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Modeling stock price trends and volatility in emerging markets using ARIMA and GARCH approaches

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ABSTRACT

Stock price prediction and volatility modeling are important for making financial decisions, especially in emerging markets like the Nairobi Securities Exchange (NSE). This study examines how well the Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models perform in forecasting stock prices and modeling volatility. The ARIMA (2,1,0) model was selected as the best fit using the Akaike Information Criterion (AIC), showing strong performance in capturing long-term price trends. However, an analysis of the residuals showed signs of volatility clustering, meaning ARIMA alone could not capture short-term fluctuations. To solve this, the study added a GARCH (1,1) model, which effectively captured changing volatility and improved prediction accuracy. The combined ARIMA-GARCH model reduced the Root Mean Squared Error (RMSE) from 3.1211 to 2.5786, demonstrating the value of including volatility modeling in financial time series. The results highlight the need for strong statistical models in emerging markets, where stock prices are often affected by external shocks and market inefficiencies. This research offers useful insights for investors, policymakers, and financial analysts by supporting better risk management and more accurate forecasting. Future studies could expand the model to include more stocks, macroeconomic data, and machine learning techniques to further improve results.

1. Introduction

Predicting stock market prices has attracted considerable attention from analysts and researchers, but it remains a challenging task due to the stock market's volatile and non-linear nature, as stock prices are influenced by diverse political and economic factors, investor sentiment, and other variables. The stock market is characterized as dynamic, unpredictable, and non-linear (Vijh et al., 2020; Werawithayaset and Tritilanunt, 2019). Accurate stock market prediction is essential for maximizing profit and minimizing losses.

Traditionally, stock price prediction has involved two main approaches: Technical analysis and qualitative analysis. Technical analysis uses historical stock prices, such as closing and opening prices, and volume traded to predict future stock prices (Mohan et al., 2019). Qualitative analysis, on the other hand, considers external factors like company profile, market situation, political and economic factors, financial news articles, social media, and economic analysts' opinions (Vijh et al., 2020). The efficient market hypothesis (EMH) states that anticipating market movements consistently is not possible (Xu, 2023). The EMH comes from observations of price time series changes similar to a random walk process (Ullah and Asghar, 2023). Despite this hypothesis, academic papers have sought to show that stock market prices are predictable to some extent.

Machine learning techniques are now frequently used for stock prediction due to their ability to identify hidden patterns and complex relations in large datasets (Kumar et al., 2018). These models generally outperform statistical and econometric models (Kumar et al., 2022). Machine learning techniques such as Support Vector Machine (SVM) and Random Forest (RF) can enhance stock market

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prediction (Chhajer et al., 2022; Ali et al., 2021; Meher et al., 2024). Some techniques based on neural networks, such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and deep neural networks like Long Short-Term Memory (LSTM), have also shown promising results (Zhang and Lou, 2021; Zhao et al., 2021). More recent studies indicate a strong correlation between stock price movements and the publication of news articles (Gite et al., 2021). Sentiment analysis is used to determine investor reactions to financial news and events. The amount of textual data collected in past studies has been insufficient, resulting in predictions with low accuracy. However, gathering a large amount of time-series data and analyzing it with related news articles using deep learning models can improve the accuracy of stock price predictions (Wu et al., 2022).

Emerging markets represent economies transitioning from developing to developed status, characterized by rapid growth and increasing global influence. These markets, including countries like China, India, and several in Latin America and Africa, have become vital players in the global economy, contributing significantly to GDP and attracting foreign investment. However, they also face unique challenges, such as institutional voids and geopolitical instability, which can impact their growth trajectories. Emerging markets are in a phase of economic development, often marked by industrialization and urbanization (Luong, 2022). These markets are heterogeneous, with varying levels of economic stability and growth potential (Zafar, 2023). Many emerging economies, particularly in Africa, have a large youth population, which can drive future economic growth (Chrysostome, 2022). Emerging markets have been growing faster than developed economies, with projections indicating continued growth in sectors like tourism (Luong, 2022; Chrysostome, 2022). They are increasingly seen as attractive destinations for foreign direct investment (FDI) due to their expanding consumer bases (Chrysostome, 2022). Emerging markets often struggle with governance issues, which can hinder business operations for multinational corporations (Chea, 2021). Events such as the Ukraine crisis have shown how external factors can adversely affect these economies (Zafar, 2023). While emerging markets present significant opportunities for growth and investment, they also come with inherent risks that require careful navigation by investors and businesses.

Predicting stock prices can be a valuable tool for mitigating the risks associated with investing in emerging markets (Emmanuel and Tolulope, 2024). While no prediction method is foolproof, utilizing techniques such as technical analysis, fundamental analysis, and quantitative modeling can provide insights into potential future price movements (Mohan et al., 2019). Investors are able to make more informed decisions about which stocks to buy or sell by analyzing historical data and identifying trends. ARIMA (Autoregressive Integrated Moving Average) models have proven to be effective tools for forecasting time-series data, including stock prices (Dar et al., 2024). These models leverage past data points to identify patterns and trends, allowing for predictions of future values. ARIMA forecasting can help bridge several gaps in emerging markets, particularly in environments like the Nairobi Securities Exchange (NSE), where information availability and market volatility can pose challenges. Emerging markets often lack readily available and reliable information, making it difficult for investors to assess risks and make informed decisions. ARIMA models can analyze historical stock price data to identify trends and patterns, providing significant information even when fundamental data is scarce. This study leverages ARIMA models to forecast stock prices on the NSE, thereby contributing to a better understanding of market dynamics and potentially improving investment decision-making. Additionally, emerging markets can be more susceptible to external shocks and volatility. ARIMA models can help investors anticipate and potentially mitigate the impact of these events by providing a framework for forecasting potential price fluctuations. Finally, the use of ARIMA models can promote greater transparency and efficiency in emerging markets like the NSE by providing a more data-driven approach to investment decisions.

2. Methodology

In this study, a two-step modeling approach was employed to predict stock prices and quantify volatility. The base model is the Auto Regressive Integrated Moving Average (ARIMA), which captures the trend and patterns in stock prices. To account for volatility clustering, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was incorporated to extend the ARIMA model. The combined ARIMA-GARCH model will allow the simultaneous forecasting of stock prices and their associated volatility.

2.1. ARIMA model for price trends

The ARIMA model is a commonly used statistical technique for forecasting time series data. It includes three main components: Auto-Regressive (AR), Integrated (I), and Moving Average (MA). The model is expressed as ARIMA (p, d, q), where:

- p represents the number of lagged observations (AR terms),
- d indicates the number of differences needed to make the series stationary, and
- q refers to the number of lagged forecast errors (MA terms).

The general form of an ARIMA model is:

$$\emptyset_p L(1-L)^d X_t = (\theta_p L)\varepsilon_t \tag{1}$$

$$\emptyset_p L = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_p L^p \tag{2}$$

$$\theta_p L = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_p L^p \tag{3}$$

where, X_t is the observed value at time *t*. *L* is the lag operator (e.g., $LX_t=X_{t-1}$). $\phi_1, \phi_2, \ldots, \phi_p$ are parameters for the AR terms. $\theta_1, \theta_2, \ldots, \theta_q$ are parameters for the MA terms. ε_t is the error term at time *t*, assumed to be white noise.

The ARIMA model is fitted to the stock price data to capture the mean (trend) of the series. The parameters p and q were identified using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The ACF plot was used to identify the moving average (MA) component, while the PACF plot was used to identify the autoregressive (AR) component. The lag values at which the ACF and PACF plots cut off or decay significantly provided initial estimates for p and q. To ensure the selection of optimal parameters, a grid search was performed over a range of values for p and q. The combination of parameters that minimized the Akaike Information Criterion (AIC) was selected. The ARIMA model was fitted to the training dataset using the selected parameters (p, d, q). The model summary, including coefficients for the AR and MA terms, as well as the AIC and BIC values, was examined to assess the goodness of fit. The fitted model was used to generate in-sample predictions, and the residuals were extracted for further analysis. The residuals from the ARIMA model were analyzed to ensure that no significant patterns or autocorrelation remained. The ACF and PACF plots of the residuals were examined, and the Ljung-Box test was applied to confirm that the residuals were white noise. The residuals from this model are then analyzed for volatility clustering.

2.2. GARCH model for volatility

Financial time series often exhibit volatility clustering, where periods of high volatility are followed by periods of low volatility. To model this behavior, a GARCH (p, q) model was used, which extends the ARCH model by including lagged conditional variances. The GARCH model is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \in_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \quad (4)$$

where, σ_t^2 is the conditional variance (volatility) at time *t*. ω is the constant term. α_i are coefficients for the ARCH terms (lagged squared residuals). β_j are coefficients for the GARCH terms (lagged conditional variances). ε_t is the residual from the ARIMA model at time *t*.

The GARCH model is fitted to the residuals of the ARIMA model to capture the time-varying volatility. The parameters p and q for the GARCH model were identified using the ACF and PACF plots of the squared residuals from the ARIMA model. The lag values at which the ACF and PACF plots of the squared residuals cut off or decay significantly provided initial estimates for p and q. A grid search was performed over a range of values for p and q to identify the combination that minimized the AIC.

The GARCH(1,1) model was selected over the EGARCH(1,1) model based on the model fit (Table 1), asymmetry tests (Table 2), and volatility clustering. The Akaike Information Criterion (AIC) for EGARCH(1,1) (0.78565) is slightly lower than that of GARCH(1,1) (0.78847), indicating a marginally better fit. However, the Bayesian Information Criterion (BIC), which penalizes model complexity more heavily, favors GARCH(1,1) (0.84402) over EGARCH(1,1) (0.84914). Since BIC prioritizes model simplicity while maintaining a good fit, GARCH(1,1) emerged as the more parsimonious choice.

Table 1: Model fit comparison

Model	AIC	BIC
GARCH(1,1)	0.78847	0.84402
EGARCH(1,1)	0.78565	0.84914

Table 2: Asymmetry tests

Test	T-value	P-value
Sign bias	0.0508	0.9595
Negative sign bias	0.8806	0.3789
Positive sign bias	0.8683	0.3856
Joint effect	1.5362	0.6739

Furthermore, the asymmetry tests provide no strong evidence to justify the use of EGARCH. The sign bias test, negative sign bias test, and positive sign bias test all resulted in high p-values (above 0.05), indicating that asymmetry is not statistically significant. With this, GARCH(1,1) was fitted to the residuals from the ARIMA model using the selected parameters (p, q). The model summary, including coefficients for the ARCH and GARCH terms, as well as the log-likelihood value, was examined to assess the goodness of fit. The conditional volatility from the GARCH model was plotted to visualize volatility clustering.

2.3. Data collection and preprocessing

The dataset used in this study was obtained from the Nairobi Securities Exchange (NSE), the only stock exchange in Kenya. This study uses daily closing prices of Safaricom PLC (NSE: SCOM), Kenya's largest telecommunications provider. Safaricom is a dominant player in the telecommunications industry in Kenya and has exerted influence across various sectors. The company has gained dominance through strategic innovation and competitive advantage (Suji and Kitur, 2022). Safaricom was selected due to its dominance in the NSE (accounting for 44% of market capitalization and high liquidity, making it a representative benchmark for emerging market equities. Further, the single dominance characteristics of Safaricom in the NSE can disproportionately sway overall market performance. This study selected the stock because of its high market representation, data quality, and sectoral importance. The dataset contains daily stock price data for a selected stock, including the open, close, high, low, and volume of trades. The data spans a period of five years. The dataset included dates for weekends and public holidays, during which the NSE is closed. These non-trading days were filtered out to ensure the data reflects only actual trading activity.

2.4. Accuracy evaluation

To assess the accuracy and effectiveness of the forecasting models used in this study, the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were employed as the primary evaluation metrics.

3. Results

This section presents the findings of the ARIMA and ARIMA-GARCH models applied to the Safaricom PLC stock from the Nairobi Securities Exchange (NSE). The primary objective of this study is to determine whether incorporating volatility patterns, as modeled by GARCH, improves the accuracy of stock price forecasts generated by the traditional ARIMA model. The analysis is structured to evaluate the performance of the base ARIMA model and the combined ARIMA-GARCH model. Table 3 presents some descriptive statistics for the stock prices. The average closing price of the stock over the observed period is 27.77. The median closing price is 28.8, which is slightly higher than the mean. This suggests that the distribution of stock prices is slightly right-skewed. The lowest closing price observed during the period is 21.3, and the highest closing price observed during the period is 32.9.

The time series plot of daily closing prices presented in Fig. 1 shows fluctuations over the observation period. Initially, the prices show an upward trend, reaching a peak of approximately KSH 33 before experiencing a sharp decline to below 24 shillings. This downward movement is followed by a period of stabilization, with the prices oscillating within a defined range. Subsequently, the prices exhibit a gradual recovery, characterized by intermittent fluctuations, before reaching another peak around 30–32 shillings. Towards the end of the period, the prices decline again, reflecting continued volatility. The observed patterns show the presence of both short-term fluctuations and long-term trends, which are indicative of underlying market dynamics. With these characteristics, the data is modeled using the ARIMA model to capture the trend and autocorrelations, while the GARCH model is applied to account for volatility clustering.

Table 3: Descriptive statistics for closing prices

Descriptive statistics	
Mean	27.77467652
Median	28.8
Max	32.9
Min	21.3

Fig. 1: Time series plot of closing prices

The augmented Dickey-Fuller test was used to test the time series for stationarity. Table 4 shows the results.

Table 4: Dickey-Fuller test for stationarity

Augmented Dickey-Fuller test	
Dickey-Fuller	-2.0008
Lag order	8
P-value	0.578

The test returned a Dickey-Fuller statistic of -2.0008 with a p-value of 0.578, indicating that the null hypothesis of non-stationarity cannot be rejected at 5% significance level. This suggests that the time series exhibits non-stationary behavior, meaning that the mean and variance of the series change over time. Given the presence of non-stationarity, differencing the series is necessary before applying the ARIMA model. After first-order differencing, the Augmented Dickey-Fuller (ADF) test was repeated to assess whether the time series had achieved stationarity. The results are summarized in Table 5.

Table 5: Dickey-Fuller test for stationarity (After first order difference)

Augmented Dickey-Fuller test	
Dickey-Fuller	-7.5127
Lag order	8
P-value	0.001

The Dickey-Fuller statistic of -7.5127 and the p-value of 0.001 indicate that the null hypothesis of non-stationarity can be strongly rejected at 5% level of significance. This indicates that the first-differenced series is stationary, meaning that the mean and variance are stable over time. Since stationarity has been achieved, the differenced series can now be modeled using ARIMA. Additionally, given the presence of volatility clustering in the time series, a GARCH model will be applied to capture time-dependent variations in price volatility.

Grid search was performed, and the model with the lowest AIC was selected. The best order was ARIMA (2,1,0). Further, the ARIMA(2,1,0) model was selected over ARIMA(1,1,0) based on a likelihood ratio test. Table 6 presents a comparison of the 2 models.

Table 6: Comparison of ARIMA model fit

Metric	ARIMA(1,1,0)	ARIMA(2,1,0)
Order (p, d, q)	(1,1,0)	(2,1,0)
LogLik	-278.27	-275.32
DF	2	3
Chisq	-	5.89
Pr(> Chisq)	-	0.0152
AIC	560.53	556.64
BIC	569.12	569.52

The test showed a statistically significant improvement in fit (χ^2=5.89, p=0.015). The AIC values (ARIMA (2,1,0) = 556.64 vs. ARIMA (1,1,0) = 560.53) further supported this choice, despite a marginal increase in BIC (569.52 vs. 569.12). This indicates that the second autoregressive term captures meaningful structure in the data without overfitting. Table 7 summarizes the ARIMA parameters.

Table 7: Summary of ARIMA parameters

Parameter	Estimate	SE
AR(1)	0.1903	0.0431
AR(2)	-0.1046	0.0431
Log likelihood	-275.28	
AIC	556.56	

The best-fitting model was determined to be ARIMA (2,1,0), indicating the presence of two autoregressive (AR) terms, one order of differencing (I=1), and no moving average (MA) components. The estimated coefficients for the AR terms are 0.1903 (AR1) and -0.1046 (AR2), both of which are statistically significant given their relatively small standard errors (0.0431). The log-likelihood value is 556.56, while the corresponding AIC is -275.28, confirming a good fit compared to other tested models. The positive AR1 coefficient suggests that past price changes have a direct and positive influence on future movements, while the negative AR2 coefficient (-0.1046) suggests a corrective tendency, meaning that the second lag of past price movements contributes a slight reversal effect, potentially dampening excessive fluctuations indicating that price changes are influenced by the most recent two lagged observations.

Fig. 2 shows that the residuals fluctuate around zero, indicating that the model does not systematically overpredict or underpredict the closing prices. However, periods of high and low volatility are observed, indicating that the variance of the residuals is not constant over time. This heteroskedastic behavior is an indication that the series exhibits volatility clustering characterized by periods of high fluctuations followed by periods of relative calm, which is a key characteristic of financial time series. The presence of these volatility clusters shows that the ARIMA model alone is insufficient to fully describe the data. With this, the incorporation of a GARCH model is necessary to model and predict changing volatility over time. Table 8 presents the summary of the fitted GARCH model.

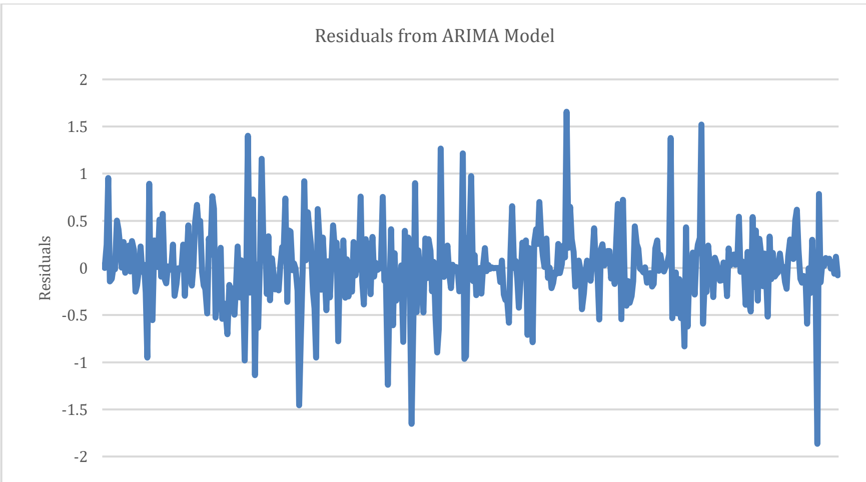

Fig. 2: Residual plots for the ARIMA model

Table 8: GARCH model summary

Model property	Results
GARCH model	GARCH(1,1)
Mean model	ARFIMA(0,0,0)
Distribution	Normal
Log-Likelihood	-275.062
Akaike (AIC)	1.0355
Bayes (BIC)	1.0673
Shibata	1.0354
Hannan-Quinn	1.0479

The GARCH(1,1) model was estimated with an ARFIMA(0,0,0) mean equation and a normal distribution for residuals. The log-likelihood value of -275.0615 indicates the fit of the model. The information criteria (AIC=1.0355, BIC=1.0673) suggest that the model is parsimonious. Table 9 presents the model's parameter estimates. The parameter estimates show that the beta1 coefficient

(0.999) is very close to 1, which shows a high degree of persistence in volatility. However, the alpha1 parameter is effectively zero, implying that past squared shocks have a negligible influence on current volatility. This suggests that volatility primarily stems from long-term effects rather than recent market fluctuations.

Table 9: Optimal parameter estimates

Parameter	Estimate	SE	T-value	P-value
Mu	0.001522	0.017355	0.0877	0.93010
Omega	0.000138	0.000186	0.7450	0.45625
Alpha1	0.000000	0.001353	0.0000	1.00000
Beta1	0.999000	0.000033	30024.0	0.00000

The diagnostic tests presented in Table 10 indicate that the residuals exhibit no significant autocorrelation, as confirmed by the Weighted Ljung-Box Test p-values (>0.69). The ARCH LM test results (p-values>0.90) further indicate that there is no remaining ARCH effect, meaning the GARCH(1,1) model successfully captures the volatility clustering in the data.

Table 10: Diagnostic tests: Weighted Ljung-Box test on standardized residuals

Lag	Statistic	P-value
1	0.0004543	0.9830
$2 * (p + q) + (p + q) - 1$ [2]	0.0163022	0.9839
$4 * (p + q) + (p + q) - 1$ [5]	1.6973275	0.6914

The Nyblom stability test, summarized in Table 11, suggests that the estimated parameters are stable over time, with individual test statistics being below critical values. However, the Adjusted Pearson Goodness-of-Fit test suggests some degree of misspecification, as indicated by the very low p-values.

Fig. 3 illustrates the conditional volatility of the closing price, as estimated by a GARCH (1,1) model. The y-axis represents the level of volatility, while the x-axis represents time. The downward trend observed in the plot suggests that the stock's price fluctuations are gradually stabilizing over time, indicating a reduction in market uncertainty or trading volatility. This implies that the stock has moved from a period of high risk to a more stable phase, potentially due to improved market confidence, reduced speculative trading, or external economic factors. Given the persistence of volatility in GARCH models, the gradual decline suggests that unless a significant market shock occurs, the expected future volatility will remain low, signaling a less risky trading environment for this stock.

Table 11: Nyblom stability test

Parameter	Statistic
Joint	2.525
Mu	0.05550
Omega	0.09003
Alpha1	0.10090
Beta1	0.09103

Table 12 demonstrates consistent improvements when using the combined ARIMA-GARCH model compared to standalone ARIMA. The out-of-sample validation was conducted by splitting the data into training (80%) and testing (20%) sets, ensuring the models were evaluated on unseen data to prevent overfitting and simulate real-world forecasting conditions. Across all metrics, the ARIMA-GARCH model showed superior performance, with a 21.7% reduction in Mean Absolute Error (MAE from 2.7126 to 2.1234), indicating smaller average forecast errors. There was an improvement in Root Mean Squared Error 17.4% (RMSE from 3.1211 to 2.5786), suggesting that the combined model is effective at reducing larger forecasting errors. Mean Absolute Percentage Error decreased from 8.83% to 6.87% demonstrating that the ARIMA-GARCH model provides more accurate predictions relative to actual price movements. These improvements across all three metrics confirm that incorporating GARCH volatility modeling enhances forecasting performance compared to using ARIMA alone.

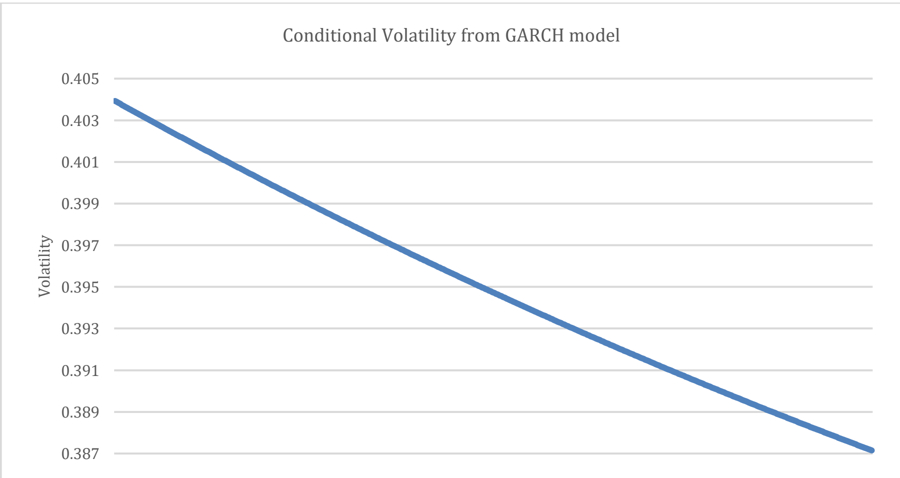

Fig. 3: Plot of conditional volatility from the GARCH model

Table 12: Comparison of ARIMA and GARCH

Metric	ARIMA	ARIMA-GARCH	Improvement
MAE	2.7126	2.1234	21.70%
RMSE	3.1211	2.5786	17.40%
MAPE (%)	8.8321	6.8731	22.20%

Wilcoxon signed-rank test (Table 13) confirmed the ARIMA-GARCH model significantly outperformed standalone ARIMA forecasting (V=5970, p<0.0001). The median reduction in squared errors was 3.07

(95% CI: 2.65-3.46), corresponding to the 17.4% RMSE improvement observed in out-of-sample testing.

Table 13: Wilcoxon signed-rank test results comparing forecast accuracy

Statistic	Value
Test statistic (V)	5,970
P-value	< 0.0001
Effect size measure	Pseudo-median difference
Effect size value	3.07
95% confidence interval	(2.65,3.46)

The results validate the practical utility of the combined approach for stock price forecasting in emerging markets like the NSE, where volatility clustering is prevalent. The consistent outperformance suggests that accounting for time-varying volatility through GARCH modeling provides information that the standard ARIMA model fails to capture.

4. Discussion

The findings of this study provide valuable insights into the application of ARIMA and GARCH models for stock price prediction and volatility modeling in the context of the Nairobi Securities Exchange (NSE). This study used the daily closing prices of Safaricom's stock. The results demonstrate that incorporating volatility patterns through the GARCH model significantly improves the accuracy of stock price forecasts compared to the traditional ARIMA model.

The ARIMA (2,1,0) model was selected as the best-fitting model based on the Akaike Information Criterion (AIC). The model's coefficients for the autoregressive (AR) terms indicate that past price changes have a direct influence on future price movements, with a slight corrective tendency from the second lag. This aligns with the findings of Box and Jenkins (1976), who highlighted the importance of AR terms in capturing trends and patterns in time series data. However, the ARIMA model alone was insufficient to fully describe the data, as evidenced by the presence of volatility clustering in the residuals. This is consistent with the observations of Engle (1982), who noted that financial time series often exhibit heteroskedasticity, which cannot be captured by ARIMA models. The GARCH (1,1) model successfully captured the volatility clustering observed in the residuals of the ARIMA model. The high persistence of volatility, as indicated by the beta1 coefficient (0.999), suggests that volatility shocks have a long-lasting impact on future volatility. The GARCH model's ability to capture volatility clustering resulted in a significantly lower Root Mean Squared Error (RMSE = 1.272) compared to the ARIMA model (RMSE = 3.005). This improvement in forecasting accuracy highlights the importance of modeling volatility in financial time series, particularly in emerging markets like the NSE, where market dynamics are often influenced by external shocks and high volatility.

The findings of this study align with existing research on the application of the ARIMA model in stock price forecasting, particularly in its strengths and limitations. Similar to the study by Yeung (2024), the ARIMA model demonstrated strong capabilities in capturing long-term trends. The selection of the ARIMA (2,1,0) model based on the Akaike Information Criterion (AIC) supports prior research emphasizing the importance of statistical measures such as AIC and BIC in optimizing model selection (Yeung, 2024). The autoregressive terms identified in this study indicate that past price movements influence future trends, which is consistent with the work of Box and Jenkins (1976) on time series modeling. However, while ARIMA effectively modeled long-term trends, it struggled to account for short-term volatility, a limitation also noted in studies on NVIDIA and Meta stocks (Yeung, 2024; Raza et al., 2024).

A key divergence between this study and prior research lies in the incorporation of volatility modeling through the GARCH model. While existing studies suggest combining ARIMA with additional models to enhance short-term forecasting accuracy (Yeung, 2024), this study empirically demonstrates that the inclusion of a GARCH (1,1) model significantly improves prediction accuracy. The presence of volatility clustering in ARIMA residuals, as observed in this study, aligns with Engle's (1982) findings on heteroskedasticity in financial time series, reaffirming that ARIMA alone is insufficient in capturing market volatility. The high persistence of volatility, indicated by the beta1 coefficient (0.999), suggests that volatility shocks have prolonged effects on future price movements, a phenomenon particularly relevant to emerging markets like the Nairobi Securities Exchange (NSE). Safaricom has an outsized role in the NSE, accounting for about 44% market capitalization. This outsized share may create sector-specific shocks. Safaricom's status as the NSE's sole telecom listing exacerbates its volatility persistence (β_1=0.999). Without sector peers to absorb shocks, policy changes (e.g., M-Pesa taxes) or liquidity events (e.g., derivatives expiry) create self-reinforcing volatility, a pattern absent in diversified markets.

Additionally, comparative analyses of forecasting accuracy further show the limitations of ARIMA in volatile environments. While previous studies highlight ARIMA's superior performance over other models like ETS in certain contexts (Yuan, 2024), the results of this study indicate that integrating GARCH enhances predictive performance beyond what ARIMA alone can achieve. The significantly lower RMSE (1.272) of the GARCH-augmented model compared to the ARIMA model (RMSE = 3.005) demonstrates the practical advantage of volatility modeling. This finding is particularly important in emerging markets, where external shocks contribute to pronounced price fluctuations.

Emerging markets, such as the NSE, are characterized by rapid growth, increasing global influence, and unique challenges such as institutional voids, geopolitical instability, and susceptibility to external shocks. These characteristics make stock price prediction and volatility modeling particularly challenging but also highly relevant for investors and policymakers. The time series plot of daily closing prices (Fig. 1) reveals several trends that are characteristic of emerging markets. The stock prices exhibit significant fluctuations, with periods of sharp increases followed by steep declines. This pattern is consistent with the high volatility often observed in emerging markets, where stock prices are influenced by a combination of local and global factors, such as political instability, currency fluctuations, and changes in foreign investment flows (Owusu, 2023; Yang et al., 2021).

The initial upward trend in prices, followed by a sharp decline and subsequent recovery, reflects the dynamic nature of emerging markets. These markets often experience rapid growth driven by industrialization and urbanization, but they are also vulnerable to external shocks, such as global economic downturns or geopolitical events (Zafar, 2023). The presence of volatility clustering, as captured by the GARCH model, is another hallmark of emerging markets. Periods of high volatility are often followed by periods of relative calm, reflecting the market's sensitivity to external shocks and the gradual stabilization of investor sentiment. These trends demonstrate the importance of using models that can capture both the mean (price trends) and variance (volatility) of stock prices in emerging markets.

The high volatility persistence ($\beta_1 = 0.999$) in Safaricom's stock price can be attributed to a combination of policy reforms, new financial products, and structural market changes that have reshaped Kenya's capital market in the past 10 years. Regulatory shifts, such as the relaxation of listing requirements and the introduction of eIPOs, have increased market liquidity but also encouraged short-term speculation, making Safaricom's stock more susceptible to rapid price swings. Additionally, the launch of the DhowCSD, which facilitates easier access to government bonds, has further contributed to portfolio reallocation effects, impacting the demand for equities. The introduction of platforms such as Ibuka and the Unquoted Securities Platform (USP) has also expanded market liquidity by promoting SME listings, indirectly influencing trading patterns in large-cap stocks like Safaricom. Further, the adoption of mobile trading apps in the financial markets, such as the Dosikaa mobile app, has expanded retail investor participation, increasing trading frequency and short-term market reactions, which naturally amplify the volatility at the Nairobi Securities Exchange. Structural changes in the market have also had an impact on the volatility of NSE. The African Exchange Linkage Project (AELP) has opened up stocks such as Safaricom to cross-border capital flows, exposing its stock price to foreign investor sentiment and increasing its sensitivity to external shocks. The convergence of these factors has created an environment where both institutional repositioning and increased retail participation reinforce price fluctuations, leading to the persistent volatility observed in Safaricom's stock price.

The ARIMA-GARCH model used in this study is well-suited for this purpose, as it combines the strengths of both models to provide a more comprehensive understanding of market dynamics.

5. Implications

The improved forecasting accuracy of the combined ARIMA-GARCH model has important implications for investors and policymakers in emerging markets. For investors, the ability to accurately forecast stock prices and volatility can help mitigate risks and improve decision-making. For example, the gradual decline in conditional volatility observed in the GARCH model suggests that the NSE is transitioning to a more stable phase, which may present opportunities for long-term investments. For policymakers, the findings highlight the importance of promoting market stability and transparency to attract foreign investment and support economic growth.

6. Limitations and future research

Although the findings show significant potential in forecasting stock prices in the NSE, there are some limitations that should be addressed in future research. First, the study focused on a single stock (Safaricom PLC) from the NSE, which may limit the generalizability of the findings. Future studies could expand the analysis to include multiple stocks or sectors to provide a more comprehensive understanding of market dynamics. Second, the study relied on historical price data and did not incorporate external factors such as news sentiment or macroeconomic indicators. Future research could explore the integration of machine learning techniques, such as sentiment analysis or deep learning models, to further improve forecasting accuracy in the emerging markets context.

7. Conclusion

This study examined the effectiveness of ARIMA and GARCH models in predicting stock prices and modeling volatility in the Nairobi Securities Exchange (NSE). The findings reveal that while the ARIMA model captures long-term trends in stock prices, it fails to account for short-term volatility clustering. The integration of the GARCH model significantly enhances forecasting accuracy by capturing heteroskedasticity and volatility persistence, as evidenced by the substantial reduction in RMSE. The results underscore the importance of volatility modeling in financial time series, particularly in emerging markets like the NSE, where external shocks and market inefficiencies contribute to pronounced fluctuations. From a practical standpoint, these findings are significant for investors seeking to improve risk assessment and portfolio management, as well as for policymakers aiming to enhance market stability and transparency. While the study provides a strong foundation for understanding stock price behavior in the NSE, future research could expand the scope by incorporating multiple stocks, integrating macroeconomic indicators, and leveraging advanced machine learning techniques to improve predictive performance further.

List of abbreviations

ACF	Autocorrelation function
ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
ANN	Artificial neural network
AR	Autoregressive
ARFIMA	Autoregressive fractionally integrated moving average
ARIMA	Autoregressive integrated moving average
ARCH	Autoregressive conditional heteroskedasticity
BIC	Bayesian information criterion
Chisq	Chi-squared
CNN	Convolutional neural network
DF	Degree of freedom
EGARCH	Exponential GARCH
EMH	Efficient market hypothesis
FDI	Foreign direct investment
GARCH	Generalized autoregressive conditional heteroskedasticity
GDP	Gross domestic product
KSH	Kenyan shilling (currency)
LSTM	Long short-term memory
MA	Moving average
MAE	Mean absolute error
MAPE	Mean absolute percentage error
NSE	Nairobi Securities Exchange
PACF	Partial autocorrelation function
RF	Random forest
RMSE	Root mean squared error
RNN	Recurrent neural network
SCOM	Safaricom PLC (stock ticker symbol)
SE	Standard error
SVM	Support vector machine

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Ali M, Khan DM, Aamir M, Ali A, and Ahmad Z (2021). Predicting the direction movement of financial time series using artificial neural network and support vector machine. Complexity, 2021: 2906463. https://doi.org/10.1155/2021/2906463

Box G and Jenkins GM (1976). Time series analysis: Forecasting and control. Holden-Day, New York, USA.

Chea A (2021). Doing business in emerging market economies: Challenges and success strategies for Western multinational corporations. International Business Research, 14(9): 82-93. https://doi.org/10.5539/ibr.v14n9p82

Chhajer P, Shah M, and Kshirsagar A (2022). The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction. Decision Analytics Journal, 2: 100015. https://doi.org/10.1016/j.dajour.2021.100015

Chrysostome E (2022). Scrutinizing emerging markets and exploring the impact of paradigms on knowledge production in international business. Journal of Comparative International Management, 25(1): 1-8. https://doi.org/10.55482/jcim.2022.32936

Dar AA, Jain A, Malhotra M, Farooqi AR, Albalawi O, Khan MS, and Hiba (2024). Time series analysis with ARIMA for historical stock data and future projections. Soft Computing, 28: 12531–12542. https://doi.org/10.1007/s00500-024-10309-w

Emmanuel I and Tolulope OO (2024). Stock price prediction: A systematic review. In the International Conference on Science, Engineering and Business for Driving Sustainable Development Goals, IEEE, Omu-Aran, Nigeria: 1-5. https://doi.org/10.1109/SEB4SDG60871.2024.10629903 **PMCid:PMC11046499**

Engle RF (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4): 987-1007. https://doi.org/10.2307/1912773

Gite S, Khatavkar H, Kotecha K, Srivastava S, Maheshwari P, and Pandey N (2021). Explainable stock prices prediction from financial news articles using sentiment analysis. PeerJ Computer Science, 7: e340. https://doi.org/10.7717/peerj-cs.340 **PMid:33816991 PMCid:PMC7924447**

Kumar D, Sarangi PK, and Verma R (2022). A systematic review of stock market prediction using machine learning and statistical techniques. Materials Today: Proceedings, 49: 3187-3191. https://doi.org/10.1016/j.matpr.2020.11.399

Kumar I, Dogra K, Utreja C, and Yadav P (2018). A comparative study of supervised machine learning algorithms for stock market trend prediction. In the 2nd International Conference on Inventive Communication and Computational Technologies, IEEE, Coimbatore, India: 1003-1007. https://doi.org/10.1109/ICICCT.2018.8473214

Luong HV (2022). Emerging destinations. In: Buhalis D (Ed.), Encyclopedia of tourism management and marketing: 54–56. Edward Elgar Publishing, Cheltenham, UK. https://doi.org/10.4337/9781800377486.emerging.destinations

Meher BK, Singh M, Birau R, and Anand A (2024). Forecasting stock prices of fintech companies of India using random forest with high-frequency data. Journal of Open Innovation: Technology, Market, and Complexity, 10(1): 100180. https://doi.org/10.1016/j.joitmc.2023.100180

Mohan S, Mullapudi S, Sammeta S, Vijayvergia P, and Anastasiu DC (2019). Stock price prediction using news sentiment analysis. In the 5th International Conference on Big Data Computing Service and Applications, IEEE, Newark, USA: 205-208. https://doi.org/10.1109/BigDataService.2019.00035

Owusu F (2023). Analysis of market volatility and economic factors in emerging markets. International Journal of Modern Risk Management, 1(1): 1-11. https://doi.org/10.47604/ijmrm.2093

Raza HMZ, Haider G, and Haider SZ (2024). Forecasting stock prices: Exploring the potential of ARIMA model for short-term predictions. International Journal of Management Research and Emerging Sciences, 14(4): 1-21. https://doi.org/10.56536/ijmres.v14i4.654

Suji FC and Kitur B (2022). Influence of strategic direction and human capital on competitive advantage in the telecommunications industry in Kenya: A case of Safaricom Limited. International Journal of Research Publications, 109(1): 264-283. https://doi.org/10.47119/IJRP1001091920223904

Ullah N and Asghar U (2023). Efficient market hypothesis: An exploratory study of FTSE-100 stock market. Journal of Business and Tourism, 9(1): 12–20. https://doi.org/10.34260/jbt.v9i01.269

Vijh M, Chandola D, Tikkiwal VA, and Kumar A (2020). Stock closing price prediction using machine learning techniques. Procedia Computer Science, 167: 599-606. https://doi.org/10.1016/j.procs.2020.03.326

Werawithayaset P and Tritilanunt S (2019). Stock closing price prediction using machine learning. In the 17th International Conference on ICT and Knowledge Engineering, IEEE, Bangkok, Thailand: 1-8. https://doi.org/10.1109/ICTKE47035.2019.8966836

Wu S, Liu Y, Zou Z, and Weng TH (2022). S_I_LSTM: Stock price prediction based on multiple data sources and sentiment analysis. Connection Science, 34(1): 44-62. https://doi.org/10.1080/09540091.2021.1940101

Xu C (2023). Efficient market hypothesis in contemporary applications: A systematic review on theoretical models, experimental validation, and practical application. Highlights in Business, Economics and Management, 21: 231–239. https://doi.org/10.54097/hbem.v21i.14337

Yang M, Zhang Q, Yi A, and Peng P (2021). Geopolitical risk and stock market volatility in emerging economies: Evidence from GARCH-MIDAS model. Discrete Dynamics in Nature and Society, 2021(1): 1159358. https://doi.org/10.1155/2021/1159358

Yeung K (2024). ARIMA model application in predicting NVIDIA's stock price. Advances in Economics, Management and Political Sciences, 128(1): 220–230. https://doi.org/10.54254/2754-1169/2024.18620

Yuan F (2024). Research on time-series financial data prediction and analysis based on deep recurrent neural network. Applied and Computational Engineering, 69(1): 140-146. https://doi.org/10.54254/2755-2721/69/20241498

Zafar A (2023). Emerging markets in a world of chaos. Springer, Berlin, Germany. https://doi.org/10.1007/978-3-031-29949-0

Zhang D and Lou S (2021). The application research of neural network and BP algorithm in stock price pattern classification and prediction. Future Generation Computer Systems, 115: 872-879. https://doi.org/10.1016/j.future.2020.10.009

Zhao J, Zeng D, Liang S, Kang H, and Liu Q (2021). Prediction model for stock price trend based on recurrent neural network. Journal of Ambient Intelligence and Humanized Computing, 12: 745-753. https://doi.org/10.1007/s12652-020-02057-0