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Evaluating the Forecast Accuracy of MGARCH Models and LSTM Networks for Multivariate Financial Time Series

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Abstract: **Forecasting financial time series is a fundamental challenge in finance and econometrics, largely due to the complexity of volatility dynamics and interdependencies among assets. This study evaluates and compares the forecasting performance of MGARCH models, BEKK GARCH and DCC GARCH, with two deep learning networks, Single LSTM and BiLSTM, across short, medium and long-term forecast horizons. Two datasets, comprising simulated data and bank stock data were used. Forecast accuracy was assessed using Root Mean Squared Error (RMSE) on both simulated data and real-world stock returns. The findings from simulated data reveals that deep learning models, particularly BiLSTM, consistently outperform traditional GARCH models, with performance gains increasing over longer horizons. Similar trends are observed in the real data, where LSTM networks maintain lower RMSE values, indicating greater robustness in capturing complex time series patterns.**

Keywords: **Multivariate Time Series, Forecasting, MGARCH, Deep Learning, LSTM, Rooted Mean Square Error (RMSE).**

I. INTRODUCTION

Forecasting financial time series is a crucial task in finance and econometrics, particularly for modeling volatility dynamics and capturing interdependencies among assets. Accurate and reliable forecasts are essential for informed decision-making in areas such as risk management, asset allocation and economic policy formulation. However, this task remains exceptionally challenging due to the intrinsic complexity of financial markets, which are characterized by high volatility, stochastic behavior and intricate interdependencies among variables. The ability to anticipate asset price movements, volatility dynamics and cross-asset correlations confers a significant strategic advantage, enabling market participants to optimize investment strategies, mitigate risks and design responsive policy interventions [1].

Conventional econometric models, particularly those in the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) framework, are widely employed to model financial volatilities and relationships, successfully capturing time-varying covariances and volatilities in financial markets [2]. However, they rely on assumptions of linearity and stationarity, which are restrictive for real-world financial data that often exhibit structural breaks, long-memory dependencies and nonlinear dynamics [3]. As a result, traditional models struggle to capture complex patterns, fat-tailed distributions and market shocks, leading to diminished forecasting accuracy, particularly in volatile or rapidly changing markets.

Given the limitations of traditional econometric models, recent advances in machine learning, particularly deep learning, have introduced more flexible alternatives for forecasting financial time series. Architectures like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have proven effective in capturing nonlinearities, long-

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term dependencies and non-stationary patterns inherent in financial data [4]. LSTMs, a type of recurrent neural network, excel at modeling sequential data by learning complex temporal structures directly from raw inputs, bypassing the need for predefined parametric assumptions [5]. Variants such as Stacked and Bidirectional LSTMs further enhance predictive performance, making them highly suitable for multivariate forecasting tasks in volatile, data-rich financial environments [6]. These models have shown promise in applications such as asset price prediction, risk assessment and market regime detection [7].

[8] compared three models for forecasting daily financial time series: Bivariate Neural Networks (NN), NN-based fuzzy time series and an NN-based fuzzy model incorporating substitutes. Their findings indicated that the model with substitutes variables achieved the highest accuracy, while the standard NN-based fuzzy model was the least effective. [3] reviewed MGARCH models, noting trade-offs between flexibility, simplicity and interpretability. Although models like BEKK and DCC captured key volatility dynamics, they were limited in handling nonlinearities and regime shifts. [9] compared neural networks and conditional heteroscedastic models like ARCH and GARCH for forecasting exchange rate series, finding that neural networks, particularly RBF networks, outperformed traditional econometric models in predictive accuracy.

Recent studies have highlighted the superior performance of deep learning methods in financial forecasting. [10] found that LSTM models significantly outperformed ARIMA, particularly in modeling nonlinear and long-term dependencies. [11] demonstrated that advanced LSTM variants, especially those with attention mechanisms, enhanced prediction accuracy and robustness in stock market forecasting. Similarly,[12] showed that deep learning models, including BiLSTM and Stacked LSTM, consistently outperformed MGARCH models, especially under high-volatility market conditions, emphasizing the adaptability of deep networks to complex financial patterns. Additionally, [13] compared ARIMA and LSTM models for foreign exchange forecasting, finding that LSTM models provided more accurate predictions, underscoring the advantages of deep learning approaches in capturing complex market dynamics. This study aims to evaluate and compare the forecasting accuracy and robustness of MGARCH models and LSTM networks for multivariate financial time series.

II. MATERIALS AND METHODS

Data

This study utilizes two datasets: one simulated and one real-world, to evaluate the forecasting performance of MGARCH and LSTM models under different conditions. The simulated dataset was generated using a multivariate stochastic process designed to replicate key characteristics of financial time series. The real-world dataset consists of daily closing prices of GTCO, FBN and Zenith Bank from February, 2012, to December, 2023. Figure one

Figure 1 shows three simulated asset all displaying non-stationary, volatile behavior. Variable1 trends downward, Variable2 fluctuates mid-range and Variable3 rises with growing volatility. For the Bank Stock (Figure 2), the price, all assets show cyclical price behavior, with Zenith and GTCO experiencing greater growth and price swings, while FBN remains relatively subdued.

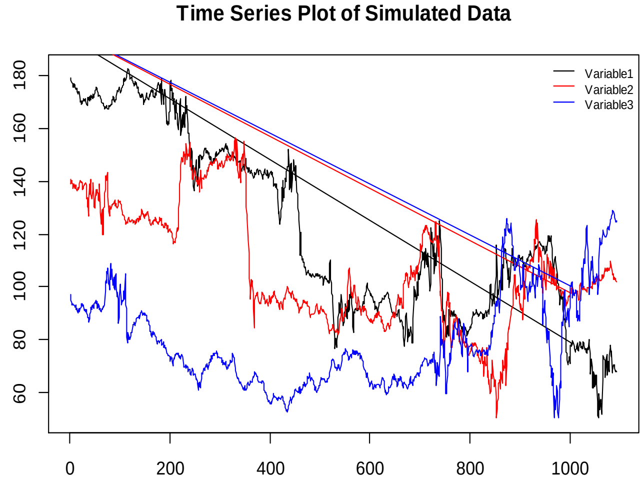

Figure 1: Time series plot of Simulated Datasets

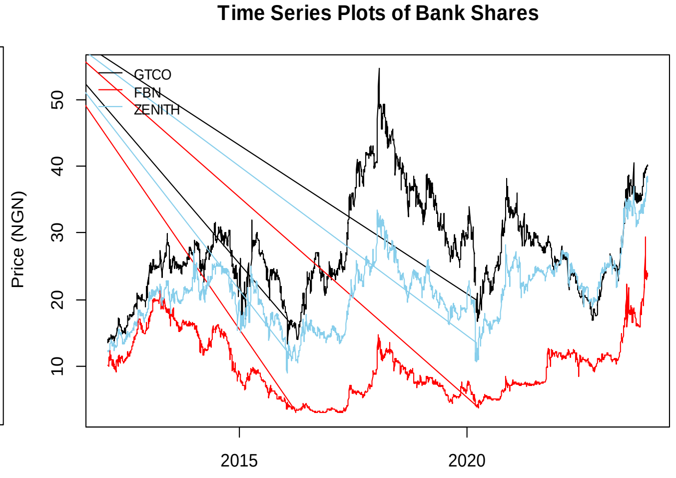

Figure 2: Time series plot of Bank Stocks Datasets

Asymmetric Baba-Engle-Kraft-Kroner GARCH (BEKK-GARCH) Model

The Asymmetric BEKK-GARCH model, an extension of the standard BEKK formulation by [14], was proposed by [15]. It introduces an additional term to capture asymmetries in the response of volatility to past shocks. This extension allows the model to reflect the leverage effect, where negative shocks increase volatility more than positive ones of the same magnitude. The model is expressed as:

$$H_t = CC' + A\varepsilon_{t-i}\varepsilon'_{t-i}A' + GH_{t-i}G'\varepsilon_t|\psi_{t-i} \sim N(0, H_t) \tag{1}$$

Where;

H_t: N x N conditional variance covariance matrix,

C: N × N lower triangular matrix of constants;

A: N × N matrix capturing past innovations;

G : N × N matrix capturing past covariances;

ε_t : N × 1 innovation vector;

ψ_{t-i} : Information set at time $t - i$.

Dynamic Conditional Correlation (DCC- GARCH)

The DCC-GARCH model, proposed by [16], extends the Constant Conditional Correlation (CCC) model to allow for time-varying correlations. The conditional variance-covariance matrix H_t is given by:

$$H_t = D_t R_t D_t \tag{2}$$

Where;

D_t is a diagonal matrix of conditional standard deviations and R_t is a matrix of conditional correlations. The Dynamic Conditional Correlation process is specified as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\mu_{t-1}\mu'_{t-1} + \beta Q_{t-1} \tag{3}$$

Where $Q_t$is the dynamic conditional correlation matrix at time t. $\bar{Q}$ is a diagonal matrix containing the standardized innovations, $\mu_{t-1}$is a vector of standardized innovations at time $t - 1$, α and β are parameters controlling the persistence of the correlation dynamics

Long Short Term Memory Networks (LSTM)

Long Short-Term Memory (LSTM) networks, introduced by [17], are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs use memory cells with specialized gates; input, forget and output gates that regulate the flow of information, enabling the model to retain and update memory states over time.

i. Forget gate layer: Determines what proportion of the previous cell stateC_{t-1} to retain

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t,] + b_f) \tag{4}$$

ii. Input Gate Layer: Controls which new information to store in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$g_t = \tanh\left(W_g \cdot [h_{t-1}, x_t] + b_g\right) \tag{6}$$

Cell state update: Combines the retained memory and new information:

$$C_t = f_t * C_{t-1} + i_t * g_t \tag{7}$$

iii. The output gate layer: Determines the output based on the updated cell state:

$$o_t = \sigma\,(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{8}$$

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$$h_t = O_t * \tanh(C_t) \tag{9}$$

Where:

x_t: Input at time t.

h_t, h_{t-1}: Current and previous hidden states is the hidden state or output at time t

C_t, C_{t-1}: Current and previous cell state

i_t, f_t, o_t and g_t: Input, forget, output and candidate vectors

σ: Sigmoid activation function

tanh: Hyperbolic tangent activation function

W_f, W_i, W_o and W_g: Weight matrices for the respective gates.

b_i, b_f, b_o and b_g: Bias vectors for the respective gates

∗: Element-wise (Hadamard) product

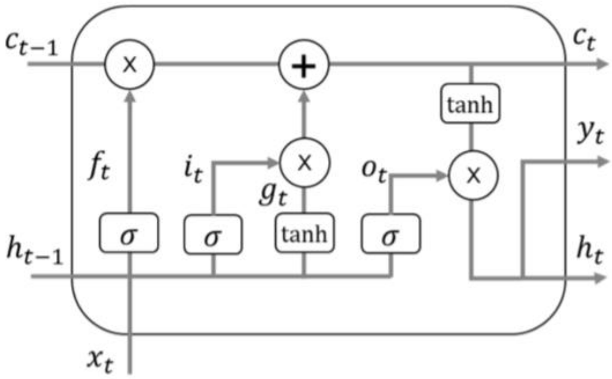

Figure 3: LSTM cell diagram

Single LSTM: A unidirectional LSTM processes input sequences from the beginning to the end, capturing temporal dependencies in a forward manner. It is suitable for modeling time series where past data points are the primary predictor of future values.

Bidirectional LSTM (BiLSTM): Introduced by Schuster [18], this variant processes input sequences in both forward and backward directions, allowing the network to capture dependencies from both past and future contexts. Bidirectional LSTMs are particularly useful for tasks where information from both the past and future may enhance the prediction, as they can better handle complex temporal patterns.

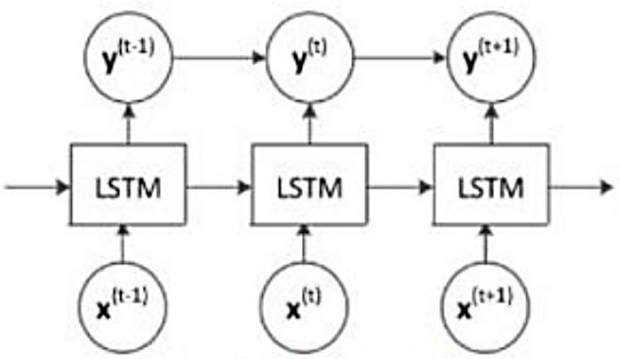

Figure 4: Single LSTM Architecture

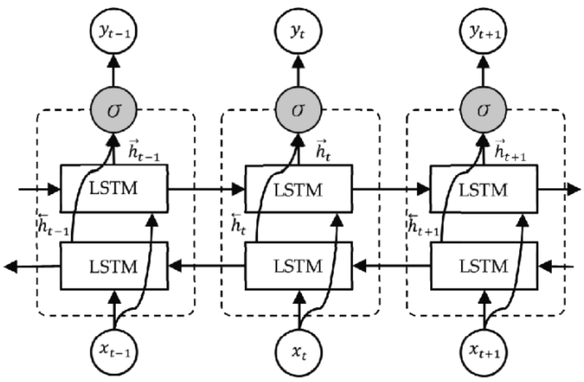

Figure 5: Bidirectional LSTM Architecture

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Performance Metrics

The Root Mean Square Error (RMSE) is a metric that calculates the square root of the average squared differences between the actual and predicted values. The formula for RMSE is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\sum_{i=1}^{p}(y_{it} - \hat{y}_{it})^2} \tag{10}$$

Where y_{it} is the actual observed value of ith variable in the period t and $\hat{y}i_t$ is the estimated value of i^{th} variable in the same period, n is length of the set and p is the number of variables in the multivariate time series

III. RESULTS AND DISCUSSION

This section presents the statistical characteristics of the datasets and compares the forecasting accuracy of MGARCH models and LSTM networks across multiple forecast horizons.

Descriptive Statistics

Descriptive statistics reveal key patterns, anomalies and volatility characteristics of the return series for both the simulated data and Nigerian bank stocks. Figure 5 demonstrates typical financial time series features in the simulated returns, including volatility clustering and mean-reverting, stationary behavior. Variable 3 shows more persistent volatility, particularly in later periods, with increasing divergence from Variable 2. Figure 6 depicts similar patterns in the bank stock returns, showing clear volatility clustering and stationarity.

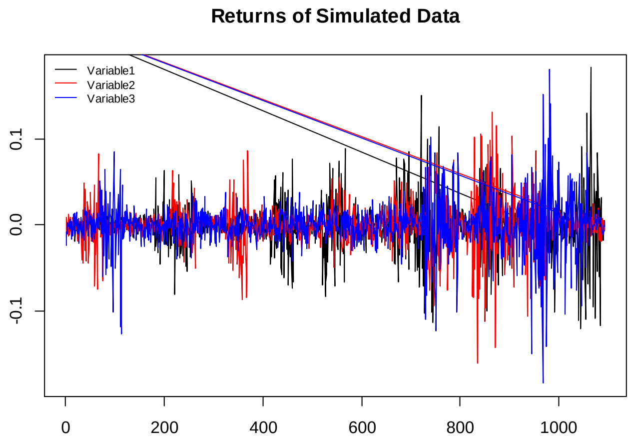

Figure 6a: Time series plot of Simulated Returns

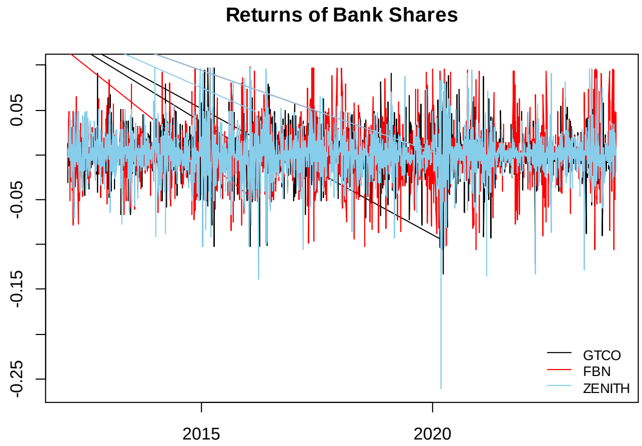

Figure 6b: Time series plot of Bank Stocks Returns

Table I summarize the statistical properties of simulated return series and selected bank stocks. All return series show near-zero means, indicating minimal long-run bias and moderate volatility levels, with FBN being the most volatile among the bank stocks. Distributions are generally non-normal, as evidenced by skewness, excess kurtosis and strongly rejected Jarque-Bera (JB) tests. This suggests the presence of asymmetry and fat tails. The Augmented Dickey-Fuller (ADF) test results confirm stationarity across all series, while significant Lagrange Multiplier (LM) test outcomes indicate the presence of ARCH effects. Together, these support the use of GARCH-type models for capturing time-varying volatility in both simulated and actual return.

TABLE I: Descriptive statistics of Return

Metric	Simulated Variables			Bank stocks		
	Variable 1	Variable 2	Variable 3	GTCO	FBN	Zenith
Mean	-0.0009	-3.017e-04	2.346e-04	0.0004	0.0003	0.0004
Median	-0.0004	4.849e-05	7.360e-06	0.0000	0.0000	0.0000
Min	-0.1206	-1.616e-01	-1.848e-01	-0.1328	-0.1054	-0.2615

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Max	0.1834	1.319e-01	1.807e-01	0.0974	0.0976	0.0972
Std. Dev.	0.0274	0.0263	0.0288	2.2132e-02	2.7299e-02	2.3675e-02
Skewness	0.2260	-0.1629	-0.2241	-0.1297	0.2149	-0.6324
Kurtosis	6.7358	5.6819	7.2295	4.5844	2.8012	9.4188
JB Test	2088.5***	1484.7***	2404***	2588.6***	986.57***	11083***
ADF Test	-10.539***	-10.846***	-9.8927***	-14.167***	-13.333***	-15.122***
LM Test	228.09***	89.895***	108.53***	283.85***	265.78***	164.34***

***Significance at the 1% level

Unconditional correlations (Table II) shows that the simulated variable 1 and variable 2 exhibit a strong positive correlation, suggesting they move together closely, while correlations involving variable 3 are weak and near zero, indicating minimal association.

Table II: Correlation Matrix for Simulated Variables

	Variable 1	Variable 2	Variable 3
Variable 1	1.0000		
Variable 2	0.0347	1.0000	
Variable 3	0.7203**	-0.0981	1.0000

**Significance at the 5% level.

Table III shows the correlation matrix for the bank stock returns. Zenith and GTCO returns exhibit a strong positive correlation, suggesting they often move together, possibly due to similar market exposures or macroeconomic factors. Zenith also shows a moderate correlation with FBN, while GTCO and FBN display a weak association, indicating largely independent return behavior between these two.

Table III: Correlation Matrix for Bank Stock Returns

	GTCO	FBN	Zenith
GTCO	1.0000		
FBN	0.5680**	1.0000	
Zenith	0.1432	0.7304**	1.0000

**Significance at the 5% level.

Forecast Accuracy

This table presents the Root Mean Square Error (RMSE) of the forecasting models over short, medium and longterm forecast horizons for both simulated and bank stocks returns. The Single LSTM consistently yields the lowest RMSE across all horizons for simulated data, indicating superior forecasting accuracy. For bank stocks, BiLSTM outperforms others at short horizons, while Single LSTM remains competitive. Traditional GARCH models, particularly BEKK GARCH, perform moderately well, but lag behind LSTM-based models, especially over longer horizons.

Table IV: Forecasting Accuracy (RMSE) of Models Across Horizons

Model	Forecast Horizon	Simulated	Bank Stocks
		RMSE	RMSE
BEKK GARCH	Short Term	0.01121	0.007944
	Medium Term	0.01604	0.013342
	Long term	0.02429	0.018651
DCC GARCH	Short Term	0.021714	0.018034
	Medium Term	0.022494	0.022172
	Long term	0.030651	0.02638

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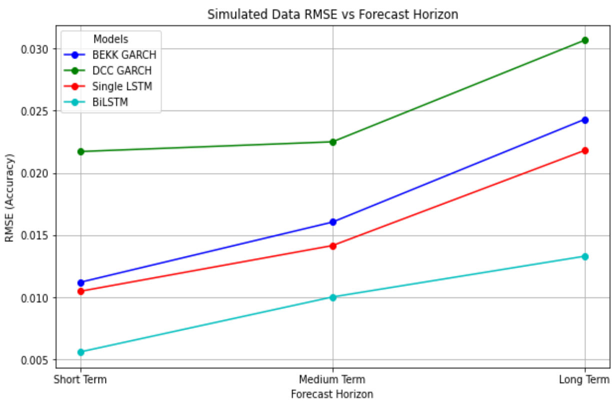
Single LSTM	Short Term	0.010484	0.007174
	Medium Term	0.014152	0.011147
	Long term	0.02379	0.01731
BiLSTM	Short Term	0.00561	0.00671
	Medium Term	0.01002	0.010927
	Long term	0.017292	0.01244



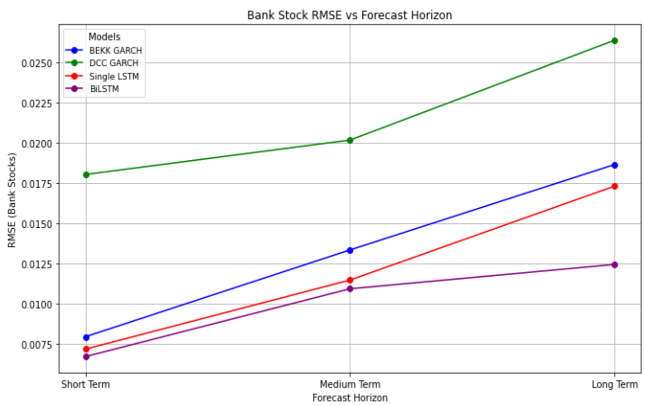
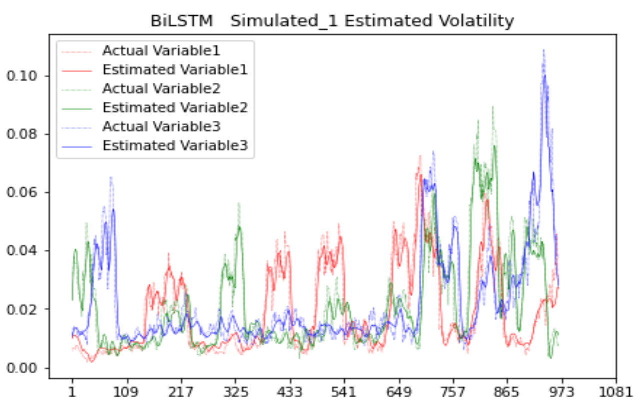


Figure 7: RMSE across Forecast Horizons for Simulated Data **Figure 8: RMSE across Forecast Horizons for Simulated Data**

Figures 7 and 8 present the RMSE values for four forecasting models across short, medium and long-term horizons for both simulated data and real bank stock data, respectively. In both cases, the DCC GARCH model exhibits the highest RMSE, indicating the poorest performance, while the BEKK GARCH model performs marginally better. The LSTM-based models, particularly BiLSTM, consistently achieve the lowest RMSE values across all horizons, demonstrating their superior accuracy and robustness in volatility forecasting.



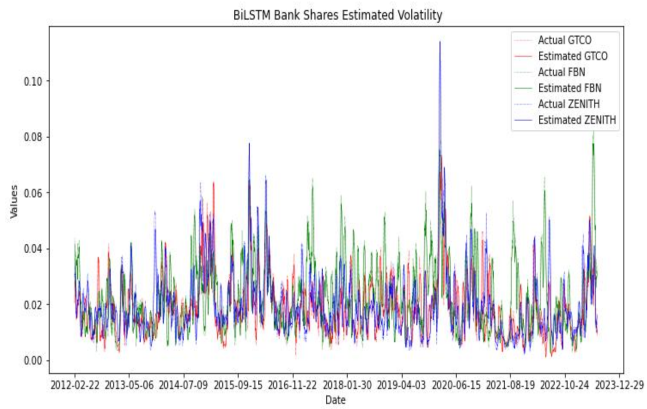


Figure 9: BiLSTM Estimation on Simulated Data **Figure 10: BiLSTM Estimation on Bank Stock**

Figures 9 and 10 compare the actual and BiLSTM-forecasted volatilities of simulated variables and bank stocks over time, demonstrating that the BiLSTM model effectively captures volatility trends.

IV. CONCLUSION

This study compares the performance of MGARCH models and deep learning networks in forecasting multivariate volatility using simulated and real-world bank stock data. The BiLSTM model, employed as a forecasting framework, demonstrated superior performance by achieving the lowest RMSE across all forecast horizons. In particular, BiLSTM exhibited strong predictive accuracy in long-term forecasts, effectively capturing complex, nonlinear dependencies that traditional models fail to represent. These findings affirm BiLSTM's robustness and suitability for modeling the dynamic behavior of financial time series.

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