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# Assessing the Impact of Bitcoin Prices on Nigeria's Exchange Rate Dynamics: A SARIMA Time Series Approach

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## Abstract

Cryptocurrencies, particularly Bitcoin, have emerged as disruptive financial instruments with significant implications for global and national economies. In Nigeria, where exchange rate volatility poses persistent challenges, understanding the influence of Bitcoin prices on exchange rate dynamics is crucial for informed policy and investment decisions. This study aims to assess the impact of Bitcoin prices on the Nigerian Naira using a Seasonal Autoregressive Integrated Moving Average (SARIMA) time series approach. Monthly data covering June 2021 to September 2021 were obtained from the Luno Exchange and analysed using R statistical software. The SARIMA model, specified as (2, 1, 2) $(2, 1, 1)_{12}$, was selected after rigorous diagnostic checks, including autocorrelation and partial autocorrelation analysis, residual tests, and Akaike Information Criterion (AIC) comparisons. Results reveal notable seasonality and irregular fluctuations in Bitcoin-to-Naira exchange rates, with forecasts indicating a steady upward trend in Bitcoin prices. These findings highlight Bitcoin's potential role in facilitating international transactions, reducing reliance on intermediaries, and fostering a savings culture, while also underscoring the risks associated with volatility and regulatory uncertainty. The study concludes that Bitcoin adoption could enhance Nigeria's economic resilience and financial inclusion if supported by clear regulatory frameworks and public awareness initiatives. Overall, the research demonstrates the relevance of SARIMA modelling in capturing cryptocurrency price dynamics and provides insights for policymakers, investors, and stakeholders navigating Nigeria's evolving financial landscape.

**Keywords:** Bitcoin; exchange rate; Nigeria; time series analysis; SARIMA model; cryptocurrency.

## 1. Introduction

Cryptocurrencies, operating on decentralised blockchains, represent a dynamic form of monetary value marked by volatility. Blockchain transparency and accountability make them an appealing investment compared to traditional transactions. The potential for societal disruption, fueled by the anonymity of cryptocurrency transactions, contributes to their extreme price volatility. In this context, artificial intelligence (AI) emerges as a crucial tool to mitigate volatility, particularly in the realm of automated trading. A noteworthy study by Fleischer *et al*. (2022) delves into the application of Long Short-Term Memory (LSTM) in forecasting cryptocurrency prices, shedding light on the intersection of blockchain, cryptocurrency, and AI. Bitcoin, introduced in 2008 by the pseudonymous Satoshi Nakamoto, stands as the pioneering form of electronic money, operating without a central administrator or bank. Functioning on a decentralised peer-to-peer network, Bitcoin allows direct transactions between users, eliminating the need for intermediaries like banks. Most cryptocurrencies, including Bitcoin, leverage blockchain technology and embody characteristics such as decentralisation, transparency, and immutability. The blockchain records network transactions permanently, with each entry encrypted and featuring the block's cryptographic hash. This technology, secured by a complex mechanism known as a secure shell, aims to safeguard data against alteration, hacking, or fraudulent activities.

The journey of Bitcoin's price evolution has been remarkable, with its value surpassing USD 20,000 by 2017 and achieving a daily average market volume of approximately USD 19.45 billion in December 2019. Notably, in April 2021, Bitcoin reached an all-time high price of around $65,000. Despite the lucrative returns on investments, the inherent volatility of most cryptocurrencies poses challenges and risks, necessitating a robust forecasting strategy to anticipate price fluctuations.

Acknowledging the global concern arising from sharp Bitcoin price variations, it becomes imperative to predict these changes accurately. Nair *et al.* (2023) address this aspect in their research titled "Prediction of Cryptocurrency Price using Time Series Data and Deep Learning Algorithms." The study emphasises the inadequacy of older methods reliant on linear hypotheses, advocating for the use of deep learning (DL) methods due to their success in comparable domains. These DL methods, with their noise resistance, native handling of data sequences, and ability to recognise non-linear temporal correlations, emerge as a promising solution for effective time series forecasting.

In the context of Bitcoin's impact on exchange rates in Nigeria, the inherent volatility of cryptocurrencies and the potential effects on global markets make forecasting Bitcoin prices a critical aspect of financial decision-making. The study by Frohmann *et al.* (2023) explores the use of sentiment analysis for predicting Bitcoin prices, emphasising the importance of understanding market sentiment and its potential implications for financial outcomes. As Nigeria navigates the complexities of cryptocurrency adoption and its influence on exchange rates, these insights contribute to the broader understanding of Bitcoin's impact on the economic landscape.

The extreme volatility of cryptocurrencies, notably Bitcoin, presents challenges and opportunities in the global financial landscape. Blockchain technology's decentralised nature and features like transparency make it appealing, yet its price fluctuations create uncertainties. Artificial intelligence (AI), especially in automated trading and predictive models like Long Short-Term Memory (LSTM), is recognised as a tool to address cryptocurrency volatility. Existing studies explore AI applications but lack a comprehensive understanding of their effectiveness and implications for specific contexts, such as Nigeria's unique economic environment.

Research by Nair *et al.* (2023) highlights the potential of deep learning methods but falls short in applying them to country-specific scenarios, leaving a gap in understanding their impact on exchange rates. Additionally, the study by Frohmann *et al.* (2023) on sentiment analysis for predicting Bitcoin prices introduces a novel approach, yet its application to Nigeria's exchange rates remains unexplored. Bridging these gaps is essential to developing informed strategies for investors, policymakers, and businesses navigating the Nigerian cryptocurrency market. The literature review provides a comprehensive overview of studies that predict Bitcoin prices using diverse methodologies, with particular emphasis on machine learning-based approaches. Frohmann *et al.* (2023) introduced an innovative hybrid model that combines time series forecasting and sentiment prediction, leveraging a finely tuned Bidirectional Encoder Representations from Transformers (BERT) model and a unique weighting scheme. Their research highlights the effectiveness of linear regression-based hybrid models, underscoring the importance of simplicity for enhanced generalisation and interpretability. Moreover, they suggest exploring alternative weighting functions and extending the approach to predict prices of other cryptocurrencies, indicating avenues for future research in this domain.

Similarly, Iqbal *et al*. (2021) delved into machine learning techniques, employing ARIMA, Facebook Prophet (FB Prophet) model, and eXtreme Gradient Boosting (XGBoost) for Bitcoin price prediction. Through their investigation, they ascertained ARIMA as the optimal model, showcasing its potential value for investors navigating the cryptocurrency market. Their study underscores the significance of hyperparameter tuning to further refine forecasting accuracy, shedding light on the intricacies of model optimisation in this context. Additionally, Mudassir *et al*. (2020) contribute valuable insights into time-series forecasting of Bitcoin prices, utilising high-dimensional features and machine learning approaches. Their research extends beyond traditional one-day forecasts to encompass short- and medium-term predictions, achieving commendable accuracy levels. Importantly, they highlight the inherent challenges associated with predicting market fluctuations and propose future research directions, including the integration of artificial intelligence to model cryptocurrency prices for measuring financial risk and detecting fraudulent activities.

Adhikari and Agarwal (2013) provide insights into the principles underlying ARIMA modelling, emphasising the integration process as a means to transform non-stationary time series variables into stationary ones, thereby facilitating model development and forecasting accuracy. Additionally, Box and Jenkins (1976) proposed a comprehensive three-step technique for selecting the optimal ARIMA model, underscoring the importance of parsimony in model selection to avoid overfitting.

Support Vector Regression (SVR) emerges as a robust machine learning technique for time series forecasting, particularly adept at handling non-linear regression problems. Samsudin, Shabri, and Saad (2010) highlight the efficacy of SVR in capturing complex relationships inherent in cryptocurrency price data, thereby offering a promising avenue for predictive modelling in the crypto market. With the continuous evolution of algorithms and methodologies, an increasing number of studies are focusing on leveraging SVR for cryptocurrency price prediction, further fueling research endeavours in this domain.

Moving forward, Adamu *et al.* (2023) conducted a comparative study evaluating different regression algorithms for forecasting Bitcoin prices. Their research aimed to assess the efficacy of various regression models in predicting the price dynamics of Bitcoin, leveraging secondary historical data from Kaggle spanning seven years. The dataset comprises 24 variables updated daily, capturing the multifaceted nature of Bitcoin's market dynamics. Given the inherent volatility of Bitcoin data, the researchers implemented robust preprocessing techniques to enhance prediction accuracy. The study evaluates and compares several regression algorithms, including Linear Regression, Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO) Regression, and Elastic Net Regression. Through meticulous experimentation and analysis, Adamu *et al*. (2023) found that the Elastic Net Regression model outperformed other regression algorithms, exhibiting a Root Mean Squared Error (RMSE) of 0.0228, indicative of superior predictive accuracy. Importantly, the Elastic Net Regression model demonstrated robustness against overfitting, bolstering its suitability for forecasting Bitcoin prices amidst the cryptocurrency market's inherent volatility.

In conclusion, the research conducted by Adamu *et al.* (2023) contributes significantly to the literature on cryptocurrency price prediction by providing empirical evidence of the effectiveness of regression models. Their study underscores the importance of rigorous model evaluation and comparative analysis in identifying optimal forecasting techniques for Bitcoin prices. By leveraging comprehensive historical data and employing advanced regression algorithms, the research sheds light on promising avenues for enhancing predictive accuracy in the volatile cryptocurrency market.

The literature review summarises the rapidly increasing interest in machine learning applications for predicting Bitcoin prices, showcasing a diverse array of methodologies and highlighting the imperative for simplicity, realism, and ongoing exploration of research avenues in this rapidly evolving field.

## 2. Materials and Methods

### 2.1. Data sources

Due to the nature of this research work, we sourced data from Luno Exchange.

### 2.2. Method of Analysis

In regard to the nature of the work we embarked upon, we made use of statistical software known as "R software" to quantitatively analyse the data obtained from Luno Exchange.

The method applied to analyse the data and obtain useful results capable of showing the necessary information required for the study is the Seasonal Autoregressive Integrated Moving Average (SARIMA). It is applied to data with seasonality. In this regard, it would be used to measure seasonality.

### *2.2.1. Seasonal Autoregressive Integrated Moving Average (SARIMA)*

The SARIMA model combines non-seasonal and seasonal components and can be specified as SARIMA (p, d, q) × (P, D, Q)$_s$, where p, d, and q refer to the orders of the non-seasonal autoregressive (AR), non-seasonal differencing, and non-seasonal moving average (MA) parts of the model. P, D, and Q refer to the orders of the seasonal AR, seasonal differencing, and seasonal MA parts of the model, and "s" is the length of the seasonal period. The AR process accounts for previously observed values up to a specified maximum lag, plus an error term. The process of differencing is referred to as the integration part that accounts for stabilisation of the data by removing seasonality or trend, while the MA process accounts for previous error terms, making forecasting easier. The algebraic form of the SARIMA model is given as

$$\Phi_p(B^s)\emptyset(B)\nabla_s^D\nabla_d x_t = \Theta_Q(B^s)\theta(B)w_t \tag{1}$$

where, $w_t$ is the non-stationary time series, and the usual Gaussian white noise process, S is the period of the time series, $\emptyset(B)$ and $\theta(B)$ are the ordinary autoregressive and moving average component are, represented by polynomials of orders p and q, $\Phi_p(B^s)$ and $\Theta_Q(B^s)$are the seasonal autoregressive and moving average components are where P and Q are their orders, $\nabla_d$ and $\nabla_s^D$ are the ordinary and the seasonal difference components, and B is the backshift operator; the expressions involve both the seasonal and non-seasonal factors as given below.

The non-seasonal factors are given as:

$$AR: \emptyset(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p \tag{2}$$

$$MA: \theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q \tag{3}$$

The Seasonal factors are given as:

$$AR: \emptyset_p(B^s) = 1 - \Phi_1 B^s - \Phi_2(B^{2s}) - \cdots - \Phi_p B^{ps} \tag{4}$$

$$MA: \Theta_Q(B^s) = 1 + \Theta_1(B^s) + \Theta_2 B^{2s} + \cdots + \Theta_Q B^{Qs} \tag{5}$$

$$\nabla^d = (1 - B)^d \tag{6}$$

$$\nabla_S^D = (1 - B^S)^D \tag{7}$$

$$B^k x_t = x_{t-k} \tag{8}$$

In this paper, we concentrate on the monthly price of Bitcoin using the seasonal period of the series (s) of 12. There are three steps we will take to achieve the aim of the research work, and these are: model identification; model estimation; and model diagnostics and forecasting accuracy.

**Model Identification:** Identification of the model consists of specifying the appropriate structure (AR, MA, or ARMA) and order of the model. Models can also be identified by looking at plots of the autocorrelation function (ACF); the test statistic is given as

$$r_k = \frac{\sum_{t=k+1}^{n-k} (x_{t-k}-\bar{x})(x_t-\bar{x})}{\sum_{t=1}^{n} (x_t-\bar{x})^2} \tag{9}$$

where k is the lag; k = 1, 2 …; $x_t$ is the value of x at row t; $\bar{x}$ is the mean of x; n is the number of observations in the series.

The partial autocorrelation function (PACF) helps to determine how many autoregressive (AR) terms, p, are necessary. The error terms are the errors of the AR models of the respective lags. The errors $\mathcal{E}_t$ and $\mathcal{E}_{t-1}$ are the errors from the following equations, given in the form of

$$y_t = c + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_q y_{t-q} + \varepsilon_t \tag{10}$$

$$y_{t-1} = c + \beta_1 y_{t-2} + \beta_2 y_{t-3} + \cdots + \beta_q y_{t-(q+1)} + \varepsilon_{t-1} \tag{11}$$

Thus, making sure that the variables are stationary, identifying seasonality in the series is done by using the time plots of the ACF and PACF series to decide if an autoregressive or moving average component should be used in the model, Box -Jenkins (1970).

**Model Estimation:** Coefficients of the models can be estimated by maximum likelihood estimation or non-linear least-squares estimation methods. Estimation of parameters of AR, MA, and ARMA models usually requires a more complicated iteration procedure Box-Jenkins, 1970; Chatfield, 2004). Parameters of the model in step 1 were estimated to verify that all the parameters in the plausible model were significant.

**Model Diagnostic Check:** The adequacy of the SARIMA model is checked by ensuring residuals are random and parameters are statistically significant. Residual diagnostics include plotting mean and variance over time, examining autocorrelation and partial autocorrelation, and applying the Ljung-Box test. In this study, the residuals of the fitted model were used to generate the ACF plot and conduct the Box-Ljung test, with the test statistic confirming whether the model was well specified.

$$Q(k) = n(n+2)\sum\left(\frac{r_m^2}{(n-m)}\right)` \tag{12}$$

where n is the number of observations in a series; $r_m^2$ is the estimated autocorrelation at lag m; m = 1, 2… k; and k is the lag; k = 1, 2, The residuals of the white noise would be used to test for normality of the residuals, and if all the diagnostic test results are within acceptable limits, the SARIMA model in step 2 is appropriate.

#### *2.2.2. Identification of Parameter Model*

Ascertain the ARIMA model's moving average (MA) and autoregressive (AR) component orders. These are represented as p and q, in that order. To find possible values for p and q, use plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Prominent peaks in these diagrams suggest possible AR and MA order values.

### 2.3. Forecasting Accuracy

The selected SARIMA model was applied to forecast Bitcoin price per Naira from June to September 2021, with actual prices used for validation. Forecast precision was evaluated using performance measures such as AIC, SBIC, and HQIC, with AIC guiding the choice of the best model based on the lowest values. Additional checks like RMSE and MAE further assessed accuracy, and once parameters were estimated, the model was used to predict future values of the time series.

## 3. Results and Discussions

### 3.1. Data Presentation

The data collected for this research work, as earlier stated, are secondary data of the daily exchange rate between Bitcoin and the Nigerian Naira from 1st June, 2021 to the 27th of September, 2021.

### 3.2. Data Analysis

The method of data analysis employed in this research work was considered using the approach of the Seasonal Autoregressive Integrated Moving Average (SARIMA) approach, with the aid of R programming Software. The analysis shows what the study observed in an attempt to determine the exchange rate between Bitcoin and the Nigerian Naira between the months of June, 2021 and September, 2021.

#### *3.2.1. Seasonal Autoregressive Integrated Moving Average (SARIMA)*

The SARIMA non-seasonal and seasonal differencing was conducted to achieve stationarity of the time series by eliminating the trend and seasonality. From the non-seasonal and seasonal differenced data, the non-seasonal and seasonal components of the model were formulated by examining their autocorrelation function (ACF) and partial autocorrelation function (PACF). The ACF and PACF were used to determine the degree of differencing and appropriate autoregressive and moving average terms. The approaches are plotting the time plot, fitting of auto-regression model to the series and test on the coefficient whether less than one using the ADF test on the series.

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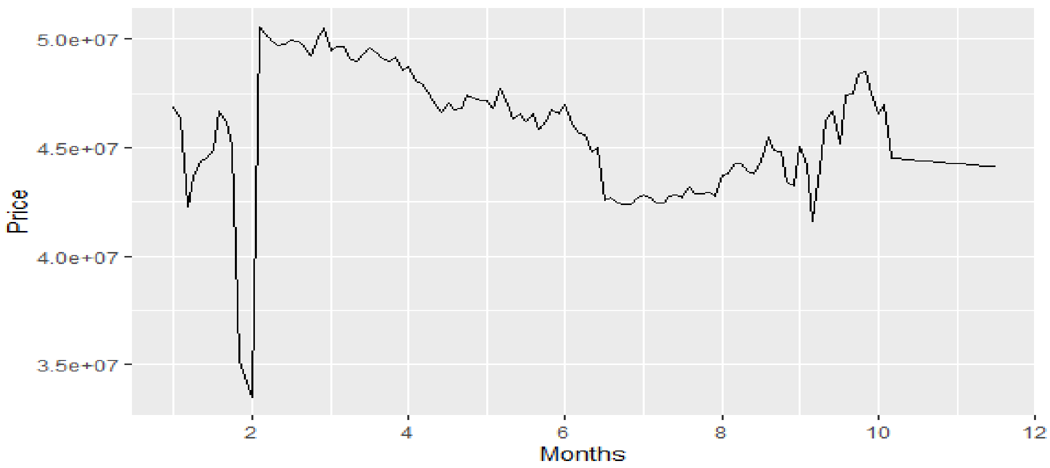


**Figure 1.** Bitcoin per Naira Price.

The time series data cover June 2021 to September 2021, and depict notable seasonality and an irregular trend (upward and downward trend) of the prices of Bitcoin per Naira as shown in Figure 1**.** The data are clearly non- stationary with some seasonality, so we therefore employed seasonal differencing to eliminate the effect of seasonality in our data and to seek a better model fit.

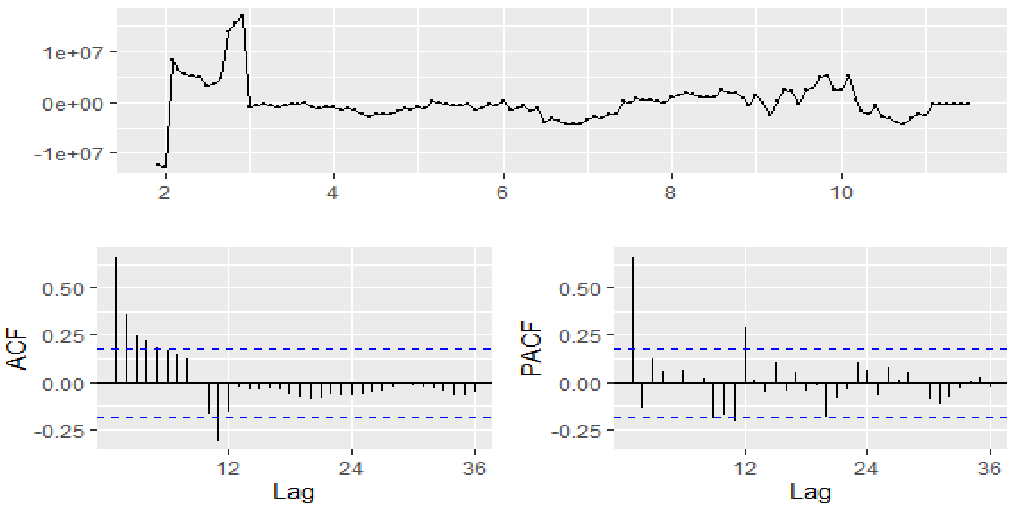


**Figure 2.** The Original data set of the ACF and PACF

The non-seasonal component of our model was identified by examining the ACF and PACF plots (Figure 2) of the non-seasonal differencing of Bitcoin per Naira. The PACF

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values in Figure 2 suggest sharply tailed-out spikes of 1 lag and while the ACF it suggest the values decay exponentially in a sine-wave fashion, having a steady decline after the first lag. This suggests a moving average of order 1, resulting in an autoregressive moving average (2, 1, 1)$_{12}$ model (i.e. p = 2, d = 1 and q = 1).

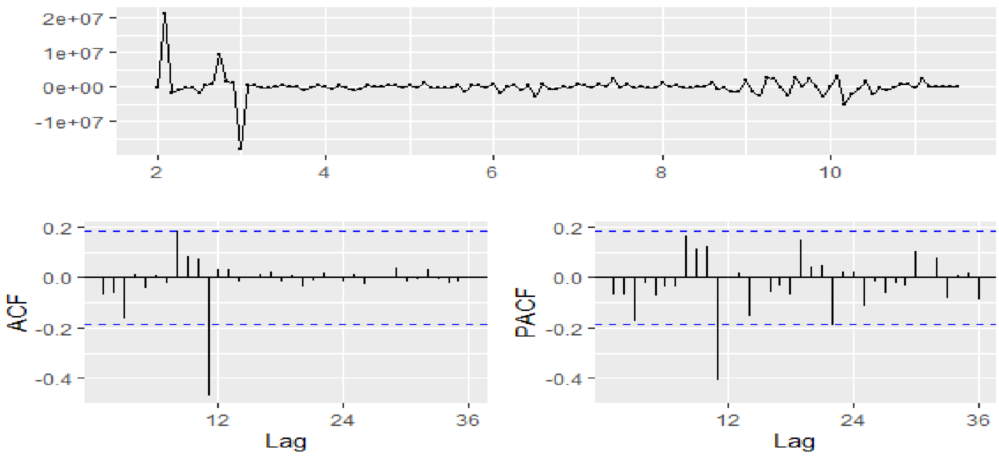


**Figure 3.** The First seasonal differencing of the Bitcoin per Naira price.

Figure 3 shows the ACF and PACF plots of the prices of Bitcoin per Naira after the seasonal differencing. The ACF cuts off at 1 lag, crossing the significance limit, which suggests a seasonal moving average MA (1) model, while the PACF plot cuts off at 1 lag, also crossing the significance limit, which suggests a seasonal autoregressive AR (1) model.

Therefore, based on the non-seasonal differencing and seasonal differencing, seasonality was eliminated from the time series data, and a stationary mean (i.e. D = 1) was achieved. The result indicates that we should consider the following models and choose a better model based on AIC. This resulted in the identification of five plausible SARIMA models: SARIMA (1, 1, 1) (2,1,1)$_{12}$, SARIMA (2,1,2) (2,1,1)$_{12}$, SARIMA (2,1,1) (1,1,1)$_{12.}$ SARIMA (1, 1,1 )(1,1,0)$_{12}$ and SARIMA (1,1,2)(1,1,1)$_{12.}$. The optional models and the correlation values are shown in Table 1. Obviously, the SARIMA (2, 1, 2) (2, 1, 1)$_{12}$ model has the smallest value of AIC, and then we have the SARIMA (2, 1, 2) (2, 1, 1)$_{12}$ model as the best and having a better forecasting accuracy for predicting Bitcoin per Naira.

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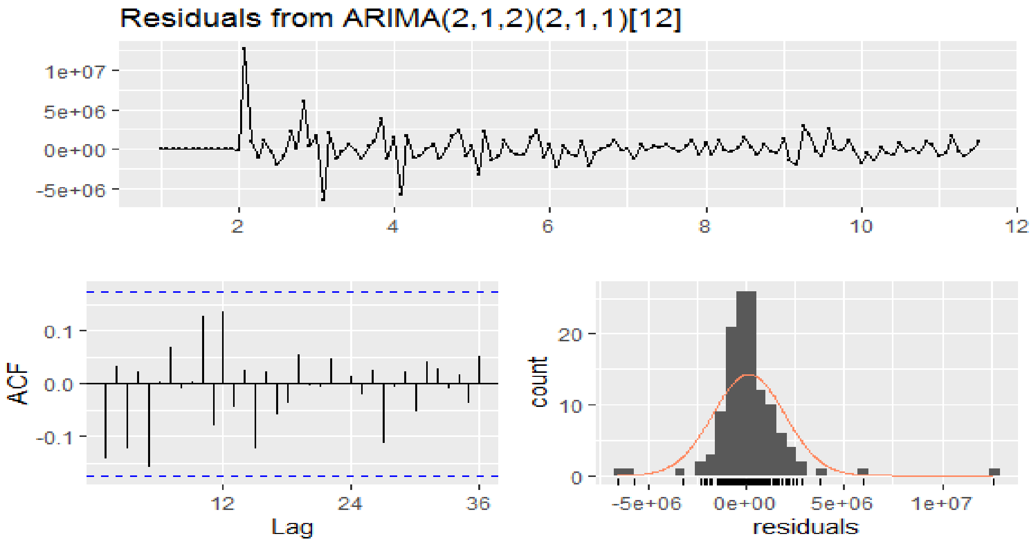


**Figure 4.** The Residual of White Noise

The forecast for the model SARIMA (2, 1, 2) (2, 1, 1)$_{12}$ is displayed in Figure 4. The standardised residual shows no obvious patterns; the lags of the ACF plot do not cross the significance limit, and the residual is normally distributed; hence, the **Ljung-Box test for residuals from SARIMA (2, 1, 2)(2, 1, 1)$_{12}$.**

$H_{0:}$ P > 0.05 (There is no serial correlation)

$H_{1:}$ P < 0.05(There is serial correlation)

**Table 1.** Residual Normality Test

| Q* Statistic | Degree of Freedom | No. of Lags | P - Value |
|---|---|---|---|
| 18.975 | 17 | 24 | 0.33 |

The decision: if the LB is greater than the critical value, then we do not reject the null hypothesis. This means that a small value of Ljung Box statistics will be in support of no serial correlation or i.e. the error is normally distributed. This is concerned with model accuracy.

Conclusion: From the analysis conducted on the Ljung-Box test, it reports that Ljung-Box has a p-value (0.33) > p- value (0.05); we do not reject the null hypothesis, which confirms the absence of serial correlation.

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**Table 2.** Model Comparison

| MODELS | AIC |
|---|---|
| SARIMA $(1,1,1)(2,1,1)_{12}$ | 3656.46 |
| SARIMA $(2,1,2)(2,1,1)_{12}$ | 3653.37 |
| SARIMA $(2,1,1)(1,1,1)_{12}$ | 3656.67 |
| SARIMA $(1,1,1)(1,1,0)_{12}$ | 3669.03 |
| SARIMA $(1,1,2)(1,1.1)_{12}$ | 3654.98 |

**Table 3.** The Estimate of the coefficients of the SARIMA (2, 1, 2) (2, 1, 1) [12] model

| MODELS | AR1 | AR2 | MA1 | MA2 | SAR1 | SAR2 | SMA 1 |
|---|---|---|---|---|---|---|---|
| COEFFICIENTS | 0.0733 | -0.8835 | 0.0669 | 1.0000 | -0.0727 | 0.0065 | -0.7316 |
| STANDARD ERROR | 0.0632 | 0.0555 | 0.0420 | 0.0661 | 0.3202 | 0.2747 | 0.3467 |

In Table 3, the AR (1) coefficient (-0.8835) tells us that the next value in the series is taken as a reduced previous value by a factor of (0.0733), and it depends on the previous error lag. Finally, a prediction based on the fitted model for the next 3 years is shown in Figure 5.

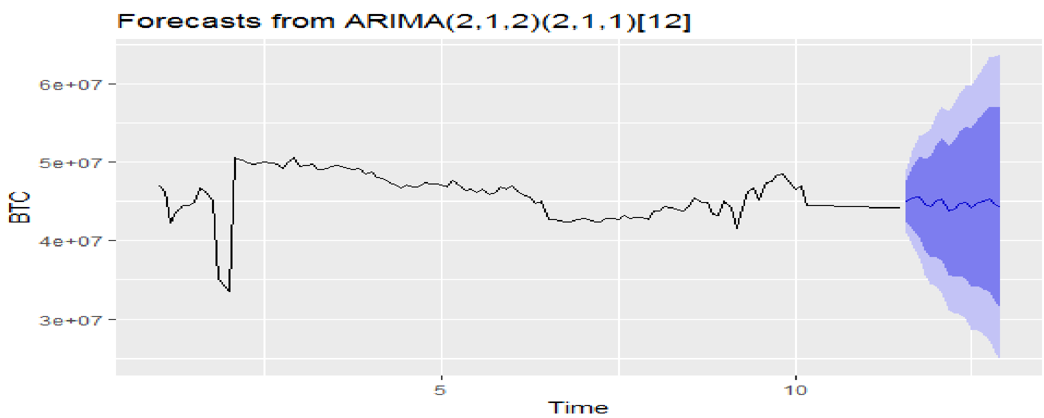


**Figure 5.** Forecast of Bitcoin per Naira

The selected SARIMA (2, 1, 2)$(2, 1,1)_{12}$ model was used to forecast monthly Bitcoin prices from June 2021 to December 2023. The plot observed in Figure 5 is the forecast of the Bitcoin trend for the next three years. This plot shows that Bitcoin prices will continue to fluctuate, and this will be because, with rising interest rates, volatile investments like cryptocurrencies become less attractive when compared to government bonds due to the low levels of income generated.

## 3. Conclusion

In summary, the study analysed the impact of Bitcoin on Nigeria's exchange rate using time series data from June to September 2021. SARIMA modelling captured seasonality and irregular trends, forecasting a steady rise in Bitcoin prices. Findings highlighted Bitcoin's potential to facilitate international transactions, reduce reliance on intermediaries, and strengthen savings culture, contributing to economic resilience.

Conclusively, the research emphasised Bitcoin's transformative role in Nigeria's financial system, offering independence from traditional intermediaries and positioning it as a store of value despite volatility. SARIMA results supported a positive outlook for Bitcoin prices, but risks such as regulatory uncertainty and market fluctuations remain. By leveraging Bitcoin's innovative features, Nigeria could achieve sustained growth and financial inclusivity and recommend that Nigeria establish clear regulatory frameworks to protect consumers and encourage responsible investment, while promoting financial literacy to educate citizens on risks and opportunities. Investment in digital infrastructure and cybersecurity is essential to support adoption, alongside international collaboration with regulators and financial institutions. Implementing these measures would enable Nigeria to harness Bitcoin's potential for economic growth and global digital integration.

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