GARCH simulations reveal a poor relationship between volatility and returns in almost all of the sectors. Yet, a semi-parametric study indicates a significant adverse correlation in practically all marketplaces. In addition, Researchers explore the heterogeneous behavior of volatility to both favorable and adverse shocks in stock returns, and find opposite asymmetry in nearly every situation. Lee et al. (2001) study the time-series traits of return on investment and variability in four Chinese equity markets, with an emphasis on the link between the two. Variance ratio tests reveal that market returns do not adhere to a random move, and proof of a persistent recall in yields is found. The EGARCH and GARCH approaches offer substantial evidence of time-varying volatility, which is both extremely persistent and predictable. However, GARCH-M findings show no link between predicted returns and risk. Furthermore, daily trading volume, when considered as a proxy for information arrival, does not meaningfully explain the conditional volatility of daily returns.

Zhao & Chen (2021) The RCSNet (Residual-CNNSeq2Seq) model is introduced in this work as a novel machine learning strategy for forecasting stock price changes. RCSNet is a complex deep learning model that combines the ARIMA model with a convolutional neural network (CNN) and a sequence-to-sequence long short-term memory network (LSTM). RCSNet predicts short- and long-term interdependence in complicated time series by capturing both linear and nonlinear patterns in stock data. RCSNet beats older models when tested on S&P 500 data from January 2000 to August 2016, providing vital new views on stock market forecasting. Bhatnagar et al. (2022) This paper investigates the complex link between risk and return in the Indian fintech industry, with a particular emphasis on its performance in the larger stock market. The research uses secondary data from the Bombay Stock Exchange's fintech category from January 2017 to July 2022 to undertake a complete examination of price volatility and investment opportunities. Using the Mean-GARCH (GARCH-M) model, the study reveals dynamic interactions between risk and return, emphasizing the vital need to consider risk while making fintech investments. The findings indicate that for investors prepared to take risks, the Indian fintech industry provides significant long-term gains, affecting portfolio management methods and investment horizons. Dwarika (2022) This work provides a significant contribution both locally and internationally by being the first to investigate GARCH-M models with different innovation distributions. The study examined JSE ALSI returns from October 5, 2004, to October 5, 2021, and discovered that, while the EGARCH (1,1)-M model with Skewed Student-t distribution outperformed traditional models, it still failed to adequately represent the market's asymmetric and volatile character. To improve prediction, the study used nonnormal distributions such as Pearson Type IV, Generalised Extreme Value, and Stable. The Pearson Type IV distribution outperformed others, indicating that it may be used with EGARCH-M for superior risk modeling. The study shows that typical GARCH models are unsuccessful in volatile developing markets and suggests looking into alternate distributions.

2. Research Methodology

Research objectives

Q1: To examine the volatility pattern of the Indian stock market.

Q2: To find out the association between stock Return and Market Volatility**.**

This study is descriptive-cum-analytical. In this study, descriptive statistics like Mean, Median, Standard Deviation, Skewness, and Kurtosis are calculated to specify the distributional properties of the daily return series. The target group of the study is restricted only to the market indices BSE Sensex. The present study covers the last 10 years data from January 01, 2014, to December 31, 2023. According to Engle & Mezrich (1995), proper GARCH estimation requires at least 8 years of data. The sample size consists of 2,471 observations of the daily closing prices for the indices to analyze the volatility of the Indian stock market.

Secondary Data for the study will be collected from the official website of BSE (www.bseindia.com). The daily closing price of BSE SENSEX is to be considered for the study. Volatility is estimated on daily index returns. Daily return will be calculated by using the following formula:

$$R_t = \log (P_t / P_{t-1}) * 100 \quad (1)$$

where: R_t is the daily return of the stock, P_t is the price of the stock on day t and P_{t-1} is the price of stock on day $_{t-1}$.

Jarque–Bera (J-B) test, Philips-Perron (PP) test, Augmented Dickey-Fuller (ADF) test, Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests, GARCH (1,1) and GARCH-M models were applied to check the existence of volatility. The analysis was made using E-views 10 software.

The GARCH model (Bollerslev, 1986), enables the conditional variance to depend on prior own lags; this may be expressed in the simplest form as follows:

$$\sigma^2_t = \alpha_0 + \alpha_1\mu^2_{t-1} + \beta_1\sigma^2_{t-1} \quad (2)$$

where: $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$.

GARCH-M model

The volatility time series' short-run dynamics are determined by the magnitude of the parameters α1 and β1. Whenever the total of the variables is one, a disturbance will result in an irreversible shift across all potential outcomes. As a result, disturbances to the conditional variance are "persistent." The amount you earn on an investment may be affected by its volatility. To describe such a thing, think about the GARCH-M model, where M refers to GARCH in the mean. The GARCH (p, q)-M model can be specified as:

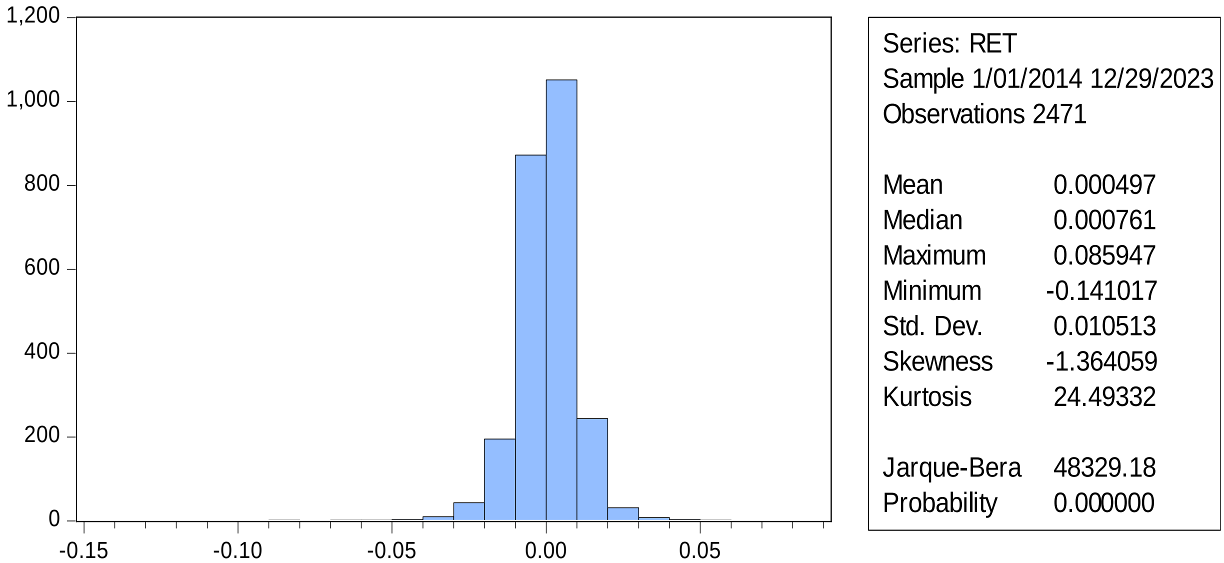
$$Y_t = pY_{t-1} + \gamma\sigma_t^2 + \varepsilon_t \quad (3)$$

The purpose of utilizing GARCH-M was to investigate how price discovery responds to changes in conditional volatility, which is substantial and positive when correlated with returns. GARCH-M models allow conditional mean to depend on its conditional variance.

$$ht = \alpha + \beta_1 y_{t-1} + \beta_2\varepsilon_{t-1} + \beta_3\sigma_t^2 \quad (4)$$

Results and Discussion

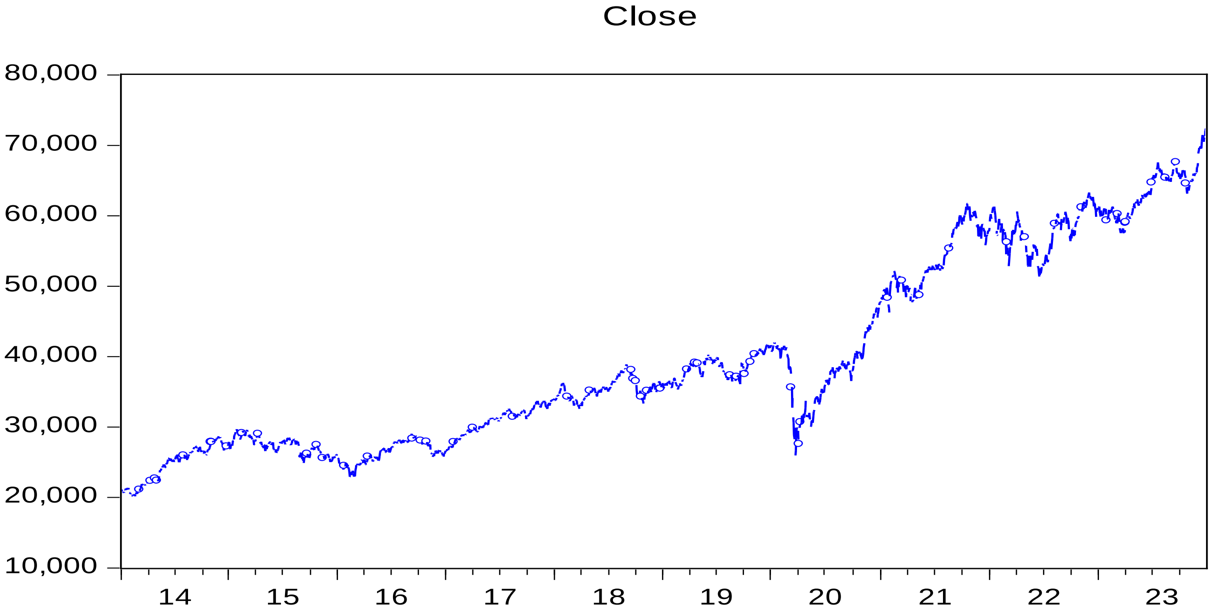
Figure 1. Descriptive statistics



Source: Authors' EViews 10 calculation

Figure 1 depicts a summary of SENSEX market returns during the period. As seen in the table, the mean is 0.000497 with an SD of 0.010513. The return mean is positive, indicating that the share price has risen throughout that period. The skewness of the distributions is negative, indicating a larger likelihood of earning returns greater than the mean. The kurtosis of the distributions of BSE SENSEX index returns is leptokurtic (>3), indicating that they are fat-tailed rather than following a normal distribution. It is further supported by the JB test, which is significant at the 1% level. Therefore, the null hypothesis of normalcy is not accepted.

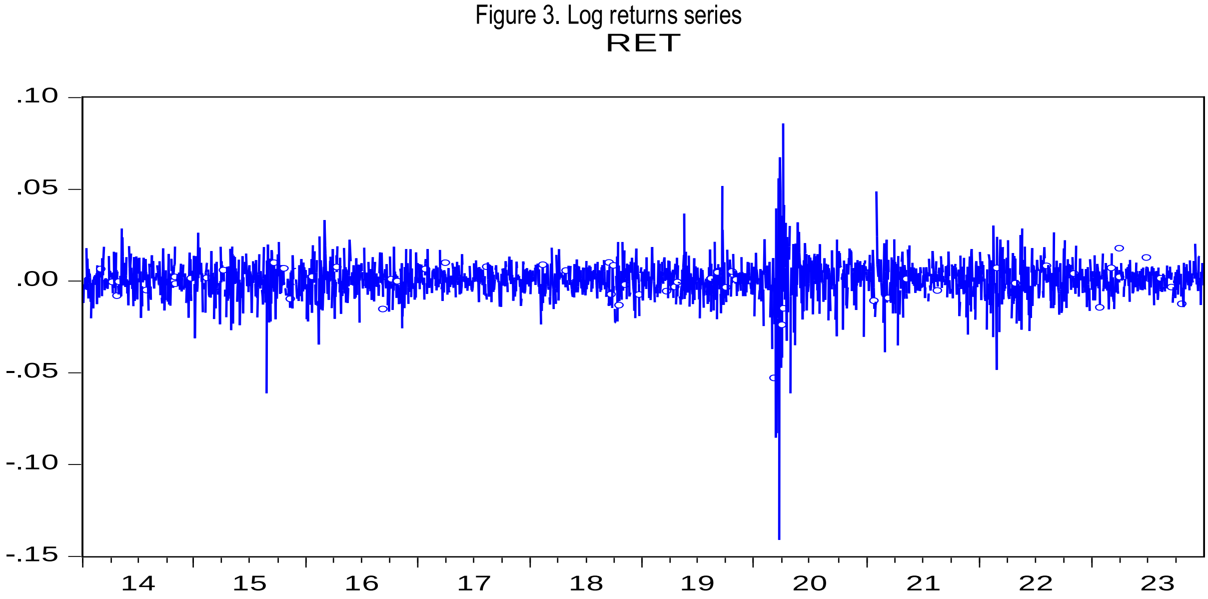
Figure 2. Trend of BSE SENSEX Index (individual chart)



Source: Authors' EViews 10 calculation

Figure 2 shows that the global financial crisis has had a significant influence on the series returns. This crisis has resulted in significant market drops, but investors, academics, and researchers must examine the post-crisis era and favorable return ratios. This data indicates investor confidence in long-term investments. Furthermore, the BSE SENSEX index displays a combination of constant regular volatility rates and rare abnormal movements. The BSE SENSEX index, which covers 30 different economic sectors, provides significant assistance in supporting healthy growth in financial returns. This diversification strengthens the financial series' durability and robustness.

Figure 3. Log returns series



Source: Authors' EViews 10 calculation

Figure 3 portrays the volatility clustering of BSE SENSEX's return from January 2014 to December 2023. It has been observed that the moment of low volatility has a propensity to be followed by the stage of low volatility for a longer duration, and the period of heightened volatility is followed by the region of high volatility for a greater amount of time. This indicates that while the variance is variable over time, the volatility is clustered and the SENSEX index return series fluctuates around the constant mean.

Table 1. Stationarity test

Value	ADF	PP
T-Statistic	-17.94347	-50.05345
Prob.	0.0000	0.0001
Critical Value		
1%	-3.432810	-3.432803
5%	-2.862513	-2.862510
10%	-2.567333	-2.567331

Source: Authors' EViews 10 Calculation

Table 1 depicts the existence of unit roots in the series examined using ADF and PP tests. It shows that the ADF and PP tests did not accept the hypothesis at the 1% level, with a critical value of -3.43 for both ADF and PP tests of a unit root in the return series. Also, ADF and PP's p values are below 0.05. Therefore, it is confirmed by the results of both tests that the series is stationary.

Table 2. ARCH test

Heteroskedasticity Test: ARCH LM			
F-statistic	0.515238	Prob. F (1,2462)	0.4729
Obs*R-squared	0.515549	Prob. Chi-Square (1)	0.4727

Source: Authors' EViews 10 Calculation

Table 2 shows the ARCH-LM test findings, which investigate heteroskedasticity in residuals from the GARCH approach. The test outcomes show that the residuals are not heteroscedastic, as evidenced by a p-value larger than 0.05. As a result, the ARCH-LM tests indicate that there is no more ARCH influence in the residuals.

Table 3. GARCH (1, 1) model

GARCH = C (4) + C (5) *RESID (-1) ^2 + C (6) *GARCH (-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000820	0.000154	5.322350	0.0000
Variance Equation				
C	1.96E-06	4.58E-07	4.280992	0.0000
RESID (-1) ^2 (α)	0.088970	0.008004	11.11555	0.0000
GARCH (-1) (β)	0.891644	0.011164	79.86587	0.0000
α + β	0.980614			
Durbin-Watson stat	Akaike info. Criterion	Schwarz Criterion		
1.995876	-6.625155	-6.611013		

Source: Authors' EViews 10 Calculation

Table 3 represents the estimated outcome of the GARCH (1, 1) model. The constant value in the mean equation is substantial and positive ($p < 0.05$). The coefficients of variance on both sides RESID (-1) ^2 and GARCH (-1) are found to be significant. suggests that volatility is prevalent and the total of these values α and β is 0.980614, which is near to 1 and indicates that volatility is extremely persistent. Therefore, the GARCH framework demonstrated that conditional variance occurs continuously in the Indian equity market. The AIC and SC parameters for the test are -6.625155 & -6.611013 respectively. The Durbin-Watson statistics value is 1.995876, which is near 2. It indicates there is no autocorrelation between the error terms, showing that the statistical model is suitable and fit. The complete equation for the GARCH (1, 1) model relying on the BSE SENSEX Index data series is: σ2 = α0 + α1ε2t-1 + β1σ2t-1 and the results (α1) +(β1) = 0.088970 + 0.891644 = 0.980614 < 1.

The GARCH (1, 1) model precisely predicted volatility in the SENSEX (Bombay Stock Exchange Index), yielding a value of 0.980614, which is less than or near to one. It signifies that the series has a high volatility level and a significant influence on listed equities. The GARCH (1,1) type compositions comprise a single ARCH component and one GARCH component. The findings suggest that making long-term investments in any companies in the BSE index would be profitable and may generate a high degree of returns.

Table 4. Estimated result of GARCH-M model

GARCH = C (5) + C (6) *RESID (-1) ^2 + C (7) *GARCH (-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000596	0.000264	2.256120	0.0241
GARCH (risk premium)	3.282659	3.170618	1.035337	0.3005
Variance Equation				
C	1.98E-06	4.66E-07	4.252618	0.0000
RESID (-1) ^2 (α)	0.085017	0.008055	11.12825	0.0000
GARCH (-1) (β)	0.089634	0.011265	79.07521	0.0000
Durbin-Watson stat	Akaike info. Criterion		Schwarz Criterion	
1.981401	-6.624913		-6.608414	

Source: Authors' EViews 10 calculation

It can be seen from Figure 6 that the coefficients of variance in the mean equation (GARCH) are not statistically significant as their probability values exceed 0.05. Therefore, we see no strong evidence that there are higher returns during the time of higher volatility in Sensex. The variance term "GARCH" is not statistically significant in the mean equation but its inclusion substantially increases the significance of the GACH term in the variance equation. The risk premium is not substantial enough to protect against perilous asset holdings. Also, the asset may not be risky to retain. If we want to hedge against risk, the risk premium is not very high. It means that taking risks does not give you more returns. The formal application of GARCH-M reveals that there is no strong evidence that periods of high volatility always cause high returns.

Conclusions

The study find out whether the returns of the Sensex from the previous day could explain today's Sensex returns by employing a GARCH (1, 1) model. The findings reveal that the parameter is both statistically significant and positive, suggesting that past Sensex returns exhibit a GARCH effect on today's Sensex returns. The primary objective was to analyze the volatility of the BSE SENSEX index in the stock market spanning from January 2014 to December 2023. These methods effectively account for volatility clustering and the leverage effect observed throughout the study period. Tests were conducted to verify the presence of unit roots, volatility clustering, and ARCH effects, all of which were established conclusively.

The results of the ARCH-LM test show that there is no heteroscedasticity in the residuals obtained from the regression estimation ($p>0.05$). Therefore, the ARCH-LM outcome does not keep any further ARCH impact residual. The mean equation and constant value in GARCH are significant and positive at $p<0.05$. The parameters α and β added together are 0.980614, nearly equal to 1, indicating that volatility is highly repeated in nature. Therefore, conditional variance continues in the Indian stock market, as demonstrated by the GARCH model. The findings of the GARCH-M model showed that the slope coefficient of the GARCH-M model equation was not significant. As a result, it is possible to conclude that the volatility of the index returns had no major influence on their returns. So, we can say that there was no association observed between market volatility and stock returns. The statistical summary indicates a risk degree of 0.010513, with mean and median returns close to zero. Analysis of 10-year daily market data, comprising 2,471 observations, reveals a negative skewness. Bollerslev & Tylor (1986) demonstrated that the GARCH (1, 1) model fits well with financial data, notably capturing changes in market volatility since 2020. Specifically, the presence of high kurtosis and negative skewness suggests a heightened likelihood of earning returns, though accompanied by a lower degree of standard deviations, thus offering the potential for higher returns on investments but entailing some risks.

Implications

The study of stock market volatility in India is critical, especially given the predicted rapid economic expansion and increased interest from overseas investors. It is critical to understand how this volatility varies over time, is enduring, and is predictable. A strategy could assist in balancing the investments while creating hedging precautions. Forecasts of volatility are useful for portfolio allocation and performance measurement. This study will help the investor to understand the past, Current, and future scenarios of the Indian stock market, from the investor's point of view in understanding the future trend based on past data and thus making rational decisions to Invest in the stock market.

Limitations of the Study

This study relies on secondary data, so the accuracy of the findings depends on the reliability of that data. The BSE Sensex represents the Indian stock market, though other indices could also be used to study volatility. The analysis is based on daily data but could have been conducted with monthly, quarterly, or annual data. It covers a 10-year period, researchers can extend this duration based on data availability and their preferences.

Credit Authorship Contribution Statement

R. R. M. is responsible for the conceptualization and design of the study. He conducted the statistical and econometrical analysis using various GARCH models and write the paper. S.M. reviews the results, supervise modifications and make important contributions to the final version.

Conflict of Interest Statement

The authors declare that the research was conducted without any commercial or financial link that may lead to conflicts.

References

[1] Agarwal, A. (2020). A study on stock market volatility pattern of BSE and NSE in India. *International Journal of Trend in Scientific Research and Development*. https://www.ijtsrd.com/papers/ijtsrd33259.pdf

[2] Aggarwal, K., & Jha, M. K. (2022). Stock returns seasonality in emerging Asian markets. *Asia-Pacific Financial Markets*, *30*(1), 109–130. https://doi.org/10.1007/s10690-022-09370-y

[3] Ali, I. (2016). Stock Market Volatility and Returns: A Study of NSE & BSE in India. *International Journal of Humanities & Social Science Studies*, 202-211.

[4] Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *Review of Financial Studies/the Review of Financial Studies*, *13*(1), 1–42. https://doi.org/10.1093/rfs/13.1.1

[5] Bhatnagar, M., Özen, E., Taneja, S., Grima, S., & Rupeika-Apoga, R. (2022). The Dynamic Connectedness between Risk and Return in the Fintech Market of India: Evidence Using the GARCH-M Approach. *Risks*, *10*(11), 209. https://doi.org/10.3390/risks10110209

[6] Bhowmik, R., & Wang, S. (2020). Stock market volatility and return analysis: A systematic literature review. *Entropy*, *22*(5), 522. https://doi.org/10.3390/e22050522

[7] Birău, R., & Trivedi, J. (2015). Estimating long-term volatility on National Stock Exchange of India. *Procedia Economics and Finance*, *32*, 574–579. https://doi.org/10.1016/s2212-5671(15)01434-3

[8] Chancharat, S., & Sinlapates, P. (2023). Dependences and dynamic spillovers across the crude oil and stock markets throughout the COVID-19 pandemic and Russia-Ukraine conflict: Evidence from the ASEAN+6. *Finance Research Letters*, *57*, 104249. https://doi.org/10.1016/j.frl.2023.104249

[9] Das, K. C. (2023). Indian start-ups going public: return and volatility of stocks during bear and bull regimes. *International Journal of Emerging Markets*. https://doi.org/10.1108/ijoem-06-2022-0898

[10] Dimitriou, D., & Simos, T. (2011). The Relationship between Stock Returns and Volatility in the Seventeen Largest International Stock Markets: A Semi-Parametric Approach. *Modern Economy*, *02*(01), 1–8. https://doi.org/10.4236/me.2011.21001

[11] Dixit, J. K., Agrawal, V., & Agarwal, S. (2022). Measuring stock market volatility - A study in India's perspective. *International Journal of Economic Policy in Emerging Economies*, *16*(1), 1. https://doi.org/10.1504/ijepee.2022.124655

[12] Dwarika, N. (2022). The risk-return relationship in South Africa: tail optimization of the GARCH-M approach. *Data Science in Finance and Economics*, *2*(4), 391–415. https://doi.org/10.3934/dsfe.2022020

[13] Fakhfekh, M., Jeribi, A., & Salem, M. B. (2021). Volatility dynamics of the Tunisian stock market before and during the COVID-19 outbreak: Evidence from the GARCH family models. *International Journal of Finance & Economics*, *28*(2), 1653–1666. https://doi.org/10.1002/ijfe.2499

[14] Srihari, G., Kusuma, T., Chetanraj, D. B., Kumar, J. S., & Aluvala, R. (2024). Predictive modeling of return volatility in sustainable investments: An in-depth analysis of ARIMA, GARCH, and ARCH techniques. *Investment Management & Financial Innovations*, *21*(1), 213. https://doi.org/10.21511/imfi.21(1).2024.17

[15] Khan, A. A., & Zia, A. (2019). Market volatility of banking stock return vis-à-vis banks merger: An application of GARCH model. *Management Science Letters*, 629–638. https://doi.org/10.5267/j.msl.2019.2.008

[16] Lee, C. L. (2017). An examination of the risk-return relation in the Australian housing market. *International Journal of Housing Markets and Analysis*, *10*(3), 431–449. https://doi.org/10.1108/ijhma-07-2016-0052

[17] Macrosynergy. (2015, August 1). *Modelling the relation between volatility and returns*. https://macrosynergy.com/research/modelling-the-relation-between-volatility-and-returns/#macro-information-inefficiency

[18] Meher, B. K., Puntambekar, G., Birau, R., Hawaldar, I. T., Spulbar, C., & Simion, M. L. (2023). Comparative investment decisions in emerging textile and FinTech industries in India using GARCH models with high-frequency data. *Industrial Textile*, *74*(06), 741–752. https://doi.org/10.35530/it.074.06.202311

[19] Mishra, A. K., Agrawal, S., & Patwa, J. A. (2022). Return and volatility spillover between India and leading Asian and global equity markets: an empirical analysis. *Journal of Economics Finance and Administrative Science*, *27*(54), 294–312. https://doi.org/10.1108/jefas-06-2021-0082

[20] N, N. M., Chakraborty, S., M, L. B., Ledwani, S., & Satyakam, N. (2023). Modeling Indian Bank Nifty volatility using univariate GARCH models. *Banks and Bank Systems*, *18*(1), 127–138. https://doi.org/10.21511/bbs.18(1).2023.11

[21] Singh, S., & Tripathi, L. (2016). Modelling Stock Market Return Volatility: Evidence from India. *Research Journal of Finance and Accounting*, *7*(13), 93–101. https://www.iiste.org/Journals/index.php/RJFA/article/download/31818/32690

[22] Subburayan, B. (2023). Causality and volatility spillovers of banks' stock price returns on BSE Bankex returns. *Journal of Corporate Accounting & Finance*, *35*(1), 59–75. https://doi.org/10.1002/jcaf.22648

[23] Umar, M., Mirza, N., Rizvi, S. K. A., & Furqan, M. (2023). Asymmetric volatility structure of equity returns: Evidence from an emerging market. *The Quarterly Review of Economics and Finance*, *87*, 330–336. https://doi.org/10.1016/j.qref.2021.04.016

[24] Zhao, Y., & Chen, Z. (2021). Forecasting stock price movement: new evidence from a novel hybrid deep learning model. *Journal of Asian Business and Economic Studies*, *29*(2), 91–104. https://doi.org/10.1108/jabes-05-2021-0061