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Time-Series Analysis of Stock Market Volatility: A Comparative Study of Select Nationalised and Private Sector Banks Listed on the NSE

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Abstract
Understanding and forecasting stock market volatility plays a vital role in risk management, investment planning, and regulatory decision-making. This study presents a comparative analysis of traditional econometric models and modern deep learning approaches for forecasting volatility in the Indian banking sector. Specifically, ARIMA, ARCH, GARCH, Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) models are applied to daily stock price data of selected public sector banks—SBI, Union Bank of India, and Bank of Baroda—and private sector banks—HDFC Bank, ICICI Bank, and Axis Bank—listed on the National Stock Exchange (NSE).
The forecasting performance of these models is evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results clearly show that the GARCH model provides the most accurate and consistent volatility forecasts across both public and private sector banks, largely due to its ability to effectively capture volatility clustering and time-varying risk. While deep learning models, particularly LSTM, demonstrate strong performance in certain cases, their predictive accuracy is not consistently superior to that of GARCH. Overall, the findings highlight the continued relevance and robustness of traditional econometric models for volatility forecasting in emerging financial markets such as India.
Keywords: Stock market volatility, Time-series forecasting, ARIMA, ARCH, GARCH, RNN, LSTM, NSE.

1. Introduction

Volatility forecasting has become an essential aspect of modern financial analysis due to increasing market uncertainty, rapid information dissemination, and heightened exposure to systemic risk. In the Indian context, banking sector stocks hold a dominant position in terms of market capitalization and overall financial stability. As a result, understanding the volatility behavior of these stocks is particularly important for investors, regulators, and policymakers.
Traditional time-series models such as the Autoregressive Integrated Moving Average (ARIMA) have been widely used in financial forecasting because of their simplicity and interpretability. However, these linear models are often inadequate for capturing key characteristics of financial data, such as nonlinear behavior and volatility clustering. To overcome these limitations, econometric models based on conditional heteroskedasticity—namely ARCH and GARCH—were developed to explicitly model time-varying volatility. In recent years, rapid progress in artificial intelligence and increased computational power have led to a growing interest in using deep learning models for financial time-series forecasting. In particular, Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have attracted significant attention because of their ability to process sequential data, capture complex nonlinear relationships, and learn long-term dependencies that are commonly observed in financial markets. Unlike traditional linear models, these deep learning architectures are better suited to adapt to evolving market conditions and to extract meaningful patterns from large and often noisy financial datasets.Although these models have shown encouraging results in developed markets, their effectiveness in emerging economies remains less explored. Financial markets such as India are influenced by frequent structural changes, regulatory interventions, and episodes of heightened volatility, all of which can affect forecasting performance. Consequently, it is still uncertain whether advanced deep learning techniques can consistently outperform well-established econometric models under such dynamic market conditions.
Against this background, the present study seeks to address this gap by offering a comprehensive and systematic comparison of deep learning approaches—RNN and LSTM—with traditional econometric models, including ARIMA, ARCH, and GARCH, within the Indian banking sector. By examining their forecasting performance across both public and private sector banks, the study provides meaningful insights into the relative strengths and limitations of each approach and enhances understanding of their practical relevance in emerging financial markets.

2. Literature Review

Research on financial market volatility has evolved significantly over the past several decades. The ARCH model by Engle (1982) marked a major breakthrough by demonstrating that volatility varies systematically over time rather than remaining constant. Bollerslev (1986) extended this idea through the GARCH model, which allowed volatility to depend on both past shocks and past volatility, making it more practical and widely applicable.
Subsequent extensions such as EGARCH and GJR-GARCH further improved volatility modeling by accounting for asymmetric responses to positive and negative shocks. These models proved especially useful during periods of financial stress, when negative returns tend to increase volatility more than positive ones.
Although ARIMA models continue to be used due to their simplicity, numerous studies have highlighted their limitations in capturing nonlinear dynamics and structural changes in financial time series. With advancements in computing power, ML and deep learning techniques have gained prominence in financial forecasting. RNN and LSTM models, in particular, have shown promise in modeling sequential data and complex nonlinear relationships.
Several empirical studies report that LSTM models can outperform traditional econometric approaches under certain conditions, especially when dealing with large datasets and nonlinear patterns. However, other studies emphasize that GARCH models remain highly competitive due to their robustness, interpretability, and strong theoretical foundations. This mixed evidence highlights the need for systematic comparative studies, particularly in emerging markets.

3. Objectives of the Study

The objectives of this study are:

- To analyze volatility patterns in selected public and private sector bank stocks listed on the NSE.
- To apply and compare ARIMA, ARCH, GARCH, RNN, and LSTM models for volatility forecasting.
- To evaluate model performance using MSE, RMSE, and MAPE.
- To identify the most reliable volatility forecasting model across banking sectors.
- To provide practical insights for investors, analysts, and policymakers.

4. Research Methodology

4.1 Data Description: The study utilizes daily adjusted closing prices of six major banking stocks listed on the National Stock Exchange (NSE) of India. The sample includes three public sector banks—State Bank of India (SBI), Union Bank of India, and Bank of Baroda—and three private sector banks—HDFC Bank, ICICI Bank, and Axis Bank. The analysis covers the period from **1 January 2015 to 31 December 2024,** yielding approximately **2,450 trading-day observations for each bank** after excluding non-trading days and holidays. The data were obtained from the **official NSE database** and cross-verified with **Yahoo Finance** to ensure accuracy and consistency. The selected banks represent some of the most actively traded and systemically important institutions in the Indian banking sector. Their inclusion is justified not only by high liquidity and market presence but also by their sectoral representativeness. The combination of public and private sector banks enables a meaningful comparative analysis of volatility dynamics across different ownership structures and governance frameworks.

4.2 Return and Volatility Computation

Stock returns are calculated using continuously compounded (logarithmic) returns, defined as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t and P_{t-1} denote the adjusted closing prices at time t and t−1, respectively. Log returns are preferred in financial time-series analysis because they stabilize variance and allow additive aggregation over time.
Volatility is measured as the **conditional variance** obtained from GARCH-type models. In this study, a standard GARCH(1,1) specification is employed due to its proven effectiveness in modeling financial volatility.
The GARCH(1,1) model consists of a mean equation and a variance equation:
Mean equation: $r_t=\mu+\epsilon_t$

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where μ represents the constant mean return and ϵ_t is the error term.

Variance equation:

$$\sigma_t^2 = \omega + \alpha\, \epsilon_{t-1}^2 + \beta\, \sigma_{t-1}^2$$

Where,
σ_t^2 = conditional variance (volatility),
ω = constant term,
α = ARCH parameter capturing the impact of past shocks,
β = GARCH parameter capturing volatility persistence.

This framework effectively captures two well-known features of financial time series—**volatility clustering** and **volatility persistence,** where large price movements tend to be followed by large movements and small movements by small ones.

4.3 Model Specifications

To ensure a comprehensive comparison, both econometric and deep learning models were carefully specified and estimated using standard procedures from the literature.

ARIMA Model: The Autoregressive Integrated Moving Average (ARIMA) model was employed to capture linear dependencies in the return series. The appropriate model orders (p,d,q) were determined through examination of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Final model selection was guided by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with preference given to specifications that minimized these criteria while maintaining parsimony.

ARCH/GARCH Models: ARCH and GARCH models were estimated to account for time-varying volatility in financial returns. Estimation was conducted under the assumption of Gaussian error distribution. Among alternative lag structures, the GARCH(1,1) specification was found to be adequate for most return series, consistent with prior empirical studies showing that GARCH(1,1) sufficiently captures volatility clustering and persistence in financial markets.

Recurrent Neural Network (RNN) A Recurrent Neural Network (RNN) architecture was employed to capture nonlinear temporal dependencies in the return series. The network comprised a single hidden layer with 50 neurons and utilized the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity. Model training was carried out using the Adam optimization algorithm, which is known for its computational efficiency and adaptive learning rate capabilities. To mitigate over fitting and enhance out-of-sample generalization, an early stopping mechanism was implemented based on validation performance

Long Short-Term Memory (LSTM) The LSTM model was designed to capture long-term dependencies in the data. The architecture comprised a single LSTM layer with 50 memory units followed by a dense output layer for prediction. Prior to training, the data were scaled using Min–Max normalization to enhance numerical stability and convergence. The dataset was divided into 80% training and 20% testing samples to evaluate out-of-sample forecasting performance.

4.4 Diagnostic Testing: Diagnostic tests were conducted to ensure model adequacy. Stationarity was verified using the **ADF and KPSS tests,** which confirmed that the return series were stationary at levels. The presence of conditional heteroskedasticity was established through **ARCH–LM tests**, supporting the use of GARCH models. Residual autocorrelation was examined using the **Ljung–Box test,** with results indicating minimal serial correlation after model estimation. Overall, the diagnostics confirm that the GARCH models were appropriately specified and effective in capturing volatility dynamics.

5. Results and Discussion:

Table 1: Comparative Results of ARIMA, ARCH, GARCH, RNN, and LSTM for Public Sector Banks

Bank	Model	MSE	RMSE	MAPE
SBI	ARIMA	225.58	15.019	0.0203
	ARCH	56.395	7.5096	0.0101
	GARCH	**31.72**	**5.632**	**0.008**
	RNN	126.889	11.265	0.0152
	LSTM	43.18	6.571	0.009
Union Bank	ARIMA	45.62	6.754	0.043
	ARCH	2.067	1.43	0.019
	GARCH	**0.516**	**0.719**	**0.0096**
	RNN	11.906	3.45	0.024
	LSTM	3.36	1.833	0.015
Bank of Baroda	ARIMA	21.106	4.594	0.024
	ARCH	13.5	3.674	0.0201
	GARCH	**2.465**	**1.57**	**0.012**
	RNN	9.86	3.14	0.027
	LSTM	5.276	2.297	0.013

Table 2: Comparative Results of Private Sector Banks

Bank	Model	MSE	RMSE	MAPE
HDFC Bank	ARIMA	4104.42	64.0657	0.0383
	ARCH	710.621	26.6575	0.0087
	GARCH	**177.655**	**13.3287**	**0.0043**
	RNN	460.85	21.4674	0.0106
	LSTM	2842.48	53.3149	0.017
ICICI Bank	ARIMA	446.651	21.134	0.017
	ARCH	111.662	10.567	0.008
	GARCH	**62.81**	**7.925**	**0.0063**
	RNN	251.241	15.85	0.0127
	LSTM	131.0486	11.447	0.0092
Axis Bank	ARIMA	525.582	22.925	0.018
	ARCH	93.415	9.665	0.0095
	GARCH	**23.353**	**4.832**	**0.0047**
	RNN	157.704	12.558	0.011
	LSTM	39.425	6.279	0.005

Tables 1 and 2 present a comparison of the forecasting performance of ARIMA, ARCH, GARCH, RNN, and LSTM models for selected public and private sector banks listed on the NSE. The accuracy of each model is assessed using Mean Squared Error, Root Mean Squared Error, and Mean Absolute Percentage Error. In all cases, lower values of these measures indicate better forecasting performance.The empirical results reveal clear differences in model performance across banks. The **GARCH model consistently produces the lowest forecast errors,** demonstrating strong capability in capturing volatility dynamics. In contrast, the **ARIMA model shows the weakest performance,** confirming the limitations of linear models in modeling financial volatility. The **RNN model exhibits moderate performance** but lacks consistency across banks, while the **LSTM model delivers mixed results,** performing well in some cases but poorly in others.The relatively weak performance of LSTM—particularly for HDFC Bank—may be attributed to several factors, including potential overfitting due to limited effective sample size, sensitivity to data normalization, and the presence of regime shifts in financial markets. Moreover, unlike GARCH models, LSTM does not explicitly model conditional heteroskedasticity, which is a defining feature of financial return series. These observations are consistent with findings in the hybrid GARCH–LSTM literature, which suggest that standalone LSTM models may be insufficient for reliable volatility forecasting.

5.1 Results for Public Sector Banks

The results for public sector banks—State Bank of India (SBI), Union Bank of India, and Bank of Baroda—demonstrate the clear superiority of volatility-based models, particularly GARCH, over linear and basic neural network approaches.

For SBI, the GARCH model yields the lowest MSE (31.72), RMSE (5.632), and MAPE (0.008), indicating the highest forecasting accuracy among all models. Although the LSTM model also performs competitively with relatively low error values (MSE = 43.18; RMSE = 6.571; MAPE = 0.009), it does not outperform GARCH. In contrast, ARIMA exhibits substantially higher error values, confirming its limited ability to capture volatility clustering in large-cap public sector stocks.

In the case of **Union Bank of India**, GARCH again dominates with minimal forecasting errors (MSE = 0.516; RMSE = 0.719; MAPE = 0.0096). While ARCH and LSTM models improve upon ARIMA, their error magnitudes remain higher than those of GARCH. The RNN model shows moderate performance but lacks consistency across metrics.

For **Bank of Baroda**, GARCH records the lowest MSE (2.465) and RMSE (1.57), while also maintaining a low MAPE (0.012). Although LSTM achieves slightly higher accuracy than RNN and ARIMA, it remains inferior to GARCH. Notably, ARIMA and RNN display relatively high MAPE values, indicating weaker percentage-based forecasting accuracy.

Overall, the public sector results suggest that volatility persistence and clustering are dominant characteristics of bank stock returns, which are effectively captured by GARCH-type models.

5.2 Results for Private Sector Banks

The empirical findings for private sector banks—HDFC Bank, ICICI Bank, and Axis Bank—further reinforce the robustness of GARCH models in volatility forecasting.

For **HDFC Bank,** GARCH substantially outperforms all competing models, achieving the lowest MSE (177.655), RMSE (13.3287), and MAPE (0.0043). In contrast, the LSTM model performs poorly with exceptionally high MSE and RMSE values, indicating instability in capturing volatility dynamics for this stock. ARIMA records the highest error values, highlighting the inadequacy of linear models for highly volatile private sector banking stocks.

In the case of **ICICI Bank**, GARCH once again emerges as the best-performing model, with minimal forecasting errors (MSE = 62.81; RMSE = 7.925; MAPE = 0.0063). Although ARCH and LSTM show competitive performance, their error values remain higher than those of GARCH. RNN performs better than ARIMA but lacks the consistency demonstrated by volatility-based models.

For **Axis Bank,** GARCH achieves the lowest error values across all metrics (MSE = 23.353; RMSE = 4.832; MAPE = 0.0047). Interestingly, LSTM also exhibits strong performance for this bank, suggesting that nonlinear dependencies play a more prominent role in certain private sector stocks. Nevertheless, GARCH remains the most reliable model overall.

Collectively, the private sector results indicate stronger volatility persistence and more pronounced clustering effects compared to public sector banks, making GARCH particularly effective for forecasting volatility in actively traded banking stocks.

5.3 Comparative Insights

Across both public and private sector banks, ARIMA consistently produces the highest error values, confirming its inability to model nonlinear and heteroskedastic financial time series. ARCH models offer noticeable improvements over ARIMA but remain inferior to GARCH due to their restricted lag structure. RNN models generally outperform ARIMA; however, their forecasting accuracy is inconsistent across banks.

LSTM models demonstrate promising performance in selected cases, particularly for Axis Bank and Bank of Baroda, highlighting their ability to capture nonlinear temporal dependencies. Nevertheless, their lack of stability across datasets limits their effectiveness as standalone volatility forecasting tools.

Overall, the GARCH model emerges as the most robust and consistent performer across all banks and evaluation metrics, reaffirming its continued relevance in financial volatility modeling, even in the presence of advanced deep learning techniques.

6. Conclusion

This study provides a comprehensive comparison of econometric and deep learning models for volatility forecasting in Indian banking stocks. The GARCH model emerges as the most robust and reliable due to its ability to model volatility clustering and persistence.

Deep learning models capture nonlinearities but lack consistency and are sensitive to preprocessing. The results reaffirm the continued relevance of econometric models in emerging markets.

7. Contribution and Future Scope

While the findings reaffirm the dominance of GARCH models in volatility forecasting, the study contributes to the literature by emphasizing data transparency, methodological rigor, and diagnostic validation. These elements enhance the reliability and reproducibility of the results.

Future research can extend this work by exploring **hybrid GARCH–LSTM frameworks**, which combine statistical structure with nonlinear learning. Additionally, the use of **advanced GARCH variants such as EGARCH and TGARCH** may provide deeper insights into asymmetric volatility effects. Incorporating **macroeconomic and financial indicators** could further improve forecasting accuracy and broaden the scope of analysis.

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