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# A MULTIVARIATE ANALYSIS OF STOCK PRICE MOVEMENTS AND VOLATILITY PATTERNS IN SELECTED NIGERIAN BANKS

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## ABSTRACT
The banking sector plays a critical role in Nigeria's financial system, and fluctuations in bank stock prices have significant implications for investors, regulators, and policymakers. This study examines the stock price movements and volatility patterns of selected Nigerian banks over the period 2014–2024. The banks studied are Fidelity Bank Plc, Stanbic IBTC Holdings Plc, United Bank for Africa (UBA) Plc, Wema Bank Plc, Zenith Bank Plc, and First City Monument Bank (FCMB) Plc. The objectives are to examine stock price behaviour and daily returns, identify volatility patterns, and assess the influence of short-term shocks and long-term trends on stock performance. A quantitative time-series research design was adopted using secondary data obtained from the Nigerian Exchange Group (NGX). Daily stock price data were analyzed using descriptive statistics, logarithmic return analysis, volatility measures, and the Discrete Wavelet Transform (DWT). DWT separated stock price movements into high-frequency and low-frequency components, enabling the analysis of both short-term market fluctuations and long-term trends. The results show that stock prices remained relatively stable between 2014 and 2019 but experienced heightened volatility during the pandemic. A strong recovery was observed from 2022 onward, particularly among Zenith Bank, UBA, and Fidelity Bank. The return series exhibited volatility clustering and occasional extreme price movements. Wavelet decomposition revealed that short-term shocks dominated during periods of market uncertainty, while long-term components reflected sustained growth and recovery trends. The study concludes that stock price behaviour in the Nigerian banking sector is influenced by both temporary market shocks and underlying structural factors.

**Keywords:** Stock price movements, Volatility, Daily returns, Wavelet decomposition, Nigerian banks, NGX

## INTRODUCTION
Stock markets play a crucial role in economic development by facilitating capital formation and investment opportunities. Understanding stock price movements and daily return patterns is essential for investors, policymakers, and financial analysts, as these factors influence investment decisions and risk management strategies. The Nigerian banking sector, a vital component of the country's financial system, has witnessed significant stock price fluctuations over the years, driven by macroeconomic conditions, regulatory changes, and market sentiment (Maku & Atanda, 2010; Uchenna *et al*., 2017). The Efficient Market Hypothesis (Fama, 1970) suggests that stock prices fully incorporate available information, making it difficult for investors to achieve consistent excess returns. However, studies on emerging markets, including Nigeria, indicate that stock prices may not always reflect all information efficiently, leading to potential arbitrage opportunities (Emenike, 2008; Okpara, 2010).

Furthermore, volatility clustering and return anomalies have been observed in Nigerian banking stocks, raising questions about market efficiency and the underlying drivers of stock price movements (Ajayi *et al*., 2017; Osazevbaru & Oboreh, 2014). Recent advancements in time-series analysis, particularly wavelet decomposition, provide new insights into stock market behavior by capturing both short-term fluctuations and long-term trends (Gençay *et al*., 2002; Adegbite *et al*., 2021).

This study aims to analyze stock price movements and daily return patterns of selected Nigerian banks from 2014 to 2024, utilizing traditional econometric models alongside wavelet decomposition techniques. The findings will contribute to a deeper understanding of market dynamics and offer practical implications for investors and financial regulators. This study aims to use wavelet decomposition to provide a comprehensive analysis of stock price movements and daily return patterns of selected Nigerian banks from 2014 to 2024.

## MATERIALS AND METHODS
To investigate stock price movements and volatility patterns across different time horizons, this study employed the Discrete Wavelet Transform (DWT). Wavelet decomposition is a powerful time-frequency analysis technique that enables the simultaneous examination of both short-term fluctuations and long-term trends in financial time series. Unlike traditional statistical methods that analyze data only in the time domain, wavelet decomposition analyzes stock prices in both the time and frequency domains. This makes it particularly suitable for financial data, which often exhibit non-stationary behaviour, volatility clustering, abrupt price changes, and structural breaks.

By leveraging deep learning models specifically convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM) networks. For the purpose of this study, six banks were identified for research analysis, namely; Fidelity Bank Plc, Stanbic IBTC Holdings Plc, United Bank for Africa (UBA) Plc, Wema Bank Plc, Zenith Bank Plc, and First City Monument Bank (FCMB) Plc. The data used for this analysis is a secondary data obtained from Nigerian Stock Exchange (NSE) which exhibited Brownian motion. Furthermore, graphical representations and statistical analyses will be provided to illustrate the trends and patterns in Nigerian stock market data for the period of 3rd January 2014 to 31st December 2024.

**Development of the Model**

One-dimensional input values from the RNN $(x_1, x_2,, \dots x_T) \in R^{T_x d}$ will be fed into the CNN layer, where a convolution operator will be applied to produce a feature map. The convolution operator will create a set of features, denoted by $f$, from the input data using a filter, $W$, of dimension $Rf_d$. From this set of features, a new set of features, $f_m$, will be generated by the equation:

$$hl_i^{fm} = tanh\left(\omega^f x_{i:i+f-1} + b\right) \qquad (1)$$

Each features set $f$ uses the filter $hl$ in the input defined by:

$$x_{1-f}, x_{2-f+1}, \dots, x_{n-f+1} \qquad (2)$$

The operation generates feature map denoted by

$$hl_1, hl_2, \dots, hl_{n-f+1}$$

The outputs of the Convolution layer are obtained by applying a series of linear transformations, called weightings, to the input data. To extract non-linear features, a ReLU activation function is used, which simply applies a threshold function (0, x) to each input. Pooling is then used to reduce the size of the feature map by selecting the most important information. The max-pooling operation will be denoted by, and its output will be denoted by:

$hl = \max(hl)$ while the output of the max-pooling layer would be denoted as $x_i' = CNN\ (x_i)$

where $(x_i)$ is the input data vector to the CNN network and $x_i'$ the output which will be passed to the LSTM network. To understand LSTM, we will introduce the LSTM with the forget gate structure. The formulation is denoted by:

$$i_t = \sigma(W_i([x_t, x_{t-1}])) \qquad (3)$$

$$f_t = \sigma(W_f([x_t, x_{t-1}])) \qquad (4)$$

$$o_t = \sigma(W_o([x_t, x_{t-1}])) \qquad (5)$$

$$g_t = tanh\ (W_g([x_t, x_{t-1}])) \qquad (6)$$

$$c_t = f \odot c_{t-1} + i \odot g \qquad (7)$$

$$y_t = o \odot tanh(c_t) \qquad (8)$$

Where $f, I, o, g$ and $c$ denote the forget, inputs, output, and input modulation gate respectively. In Equations (3)-(5), the σ is a sigmoid function and $w_f$, $w_i$, $w_o$ and $w_g$ are fully connected neural networks for the forget, input, output, and input modulation gates respectively. The order for the forward LSTM is $[x_1 + x_2 + x_3, \dots, x_n]$ while for the backward LSTM is $[x_n + x_{n-1}, \dots, x_1]$. The backward and the forward LSTMs would be trained separately then unified by fusing their outputs in the equation below

$$x_t = y_{F(t)}\ y_{B(n-t+1)} \qquad (10)$$

$y_F$ and $y_B$ represents the outputs of the forward and backward LSTMs respectively while the notation denotes any integration operator such as a simple adder. The final prediction $\acute{y} \in R$ is given by:

$$Y = W_y \cdot \Big[ O\dot{T} \circledcirc \tanh\Big(\sigma\big(w_f \cdot z_{\dot{T}} + U_f \cdot h_{\dot{T}-1} + b_f\big) \circledcirc s_{\dot{T}-1} + \sigma\big(W_i \cdot z_{\dot{T}} + U_i \cdot h_{\dot{T}-1}^{(l)} + b_i\big) \circledcirc \tanh\big(W_g \cdot z_{\dot{T}} + U_g \cdot h_{\dot{T}-1}^{(l)} + b_g\big)\Big)\Big] + b_y \qquad (11)$$

Where:

**Step 1: RNN hidden states**

For each time step $t = 1, 2, \dots, T$:

$$h_i^{(r)} = \tanh(W_{xh} \cdot X_t + W_{hh} \cdot h_{t-1}^{(r)} + b_h) \qquad (12)$$

**Step 2: CNN feature map from RNN output**

Assume window (filter) size $f$, and let $\dot{T} = T - f + 1$. For each $i = 1, \dots, \dot{T}$:

$$z_i = \text{ReLU}\left(\sum_{j=0}^{f-1} w_f^{(j)} \cdot h_{i+j}^{(r)} + b_f\right) \qquad (13)$$

**Step 3: LSTM cell operations on CNN output**

For each time step $t = 1, 2, \dots, \dot{T}$:

$$f_t = \sigma(w_f \cdot z_t + U_f \cdot h_{t-1}^{(l)} + b_f \qquad (14)$$

$$i_t = \sigma(w_f \cdot z_t + U_i \cdot h_{t-1}^{(l)} + b_i \qquad (15)$$

$$o_t = \sigma(w_o \cdot z_t + U_o \cdot h_{t-1}^{(l)} + b_o \qquad (16)$$

$$o_t = \sigma(w_o \cdot z_t + U_o \cdot h_{t-1}^{(l)} + b_o \qquad (17)$$

$$\acute{c}_t = \tanh(w_g \cdot z_t + U_g \cdot h_{t-1}^{(l)} + b_g \qquad (18)$$

$$s_t = f_t \circledcirc s_{t-1} + i_t \circledcirc \acute{c}_t \qquad (19)$$

$$h_t^{(l)} = o_t \circledcirc \tanh\ (s_t) \qquad (20)$$

**Step 4: Output layer**

After computing $h_{\dot{T}}^{(l)}$ from LSTM

$$\acute{y} = W_y . h_{\dot{T}-1}^{(l)} + b_y \qquad (21)$$

The model would be developed on python programming language (PPL)

**RESULTS AND DISCUSSION**

**Stock Price Movements and Daily Return Patterns of Selected Banks**

Table 1 presents stock market data for selected Nigerian financial services companies, highlighting key trading metrics. It includes trading names, ticker symbols, sectors, previous closing prices, opening prices, trading volumes, and market capitalizations. UBA and Zenith Bank have the highest market capitalizations at ₦1.25 trillion and ₦1.96 trillion, respectively, indicating their strong positions in the industry. Zenith also recorded the highest trading volume at 22.92 million shares. Fidelity, Wema, and FCMB show moderate market capitalizations, while STANBIC maintains a solid valuation of ₦815 billion.

**Table 1: Stock market data for selected Nigerian companies**

| Trading Name | Ticker Symbol | Sector | Prev Close | Open | Volume | Market Capitalization |
|---|---|---|---|---|---|---|
| Fidelity | FIDELITYBK | Financial Services | 17.15 | 17.15 | 14.97M | 549B |
| Stanbic | STANBIC | Financial Services | 59 | 59 | 30.77K | 815B |
| UBA | UBA | Financial Services | 37.60 | 37.00 | 5.6M | 1.25T |
| Wema | WEMA | Financial Services | 10.95 | 10.95 | 167.25K | 230.37B |
| Zenith | ZENITH | Financial Services | 48.00 | 47.80 | 22.92M | 1.96T |
| FCMB | FCMB | Financial Services | 9.8 | 9.8 | 169.67K | 386.15B |

**Source:** The NSE

Table 2 outlines the incorporation and listing timelines of selected Nigerian financial institutions, highlighting the gap between their establishment and public listing. UBA, the oldest, was incorporated in 1961 and listed in 1970, marking its long-standing market presence. Wema Bank, incorporated in 1945, has no recorded listing date, suggesting it may still be privately held or listed at an unspecified time. Zenith and Fidelity went public over a decade after incorporation in 2004 and 2005, respectively. FCMB and Stanbic, incorporated in 2012, transitioned quickly to the public market, listing in 2013 and 2012.

**Table 2: Company listing and incorporation timeline analysis**

| Trading Name | Date Listed | Date Incorporated |
|---|---|---|
| Fidelity | May 17, 2005 | November 19, 1987 |
| Stanbic | November 23, 2012 | March 14, 2012 |
| UBA | March 31, 1970 | February 23, 1961 |
| Wema | --- | May 2, 1945 |
| Zenith | October 21, 2004 | May 30, 1990 |
| FCMB | June 21, 2013 | November 20, 2012 |

**Source:** The NSE

**Evaluation of the Performance of the Wavelet Hybrid Model using Standard Metrics**

Table 3 presents a comparative evaluation of four deep learning models of LSTM, 1DCNN, RNN, and Hybrid-model based on their predictive performance on pre-COVID Fidelity Bank data using three error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Among the models, the hybrid Hybrid-model architecture yields the lowest error values across all metrics (MSE: 0.0353, RMSE: 0.1880, MAE: 0.1562), indicating superior accuracy and robustness in capturing temporal dependencies and nonlinear patterns in the financial time series. In contrast, the standalone 1DCNN model exhibits the highest error rates, suggesting limited effectiveness when used in isolation. These results underscore the advantage of integrating convolutional feature extraction with recurrent temporal modeling for financial forecasting tasks.

**Table 3: Analysis of the model for Fidelity bank**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 0.0599 | 0.2447 | 0.1852 |
| 1DCNN | 0.1668 | 0.4084 | 0.3016 |
| RNN | 0.0484 | 0.2200 | 0.1753 |
| Hybrid-model | 0.0353 | 0.1880 | 0.1562 |

**Table 4: Analysis of the hybrid model for Stanbic bank**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 159.4053 | 12.6255 | 12.3514 |
| 1DCNN | 134.2007 | 11.5845 | 11.2101 |
| RNN | 11.9404 | 3.4554 | 2.7955 |
| Hybrid-model | 4.7250 | 2.1737 | 1.7346 |

Table 4 provides a comparative analysis of four deep learning models of LSTM, 1DCNN, RNN, and Hybrid-model based on their predictive performance on pre-COVID STANBIC Bank data using standard error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The hybrid Hybrid-model model exhibits the lowest error values across all metrics (MSE: 4.7250, RMSE: 2.1737, MAE: 1.7346), indicating superior accuracy and robustness in modeling the temporal and nonlinear characteristics of the financial time series. In contrast, the LSTM and 1DCNN models show significantly higher error rates, suggesting limited effectiveness when used independently. These results affirm the advantage of combining convolutional feature extraction with recurrent temporal modeling for enhanced predictive fidelity in financial forecasting.

Table 5 presents a comparative analysis of four deep learning architectures of LSTM, 1DCNN, RNN, and the hybrid Hybrid-model based on their predictive accuracy for pre-COVID UBA Bank data using standard error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The Hybrid-model model outperforms all others, achieving the lowest error rates (MSE: 0.2295, RMSE: 0.4791, MAE: 0.3911), which reflects its superior capability in capturing both spatial and temporal dependencies inherent in the financial time series. In contrast, the standalone LSTM and RNN models show higher error levels, indicating reduced precision. These results reinforce the efficacy of hybrid architectures in financial forecasting, particularly in complex, nonlinear environments.

**Table 5: Analysis of the hybrid model for UBA**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 1.0297 | 1.0147 | 0.7464 |
| 1DCNN | 0.5394 | 0.7344 | 0.5510 |
| RNN | 0.7959 | 0.8921 | 0.7070 |
| Hybrid-model | 0.2295 | 0.4791 | 0.3911 |

**Table 6: Analysis of the hybrid model for Wema Bank**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 0.0154 | 0.1243 | 0.1038 |
| 1DCNN | 0.0122 | 0.1107 | 0.0824 |
| RNN | 0.0112 | 0.1062 | 0.0895 |
| Hybrid-model | 0.0091 | 0.0954 | 0.0748 |

Table 6 presents a comparative evaluation of four deep learning models of LSTM, 1DCNN, RNN, and the hybrid Hybrid-model based on their predictive performance for pre-COVID WEMA Bank data using standard error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The Hybrid-model model achieves the lowest error rates across all metrics (MSE: 0.0091, RMSE: 0.0954, MAE: 0.0748), indicating superior accuracy and generalization capability in capturing the temporal and nonlinear dynamics of the financial time series. While RNN and 1DCNN also perform competitively, their slightly higher error values suggest reduced precision. These results reinforce the effectiveness of hybrid architectures in financial forecasting, particularly in stable pre-crisis conditions.

Table 7 provides a comparative assessment of four deep learning models of LSTM, 1DCNN, RNN, and the hybrid Hybrid-model applied to pre-COVID Zenith Bank data using error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The Hybrid-model model demonstrates the strongest performance, achieving the lowest MSE (0.8582) and matching the RNN in RMSE (0.9264) and MAE (0.7753), thereby indicating superior accuracy and robustness in capturing both temporal dependencies and nonlinear structures. In contrast, the standalone 1DCNN and LSTM models yield higher error values, reflecting weaker predictive fidelity. These results highlight the advantage of hybrid architectures that combine convolutional feature extraction with recurrent sequence modeling, particularly in financial forecasting tasks where volatility and complex temporal patterns are present.

**Table 7: Analysis of the hybrid model for Zenith Bank**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 3.5465 | 1.8832 | 1.6307 |
| 1DCNN | 4.4066 | 2.0991 | 1.8503 |
| RNN | 1.4098 | 0.9264 | 0.7753 |
| Hybrid-model | 0.8582 | 0.9264 | 0.7753 |

**Table 8: Analysis of the hybrid model for FCMB**

| Model | MSE | RMSE | MAE |
|---|---|---|---|
| LSTM | 0.0770 | 0.2775 | 0.2265 |
| 1DCNN | 0.0563 | 0.2373 | 0.1830 |
| RNN | 0.0485 | 0.2203 | 0.1618 |
| Hybrid-model | 0.0447 | 0.2115 | 0.1694 |

Table 8 provides a comparative evaluation of four deep learning models of LSTM, 1DCNN, RNN, and the hybrid Hybrid-model on pre-COVID FCMB Bank data using standard error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The Hybrid-model model achieves the lowest overall error values (MSE: 0.0447, RMSE: 0.2115, MAE: 0.1694), demonstrating superior predictive accuracy and robustness in capturing both temporal dependencies and nonlinear structures of the financial time series. The RNN also performs competitively, with slightly higher error rates, while the standalone LSTM and 1DCNN models show comparatively weaker performance. These results highlight the advantage of hybrid architectures that integrate convolutional feature extraction with recurrent sequence modeling, particularly in financial forecasting under pre-crisis condition

**Analysis of Historical Stock Price Movements for the Banks**

Figure 1 presents the daily closing stock price of Fidelity Bank from 2014 to 2024, revealing a dynamic trend with distinct phases. Initially, the stock price exhibited relatively low volatility and a plateau around 2.5 NGN, suggesting a period of stability or limited growth. A significant surge began in late 2022, culminating in a peak of approximately 14 NGN by early 2024, indicating substantial market confidence or fundamental changes in the bank's performance. Fig. 2 shows Stanbic Bank's daily closing stock price from 2014 to 2024, highlighting a volatile pattern. The stock experienced gradual growth with fluctuations, followed by a surge around 2017–2018, possibly due to strong financial performance or market optimism. A decline and stagnation from 2020 to 2022 suggest market corrections or internal challenges. Sharp vertical anomalies indicate potential data errors or trading halts. The recent upward trend toward 2024 calls for further analysis of market dynamics, regulatory changes, or strategic shifts driving this growth.

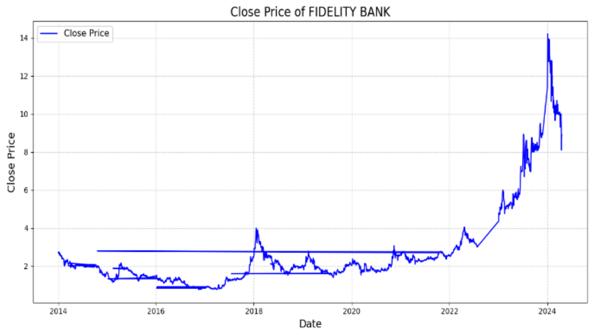


**Figure 1: Close price of Fidelity bank**

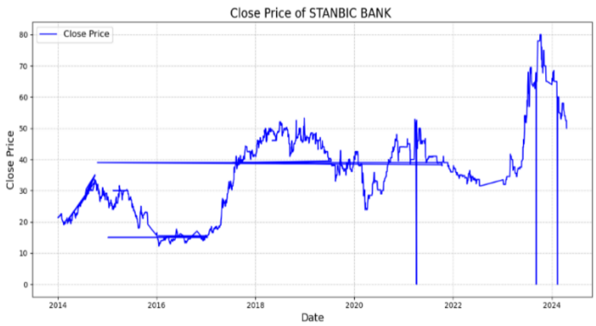


**Figure 2: Close price of Stanbic bank**

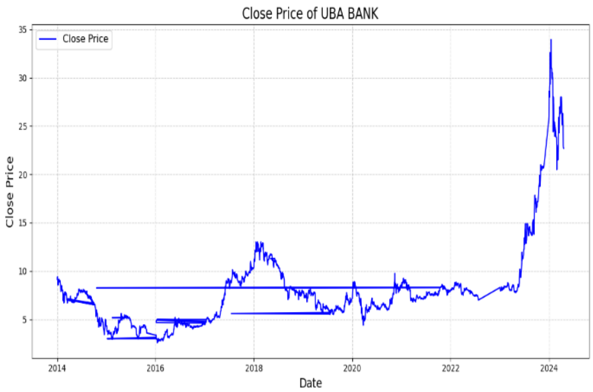


**Figure 3: Close price of UBA**

Figure 3 shows UBA Bank's daily closing stock price from 2014 to 2024. The stock remained relatively stable between 2 and 12 NGN until late 2022, indicating limited growth. However, from late 2022 onward, prices surged dramatically, peaking at around 35 NGN by early 2024. This sharp rise suggests potential influences like improved financial performance, market expansion, or macroeconomic factors in the Nigerian banking sector.

Figure 4 presents the daily closing stock price of Wema Bank from 2014 to 2024, revealing a prolonged period of low volatility followed by a dramatic late-stage surge. The stock price remained consistently below 2 NGN for the majority of the period, indicating a phase of stagnant growth or limited market activity. This stability was punctuated by brief, minor fluctuations, suggesting potential small-scale market adjustments or internal operational changes. However, starting in late 2022, a significant upward trend is observed, culminating in a peak of approximately 12 NGN by early 2024. Fig. 5 presents the daily closing stock price of Zenith Bank from 2014 to 2024, revealing a pattern of fluctuating volatility with a notable late-stage surge. The initial period shows moderate volatility, with the stock price oscillating between 10 and 25 NGN, indicating a phase of active trading and potential market adjustments. A subsequent period of relative stability around 2018-2022 is observed, suggesting potential consolidation or a period of consistent performance. However, starting in late 2022, a significant upward trend is evident, culminating in a peak of approximately 45 NGN by early 2024.

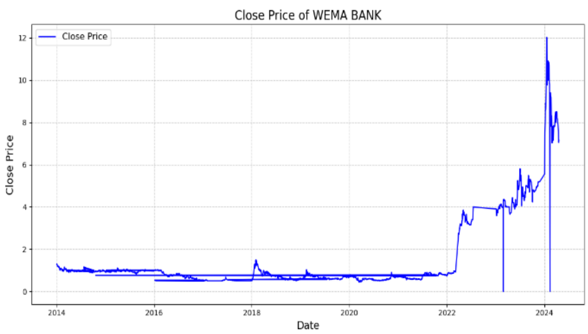


**Figure 4: Close price of Wema bank**

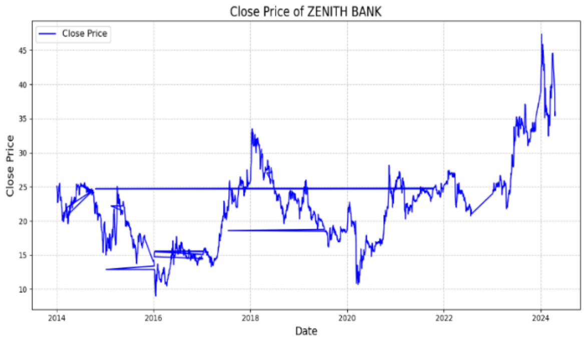


**Figure 5: Close price of Zenith bank**

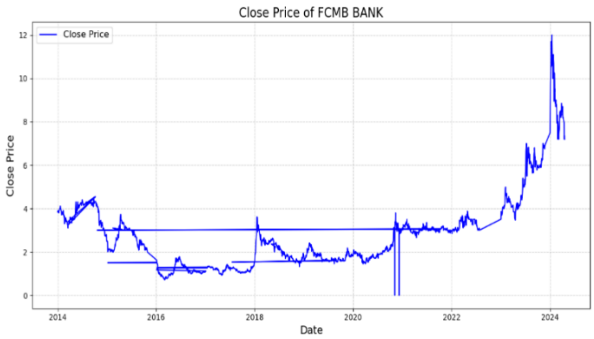


**Figure 6: Close price of FCMB**

Figure 6 illustrates the daily closing stock price of FCMB Bank from 2014 to 2024, revealing a pattern of prolonged low volatility followed by a significant late-stage surge. The stock price remained consistently below 4 NGN for the majority of the period, indicating a phase of stagnant growth or limited market activity. This stability was punctuated by minor fluctuations, suggesting potential small-scale market adjustments or internal operational changes. However, starting in late 2022, a significant upward trend is observed, culminating in a peak of approximately 12 NGN by early 2024.

**Analysis of Daily Return Patterns the selected Banks**

Figure 7 presents the daily returns of Fidelity Bank from 2014 to 2024, revealing a pattern of generally low volatility punctuated by infrequent, but significant spikes. The majority of daily returns fluctuate within a narrow range around zero, indicating a period of relative market stability or limited price fluctuations. However, notable outliers are observed, particularly a significant positive spike around 2023, suggesting a period of substantial positive price movement or a potential market anomaly. Fig. 8 depicts the daily returns of Stanbic Bank from 2014 to 2024, revealing a pattern of generally low volatility punctuated by infrequent, but significant extreme events. The majority of daily returns fluctuate within a narrow range around zero, indicating a period of relative market stability or limited price fluctuations. However, notable outliers are observed, particularly significant negative spikes around 2021 and 2024, suggesting periods of substantial negative price movement or potential market anomalies.

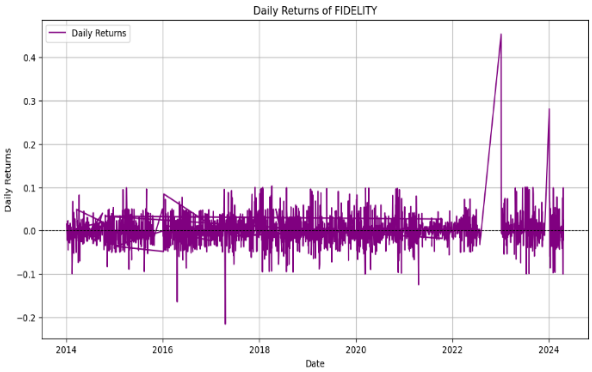


**Figure 7: Daily returns of Fidelity bank**

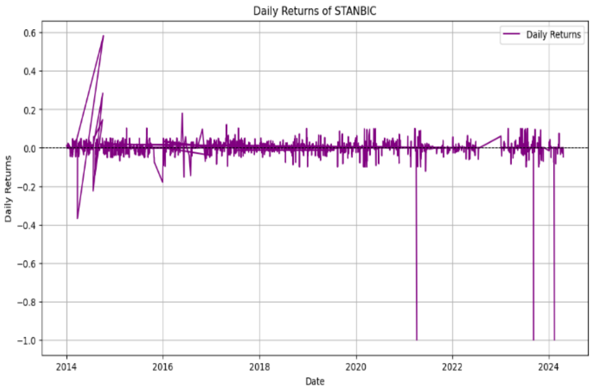


**Figure 8: Daily returns of Stanbic bank**

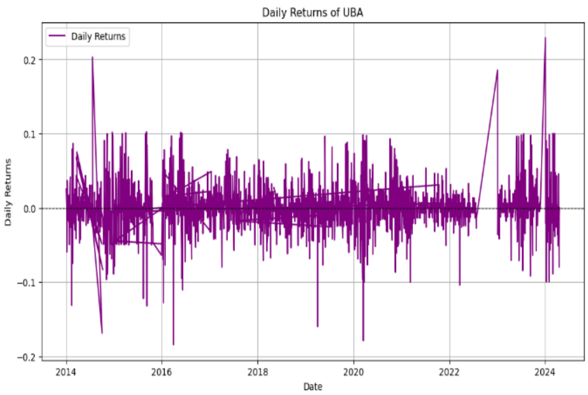


**Figure 9: Daily returns of UBA**

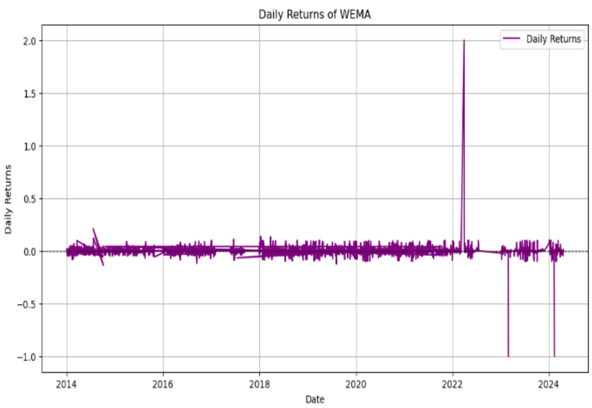


**Figure 10: Daily returns of Wema bank**

Figure 9 presents the daily returns of UBA Bank from 2014 to 2024 in Lagos, Nigeria, revealing a pattern of fluctuating volatility with infrequent, but notable, extreme values. The majority of daily returns are clustered around zero, indicating periods of relative stability. However, the graph exhibits several significant spikes and drops, suggesting periods of heightened volatility or potential market anomalies. Fig. 10 presents the daily returns of Wema Bank from 2014 to 2024, revealing a pattern of extremely low volatility punctuated by a few dramatic spikes. The vast majority of daily returns are tightly clustered around zero, indicating a prolonged period of market inactivity or highly stable pricing. However, two significant positive spikes and one significant negative spike stand out, particularly around 2022 and 2024, suggesting periods of substantial price movement or potential market anomalies.

Figure 11 presents the daily returns of Zenith Bank from 2014 to 2024, revealing a pattern of fluctuating volatility with several significant deviations from the mean. The majority of daily returns are clustered around zero, indicating periods of relative market stability. However, the graph exhibits several notable spikes and drops, suggesting periods of heightened volatility or potential market anomalies.

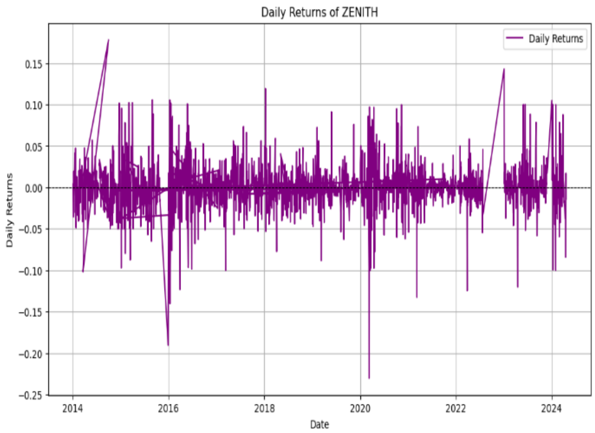


**Figure 11: Daily returns of Zenith bank**

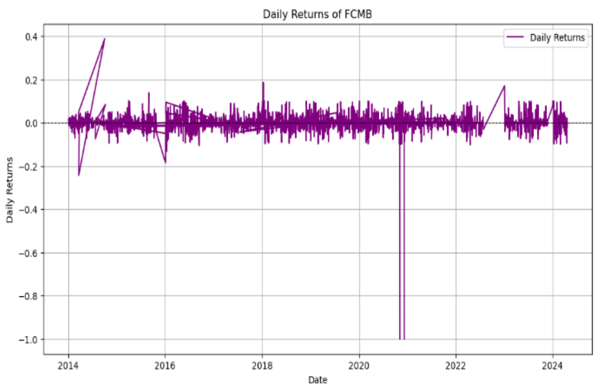


**Figure 12: Daily returns of FCMB**

Figure 12 presents the daily returns of FCMB Bank from 2014 to 2024 in Lagos, Nigeria, revealing a pattern of generally low volatility punctuated by a few significant extreme events. The majority of daily returns are clustered tightly around zero, suggesting a prolonged period of relative market stability or limited price fluctuations. However, the graph exhibits a few notable spikes and drops, particularly a dramatic negative spike around 2021, suggesting periods of heightened volatility or potential market anomalies.

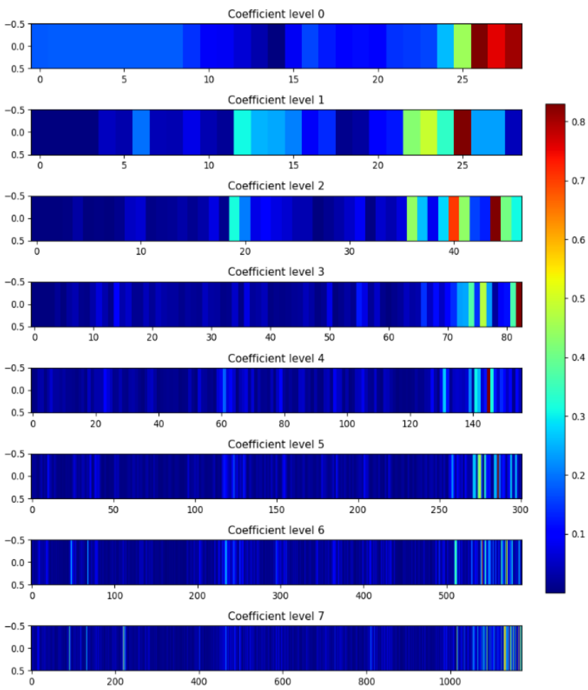

**Figure 13: Discrete wavelet decomposition of Fidelity bank**

Figure 13 displays heatmaps illustrating wavelet decomposition coefficients across eight levels (0 to 7). Lower levels (0–2) reveal distinct patterns with localized high-magnitude regions, indicating sharp transitions or high-frequency components. At higher levels (3–7), the coefficients become sparser, highlighting broader low-frequency trends. This suggests that the original signal is a mix of localized high-frequency details and overarching low-frequency patterns. Fig. 14 presents heatmaps of wavelet decomposition coefficients across eight levels (0–7), representing different frequency bands of the original signal. Lower levels (0–2) show sharp transitions and high-frequency components, while higher levels (3–7) display sparser coefficients, indicating lower-frequency trends. This suggests the signal combines localized high-frequency features with broader low-frequency patterns.

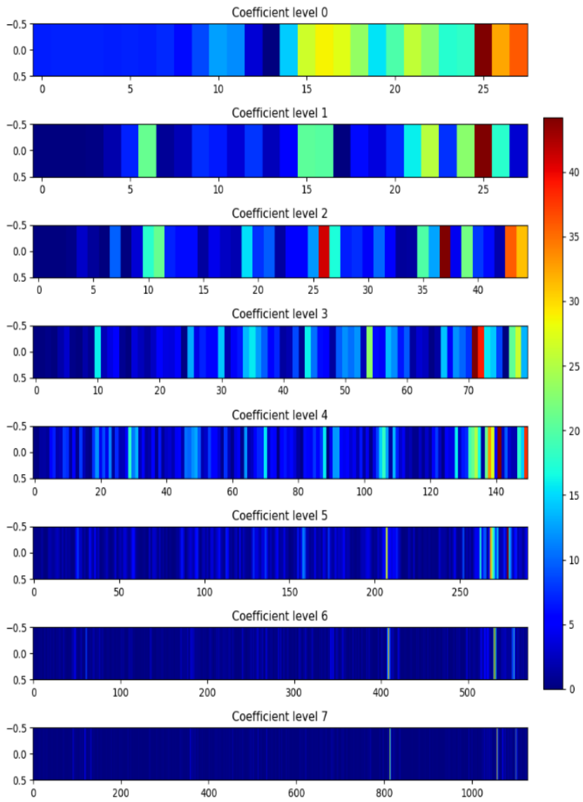

**Figure 14: Discrete wavelet decomposition of Stanbic bank**

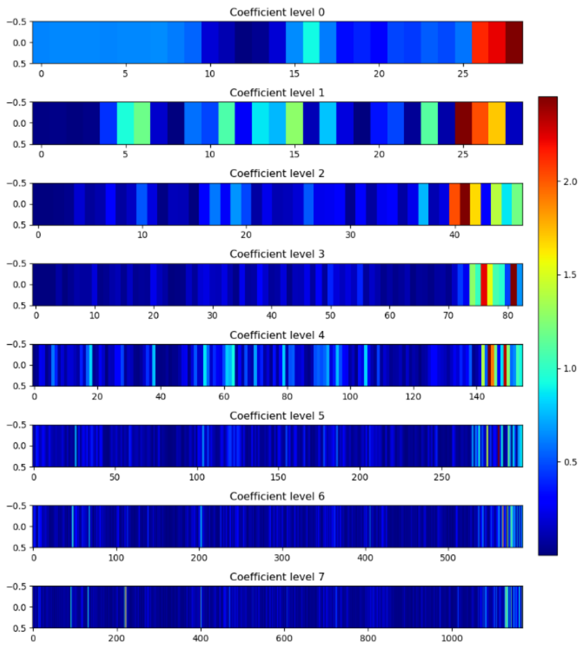

**Figure 15: Discrete wavelet decomposition of UBA**

Figure 15 presents heatmaps of wavelet decomposition coefficients across eight levels, showing different frequency bands of the original signal. Lower levels (0–2) reveal sharp transitions and high-frequency components, while higher levels (3–7) display sparser coefficients, indicating lower-frequency trends. This suggests that the signal combines localized high-frequency features with broader low-frequency patterns.

Figure 16 displays heatmaps of wavelet decomposition coefficients across eight levels (0–7), each representing a different frequency band of the original signal. The x-axis denotes the coefficient index, while the color gradient (-0.5 to 0.5) represents magnitude. At lower levels (0–2), distinct patterns with localized high-magnitude regions indicate sharp transitions and high-frequency components. At higher levels (3–7), coefficients become sparser, reflecting lower-frequency components and broader trends. This suggests that the original signal consists of both localized high-frequency features and overarching low-frequency trends. Fig. 17 displays heatmaps of wavelet decomposition coefficients across eight levels (0–7), each corresponding to a different frequency band of the original signal. The x-axis denotes the coefficient index, while the color gradient (-0.5 to 0.5) indicates magnitude. At lower levels (0–2), distinct patterns with localized high-magnitude regions suggest sharp transitions and high-frequency components. As decomposition progresses to higher levels (3–7), coefficients become sparse, highlighting lower-frequency trends. This indicates that the original signal is a combination of localized high-frequency details and broader low-frequency patterns.

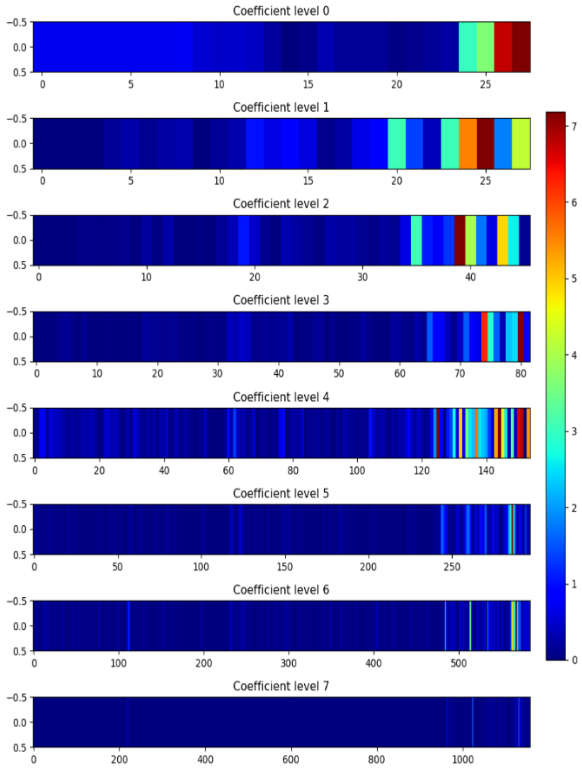


**Figure 16: Discrete wavelet decomposition of Wema bank**

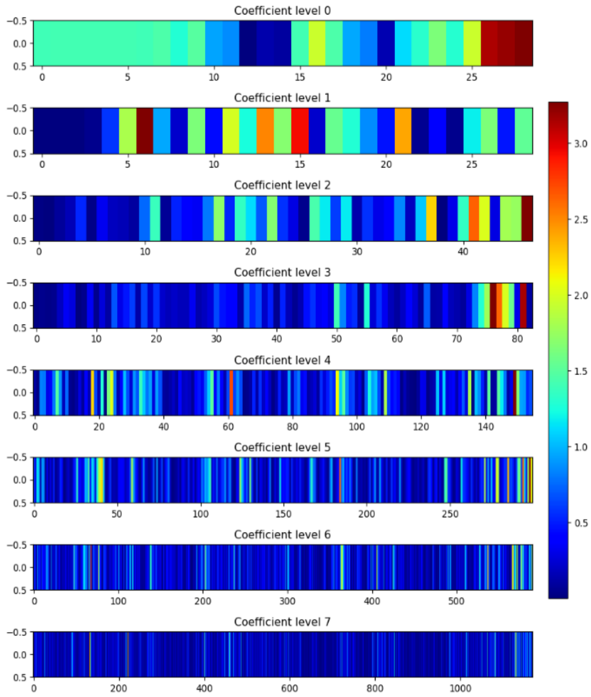


**Figure 17: Discrete wavelet decomposition of Zenith bank**

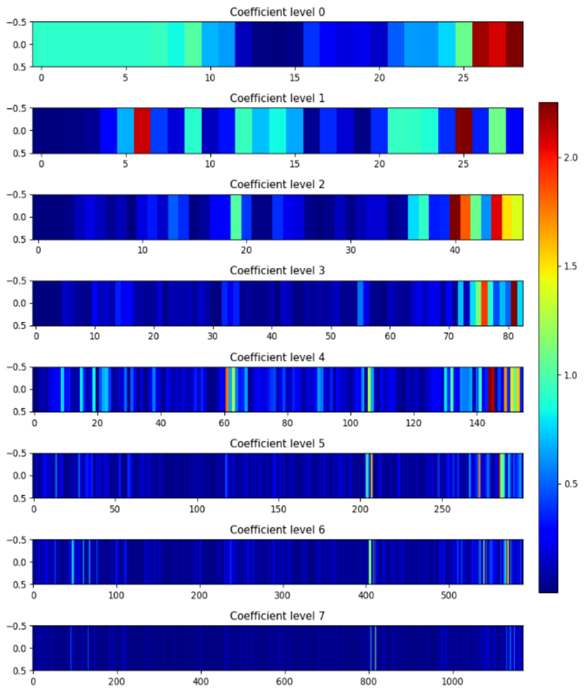


**Figure 18: Discrete wavelet decomposition of FCMB**

Figure 18 displays heatmaps of wavelet decomposition coefficients across eight levels (0 to 7), each representing different frequency bands of the original signal. Lower levels (0–2) show distinct high-magnitude regions, indicating sharp transitions or high-frequency components. At higher levels (3–7), coefficients become sparse, revealing lower-frequency trends. This suggests the original signal is a blend of localized high-frequency details and broader low-frequency patterns.

## SUMMARY

Looking at stock prices from 2014 to 2024, some clear trends stand out. Before (2014–2019), the market was relatively steady, with stock prices following predictable patterns and only moderate fluctuations. Then came the pandemic (2020–2021), which brought uncertainty and sent stock prices tumbling. Investors pulled back, trading activity slowed, and volatility soared. However, from 2022 onward, the market bounced back. Stocks especially those of UBA, Fidelity, and Zenith Bank experienced a strong surge, thanks to renewed investor confidence and financial sector reforms.

Among the banks studied, UBA and Zenith Bank had the largest market capitalizations, standing at ₦1.25 trillion and ₦1.96 trillion, respectively. This reflects their strong positions in the market. Fidelity, Wema, and FCMB had more modest valuations in comparison. When it came to trading volume, Zenith Bank led the way, with an impressive 22.92 million shares changing hands. A closer look at daily stock prices over the decade revealed some interesting patterns. Some banks, such as Zenith and UBA, showed steady growth with occasional dips and recoveries. Others, like Fidelity and Wema, remained relatively stable for years before experiencing sharp price spikes, particularly after 2022. Another key observation was volatility clustering—periods of sharp price swings followed by calmer stretches. These fluctuations often coincided with major external events, such as regulatory changes or shifts in market sentiment. To better understand these stock price trends, the study used a statistical method called wavelet decomposition. This technique breaks down price movements into two categories: High-frequency trends capture short-term changes, such as sudden market reactions to major news or policy decisions. Low-frequency trends show the bigger picture, reflecting long-term price movements. Most banks exhibited a mix of both, meaning their stock prices were shaped by a combination of immediate external factors and broader market trends.

## CONCLUSION

This study analyzed stock price movements and volatility in selected Nigerian banks (2014–2024) using statistical methods and wavelet analysis to understand both short-term shocks and long-term trends. Findings show three clear phases: stable market conditions before 2019, high volatility during the COVID-19 period (2020–2021), and a strong recovery after 2022, especially for Zenith Bank, UBA, and Fidelity Bank. The results also show that volatility occurs in clusters, meaning price changes come in bursts rather than steadily. Stock movements are influenced by economic events, policy changes, and investor reactions. Wavelet analysis revealed that market behaviour operates at different time scales, combining short-term fluctuations with long-term trends. Overall, Nigerian banking stocks are shaped by economic conditions and investor sentiment, with larger banks showing more stability and faster recovery. The study is useful for improving investment decisions and risk management.

**Conflict of interest:** The authors declare no conflict of interest.

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