“Modeling Indian Bank Nifty volatility using univariate GARCH models”

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MODELING INDIAN BANK NIFTY VOLATILITY USING UNIVARIATE GARCH MODELS

Abstract

The crumble of financial markets due to the recent crises has wobbled precariousness in the stock market and intensified the returns vulnerability of banking indices. Against this backdrop, this study intends to model the volatility of the Indian Bank Nifty returns using a battery of GARCH specifications. The finding of the present research contributes to the literature in three ways. First, volatility during the sample period, which corresponds to a time of stress (a bear market), is more persistent, with an estimated coefficient of 0.995695. Moreover, when volatility rises, it persists for a long time before returning to the mean in an average of 16 days. Second, for a positive γ, the results insinuate the possibility of an "anti-leverage effect" with a coefficient of 0.139638. Thus, the volatility of the Bank Nifty returns tends to rise in response to positive shocks relative to negative shocks of equal magnitude in India. Finally, the findings demonstrate that EGARCH with Student's t-distribution offers lower forecast errors in modeling conditional volatility.

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INTRODUCTION

Following the consistent underperformance of the benchmark Nifty 50 over the last three years, Bank Nifty has taken the brunt of the wrath. Notably, the benchmark index recorded an increase of 38%, while the Banking index plunged by 13% during the same period. However, investors frequently explore a strategy to expand exposure to high beta indices with an appetite to outperform the benchmark. In particular, an investor with a high-risk potential prefers to buy a high-beta stock (Christoffersen & Simutin, 2017). In this context, several studies in mainstream finance showed that Bank Nifty is a high beta index, reiterating its ability to generate large returns in relation to the benchmark when the market is bullish. On the contrary, academic research has been inconclusive in modeling the volatility of Bank Nifty during periods under stress (bear market). In fact, the 1987 crisis, the major global financial crisis of Asia in 1997, and the catastrophe in 2008, which walloped the economy worldwide, have demonstrated the cutting-edge volatility of the Bank Nifty index with substantial variations in the returns (Bhattacharyay, 2013).

Recently, COVID-19 had the most devastating effects on the financial markets, both in terms of scale and intensity (Rout & Mallick, 2022). As the crises intensified, the banking sector returns in India metamorphosed into acute vulnerability. Experts are of the opinion that "Vulnerabilities in credit markets, emerging countries, and banks could even cause a new financial crisis." Nevertheless, there is a dearth of academic research on banking sector volatility explicitly in emerging markets like India. Thus, the current study, motivated by this problem, employs a battery of GARCH specifications to empirically assess the asymmetric behavior of the Indian Bank Nifty returns.

1. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

As the world becomes more fast-paced and dynamic, financial institutions have become increasingly important; they help balance demand and money supply. The performance of firms, specifically the growth of banking sectors on account of diversified business activities, is of paramount importance (Anagnostopoulos, 2018). Investments in bank savings schemes are often viewed as safe, assuring fixed returns. Additionally, due to divergence in various services, the banking sector's stocks have become a popular trading and investment option (De Jonghe, 2010). Since 2004, the banking sector stocks have shown tremendous growth in market capitalization and trade volume. Considering the importance of banks for economic development, several empirical studies have been conducted by researchers and analysts hitherto.

Recent research indicates that banking crises are likely to have a spillover effect on other sectors (Candelon et al., 2016), which necessitates proper evaluation and constructive measurement of bank risks to ensure the stability of the banking industry (Begley et al., 2017). The major upheaval in the stock markets on account of the economic and financial crisis of 2008 induced government to adopt global banking rules to monitor and measure bank risk (Kumar & Prakash, 2019). For decades, one of the most prevalent notions in the banking literature has been that stock returns can capture their potential long-run performance risk (Baele et al., 2007).

A significant contribution to banking literature dates back to Diamond (1984), Brealey et al. (1977), and Diamond and Dybvig (1983) on stock returns of banks and financial intermediaries. A fundamental assumption in this literature is that market returns transmit trustworthy information about profit prospects and risk (Moshirian & Wu, 2009). Therefore, the susceptibility of banking stock returns exerts a considerable effect on the common stocks of financial institutions (Kasman et al., 2011). However, the sensitivity changes over time, and the returns are countered by an asymmetric response (Âhou & Gueyie, 2001). As a result, analyzing and capturing bank risk can be difficult. The rising complexity of the business models of the banks can make measuring and observing the underlying risks of banks more difficult (Begley et al., 2017).

Furthermore, because banks are critical to economic development, a banking meltdown can considerably impact other sectors of the economy (Hoggarth et al., 2002). Consequently, strengthening the banking system and preventing crises are of utmost importance for policymakers and regulators (Gupta, 2010). Thus, the "New Basel Capital Accord," developed by the "Basel Committee on Banking Supervision" in 2003, includes market discipline as one of its three pillars in recognition of the significance of market discipline in safeguarding banks and financial institutions (Crockett, 2002). As a result of market discipline, stock returns, and prices are used to measure the riskiness of banks (Flannery, 2001). In particular, unlike accounting-based returns, the information inherent in asset returns and prices is oftentimes a forward-looking metric, and such information might serve as a useful benchmark for market discipline (Acharya et al., 2012; Hasan et al., 2015; Stiroh, 2006). Besides, extreme movements in stock prices and returns may indicate concern about the future economic situation. As a result, volatility in the banking stock returns may signal the banking sector's performance stability of a country (Moshirian & Wu, 2009).

The asset returns dynamics have piqued the interest of several researchers. The empirical studies on volatility modeling of stock returns have garnered the attention of academicians (Thiripalraju & Acharya, 2010). Numerous scholars have proposed various methods for assessing and quantifying bank risks (Anginer et al., 2014; Baele et

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al., 2007; Bennett et al., 2015; Demirer et al., 2018; Laeven et al., 2016; Stiroh, 2006; Fratzscher & Rieth, 2015). On their part, Anginer et al. (2014) demonstrate that systemic risk measured using stock returns and bank competition are inversely related. Nonetheless, the study fails to consider banks' time-varying stock return volatility. However, stock returns often show time-varying fluctuations (Fratzscher & Rieth, 2015). As a result, the empirical findings show that the volatility of stock returns of leading global banks is dynamically connected across time (Demirer et al., 2018).

Karmakar (2005) employs the GARCH (1,1) model and estimates the parameters for BSE Sensex. Further, it claims that the GARCH model with one lag order is the suitable model in the Indian stock market for forecasting and modelling volatility. However, the study's findings contend the relevance of using asymmetric models to examine the asymmetry, persistence of volatility, and its clustering. Following this, Padhi (2006) applied EGARCH and GJR-GARCH models to investigate the presence of volatility and leverage in the Indian stock market. Further, the study suggests applying Student's t and GED distribution for asymmetric GARCH models, since are proficient at capturing fat tail and highly peaked properties. Subsequently, Karmakar (2007), to model asymmetric volatility, employs the EGARCH model with GED and corroborates the presence of asymmetry in the form of leverage effect in India. Later, Tripathy and Gil-Alana (2015) examine the volatility in India from August 1992 to September 2012, decomposing the study period into pre-crisis (1992–2008) and post-crisis (2008–2012). The findings reveal that leverage effects and volatility persistence are more significant in the post-crisis period than in the pre-crisis period. Another study was carried out by Bhatia and Gupta (2020) on the volatility between Indian Nifty Bank Index, Private Sector Bank Index, and Public Sector Undertaking Banking Index (PSUBI). In addition, they compare the volatility between two events, namely, the great recession of 2008 and COVID-19. The results show that asymmetric impact during the great recession 2008 is lower for PSUBI compared to the other two sectors. However, during the COVID period, the results are insignificant, implying that banking sector stocks were highly volatile during the Mortgage Crisis relative to COVID-19. Mahajan et al. (2022) further confirmed the existence of leverage in the Indian stock market.

Despite the difficulty of quantifying the accurate degree of the influence of market-based performance metrics on bank stability in a rapidly evolving world, it is evident that these metrics imply abrupt contractions of both financial performance and bank risk (Elnahass et al., 2021). To gauge the financial stability of the banking sector, modelling their return volatility could be a useful benchmark (Suhadak et al., 2019). It is worth mentioning, however, that such quantifications aid in forecasting future volatility and offer an extra tool for positioning adjustments.

Thus, the current study aims to disentangle the asymmetric volatility puzzle by modeling Bank Nifty returns volatility in India. Based on theoretical and empirical frameworks developed in the extant literature, the following research hypotheses are employed in this study:

H_1: Volatility shocks are highly persistent in Bank Nifty returns.

H2: Bank Nifty returns are equally sensitive to good news and bad news of the same size.

2. METHODOLOGY

2.1. Data and study period

The closing prices of the Nifty Bank Index were collected from the National Stock Exchange from June 10, 2005 to May 31, 2022, and used for modeling volatility corresponding to 4,206 observations. The 12 most liquid equities with large market capitalizations from the banking sector that are traded on the NSE make up the Bank Nifty index. Further, the index gives market intermediaries and investors a benchmark that represents the market performance of the banking sector in India.[1] The study uses long-period data for a better model fit, as the amount of time significantly affects the model fit.

1 Bank Nifty Index of NSE is a benchmark for traders and market intermediaries as it reflects the performance of the Indian banking sector's secondary market.

The returns data (R_t) are accrued as compounded returns:

$$R_t = \ln\left(\frac{p_t}{p_{t-1}}\right), \tag{1}$$

where p_t = current days' stock price; p_{t-1} = stock price of the previous day.

The financial time series may exhibit intensified market volatility when the returns are negative, known as the market asymmetry or the Leverage effect (Black & Cox, 1976). The changes in the market segment, transaction costs, and frictions are the few causes of asymmetry in the financial time series. Therefore, such behavior necessitates employing asymmetric GARCH models to capture non-linear and asymmetric volatility in Indian stock returns.

2.2. GARCH models

The increase in the asset price is always accompanied by a decline to a greater extent and in the financial time series such price fluctuations are regarded as stylized facts (Lin, 2018). Early evidence shows that the researchers predominantly used ARCH (Autoregressive conditional heteroscedasticity) models to forecast stock returns' dynamics. Later, Bollerslev (1986) suggested a superior, Generalized ARCH model, well-known as the GARCH model. The symmetric GARCH model is defined as follows:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{q} \beta_j \mu_{t-j}^2. \tag{2}$$

In equation (2), ARCH and GARCH parameters are represented by μ_{t-i}^{2} and μ_{t-j}^{2}, respectively. The α term denotes the ARCH coefficient, the β term denotes the GARCH coefficient, and p and q values indicate the model's lag order. The GARCH model with one lag order is considered as the best model to measure the volatility clustering in financial time series (Brooks & Burke, 2003). However, the symmetric GARCH models do not support the asymmetry in the asset returns since such models assume conditional variance to be constant. This necessitates the employment of asymmetric GARCH models.

2.2.1. *EGARCH model*

The linear GARCH models do not differentiate the influence of optimistic and pessimistic news on the volatility of any time series. Nelson (1991) developed Exponential GARCH, which accounts for the impact of positive and negative shocks on time series volatility (the leverage effect). The EGARCH (1,1) model can be written as follows:

Variance equation:

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \\ + \alpha_1 \left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right] - \Upsilon \frac{\varepsilon_{t-1}}{\sigma_{t-1}}, \tag{3}$$

where Υ denotes the leverage effects. $\Upsilon > 0$ implies more volatility when the news is good. However, $\Upsilon < 0$ implies that the bad news is more disruptive to returns when negative. The model is regarded to be symmetric when $\Upsilon = 0$. Further, $\ln(\sigma_t^2)$ may be negative, and the parameters in the EGARCH model have no sign restrictions.

2.2.2. *GJR-GARCH model*

This model proposed by Glosten et al. (1993) accounts for the leverage effect. The model can be expressed as follows:

$$\mu_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2 + \Upsilon \mu_{t-1}^2 I_{t-1}. \tag{4}$$

A positive shock is indicated by $\mu_{t-1} < 0$, a negative shock by $\mu_{t-1} > 0$, and a dummy variable by I_{t-1}. The coefficients $\Upsilon \neq 0$ and $\Upsilon > 0$ represent the asymmetric shocks and leverage effect, respectively. $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$ and $\alpha_1 + \Upsilon \geq 0$ are the conditions for non-negativity (Brooks, 2008, p. 405).

3. RESULTS

To eliminate biased regression in the model fit, confirming the stationary for the time series data is necessary. Furthermore, as GARCH models are developed to describe the variations in heteroscedastic data, it is essential to identify whether heteroscedasticity exists in the data. As a result, tests to determine whether the data are

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stationary (ADF test and PP test) and whether ARCH effects are present (LM test) are used as preconditions for GARCH modelling.

3.1. Test for stationarity

The results of both ADF and PP tests are reported in Table 1. Since the p-values are less than 0.05 for the tests, the null hypothesis is rejected, i.e., data have a unit root, outlining that Bank Nifty returns data are not non-stationary.

Table 1. Unit root test results

Unit root tests	t-statistic	Critical value (5%)	Probability values
Augmented Dickey-Fuller test	–58.58497	–2.862031	0.0001
Phillips-Perron test	–58.45962	–2.862031	0.0001

Note: H_0: Nifty Bank Returns have unit root one (non-stationary).

3.2. Test for ARCH effect

The test for conditional heteroscedasticity is a pre-requisite to determining volatility in the Bank Nifty returns data. Accordingly, the study applies the LM test (Engle, 1982). Table 2 displays a summary of the ARCH test results. The findings of the ARCH LM test offer strong evidence against the null hypothesis. This corroborates the presence of the ARCH effect in the Bank Nifty returns data. Apart from this, the daily returns' graphical representation affirms time-varying volatility and volatility clustering during the sample period (Figure 1). Thus, the conditional variance with the homoscedasticity assumption is no longer valid for Bank Nifty returns, and the current research can test conditional heteroscedasticity by employing the GARCH process.

Table 2. ARCH LM test results

t-statistics	Probability value [Chi-square (1)]
68.14172	0.0000

Note: H_0: There are no ARCH effects in the returns data of the Bank Nifty.

3.3. Descriptive statistics

Before processing the data, it is essential to have an overview of the summary statistics. The results of the descriptive statistics are reported in Table 3. The mean value for the 4206 observations of the returns series is 0.000548, and the observed sample standard deviation is 0.018624. The mean value is small compared to the standard deviation observed in the study, indicating high volatility during the sample period. The skewness coefficient shows a negative value (–0.195874), outlining that the Bank Nifty returns series is negatively skewed. The kurtosis of the series exceeds the standard normal distribution value (+3), demonstrating the fat tail. These findings corroborate that the distribution differs remarkably from normality (refer to Figure 2). Accordingly, the Jarque-Bera test for normality shows a t-statistic value (9,539.506) with a significant p-value at a 1% significance level. As a result, the null hypothesis is rejected, confirming that the distribution does not exhibit normality. Further, as a tool to estimate the distributional properties, the study uses a Quantile-Quantile (QQ) graph (refer to Figure 3). The graphical results confirm the findings of the Jarque-Bera test, i.e., Bank Nifty returns data do not adhere to the normal distribution.

Source: Computed Using EViews.

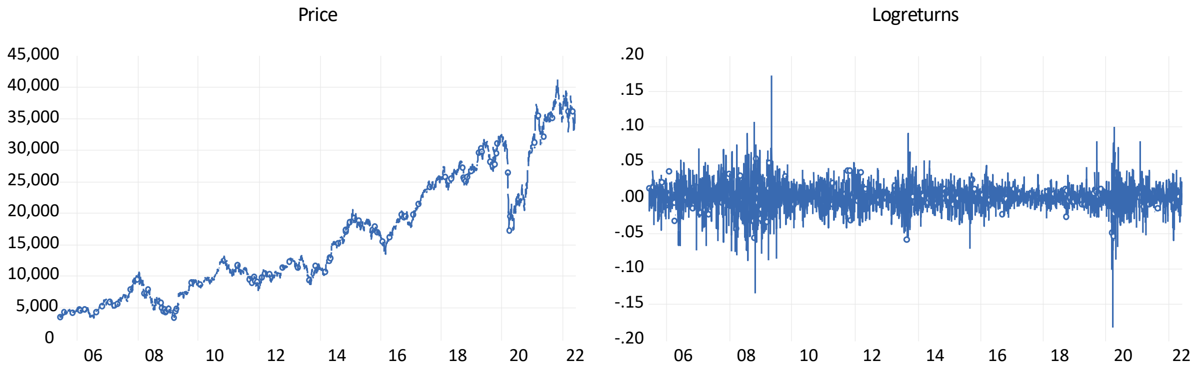

Figure 1. The trend (Closing prices) and log-returns of the Bank NIFTY index during the sample period

Source: Computed using EViews.

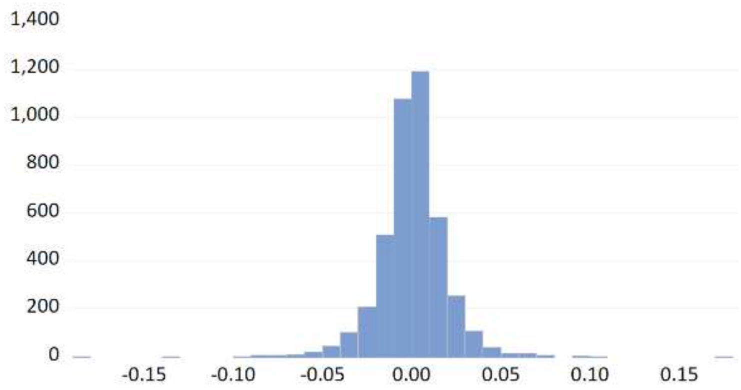

Figure 2. Histogram for Bank Nifty Index returns

Source: Computed using EViews.

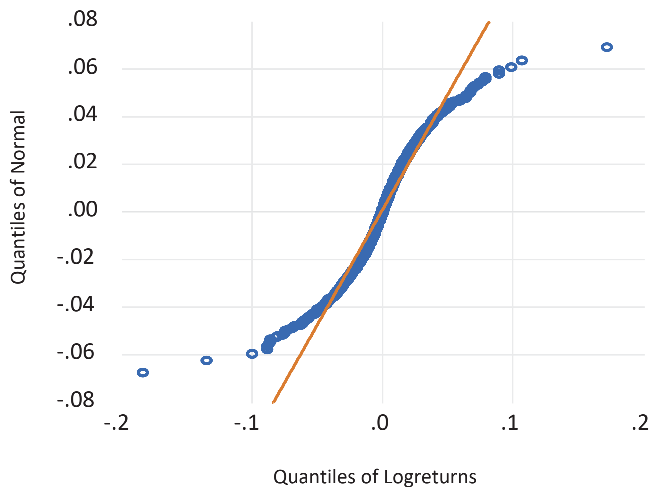

Figure 3. Normal QQ plot for daily Bank Nifty Index returns: 2005–2022

Table 3. Results showing summary statistics

Statistics	Value
Number of Observations	4206
Mean	0.000548
Median	0.000804
Max	0.172394
Min	–0.183130
Standard Deviation	0.018624
Skewness	–0.195874
Kurtosis	10.36751
Jarque-Bera t-stat	9539.506
Probability value	0.000000
Sum	2.303677
Sum of Squared. Dev	1.458463

3.3.1. Empirical results

Following the results of the LM test, the study applies asymmetric GARCH models (EGARCH and GJR-GARCH). Because the data do not conform to the normal distribution assumption, the study employs Student's t (Stud-t) and the Generalized Error Distribution (GED). Further, to choose an appropriate model and distribution, the study uses the maximum log-likelihood (LnL) approach

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Table 4. Estimation of results using GARCH models

	Distribution	GARCH (1,1)	GJR-GARCH (1,1)	EGARCH (1,1)
μ(MU)	Normal	0.000930 ***	0.000596 ***	0.000510 ***
	Stud-t	0.000818***	0.000560 **	0.000514 **
	GED	0.000900 ***	0.000654 ***	0.000608 ***
Ω (OMEGA)	Normal	0.000003 *	0.000003 **	–0.104000 ***
	Stud-t	0.000002	0.000003	–0.099659 ***
	GED	0.000002	0.000003	–0.104387 ***
α (ALPHA)	Normal	0.077638 ***	0.028178 ***	–0.065713 ***
	Stud-t	0.076559 ***	0.022394	–0.072205 ***
	GED	0.076803 ***	0.025149	–0.068601 ***
β (BETA)	Normal	0.917038 ***	0.925181 ***	0.986795 ***
	Stud-t	0.919136 ***	0.926487 ***	0.988018 ***
	GED	0.917909 ***	0.925489 ***	0.987538 ***
γ (GAMMA)	Normal	–	0.079641 ***	0.146704 ***
	Stud-t	–	0.090630 ***	0.139638 ***
	GED	–	0.084824 ***	0.144127 ***

Note: *, **, and ***: statistically significant at the 10%, 5%, and 1% level of significance, respectively.

and AIC/BIC values congruent with prior studies (Franses & Van Dijk, 1996). The EGARCH model with stud-t was found to be the best-fit model to the returns' data as it exhibits lower forecast errors and provides a better description of the conditional volatility. However, the performance of Student's t and GED performance is almost identical due to the negligible difference in their AIC and BIC values.

Table 4 reports the findings of the symmetric GARCH (1,1), EGARCH (asymmetric), and GJR GACRH (asymmetric) models with GED and Student's t distribution. The α and β terms are statistically significant in the returns series for the symmetric model. This suggests that regardless of the sign, squared-lagged innovation considerably influences conditional variance.

The results of the EGARCH model for the Bank Nifty returns series are provided in Table 4. The leverage coefficient γ for the data series is statistically significant at the 1% level, which supports the use of the asymmetric volatility model. In the model, the stated α measures how much a volatility shock today affects volatility in the following period (Campbell et al., 1997). The α for the Bank Nifty series is –0.072205. This coefficient is statistically significant, demonstrating that historical lags can affect future volatility only in the near term. However, the negative estimate on the "alpha" component indicates that negative volatility reduces the conditional variance for the following period (Brooks, 2019).

A long memory in the variance is indicated by β coefficient. The correlation structure of a specific series at long lags is referred to as having a long memory. Distance observations have persistent temporal dependency if a series demonstrates long memory. The estimated coefficient for the GARCH term (β) is 0.988018. As the coefficients approach unity, previous news is likely to continue affecting current volatility for a very long time.

For the Bank Nifty returns, the total of α and β terms is 0.915813, showing that volatility shocks are extremely persistent. Because the returns series show their volatility reverting to half its mean value within 8 days, investors should open a position on the 0th day and close it after 16 days[2]. If a shock to a given system is lasting, volatility persists for a prolonged time, and the behavior of volatility in the past can be utilized to forecast future volatility. Thus, the higher beta (β) coefficient value (close to one) indicates that volatility shocks are highly persistent in the Indian Bank Nifty series; supporting the study's first hypothesis (*H1*).

Using the EGARCH model, it has been found that the γ coefficient for Bank Nifty returns is 0.139638 (positive) and statistically significant at 0.01 (Table

2 The half-life volatility of GARCH model is a statistic to measure the mean reverting time (in terms of average days). To measure mean reverting time, we have employed the method followed by (Ahmed et al., 2018).

Table 5. Model selection criteria

Criteria	Distribution	GARCH (1,1)	GJR-GARCH (1,1)	EGARCH (1,1)
AIC (Akaike)	Normal	–5.4669	–5.4901	–5.4917
	Stud-t	–5.5119	–5.5340	–5.5350
	GED	–5.5080	–5.5283	–5.5291
BIC (Bayes)	Normal	–5.4609	–5.4796	–5.4811
	Stud-t	–5.5029	–5.5205	–5.5214
	GED	–5.5005	–5.5163	–5.5171
Log-Likelihood	Normal	11500.91	11552.76	11555.97
	Stud-t	11597.56	11647.09	11649.120
	GED	11588.38	11634.11	11635.78

Note: *, **, and ***: statistically significant at the 10%, 5%, and 1% level of significance, respectively.

4). Therefore, it becomes clear that the influence of good news/shocks is greater than the impact of bad news/shocks on the volatility of the Bank Nifty returns. This suggests that positive shocks increase volatility in the next period relative to negative shocks of equal magnitude in the Indian banking industry, known as the "anti-leverage effect." Thus, the result of the leverage coefficient (γ) provides substantial proof to reject the study's second hypothesis (*H2*), confirming that the disruption in the volatility due to positive shocks is higher than that of negative shocks, and their impact is not uniform for the Indian Banking series.

4. DISCUSSION

Recent shreds of evidence on the inconclusive findings of volatility, demonstrating the impetuous retortion of stock returns to abrupt news events, is an academic puzzle for discerning asymmetric returns behavior (Thazhungal Govindan Nair, 2022). The literature lacks a comprehensive theoretical basis that simultaneously captures such data patterns. However, a large body of literature in finance and economics demonstrates the persistence of volatility in asset returns within the financial time series (Baillie & Morana, 2009; Charfeddine & Khediri, 2016; Greene & Fielitz, 1977). In other words, the market reacts to information gradually over time rather than responding immediately to it when it enters the financial market. The findings of the EGARCH model suggest that the volatility of Bank Nifty returns is persistent over time; when it rises, it remains high for a considerable time and returns to its mean only gradually. Therefore, a new shock will have a long-term influence on the return's series.

Since information decays slowly in the Bank Nifty returns series, historical information is more significant than new knowledge for market participants. This demonstrates what is referred to be long-memory behavior. Therefore, rather than the nature of the information, these trends are probably caused by the market microstructures. The results are consistent with those reported by Patton and Sheppard (2015) and Katsiampa et al. (2019), while low volatility persistence was found by Yaya et al. (2019). However, an asset with a high β is no longer considered a safe haven or good hedge due to its inability to effectively protect investors from volatile market conditions (Elder & Serletis, 2008). Because of the persistent nature of volatility, investors need to consider the volatility shocks for forecasting long-term returns behavior and deciding optimal hedging (Abakah et al., 2020).

The result for the EGARCH asymmetry term (γ) shows a positive coefficient for Bank Nifty returns. The "anti-leverage effect," which is recognized in extant research, has been theoretically documented by Nelson (1991) and Glosten et al. (1993). Over time, various studies have shown the significance of the "anti-leverage effect" (Ghysels et al., 2005; Harrison & Zhang, 1999; Ludvigson & Ng, 2007). According to the EGARCH results, positive shocks/news cause more volatility in the subsequent period than negative shocks/news of the same size. In light of this, it is apparent that volatility rises when returns unexpectedly increase compared to when returns decline. However, a stylized feature of financial volatility is that bad news impacts volatility more than good news (Black & Cox, 1976).

According to Veronesi (1999), investors' behavior is related to the state of the business cycle

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and the impacts of macroeconomic news on the financial market instruments. In principle, positive economic advancements are projected to significantly influence the volatility of the Bank Nifty returns. This explains why the present study observed a positive gamma (γ) value corresponding to the inverse leverage effect in the Indian Bank Nifty returns. Due to the leveraging effect, a negative gamma value may be observed in risky assets (but not all). However, due to the financial and economic turmoil interwoven with COVID-19, a negative gamma value was expected during the study period. In line with the findings of Zhang et al. (2020), the recent outbreak of the COVID-19 pandemic has wobbled uncertainty in the financial markets. However, Ledwani et al. (2021) shred evidence for a faster market correction in economies like India after a negative shock. As a result, the Indian stock market tends to bounce back more quickly after negative shocks. The market correction hypothesis and the market overreaction theory support the decline and speedy recovery during such periods.

CONCLUSIONS

The objective of the study was to model the conditional variance of Bank Nifty Index returns in India. The primary analysis demonstrates that the sampling distribution of mean among Bank Nifty returns is non-normal. Therefore, to examine the long-memory and asymmetric effects, the current study has focused on a battery of GARCH specifications. However, the model selection criteria exhibit that among the GARCH-type models, the EGARCH model with Student's t distribution provides a better description for conditional variance exhibiting lower forecasting errors.

The results demonstrated that the degree of volatility of returns has a tendency to persist and return to the mean gradually. Besides, the volatility of Bank Nifty returns tends to rise in reaction to positive shocks as opposed to negative shocks of equal magnitude, suggesting the possibility of an "anti-leverage effect." This result supports the rapid market correction following the panic-induced decline in the Indian Bank Nifty returns. On the other hand, good earnings reports, an announcement of a new product, corporate acquisitions, government policies, and other positive economic indicators induce investors' behavior, causing a burlier movement in the Indian Bank Nifty returns. However, the sample period used in this study corresponds to a period under stress (a bear market); thus, interesting insights can be drawn from a comparison with a euphoric period (a bull market). Therefore, a more comprehensive examination of such comparison should be conducted in future research.

AUTHOR CONTRIBUTIONS

Conceptualization: Nikhil M. N., Lithin B. M., Sanket Ledwani.
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REFERENCES

1. Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics and Finance, 69,* 680-691. https://doi.org/10.1016/j.iref.2020.06.035

2. Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review, 102*(3), 59-64. https://doi.org/10.1257/aer.102.3.59

3. Ahmed, R. R., Vveinhardt, J., Streimikiene, D., & Channar, Z. A. (2018). Mean reversion in international markets: evidence from GARCH and half-life volatility models. *Economic Research-Ekonomska Istrazivanja, 31*(1), 1198-1217. https://doi.org/10.1080/1331677X.2018.1456358

4. Âhou, R. B. A., & Gueyie, J.-P. (2001). Canadian chartered banks' stock returns and exchange rate risk. *Management Decision, 39*(4), 285-295. https://doi.org/10.1108/EUM0000000005463

5. Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. *Journal of Economics and Business, 100,* 7-25. https://doi.org/10.1016/j.jeconbus.2018.07.003

6. Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation, 23*(1), 1-26. https://doi.org/10.1016/j.jfi.2013.11.001

7. Baele, L., de Jonghe, O., & vander Vennet, R. (2007). Does the stock market value bank diversification? *Journal of Banking and Finance, 31*(7), 1999-2023. https://doi.org/10.1016/j.jbankfin.2006.08.003

8. Baillie, R. T., & Morana, C. (2009). Modelling long memory and structural breaks in conditional variances: An adaptive FIGARCH approach. *Journal of Economic Dynamics and Control, 33*(8), 1577-1592. https://doi.org/10.1016/j.jedc.2009.02.009

9. Begley, T. A., Purnanandam, A., & Zheng, K. (2017). The Strategic Underreporting of Bank Risk. *Review of Financial Studies, 30*(10), 3376-3415. https://doi.org/10.1093/rfs/hhx036

10. Bennett, R. L., Hwa, V., & Kwast, M. L. (2015). Market discipline by bank creditors during the 2008–2010 crisis. *Journal of Financial Stability, 20,* 51-69. https://doi.org/10.1016/j.jfs.2015.06.003

11. Bhatia, P., & Gupta, P. (2020). Sub-prime Crisis or COVID-19: A Comparative Analysis of Volatility in Indian Banking Sectoral Indices. *FIIB Business Review, 9*(4), 286-299. https://doi.org/10.1177/2319714520972210

12. Bhattacharyay, B. N. (2013). Determinants of bond market development in Asia. *Journal of Asian Economics, 24,* 124-137. https://doi.org/10.1016/j.asieco.2012.11.002

13. Black, F., & Cox, J. C. (1976). Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. *The Journal of Finance, 31*(2), 351-367. https://doi.org/10.1111/J.1540-6261.1976.TB01891.X

14. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

15. Brealey, R., Leland, H. E., & Pyle, D. H. (1977). Informational Asymmetries, Financial Structure and Financial Intermediation. *The Journal of Finance, 32*(2), 371-387. https://doi.org/10.1111/j.1540-6261.1977.tb03277.x

16. Brooks, C. (2008). *Introductory econometrics for finance* (2nd ed.). Cambridge University Press.

17. Brooks, C. (2019). *Introductory Econometrics for Finance.* Cambridge University Press. https://doi.org/10.1017/9781108524872

18. Brooks, C., & Burke, S. P. (2003). Information criteria for GARCH model selection. *European Journal of Finance, 9*(6), 557-580. https://doi.org/10.1080/1351847021000029188

19. Bryant, J. (1980). A model of reserves, bank runs, and deposit insurance. *Journal of Banking and Finance, 4*(4), 335-344. https://doi.org/10.1016/0378-4266(80)90012-6

20. Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The Econometrics of Financial Markets.* Princeton University Press. https://doi.org/10.2307/J.CTT7SKM5

21. Candelon, B., Carare, A., & Miao, K. (2016). Revisiting the new normal hypothesis. *Journal of International Money and Finance, 66,* 5-31. https://doi.org/10.1016/j.jimonfin.2015.12.005

22. Charfeddine, L., & Khediri, K. B. (2016). Time varying market efficiency of the GCC stock markets. *Physica A: Statistical Mechanics and Its Applications, 444,* 487-504. https://doi.org/10.1016/j.physa.2015.09.063

23. Christoffersen, S. E. K., & Simutin, M. (2017). On the demand for high-beta stocks: Evidence from mutual funds. *Review of Financial Studies, 30*(8), 2596-2620. https://doi.org/10.1093/rfs/hhx022

24. Crockett, A. (2002). Market discipline and financial stability. *Journal of Banking and Finance, 26,* 977-987. Retrieved from https://nscpolteksby.ac.id/ebook/files/Ebook/Journal/2015/Banking%20and%20Finance/Surya%20Negara%20Vol.%2026/Volume%2026%20Issue%205/Market%20discipline%20and%20financial%20stability.pdf

25. De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability. *Journal of Financial Intermediation, 19*(3), 387-417. https://doi.org/10.1016/j.jfi.2009.04.001

26. Demirer, M., Diebold, F. X., Liu, L., & Yilmaz, K. (2018).

http://dx.doi.org/10.21511/bbs.18(1).2023.11

Estimating global bank network connectedness. *Journal of Applied Econometrics, 33*(1), 1-15. https://doi.org/10.1002/jae.2585

27. Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies, 51*(3), 393-414. https://doi.org/10.2307/2297430

28. Diamond, D. W., & Dybvig, P. H. (1983). Bank Runs, Deposit Insurance, and Liquidity. *Journal of Political Economy, 91*(3), 401-419. Retrieved from http://www.jstor.org/stable/1837095

29. Dickey, D. A., & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica, 49*(4), 1057-1072. https://doi.org/10.2307/1912517

30. Elder, J., & Serletis, A. (2008). Long memory in energy futures prices. *Review of Financial Economics, 17*(2), 146-155. https://doi.org/10.1016/j.rfe.2006.10.002

31. Elnahass, M., Trinh, V. Q., & Li, T. (2021). Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets, Institutions and Money*, *72,* 101322. https://doi.org/10.1016/j.intfin.2021.101322

32. Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007. Retrieved from https://www.jstor.org/stable/1912773

33. Flannery, M. J. (2001). The Faces of "Market Discipline". *Journal of Financial Services Research,* 20(3), 107-119. https://doi.org/10.1023/A:1012455806431

34. Franses, P. H., & Van Dijk, D. (1996). Forecasting stock market volatility using (non-linear) Garch models. *Journal of Forecasting, 15*(3), 229-235. https://doi.org/10.1002/(SICI)1099-131X(199604)15:3%3C229::AID-FOR620%3E3.0.CO;2-3

35. Fratzscher, M., & Rieth, M. (2015). *DP10370 Monetary Policy. Bank Bailouts and the Sovereign-Bank Risk Nexus in the Euro Area* (CEPR Discussion Papers No. 10370). Retrieved from https://cepr.org/publications/dp10370

36. Ghysels, E., Santa-Clara, P., & Valkanov, R. (2005). There is a risk-return trade-off after all. *Journal of Financial Economics, 76*(3), 509-548. https://doi.org/10.1016/J.JFINECO.2004.03.008

37. Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance, 48*(5), 1779-1801. https://doi.org/10.1111/J.1540-6261.1993.TB05128.X

38. Greene, M. T., & Fielitz, B. D. (1977). Long-term dependence in common stock returns. *Journal of Financial Economics, 4*(3), 339-349. https://doi.org/10.1016/0304-405X(77)90006-X

39. Gupta, A. (2010). Financial crisis enforcing global banking reforms. *Business Strategy Series, 11*(5), 286-294. https://doi.org/10.1108/17515631011080696

40. Harrison, P., & Zhang, H. H. (1999). An investigation of the risk and return relation at long horizons. *Review of Economics and Statistics, 81*(3), 399-408. https://doi.org/10.1162/003465399558337

41. Hasan, I., Siddique, A., & Sun, X. (2015). Monitoring the "invisible" hand of market discipline: Capital adequacy revisited. *Journal of Banking and Finance, 50,* 475-492. https://doi.org/10.1016/j.jbankfin.2014.03.029

42. Hoggarth, G., Reis, R., & Saporta, V. (2002). Costs of banking system instability: Some empirical evidence. *Journal of Banking & Finance, 26*(5), 825-8556. Retrieved from https://personal.lse.ac.uk/reisr/papers/02-HoggarthReisSaporta.pdf

43. Karmakar, M. (2005). Modeling Conditional Volatility of the Indian Stock Markets. *Vikalpa: The Journal for Decision Makers, 30(3).* https://doi.org/10.1177/0256090920050303

44. Karmakar, M. (2007). Asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economic Journal, 8*(1), 99-116. https://doi.org/10.1177/139156140600800106

45. Kasman, S., Vardar, G., & Tunç, G. (2011). The impact of interest rate and exchange rate volatility on banks' stock returns and volatility: Evidence from Turkey. *Economic Modelling, 28*(3), 1328-1334. https://doi.org/10.1016/j.econmod.2011.01.015

46. Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 62,* 35-52. https://doi.org/10.1016/j.intfin.2019.05.003

47. Kumar, K., & Prakash, A. (2019). Examination of sustainability reporting practices in Indian banking sector. *Asian Journal of Sustainability and Social Responsibility, 4*(1). https://doi.org/10.1186/s41180-018-0022-2

48. Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking and Finance, 69*(1), S25-S34. https://doi.org/10.1016/j.jbankfin.2015.06.022

49. Ledwani, S., Chakraborty, S., & Shenoy, S. S. (2021). Spatial tale of G-7 and Brics stock markets during COVID-19: An event study. *Investment Management and Financial Innovations, 18*(2), 20-36. https://doi.org/10.21511/imfi.18(2).2021.03

50. Lin, Z. (2018). Modelling and forecasting the stock market volatility of SSE Composite Index using GARCH models. *Future Generation Computer Systems, 79,* 960-972. https://doi.org/10.1016/j.future.2017.08.033

51. Ludvigson, S. C., & Ng, S. (2007). The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics, 83*(1), 171-222. https://doi.org/10.1016/J.JFINECO.2005.12.002

52. Mahajan, V., Thakan, S., & Malik, A. (2022). Modeling and Forecasting the Volatility of

NIFTY 50 Using GARCH and RNN Models. *Economies, 10*(5), 102. https://doi.org/10.3390/economies10050102

53. Moshirian, F., & Wu, Q. (2009). Banking industry volatility and banking crises. *Journal of International Financial Markets, Institutions and Money, 19*(2), 351-370. https://doi.org/10.1016/j.intfin.2008.02.002

54. Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59*(2), 347. https://doi.org/10.2307/2938260

55. Padhi, P. (2006). Persistence and Asymmetry Volatility in Indian Stock Market. *Journal of Quantitative Economics, 4,* 103-113. https://doi.org/10.1007/BF03546451

56. Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics, 97*(3), 683-697. https://doi.org/10.1162/REST_a_00503

57. Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika,* 75(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

58. Rout, S. K., & Mallick, H. (2022). Sovereign Bond Market Shock Spillover Over Different Maturities: A Journey from Normal to Covid-19 Period. *Asia-Pacific Financial Markets, 29,* 697-734. https://doi.org/10.1007/S10690-022-09371-X

59. Stiroh, K. J. (2006). New evidence on the determinants of bank risk. *Journal of Financial Services Research, 30*(3), 237-263. https://doi.org/10.1007/s10693-006-0418-5

60. Suhadak, S., Kurniaty, K., Handayani, S. R., & Rahayu, S. M. (2019). Stock return and financial performance as moderation variable in influence of good corporate governance towards corporate value. *Asian Journal of Accounting Research, 4*(1), 18-34. https://doi.org/10.1108/AJAR-07-2018-0021

61. Thazhungal Govindan Nair, S. (2022). Price extremes and asymmetric dependence structures in stock returns: the emerging market evidence. *Journal of Economic Studies, 49*(8), 1502-1523. https://doi.org/10.1108/JES-10-2021-0507

62. Thiripalraju, M., & Acharya, R. H. (2010). Modeling Volatility for the Indian Stock Market. *The IUP Journal of Applied Economics, 9*(1), 79-105. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1535856

63. Tripathy, T., & Gil-Alana, L. A. (2015). Modelling time-varying volatility in the Indian stock returns: Some empirical evidence. *Review of Development Finance, 5*(2), 91-97. https://doi.org/10.1016/j.rdf.2015.04.002

64. Veronesi, P. (1999). Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model. *The Review of Financial Studies, 12*(5), 975-1007. Retrieved from https://www.jstor.org/stable/2645973

65. Williams, B. (2014). Bank risk and national governance in Asia. *Journal of Banking and Finance, 49,* 10-26. https://doi.org/10.1016/j.jbankfin.2014.08.014

66. Yaya, O. O. S., Ogbonna, A. E., & Olubusoye, O. E. (2019). How persistent and dynamic inter-dependent are pricing of Bitcoin to other cryptocurrencies before and after 2017/18 crash? *Physica A: Statistical Mechanics and Its Applications, 531,* 121732. https://doi.org/10.1016/j.physa.2019.121732

67. Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36,* 101528. https://doi.org/10.1016/j.frl.2020.101528

http://dx.doi.org/10.21511/bbs.18(1).2023.11