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Measuring Asymmetric Volatility of Bank Nifty Index using Egarch Model

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Abstract: The paper examines the significance of volatility models in forecasting future volatility for effective portfolio allocation and risk reduction. It compares the performance of symmetric and asymmetric models in estimating conditional variance, as well as linear and non-linear GARCH models. Using secondary data from the National Stock Exchange's Nifty Bank index, the study applies Exponential GARCH (1,1) to measure asymmetric volatility. It conducts various tests to confirm the suitability of the data for analysis. The results indicate clustering of volatility in Nifty Bank returns over four years, with the presence of asymmetrical effects and leverage constants. The study concludes that negative information has a greater impact on volatility than positive surprises, and that market fluctuations are inversely related to stock market performance. This research provides valuable insights for portfolio selection, risk management, and asset pricing in the context of increasing volatility across various markets and industries.

Keywords: National Stock Exchange's, clustering, Nifty Bank, volatility

I. INTRODUCTION

It is essential to comprehend financial markets, where volatility appears to play a significant role. Forecasting and modelling volatility have become increasingly crucial as market and asset volatility has increased. Investors, scholars, and regulators have been paying attention to volatility because it is essential to valuing assets with uncertain future returns. Theories of economic and financial volatility are controversial. Financial markets must have volatility. Additionally, it affects business and personal investments as well as market uncertainty. In modern financial research, the variance of the rate of return is often used to describe and quantify the volatility of financial asset returns. Despite many models and methodologies, not all are effective for all stock markets, making market volatility predictions difficult. Thus, market returns and volatility pose a challenge for academics and financial professionals to predict.

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The standard econometric model assumes that the variance remains constant over time. An accurate measurement of the rate of return's variation is closely linked to the accuracy of portfolio selection, the effectiveness of risk management, and the rationality of asset pricing. Nevertheless, the validity of this assumption has been disproven due to advancements in financial theory and extensive empirical research. Furthermore, the volatility of asset prices is regarded as one of the most puzzling phenomena in the field of monetary economics. Investors encounter a substantial obstacle in fully understanding volatility (Caiado, J. 2004 [4]). The primary measure of financial market volatility is the deviation from anticipated future asset valuations. Volatility, a measure of uncertainty, represents the potential for an asset's future price to fluctuate unpredictably (Bekaert and Wu 2000 [3]). The typical quantification of this uncertainty is either variance or standard deviation. The leverage effect and the volatility feedback hypothesis are currently the prevailing theories in academia regarding the relationship between these two phenomena. Negative news often leads to a decline in stock prices due to increased leverage, which in turn raises the leverage factor and amplifies stock volatility. Conversely, volatility feedback, defined as unexpected fluctuations in stock prices that ultimately increase future risk, decreases in magnitude. A multitude of variables impact the price fluctuations of the stock market. Firstly, the stock market is significantly influenced by monetary policy. One year after implementing an accommodative monetary policy, the probability of the stock market index experiencing growth has increased. Conversely, the likelihood of a decline in the stock market index will increase if a moderately restrictive monetary policy is implemented within a year. The impact of interest rate liberalization on risk-free interest rates ranks second in importance. When examining the primary global financial markets, there is a more pronounced correlation between the fluctuations in risk-free interest rates and the current state of the stock market (Jayasuriya, S., et al, 2009) [8]. The risk-free interest rate and the cost of capital invested in the stock market tend to co-occur with the upward movement of interest rates. Consequently, it is expected that the economy will gradually strengthen as the reform dividend is distributed, leading to a higher return on investment in the stock market. Volatility refers to the tendency of prices to fluctuate sharply, although not all volatility is detrimental. Financial market volatility has a direct impact on both macroeconomic and economic stability.

Governments worldwide prioritise significant economic risks. Historically, financial economists and professionals have primarily focused their attention on the volatility of financial markets (Srinivasan and Ibrahim, 2010 [10]).

The literature has recently extensively examined various aspects of the stock market, such as the leverage effect of volatility, the short-term

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memory of volatility, and the GARCH effect. Nevertheless, some researchers have discovered that when the GARCH model integrates short-term memory, a perplexing phenomenon often arises due to the diminishing sampling interval. The assumption of a normal distribution is made to describe the extreme values of the yield, although this ideal scenario is often not confirmed.

It has been found that samples of time-series data exhibit dependence on their past values, influenced by prior information, and this is demonstrated through consistent variability. Market volatility is observed to vary over time and demonstrates clustering. Several subsequent methods were developed specifically for assessing the scedastic function, with the ARCH models being a prominent and frequently employed approach. The primary objective of developing these models was to predict future volatility, enabling more efficient portfolio allocation and risk reduction (Engle, 1982 [1]). ARCH is a tool utilized for examining the volatility of time series data. (Bollerslev 1986 [2]) proposed the GARCH method as a means of assessing stochastic volatility. Nevertheless, GARCH models facilitate the analysis of volatility clustering and leptokurtosis, which are essential for developing advanced GARCH techniques. However, they do not explain the leverage effect.

II. LITERATURE REVIEW

The Indian stock market exhibits an asymmetric volatility pattern and a risk-return relationship. (Balaban and Bayar 2005 [5]) has conducted the research to test in 14 countries the relationship between stock market returns and their forecast volatility derived from the symmetric and asymmetric conditional heteroscedasticity models. Both weekly and monthly returns, along with their volatility, are investigated. An out-of-sample testing methodology is employed using volatility forecasts instead of analysing the relation between stock returns and their in-sample volatility estimates. Expected volatility is derived from the ARCH (p), GARCH (1,1), GJR-GARCH(1,1) and EGARCH(1,1) forecast models. Expected volatility is found to have a significant negative or positive effect on country returns in a few cases. Unexpected volatility negatively impacts weekly stock returns in six to seven countries and monthly returns in nine to eleven countries, depending on the volatility forecasting model. The study by (Karmakar 2007 [6]) explores this relationship in the Indian stock market. The author analyzes the volatility dynamics of the Indian stock market using daily closing prices of the Sensex from January 2003 to December 2019. The study examines whether the Indian stock market shows volatility clustering and volatility persistence. The results confirm the presence of volatility clustering in the Indian stock market. Additionally, the study finds that Indian stock return volatility exhibits lower persistence in volatility compared to the US stock market. (Alberg, D., et al, 2008 [7]) has conducted a comprehensive empirical analysis of the mean return and conditional variance of Tel Aviv Stock Exchange (TASE) indices using various GARCH models. The prediction performance of these conditional changing variance models is compared to newer asymmetric GJR and APARCH models. They quantify the day-of-the-week effect and the leverage effect, and test for asymmetric volatility. The results show that the asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The EGARCH model, which utilises a skewed Student-t distribution, is the most successful for forecasting TASE indices. (Su, C. 2010 [9]), conducted a study with the main aim is to analyze whether the long term volatility is more extensive during the crisis period than before the crisis, and compare the movements of the return volatility of Chinese stock market to the other stock markets before and throughout the crisis period. They applied the daily data from January 2000 to April 2010 and split the time series into two parts: before the crisis and during the crisis period. They then applied both GARCH and EGARCH models. The empirical results suggest that the EGARCH model fits the sample data better than the GARCH model in modelling the volatility of Chinese stock returns. (Sharma, P. 2015 [16]) has conducted the study to compare the daily conditional variance forecasts of seven GARCH-family models. The research paper investigates whether the advanced GARCH models outperform the standard GARCH model in forecasting the variance of stock indices. The results showed that the standard GARCH model outperforms more advanced GARCH models and provides the best one-step-ahead forecasts of the daily conditional variance. The results are robust to the choice of performance evaluation criteria, different market conditions and the data-snooping bias.

(Vasudevan & Vetrivel 2016 [15]), analyzes the volatility of BSE-SENSEX Index returns in the Indian stock market using daily data from 1997-2015. It compares symmetric and asymmetric GARCH models, revealing that asymmetric models outperform symmetric models in forecasting conditional variance, confirming the presence of the leverage effect. This aligns with previous research indicating asymmetric GARCH models are more effective. (Raju, V. V. R. 2022 [19]), explores the use of GARCH family models for predicting stock prices of a subset of NIFTY 50 Indian businesses. The study employs an analytical research design and purposive sampling to analyse data from the National Stock Exchange of India's index. The researchers used various forecasting models, including the standard GARCH (1,1) model and its variants, to detect the ARCH effect. The study highlights the importance of understanding market volatility and potential returns for informed stock selection, as stock price forecasting remains a challenging topic. (Lama et al. 2015 [13]) study provided proof that the EGARCH tool was superior in predicting the global cotton prices due to its capacity for annexing asymmetrical variability. (Ndwiga and Muriu 2016 [14]) showed that volatility surprises on returns are transient in the equities markets and that no notable leverage effect has been detected. (Raja Babu et al. (2020 [17]), negative shocks in the banking index produce greater volatility than positive surprises.

(Samineni et al. 2020 [18]), The study has conducted modelling and forecasting of the volatility (conditional variance) of the SENSEX Index returns in the Indian stock market, using daily data covering the period from January 1, 1996, to January 29, 2010.

The forecasting models that are considered in this study range from the relatively simple GARCH (1,1) model to relatively complex GARCH models (including Exponential GARCH (1,1) and Threshold GARCH (1,1) models). Based on out-of-sample forecasts and a majority of evaluation measures, our result shows that the symmetric GARCH model performs better in forecasting the conditional variance of the SENSEX Index return rather than the asymmetric GARCH models, despite the presence of the leverage effect. (Kristoufek, L. 2014 [12]) study explores the leverage effect, examining the relationship between returns and volatility in energy commodities futures like Brent and WTI crude oils, natural gas, and heating oil. The study reveals long-term volatility, stationarity, and non-stationarity, with the standard leverage effect for crude oils and heating oil, and an inverse leverage effect for natural gas.

III. RESEARCH METHODOLOGY

EGARCH Model: The linear GARCH model, which states that equal positive and negative shocks produce the same fluctuations in equity prices, is insufficient for explaining the asymmetry effect in financial markets. Nelson introduced the exponential GARCH model, also known as the EGARCH model, which uses the same governing equation but with varying degrees of volatility.

$$\mathbf{Z_t = \alpha_0 + (\alpha_1 * Z_{t-1}) + E_t}$$

$$\mathbf{In\ (V_t^2) = \beta_0 + \sum^{0}_{i=1} \left(\beta_i \left|\frac{Et-1}{Vt-1}\right| + \mu_i\left(\frac{Et-1}{Vt-1}\right)\right) + \sum^{\gamma\gamma}_{i=1}(\gamma_t * In(V^2_{t-1}))}$$

Conditional Variance Equation

Where ln (Vt ^{2}) is the logarithm of conditional variance, i is the order of lagged variable, γi is the constant value for the ith order of lag, μi is a coefficient for the lag variable, and μ is generally used to check the leverage effect in the stock market data modelling. If $\mu_1 = \mu_2 = . . . = 0$ is true, then the equity price's response to news influence is asymmetric; if μi < 0 is true, then asymmetricity exists, and the influence of negative news on the market is more significant than the impact of positive news; and if μi > 0 is true, then asymmetric effect exists, but the impact of unfavorable news is weaker than favorable news.

A. Source of Secondary Data

The study considered secondary data, which was pooled from the National Stock Exchange. Nifty Bank was the index used for analysis. The closing values of Nifty Bank were collected from January 1, 2019, to December 31, 2022.

B. Volatility Measurement Tool

Exponential GARCH (1,1) was used for measuring asymmetric volatility. The time series data collected was converted to stationary, and the unit root was checked using the Augmented Dickey-Fuller Test. A heteroscedasticity test was conducted to determine the presence of an ARCH effect in the data. The data is now suitable for further analysis.

IV. RESULTS

The volatility of equity returns generally exhibits an asymmetric reaction to positive and negative shocks. Economic explanations for this phenomenon are leverage and a volatility feedback effect (Baur, D. G. 2012 [11]). The research begins with a first-differencing tool applied to the closing values of the Nifty Bank to convert the data into stationary. Figure 1 illustrates the clustering of volatility of the Nifty Bank over four years. It is assumed that massive deviations in variance of returns over an extended period and minor changes in log prices for a prolonged period indicate that volatility is clustering, but variance may vary with time.

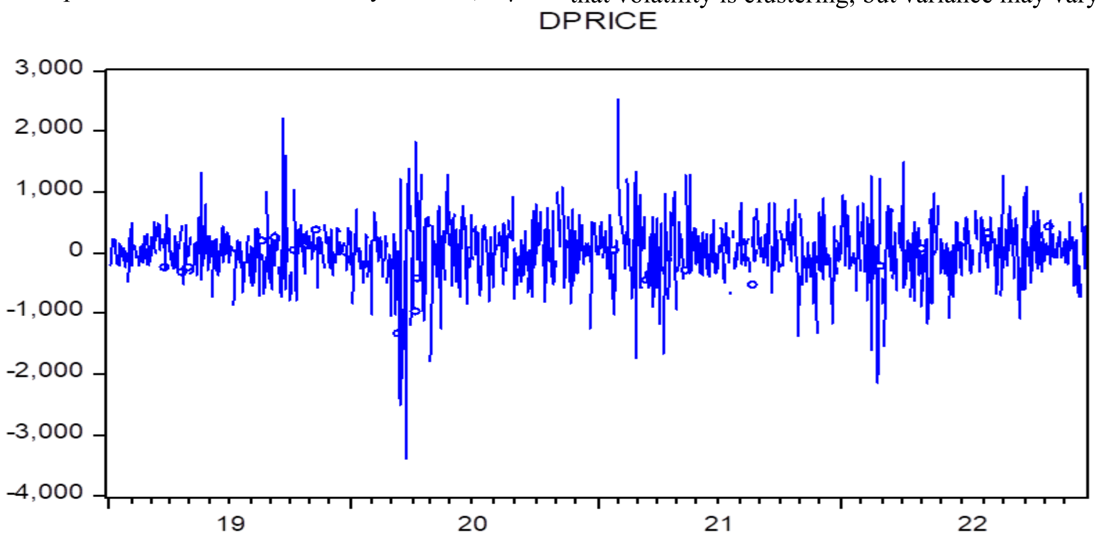

Figure. 1: Line Diagram of Nifty Bank Returns

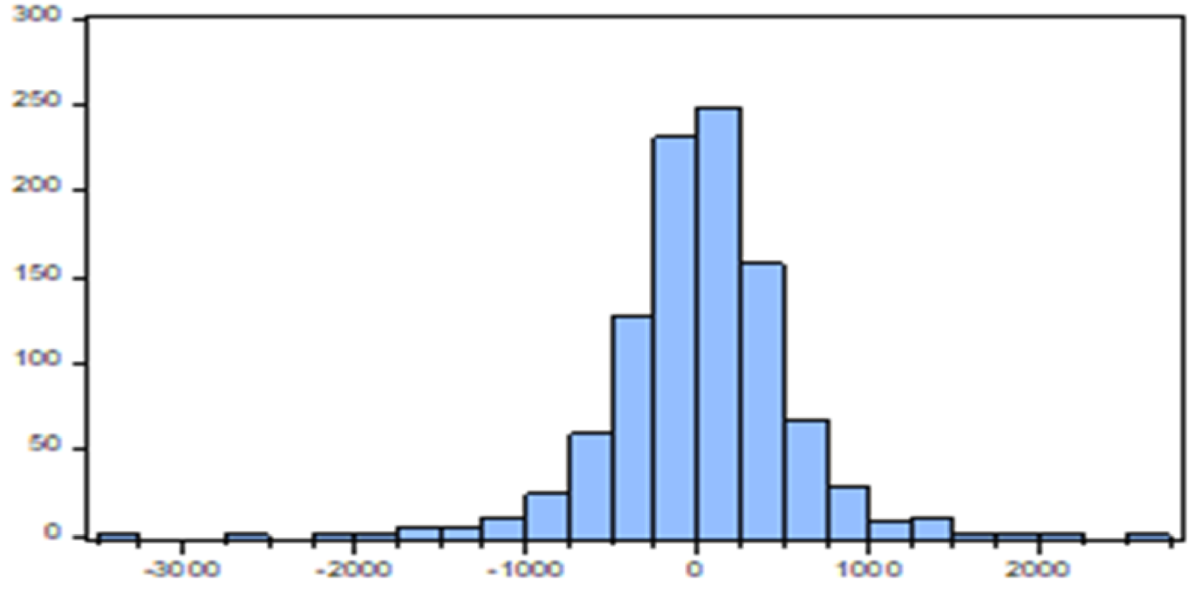

Figure. 2: Normal Distribution of Nifty Bank Index – Daily Price

Table. 1: Results of Normality Distribution

Series: DPRICE	
Sample 1/01/2019 12/30/2022	
Observations 992	
Mean	15.71981
Median	31.37500
Maximum	2523.550
Minimum	-3399.950
Std. Dev.	495.6522
Skewness	-0.499710
Kurtosis	7.949066
Jarque-Bera	1053.673
Probability	0.00000

Null Hypothesis: DPRICE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic – based on SIC, maxlag =21)

Table. 2: Results of the Unit Root Test

		t- Statistic	Prob*
Augmented Dickey–Fuller test statistic		**-29.989000**	**0.0000**
Test critical values	1% level	-3.436729	
	5% level	-2.864245	
	10% level	-2.568262	

Table. 3: ARCH-LM Test for Residuals

F-statistic	**74.84635**	**F (1,2475)**	**0**
Obs*R-squared	74.57074	Prob. Chi-Square (1)	0

Table. 4: Arch Test

Heteroskedasticity Test: ARCH			
F-statistic	10.36338	Prob F (1,989)	0.0013
Obs R-Squared	10.27665	Prob. Chi-Square (1)	0.0013

Normality Distribution was summarized in Table 1. The mean of the Nifty Bank returns is positive, suggesting that the price improved during the period—sign of negative skewness, indicating a likelihood of earnings exceeding the mean. Kurtosis greater than three signifies a leptokurtic nature. Furthermore, the Jarque-Bera statistics were 1053.6, which is statistically significant, indicating that the residuals are standard in the distribution.

Table 2 presents the Augmented Dickey-Fuller test, which is applied to determine the presence of a unit root in the data. The ADF statistic value is below the 5% level, which indicates that the data considered for the period is stationary. Hence, the outcome confirms the stationarity in the series. The Lagrange Multiplier test is used to identify heteroscedasticity in the residuals.

Test results from Table 3 are highly significant. As the p-value is less than 5%, the alternative hypothesis is accepted, indicating the presence of an arch effect in the residuals. Consequently, the result documents the assessment of a non-linear GARCH model. Thus, the EGARCH model is applied to model the volatility of returns in the index.

Table 4 illustrates that there is no arch effect during the research period. Furthermore, the researcher tests the DPRICE movement using the EGARCH Model.

Dependent Variable: DPRICE
Method: ML ARCH – Normal distribution (BFGS / Merquardt steps)
Date: 07/15/23 Time: 12:31
Sample (adjusted): 1/02/2019 12/30/2022
Included observations: 992 after adjustments
Convergence achieved after 48 iterations
Coefficient covariance computed using the outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C (2) + C(3)* ABS(RESID(-1)@SQRT(GARCJ(-1)))+C(4)*RESID (-1) @SQRT(FARCH(-1)) + C(5)*LOG(GARCH(-1))

Table 5: EGARCH Model

Variance	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	11.02331	13.12239	0840038	0.4009
Variance Equation				
C (2)	0.313048	0.101841	3.073887	0.0021
C (3)	0.182058	0.022925	7.941440	0.0000
C (4)	-0.094811	0.013254	-7.153331	0.0000
C (5)	0.963314	0.008555	112.5968	0.0000

To calculate the Nifty Bank returns, the Exponential GARCH framework is employed, and the results are displayed in Table 5.

C (4) represents the leverage constant, i.e., γ, which is negative and notable, unveiling an asymmetrical effect on return. The research reveals a negative relationship between past and future returns.

V. CONCLUSION

In the present study, asymmetric volatility in Nifty Bank returns was analysed using the EGARCH (1,1) model. The first differencing tool was applied to the time series data to convert it into stationary data. The dataset has a heteroscedastic nature. When the stock market soars, fluctuations tend to go down, and when the market declines, they get worse. The leverage effect is evident, as the asymmetric parameter is significantly negative, which means that negative information has a greater impact on volatility than positive surprises of the same magnitude.

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Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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