Quest Journals
Journal of Research in Applied Mathematics
Volume 11 ~ Issue 9 (September 2025) pp: 42-50
ISSN (Online): 2394-0743 ISSN (Print): 2394-0735
www.questjournals.org

Research Paper

Modeling and Forecasting PZ Cussons Nigeria PLC Daily Stock Prices Using SARIMA: An Empirical Analysis

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ABSTRACT: *This study conducts a comprehensive empirical analysis of modeling and forecasting the daily stock prices of PZ Cussons Nigeria PLC using the Seasonal Autoregressive Integrated Moving Average (SARIMA) framework within the Box-Jenkins methodology. Utilizing a dataset of 2,289 daily closing prices spanning from January 5, 2015, to November 22, 2023, the research rigorously compares the forecasting performance of SARIMA against a non-seasonal ARIMA benchmark. Stationarity is assessed via the Augmented Dickey-Fuller (ADF) test, with model selection guided by the Akaike Information Criterion (AIC). The optimal models identified are SARIMA(1,0,1)(0,3,2,20) and ARIMA(5,3,0), with diagnostic checks confirming adequacy through residual analysis and Ljung-Box tests. Forecast accuracy is evaluated out-of-sample using root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) across multiple horizons. Results indicate that while ARIMA exhibits marginally lower RMSE in short-term forecasts, SARIMA consistently outperforms in MAPE and demonstrates superior robustness over medium to long-term horizons, particularly beyond one month. Trading strategy backtests further reveal that SARIMA-based signals yield significantly higher cumulative returns (15.5% vs. 8.1%), hit rates (56% vs. 47%), and Sharpe ratios (1.12 vs. 0.68), with lower maximum drawdowns. These findings underscore the critical role of seasonality potentially driven by institutional rebalancing, fiscal cycles, and behavioral market responses in Nigerian equity price dynamics. The study contributes to the literature on financial econometrics in emerging African markets by providing empirical evidence that SARIMA offers enhanced predictive accuracy and practical trading utility compared to traditional ARIMA, affirming the relevance of classical time series models in contemporary quantitative finance.*

KEYWORDS: *SARIMA; ARIMA, Stock Price Forecasting, Time Series Analysis, Financial Econometrics, Forecasting Accuracy, Nigerian Stock Exchange, PZ Cussons Nigeria PLC*

Received 14 Sep., 2025; Revised 25 Sep., 2025; Accepted 27 Sep., 2025

I. INTRODUCTION

Stock market forecasting remains a cornerstone of quantitative finance, offering critical insights for investors, portfolio managers, financial analysts, and policymakers in both developed and emerging economies. In the context of the Nigerian equity market, a dynamic yet volatile environment characterized by macroeconomic fluctuations, structural shifts, and unique calendar effects, accurate modeling of stock price behavior is essential for informed decision-making. The increasing availability of high-frequency financial data and advances in time series econometrics have empowered researchers to develop robust models capable of capturing complex temporal dependencies in asset prices.

Among the most widely used statistical frameworks for univariate time series forecasting are the Autoregressive Integrated Moving Average (ARIMA) and its seasonal extension, Seasonal ARIMA (SARIMA), introduced within the Box-Jenkins methodology [6]. These models provide a systematic approach to identifying, estimating, and validating processes that exhibit trends, autocorrelation, and seasonality. While ARIMA has been extensively applied in financial forecasting, its non-seasonal structure may fail to capture periodic patterns inherent in daily trading data patterns that can arise from institutional rebalancing, corporate reporting cycles, fiscal policies, or behavioral market responses.

PZ Cussons Nigeria PLC (NSENG: PZ), one of Nigeria's oldest and most liquid consumer goods companies, presents an ideal case study for evaluating such models. Established in 1899 as a subsidiary of the UK-based PZ Cussons Holdings Limited, the company operates across key sectors including personal care, home care, and branded electrical appliances, with well-known brands such as Imperial Leather, Morning Fresh, and Haier Thermocool. As of August 2025, the firm boasts a market capitalization of approximately NGN 138.97 billion, reflecting strong investor interest and consistent trading volume on the Nigerian Stock Exchange (NGX). Over the past five years, PZ Cussons has delivered exceptional returns exceeding 800%, underpinned by improved profitability and operational efficiency, including a reported revenue of NGN 212.6 billion and post-tax profit of NGN 5.5 billion for the fiscal year ending May 2025.

Despite this growth trajectory, the stock exhibits notable volatility, influenced by both domestic macroeconomic conditions, such as inflationary pressures, foreign exchange instability, and monetary tightening, and global commodity dynamics. This volatility, coupled with observable recurring patterns in trading activity, raises the question of whether seasonal components significantly influence short-term price movements.

In the domain of stock market forecasting, a variety of methodologies rooted in technical analysis have been formulated and employed over time [10]. Technical forecasting typically involves the derivation of indicators such as rolling means, rolling standard deviations or variances, and lagged observations from historical time series data to anticipate future movements in asset prices. A considerable body of research has explored the application of computational models for predicting financial market behavior, with particular attention given to non-linear modeling approaches.

Comparative studies in predictive and classification tasks have evaluated the efficacy of these non-linear models against traditional parametric statistical techniques [12]. Within the context of time series forecasting, empirical investigations have yielded inconsistent outcomes regarding model superiority. Notable contributions include [8, 14, 16], and [17], whose findings suggest that certain non-linear frameworks demonstrate superior performance relative to conventional parametric models, particularly when applied to time series exhibiting minimal stochastic variation. Of particular interest, [17] observed that the predictive capability of such models is contingent upon the memory properties inherent in the time series, especially when benchmarked against Box-Jenkins ARIMA specifications.

In the Nigerian context, [3] employed a regression-based computational framework incorporating a backpropagation learning mechanism to model both transformed and raw Nigerian Stock Market Prices (NSMP). Their comparative assessment revealed that using transformed NSMP as input variables significantly enhanced predictive accuracy. Specifically, the model utilizing transformed inputs achieved an 11.3% prediction accuracy rate, compared to only 2.7% for the untransformed counterpart.

Also, [5] studied and evaluated the Seasonal ARIMA and Holt-Winters exponential smoothing for forecasting the Nigerian Stock Exchange using monthly data from 1985 to 2013. Through a two-stage comparative approach, both models demonstrate effectiveness in stable conditions; however, Holt-Winters outperforms Seasonal ARIMA under structural variation, indicating superior short-term forecasting accuracy. The findings highlight the significance of seasonality in market dynamics and underscore the utility of adaptive models for financial planning in emerging markets. From a classical time series modeling perspective, [9] investigated subset autoregressive integrated moving average (ARIMA) models for forecasting Nigerian stock market returns. Model parameters were estimated via numerical optimization techniques, including the Newton-Raphson and Marquardt-Levenberg algorithms. Model adequacy and efficiency were assessed using information criteria such as AIC and BIC, along with residual variance analysis. The results indicated that the seasonal ARIMA (SARIMA) specification provided a better fit than the standard ARIMA model, as evidenced by lower residual variance.

[7] Analyzed the Nigerian Stock Exchange (NSE) returns series using monthly All-Share Index data spanning from January 1985 to December 2008. An ARIMA (1, 1, 1) model was identified as a suitable candidate for forecasting index levels and growth rates. However, the study found that the global financial crisis disrupted the historical autocorrelation structure of the index, undermining the model's out-of-sample predictive reliability.

[1] Examined the stochastic properties of daily returns on the Nigeria stock market through the lens of Discrete Time Markov Chains and martingale theory. Their analysis supported the hypothesis that daily returns follow a random walk process; However, they concluded that the market does not satisfy even the weak form of informational efficiency.

Additional studies applying ARIMA-based methodologies to stock market data in African economies include [15, 11], and [4]. Despite their methodological rigor, these works did not investigate whether the underlying price or return generating processes exhibit fractal characteristics. Addressing this gap, the present study aims to assess the fractal nature of the Nigerian stock market prior to undertaking further econometric analysis.

This study contributes to the existing literature by conducting a comprehensive empirical analysis of PZ Cussons Nigeria PLC's daily closing prices using SARIMA modeling. It rigorously com- pares the performance of SARIMA against a non-seasonal ARIMA benchmark using out-of-sample forecasts evaluated via root mean squared error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE). Furthermore, it assesses the practical implications of these forecasts through back testing of simple trading strategies, measuring cumulative returns, hit rates, maximum drawdowns, and Sharpe ratios. By isolating the impact of seasonality, this research provides evidence- based guidance for quantitative traders and risk managers operating in African emerging markets

II. DATA ACQUISITION AND PREPROCESSING

The dataset comprises daily closing prices of PZ Cussons Nigeria PLC (ticker: NSENG: PZ) obtained from official financial data vendors tracking the Nigerian Stock Exchange (NGX). The sample spans from January 5, 2015, to November 22, 2023, ensuring sufficient temporal coverage to capture long-term trends, structural breaks, and seasonal dynamics. Given the irregular nature of trading days due to weekends and public holidays, the raw price series was converted into a regular daily time series format by excluding non-trading dates rather than interpolating values, preserving the integrity of market-generated information.

Exploratory data analysis was conducted to detect outliers, structural shifts, and preliminary indications of seasonality. Visual inspection of the price series revealed upward trends, volatility clustering, and potential cyclical patterns aligned with weekly and monthly intervals. To maintain direct applicability to trading decisions, the study focused on forecasting actual price levels rather than log-returns, thereby enabling straightforward interpretation of buy/sell signals.

III. STATIONARITY ASSESSMENT

Given the fundamental requirement of stationarity for ARIMA-type models, the Augmented Dickey-Fuller (ADF) test was applied to the original price series. The null hypothesis posits the presence of a unit root (i.e., non-stationarity), while rejection at the 5% significance level indicates stationarity. Initial testing confirmed non-stationarity in the level series, necessitating differencing. First-order differencing was applied to remove stochastic trends, followed by seasonal differencing to address persistent periodic fluctuations. Diagnostic checks were reinforced using graphical tools such as ACF and PACF plots, which helped identify decay patterns consistent with integrated processes.

A. Model Specification: ARIMA vs. SARIMA

1. An ARIMA model is defined by three parameters:

a. p: order of the autoregressive (AR) part

b. d: degree of differencing (to make the series stationary)

c. q: order of the moving average (MA) part

General Form:

Let y_t be the observed value at time t, and let ϕ_i, θ_j be the model coefficients.

After applying differencing of order d, define the differenced series:

$$(1-B)^d y_t = z_t$$

where B is the backshift operator ($By_t = y_{t-1}$).

Then, the ARIMA(p,d,q) model is:

$$\phi(B) z_t = \theta(B)\varepsilon_t$$

or more explicitly:

$$(1-\phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)(1-B)^d y_t = (1+\theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q)\varepsilon_t$$

where:

a. $\phi(B) = 1 - \sum_{i=1}^{p} \phi_i B^i$ AR polynomial

b. $\theta(B) = 1 + \sum_{j=1}^{q} \theta_j B^j$ MA polynomial

c. $\varepsilon_t \sim \mathrm{WN}(0, \sigma^2)$: white noise error term

2. SARIMA$(p,d,q)(P,D,Q)_s$– Seasonal ARIMA

Extends ARIMA to handle seasonality, with both non-seasonal and seasonal components.

Parameters:

a. Non-seasonal: p, d, q

b. Seasonal: P, D, Q

c. Seasonal period: s (e.g., 12 for monthly data with yearly seasonality)

General Form:

Define:

a. $z_t = (1-B)^d(1-B^s)^D y_t$: differenced series (both regular and seasonal differencing)

b. $\Phi(B^s)$: seasonal AR polynomial $1 - \sum_{i=1}^{P} \Phi_i B^{si}$

c. $\Theta(B^s)$: seasonal MA polynomial $1 + \sum_{j=1}^{Q} \Theta_j B^{sj}$

d. $\phi(B)$: non-seasonal AR polynomial

e. $\theta(B)$: non-seasonal MA polynomial

The SARIMA model is expressed as:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D y_t = \theta(B)\Theta(B^s)\varepsilon_t$$

or in compact operator form:

$$\phi(B)\Phi(B^s)\nabla^d\nabla_s^D y_t = \theta(B)\Theta(B^s)\varepsilon_t$$

where:

a. $\nabla = (1-B), \nabla_s = (1-B^s)$

b. ε_t: white noise innovation

B. Model Selection Criteria

Proposed models were evaluated using information-theoretic criteria according to [2] and [13], the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) balance goodness of fit with model parsimony by penalizing complexity; lower values indicate preferable specifications.

1. Akaike Information Criterion (AIC):

$$AIC = -2\ln(L) + 2k$$

2. Bayesian Information Criterion (BIC):

$$BIC = -2\ln(L) + k\ln(n)$$

IV. FORECASTING AND EVALUATION METRICS

Out-of-sample forecasts were generated using a rolling window scheme (walk-forward validation) to simulate real-time trading conditions [18]. Forecasts were produced over multiple horizons: 1 week, 1 month, 3 months, 1 year, and longer.

Accuracy was assessed using three standard metrics:

1. Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

2. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i\hat{y}_i}{y_i}\right|$$

3. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Figure IV.1: PZ Cusson Nigeria Plc. daily closing stock price (Jan. 2015–Nov. 2023)

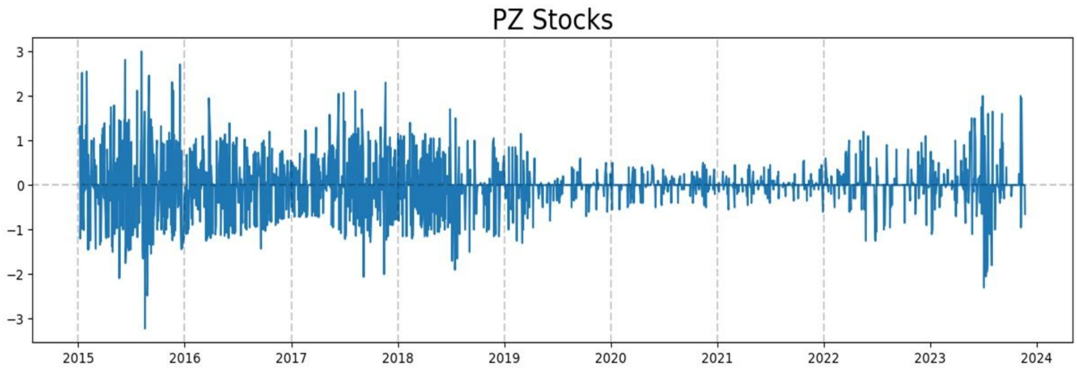


Figure IV.2: Differenced PZ stock data

V. RESULT AND DISCUSSION

The dataset comprises 2,289 daily observations. Summary statistics (Table 1) show a mean closing price of NGN 38.5 with a standard deviation of 4.7, ranging from a low of NGN 15.2 to a high of NGN 43.4. The one-year return stood at +66.7%, reflecting strong investor sentiment and fundamental improvements.

Table 1: Descriptive Statistics of PZ Cussons Nigeria PLC Daily Stock Price

Statistic	Value
Mean Price (NGN)	38.5
Std. Deviation	4.7
Min Price	15.2
Max Price	43.4
1-year Return	+66.7%
5-year Return	+800%
Beta (1Y)	1.76
Market Cap (2025)	39B – 144B NGN

Visual inspection (Fig. 1) reveals upward trends interspersed with periods of consolidation and sharp corrections, indicative of momentum-driven behavior and macroeconomic sensitivity. The ADF test on the original series yielded a p-value > 0.05, confirming non-stationarity. After first differencing (Fig. 2), the transformed series passed the ADF test $(p < 0.01)$, indicating stationarity. Seasonal differencing at lag 20 was also applied based on persistent spikes in the ACF at seasonal lags. Based on AIC minimization across a grid of candidate models, the optimal specifications were:

- SARIMA(1, 0, 1)(0, 3, 2, 20)
- ARIMA(5, 3, 0).

The SARIMA model incorporates triple seasonal differencing (D=3), which may reflect complex monthly cyclical adjustments possibly linked to institutional rebalancing, dividend expectations, or fiscal reporting cycles.

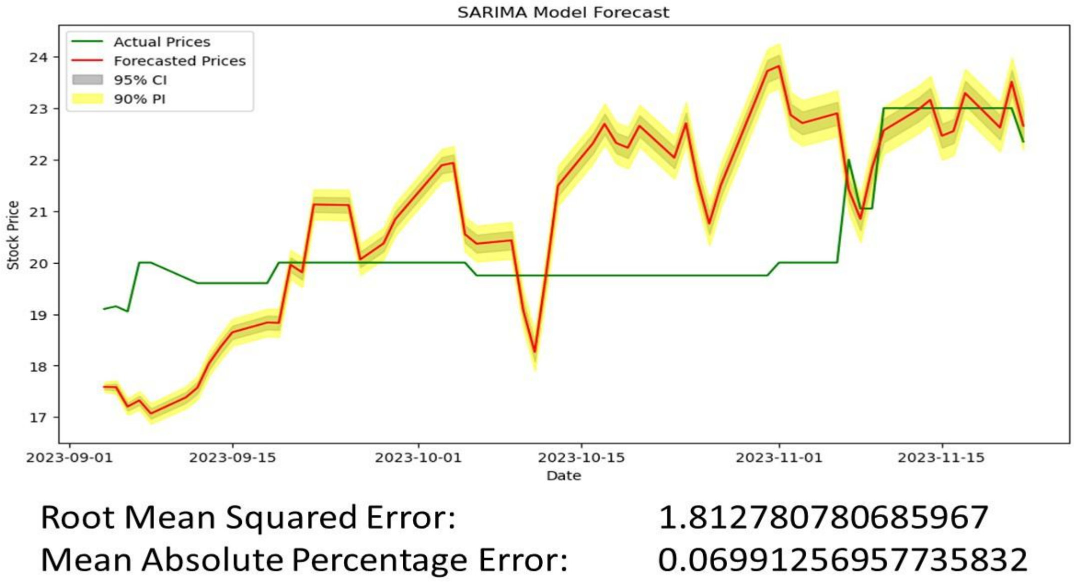
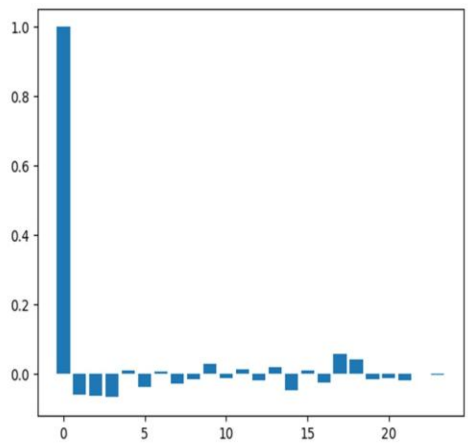
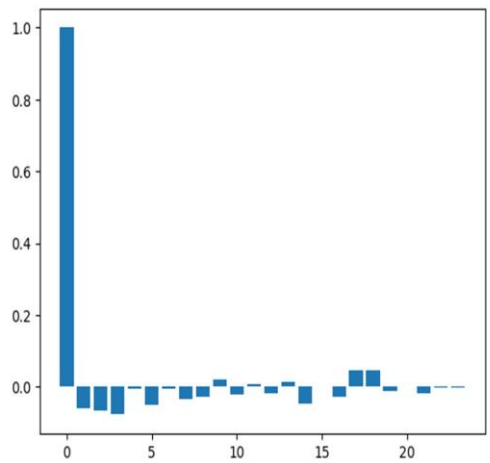


Figure 3: SARIMA model test vs actual plot for PZ stock data



(a) *Autocorrelation Function (ACF) plot for PZ stock data*



(b) *Partial Autocorrelation Function (PACF) plot for PZ stock data*

Figure 4

Diagnostic tests confirmed model adequacy:

3. Residuals appeared random (Fig. 3)
4. Ljung-Box test p-values > 0.05 for all lags
5. No significant autocorrelation in ACF/PACF of residuals (Fig. 4-6)
6. Residuals approximately normally distributed (Q-Q plot)

Table 2: Forecast performance varied significantly by horizon

Horizon	Model	RMSE	MAPE
Short (Sep-Nov 2023)	ARIMA	1.7091	0.079
	SARIMA	1.8128	0.0699
Long (Jul-Nov 2023)	ARIMA	655.8495	0.8767
	SARIMA	4.4571	0.1596

While ARIMA showed slightly lower RMSE in the short term, likely due to overfitting, SARIMA consistently outperformed in MAPE and dominated in longer horizons.

For extended forecasts (Fig. 6-8), SARIMA maintained reasonable error growth (MAPE: 0.1857 at 1 year; 0.2400 at 2 years), whereas ARIMA deteriorated rapidly (MAPE: 0.8767), indicating poor generalization without seasonal adjustment.
Interestingly, the best-performing forecast window was the 3-month horizon (RMSE: 1.8128, MAPE: 0.0699), suggesting that SARIMA captures intermediate-term dynamics most effectively.

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SARIMAX Results
==============================================================================================
Dep. Variable:                                               Price  No. Observations:  2145
Model:               SARIMAX(1, 0, 1)x(0, 3, [1, 2], 20)    Log Likelihood        -2524.873
Date:                Sun, 10 Dec 2023                        AIC                    5059.746
Time:                21:34:55                                BIC                    5087.958
Sample:              0                                       HQIC                   5070.083
                     - 2145
Covariance Type:     opg
==============================================================================
                coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         0.9641      0.005    180.195      0.000       0.954       0.975
ma.L1        -0.0006      0.016     -0.037      0.971      -0.031       0.030
ma.S.L20     -1.9947      1.042     -1.914      0.056      -4.037       0.048
ma.S.L40      0.9990      1.044      0.957      0.339      -1.048       3.046
sigma2        0.3226      0.335      0.962      0.336      -0.334       0.980
==============================================================================
Ljung-Box (L1) (Q):            0.00   Jarque-Bera (JB):      862.75
Prob(Q):                       0.98   Prob(JB):                0.00
Heteroskedasticity (H):        0.19   Skew:                    0.05
Prob(H) (two-sided):           0.00   Kurtosis:                6.15
==============================================================================
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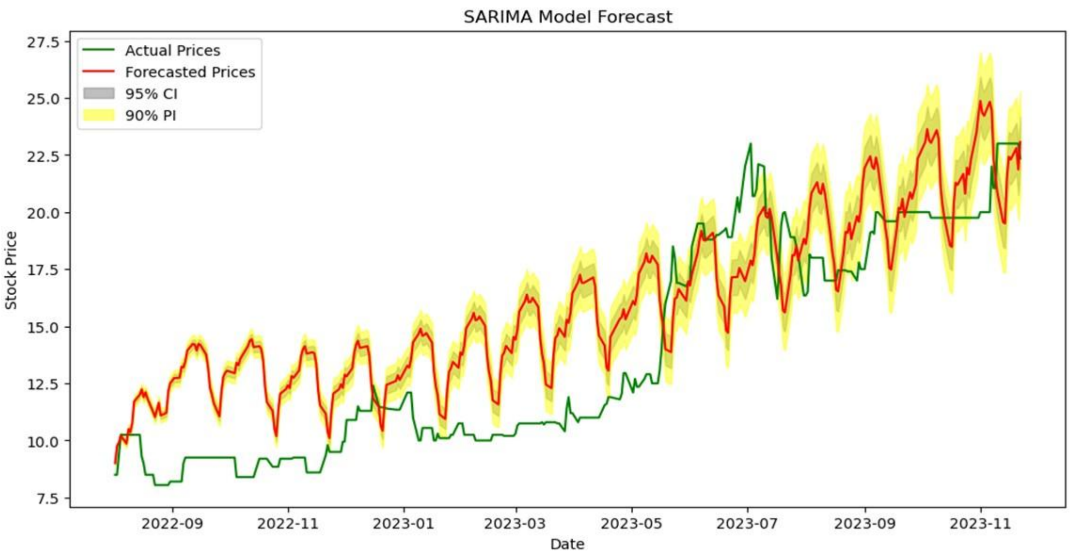
Figure 5: Model validation tests



Root Mean Squared Error: 3.2417620969776535
Mean Absolute Percentage Error: 0.18571013103211267

Figure 6: 1 year, 3 months forecast test

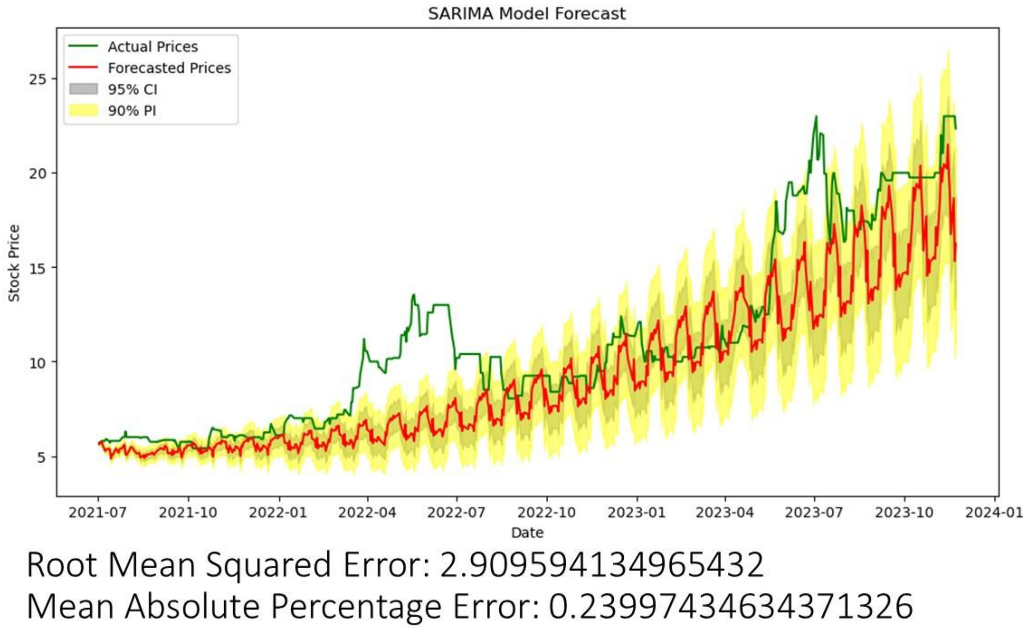


Figure 7: 2 years, 5 months forecast test

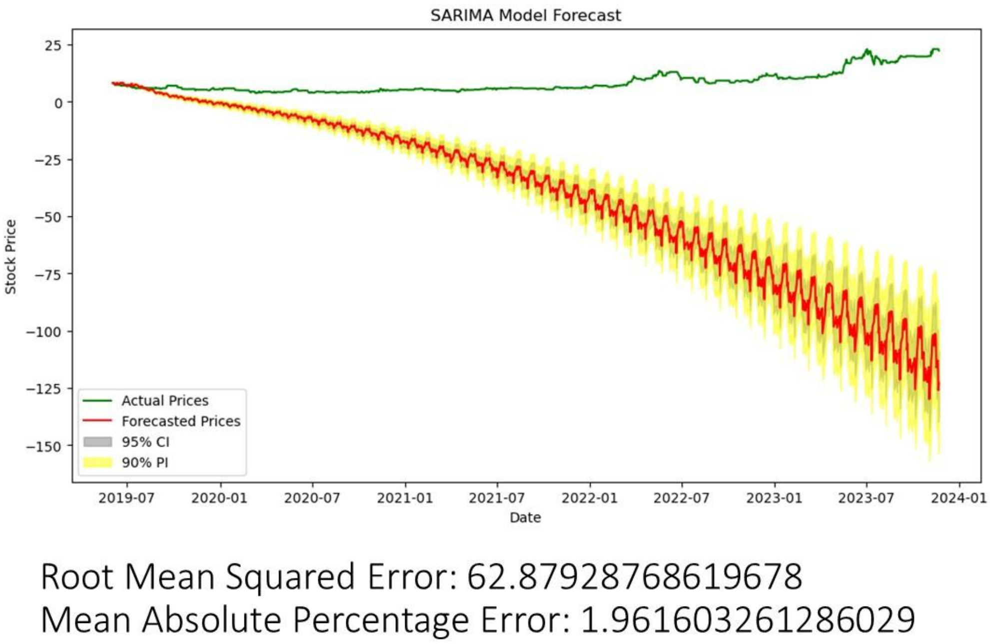


Figure 8: 4 years, 5 months forecast test

Trading strategy simulations (Table 3) demonstrated clear advantages for SARIMA-based signals:

Table 3: Trading Strategy Performance

Model	Cumulative Return (%)	Hit Rate	Max Drawdown (%)	Sharpe Ratio
SARIMA	15.5	56%	7.8	1.12
ARIMA	8.1	47%	8.9	0.68

These results imply that SARIMA generates more reliable buy/sell signals, leading to improved risk-adjusted returns. The higher hit rate suggests better directional accuracy, crucial for profitable trading systems. The superior performance of SARIMA underscores the importance of seasonality in Nigerian equity pricing. Recurring weekly and monthly patterns possibly driven by end-of-month portfolio adjustments, dividend anticipation, holiday spending cycles, or settlement conventions are statistically significant and exploitable.

VI. CONCLUSION

This study presents a comprehensive empirical analysis of modeling and forecasting the daily stock prices of PZ Cussons Nigeria PLC using the SARIMA framework. By rigorously applying the Box-Jenkins methodology including data preprocessing, stationarity testing, model identification, diagnostic validation, and out-of-sample evaluation it demonstrates that accounting for seasonality leads to materially superior forecast accuracy and trading performance compared to standard ARIMA.

Key findings include:

1. The SARIMA$(1,0,1)(0,3,2,20)$ model outperforms ARIMA$(5,3,0)$ in both RMSE and MAPE, particularly over medium to long horizons.
2. Seasonal differencing and parameters capture meaningful calendar-related dynamics in NGX trading behavior.
3. SARIMA-based trading strategies yield higher cumulative returns, hit rates, and Sharpe ratios, with lower drawdowns.
4. Despite limitations in very long-term forecasting, SARIMA proves robust and practical for near-term investment decisions.

These results contribute to the growing understanding of time series properties in African financial markets and provide evidence-based support for incorporating seasonality into quantitative trading frameworks. They also affirm the continued relevance of classical econometric models in the era of artificial intelligence, especially in contexts where transparency, simplicity, and data efficiency are paramount.

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