Forecasting the Nigerian stock exchange insurance index using ARIMA modelling

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Abstract

The insurance industry is important to the expansion and stabilization of economies in emerging markets. Stakeholders including investors insurance companies and legislators can anticipate market movements maximize investments and develop successful strategies based on accurate projections by comprehending and forecasting the Insurance Index. Especially in the insurance industry precise forecasts help with risk management resource allocation and profitability. This study fills a gap in the literature regarding insurance-specific forecasts within Nigeria's financial landscape by examining the Nigerian Insurance Index in particular in contrast to earlier research that frequently concentrates on individual stocks or more general indices like the NSE All-Share Index. To forecast the Nigerian Insurance Index the study finds and validates the best model using the Box-Jenkins ARIMA methodology. Using training data from December 20 2009 to December 25 2022 and testing data from January 1 2023 to March 19 2023 the ARIMA model—which is renowned for identifying short-term time series patterns—is applied to weekly stock prices. After a thorough diagnostic and assessment procedure ARIMA (017) is determined to be the best-fit model offering precise and timely forecasts that are essential for negotiating the intricacies of the Nigerian insurance market. For stakeholders the research offers significant value in the form of accurate predictive insights that help them make data-driven decisions create risk-averse strategies and promote long-term growth in Nigeria's insurance sector.

Keywords: ARIMA, Box-Jenkins methodology, Forecasting, insurance index, Nigerian stock exchange
JEL Classification: C51, C52, C53, G22, E37

1.0 Introduction

The insurance industry is an important part of any country's economy. It can be a source of vulnerability to the financial system, and the failure of an insurance company – an event that has occurred from time to time – can create financial instability (European Central Bank [ECB], 2009).

In Nigeria, the Nigerian Stock Exchange Insurance Index provides an investment benchmark to measure the performance of the insurance sector. As noted by Adeleke and Ibiwoye (2008), Nigerian investors' attitude towards insurance stocks is rapidly changing, with discerning investors identifying insurance stocks as an important investment line due to their impressive returns. This growing attraction has increased the intensity of volatility, the layers of complexity and the stochastic behaviour of the market thus making it difficult to accurately predict the forecasts of the Insurance Index (Agbam & Udo, 2020). It is therefore very necessary to present defining methods that would allow for an accurate forecast of the index. This will assist insurance companies, investors, researchers, government and other stakeholders in making authoritative industry specific decisions.

The question of whether stock market indices in particular can be predicted with any appreciable degree of accuracy has been the bone of contention among financial economists. There are two theories that have been found to be very dominant in this field, the Efficient Market Hypothesis (EMH) and the Random Walk Theory (RWT). The EMH states further that asset prices adjust rapidly to incorporate all relevant information; therefore, historical prices do not provide a sound basis for expecting the movement of prices in the future. Isenah and Olubusoye (2014) in their study say this also means that there are little chances for markets inefficiencies to prevail hence there is leptokurtic defects and marketability is based on history rather than speculation.

On the other hand, the RWT believes that all movements on the stock market occur due to events that are not systematically related to each other and are thus independent and random in nature. It contends that future price fluctuations cannot be deduced from historical trends, as these shifts follow no predictable pattern. However, many studies have challenged these suggestions and provided evidence that the stock market can be predicted. Padma and Mishra (2022) find that movements in stock market prices are not random and depend upon numerous factors that correlate with present and historical stock data. They also noted that every investor cannot comprehend the numerous factors that affect the stock market. As a result of these studies, researchers were motivated to design, develop and improve effective and efficient predictive models (Angadi & Kulkarni, 2015; Reddy, 2019). However, perfect predictions over time are impossible although several models are relatively accurate when forecasting stock prices (Jansson & Larsson, 2020).

The ARIMA model, also known as the Box-Jenkins methodology, is a widely utilized statistical approach in financial time series analysis and forecasting. Its popularity stems from its ability to forecast under uncertain conditions without requiring any prior knowledge of underlying models or relationships unlike some other methods. Instead, ARIMA focuses on past values of the series and prior error terms to generate accurate predictions (Adewumi, Ariyo, & Ayo, 2014a; Gujarati & Porter, 2009). However, to make the most of the ARIMA model for forecasting, it's important to conduct thorough data analysis, carefully select the appropriate parameters, and ensure the data is reliable and robust. This study, therefore, is to develop the best-fit ARIMA model to forecast the Nigerian Stock Exchange Insurance Index prices accurately and reliably. This involves understanding and incorporating the characteristics of the data, selecting the appropriate model parameters, validating the model using appropriate statistical methods and evaluating the forecasting accuracy of the results.

Existing research in Nigeria has explored the use of ARIMA in forecasting time series variables and financial metrics like the All-Share index (encompasses the performance of all listed companies), prices of individual company stocks, inflation and gross domestic product, there exists a notable gap in research concerning its application specifically for forecasting the insurance index. While forecasting the All-Share index is valuable, this broader index might not capture the unique dynamics specific to the insurance sector. Hence, this provide insights into the behavior of the insurance stock market in Nigeria that can assist investors, policymakers, and stakeholders make informed decisions.

2.0 Literature review

Empirical and theoretical review

Random Walk Theory

The argument by Fama (1965) of unpredictable movements in future values of stock prices is the foundation of the random walk theory (RWT). Proponents of the RWT believe that stock market prices change according to a random walk and that the change in the price of a security is independent of the changes in the price of another security and its historical prices. This theory postulates that new information concerning stocks is disseminated randomly over time, and consequently, changes in stock prices are random and bear no relation to previous price changes. This implies that it is pointless to attempt to predict future stock prices through fundamental or technical analysis.

The significant impact of the stock market on the economy has led to considerable attention from researchers focused on forecasting its movements. A large portion of the empirical literature has concentrated on identifying the most suitable ARIMA model for accurate predictions, as it is widely used for forecasting stock prices. Furthermore, many recent ARIMA models in stock market forecasting draw attention to the need for model parameters (p, d, q) to be set through identification and validation of the model. For example, Amin & Aziz, (2023) show how the ARIMA models worked in forecasting average daily stock returns on major stock exchanges like the S & P 500 and the Nasdaq. They have employed the ARIMA configurations (ARIMA (p d q)) in question and examined how their models performed in FOREX using parameters AIC BIC and RMSE. Volatility clustering was also a component of the study's analysis and it was revealed that ARIMA models were competent. Nevertheless, they recommended a combination of ARIMA and GARCH models in order to improve forecasting performance. The analysis revealed that hybrid models made for better long-term forecasting while ARIMA (1 1 1) and ARIMA (2 1 2) models made the best short-term forecasters. In the same fashion, Wang and Zhang (2022) applied ARIMA models in predicting stock market trends in developing countries such as India and Brazil. They used a range of selection criteria such as MAE MAPE and RMSE to evaluate forecasting performance in comparison of traditional ARIMA models with hybrid models including ARIMA-SVM and ARIMA-GARCH. While ARIMA (1 1 2) was better suited for the Indian market their results showed that ARIMA (2 1 1) was the best model for predicting the Brazilian stock market. The study found that while hybrid models improved forecast accuracy for both markets more improvement was required to reach the best results.

Also, Kumar & Jha (2021) investigated how to forecast the stock market by combining ARIMA models with machine learning methods like random forests and neural networks. In their study machine learning models were applied to improve predictions after ARIMA models were first used to capture linear trends. Forecasting errors and prediction consistency were the main areas of evaluation. ARIMA (1 1 2) was the best model for predicting the Indian stock market according to the study although hybrid models performed better overall in terms of forecasting accuracy. The authors stressed that ARIMAs accuracy declined for long-term projections despite its strong performance for short-term forecasts. The efficiency of forecasting stock price indices using ARIMA models on the Shanghai Stock Exchange (SSE) was also investigated by Liu & Chen (2020). In attempts to forecast the indices, they had to look for the best model for short- and long-term predictions, and therefore, compared various configurations and conventional time series methods to several ARIMA (p d and q) models. Out of the many ARIMA models implemented in the study ARIMA (21 1) gave the best estimates of forecasting daily stock prices. They suggested that ARIMA models can adequately model linear relationships, but their forecasts would be more accurate if external variables were included as well. Singh and Sharma (2020) have also examined the extent to which ARIMA models fitted US (S & P 500) and UK (FTSE 100) stock market trends. Their focus included MAPE RMSE and out-of-sample prediction accuracy in the performance comparison of different ARIMA models. According to their research, the ARIMA (2 1 2) model is more appropriate for the UK stock exchange, while ARIMA (1 1 1) outperformed other models used on the US stock exchange. The authors noted that while ARIMA up to the order that can forecast values at short-run periods are feasible, they might need to be modified for unanticipated shifts in market volatility. And also, the application of ARIMA models for forecasting Nigerian Stock Exchange (NSE) All Share Index was explored by Adewumi & Ayo (2019). This involved the determination of an appropriate ARIMA model from amongst others for temporal forecasting of stock prices with the aid of monthly data and model selection criteria such as AIC BIC and MSE. In this case, Boreiko & Cubo observed that ARIMA excesses model (1 1 1) produced satisfactory short-term forecasts for the All Share Index of the Nigerian Stock Exchange.

In addition, they emphasized the importance of model parameter adjustment for obtaining accurate forecasting results. In another study Adebayo Shangodoyin and Sivasamy (2014) focused on stock market forecasting in Botswana and Nigeria utilizing the most effective ARIMA model as per other findings. To determine how well the various ARIMA models performed in forecasting, they applied several of these model selection criteria including AIC BIC HQC RMSE and MAE. The aim in this case was to determine the best ARIMA model that would be able to predict the stock market patterns of the two countries. It was found that the best for the Nigerian stock market was ARIMA (1 1 4) while the best for Botswana was ARIMA (3 1 1). Likewise, Eze Daniel Obiora-Ilouno and Uzuke (2016) predicted the movement of the Nigerian Stock Exchange All Share Indexthrough the Box-Jenkins methodology which incorporates model identification parameter estimation and model checking. The forecasting accuracy was measured with MAE MAPE and MSE and they came to the conclusion that ARIMA (2 1 0) suited best for index prediction. In the next two years, the analysis was made, and Pillay (2020) demonstrated that the methodology was effective and that ARIMA (4 1 4) is the best model for forecasting the Johannesburg Stock Exchange share price index.

Finally, a stock price prediction model based on the ARIMA model was developed by Adewumi Ariyo and Ayo (2014b) using stock data from the Nigerian Stock Exchange (NSE) and the New York Stock Exchange (NYSE). The Nokia Stock Index from the NYSE and the Zenith Bank Index from the NSE were both predicted using this model. Their research demonstrated that the ARIMA model can successfully compete with new methods for short-term stock price prediction and has significant potential for short-term forecasting.

In conclusion while ARIMA models are a powerful tool for identifying linear relationships in stock price movements a number of studies indicate that they can significantly improve forecasting accuracy especially in periods of high market volatility when combined with other methods like machine learning models GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models or exogenous variables. In light of this the current study forecasts the Nigerian Insurance Index in an effort to close a gap in the body of knowledge about predictions unique to Nigerias financial sector. In order to better predict the insurance industry and investigate the distinctive dynamics of the Nigerian market this study employs the Box-Jenkins ARIMA methodology.

3.0 Materials and methods

The study employed a research design utilizing data and statistical analysis to make precise forecasts of the Nigerian Stock Exchange Insurance Index through the ARIMA model with analysis conducted using the R statistical programming language.

Data, from the Investing website (www.investing.com) was utilized as data source for this study. It included the historical weekly stock prices of the Nigerian Stock Exchange Insurance Index comprising close price details like open price range and percentage change values as well as high and low prices data points for comprehensive analysis purposes. During the examination of this dataset for insights and trends in the market performance of the index over time periods under consideration closing price information was particularly focused upon due, to its ability to encapsulate all trading activities associated with the index. The time frame covered in the analysis runs from December 20th, 2009 to March 19th, 2023 totaling 13 years' worth of data observations split into training and testing sets for analysis purposes. The training dataset spans, from December 20th, 2009, to December 25th, 2022. Consists of 680 data points allowing for model estimation and forecasting for the twelve weeks of the year 2024. On the hand the testing data covers January 1st to March 19th in the year 2024 with a total of twelve observations utilized to assess forecast accuracy.

To apply the methodology, time Series Analysis: Forecasting and Control. However, before this methodology can be applied, the time series data was ensured to be stationary after one or more differencing. The basic principle behind stationarity is that the probability laws behind the behavior of the process does not change over time, that is, the process is in statistical equilibrium; the process is marginally identically distributed with the mean and variance constant over time, (Chan & Cryer, 2008). If the way the process changes does not change over time, this means that it should be possible to predict the process.

4.0 Results

Descriptive Statistics and Stationarity

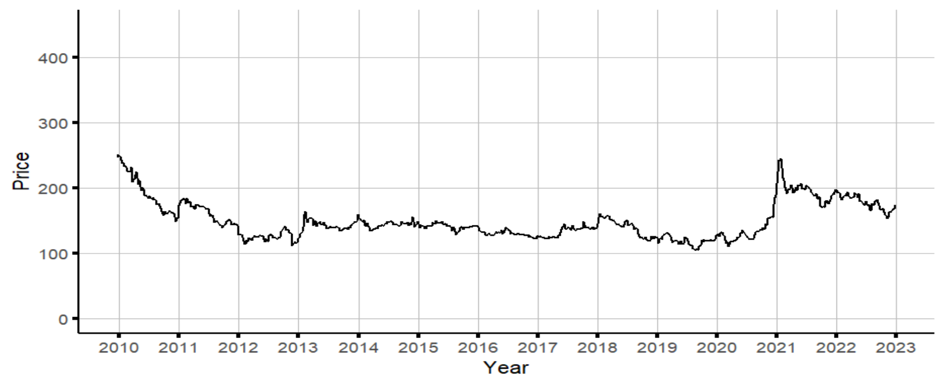
Table 1. Summary Statistics of the Training Data

Mean	Standard Deviation	Variance	Median	Minimum	Maximum
149.8	27.85369	775.8278	142.2	105.5	251.5

Source: Author's computation using R.

Table 1 shows the summary statistics of the index. Figure 2 shows a line graph of the closing prices plotted against time. It indicates a fluctuating trend with several sharp and prolonged changes, suggesting that the mean and variance are not constant over time. This implies that the series is non-stationary.

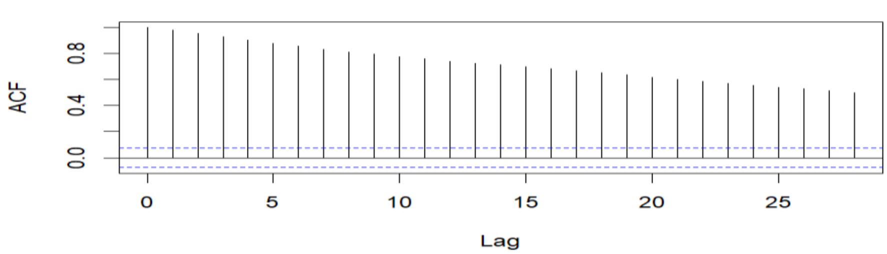
Figure 2. Line Chart of Training Data Plotted Against Time



Source: Author's computation using R.

The ACF correlogram of the training data presented in Figure 3 further supports this. It shows a slow decay in autocorrelation coefficients and significant correlations across all the lags, indicating that the series is non-stationary.

Figure 3. ACF Correlogram of the Training Data



Source: Author's computation using R.

Identification of the Model

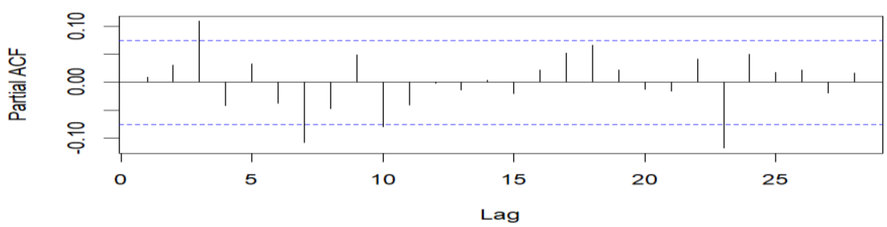
The first step is to identify the d parameter, which is the number of differencing to make the data stationary. Using the ndiffs function, the result displayed in Figure 4 indicates that the series requires differencing once to achieve stationarity. Since the data will become stationary after the first difference, the model is integrated of order 1, I(1).

Figure 4. ndiffs Result

```
> ndiffs(
+    training_data$Price,
+    alpha = 0.05,
+    test = c("kpss", "adf", "pp"),
+    max.d = 2)
[1] 1
```

Source: Author’s computation using R.

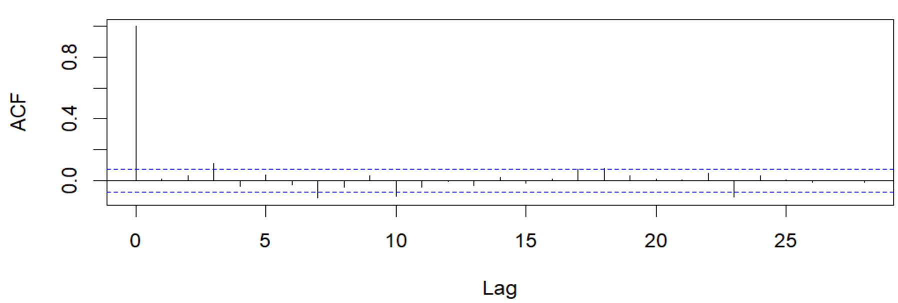
Figure 5. PACF Correlogram of the Differenced Training Data



Source: Author’s computation using R.

The PACF correlogram of the data after differencing once in Figure 5 shows significant spikes at lags 3 and 7. This indicates some degree of autocorrelation at these specific lags. However, the PACF values at these lags is relatively moderate, suggesting that while there is some autoregressive behavior, it is not strong. This implies that while there is some autoregression, it may not be strong enough to necessitate a high-order AR model. Therefore, this study will consider AR (0), AR (3) and AR (7) as potential orders for the AR component.

Figure 6. ACF Correlogram of the Differenced Training Data



Source: Author’s computation using R.

Important spikes at lags 3 and 7 are visible in the ACF correlogram shown in Figure 6. A possible MA component is hinted at. These moderate spikes however point to the presence of an MA. Although it isnt dominant the process might exist. At lags three and seven the ACF shows notable spikes. A possible MA component is hinted at. These moderate spikes however point to the presence of an MA. procedure. might exist but its weak. The pattern suggests that an MA order of three or seven may be possible. without a higher-order model being required. The risk of overfitting may cause higher orders of MA and AR terms to be ignored. not always improve model performance.

The models estimation.

To find the best-fit several ARIMA models are estimated using the training set. The following are the ARIMA values: (013) (017) (313) (713) and ARIMA. ARIMA (717) and (317) are selected according to the parameters that were determined. They are then assessed. and contrasted to choose the one that best fits the data.

Figure 7. ARIMA (0,1,3) Results

```
Call:
arima(x = training_data$Price, order = c(0, 1, 3))

Coefficients:
         ma1     ma2     ma3
      0.0363  0.0321  0.1254
s.e.  0.0384  0.0391  0.0404

sigma^2 estimated as 19.79:  log likelihood = -1976.89,  aic = 3
961.77

Training set error measures:
                      ME    RMSE      MAE         MPE
Training set -0.08866053 4.44491 2.977249 -0.07433876
                 MAPE      MASE         ACF1
Training set 1.960541 0.9909278 -0.004242204
```

Source: Author's computation using R.

Figure 8. ARIMA(0,1,7) Results

```
Call:
arima(x = training_data$Price, order = c(0, 1, 7))

Coefficients:
         ma1     ma2     ma3      ma4     ma5      ma6
      0.0255  0.0457  0.1140  -0.0626  0.0506  -0.0635
s.e.  0.0381  0.0383  0.0385   0.0399  0.0401   0.0385
          ma7
      -0.0975
s.e.   0.0376

sigma^2 estimated as 19.48:  log likelihood = -1971.56,  aic = 3
959.12

Training set error measures:
                     ME     RMSE      MAE        MPE
Training set -0.1085665 4.409825 2.957606 -0.0904715
                 MAPE    MASE       ACF1
Training set 1.947941 0.98439 0.00241334
```

Figure 9. ARIMA (3,1,3) Results

```
Call:
arima(x = training_data$Price, order = c(3, 1, 3))

Coefficients:
         ar1     ar2      ar3      ma1      ma2     ma3
      0.4502  0.0986  -0.7110  -0.4076  -0.1133  0.8036
s.e.  0.0977  0.1275   0.0912   0.0834   0.1086  0.0802

sigma^2 estimated as 19.56:  log likelihood = -1973.17,  aic = 3960.33

Training set error measures:
                      ME     RMSE      MAE         MPE     MAPE
Training set -0.09936079 4.419391 2.986057 -0.08295604 1.966705
                  MASE        ACF1
Training set 0.9938593 -0.01900908
```

Source: Author's computation using R.

Figure 10. ARIMA (3,1,7) Results

```
Call:
arima(x = training_data$Price, order = c(3, 1, 7))

Coefficients:
         ar1      ar2     ar3      ma1     ma2      ma3      ma4     ma5
      0.1959  -0.1527  0.9508  -0.1565  0.1907  -0.8459  -0.0921  0.0201
s.e.     NaN   0.0134     NaN   0.0444  0.0434   0.0410   0.0543  0.0414
         ma6     ma7
      -0.120  0.0037
s.e.   0.039  0.0352

sigma^2 estimated as 19.36:  log likelihood = -1970.22,  aic = 3962.45

Training set error measures:
                     ME     RMSE      MAE        MPE    MAPE     MASE
Training set -0.1566614 4.397033 2.986005 -0.1240334 1.97209 0.993842
                     ACF1
Training set -0.001028517
```

Source: Author's computation using R.

Figure 11. ARIMA (7,1,3) Results

```
Call:
arima(x = training_data$Price, order = c(7, 1, 3))

Coefficients:
         ar1      ar2     ar3      ar4     ar5      ar6      ar7
      0.7316  -0.7037  0.6101  -0.1217  0.1291  -0.1652  -0.0135
s.e.  0.3601   0.3411  0.2845   0.0725  0.0701   0.0775   0.0725
          ma1     ma2      ma3
      -0.7027  0.7253  -0.5082
s.e.   0.3582  0.3328   0.2846

sigma^2 estimated as 19.41:  log likelihood = -1970.48,  aic = 3962.97

Training set error measures:
                     ME     RMSE      MAE         MPE     MAPE    MASE
Training set -0.1140002 4.402747 2.957666 -0.09443299 1.947362 0.98441
                      ACF1
Training set -0.0002674643
```

Source: Author's computation using R.

Figure 12. ARIMA(7,1,7) Results

```
Call:
arima(x = training_data$Price, order = c(7, 1, 7))

Coefficients:
          ar1     ar2     ar3      ar4      ar5     ar6     ar7     ma1
      -0.0873  0.3101  0.2344  -0.1104  -0.3887  0.4963  0.5305  0.1133
s.e.   0.5920  0.3794  0.0964   0.1732   0.1840  0.1495  0.4389  0.5943
          ma2      ma3     ma4     ma5      ma6      ma7
      -0.2780  -0.1399  0.0650  0.4013  -0.5577  -0.6038
s.e.   0.3626   0.0987  0.1255  0.1292   0.1835   0.4851

sigma^2 estimated as 19.08:  log likelihood = -1965.45,  aic = 3960.91

Training set error measures:
                     ME     RMSE      MAE        MPE     MAPE      MASE
Training set -0.1837187 4.364405 2.988628 -0.1448341 1.975059 0.9947151
                   ACF1
Training set 0.00548458
```
Source: Author’s computation using R.

The ARIMA (0,1,7) model was identified as the most suitable, with an AIC of AIC of 3959.12, the lowest among the models considered. This model also had a higher log-likelihood of -1971.56, suggesting a better fit to the data. Its training set error metrics were competitive, with relatively low RMSE of 4.4098 and MAE of 2.9576, and a MAPE of 1.9479.

While higher-order models such as ARIMA (7,1,3) and ARIMA (7,1,7) showed slightly better error measures, their higher AIC values suggest potential overfitting. The ARIMA (0,1,7) model provides a robust and practical choice, balancing fit and simplicity without the complexity associated with higher-order models.

In summary, the ARIMA (0,1,7) model is chosen due its lower AIC and stable coefficient estimates. This model strikes a balance between goodness of fit and simplicity.

Diagnostic Checking

To ensure that it is white noise, the estimated model’s residuals are checked. The Box-Ljung test assesses whether there are significant autocorrelations in the residuals of the ARIMA (0, 1, 7) model. In the results presented in Table 2 below, the p-value of 0.9497 indicates that there is no significant autocorrelation in the residuals up, supporting the assumption of white noise.

Table 2. Results of the Box-Ljung Test

X-Squared	Degrees of Freedom	p-value
0.003978	1	0.9497

Source: Author’s computation using R.

Forecasting the Insurance Index

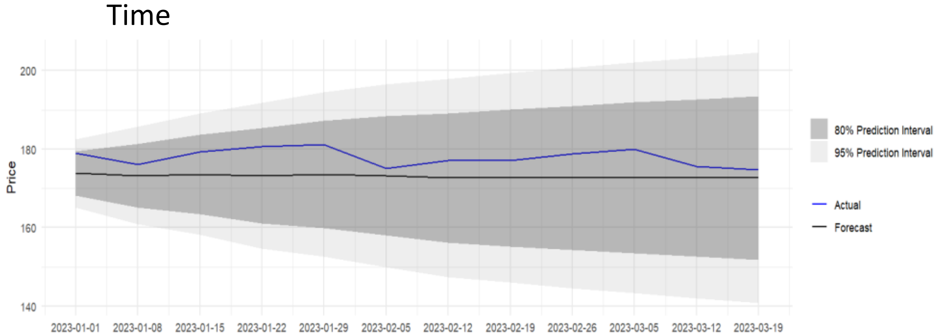
The ARIMA (0,1,7) model is used to forecast the first twelve weeks of 2023 of the Insurance Index. Table 3 presents the forecasts for the first twelve weeks of 2022 along with the actual values and prediction intervals.

Table 3. Actual and Forecasted Values of the Insurance Index

Date	Actual	Forecast	80% Prediction Interval		95% Prediction Interval	
			Low	High	Low	High
1/1/2023	179.03	173.85	168.19	179.51	165.20	182.50
1/8/2023	176.10	173.27	165.17	181.38	160.89	185.66
1/15/2023	179.24	173.62	163.51	183.74	158.15	189.09
1/22/2023	180.62	173.26	161.13	185.39	154.70	191.82
1/29/2023	181.10	173.58	159.89	187.28	152.64	194.53
2/5/2023	175.08	173.20	157.98	188.42	149.93	196.47
2/12/2023	177.15	172.66	156.20	189.12	147.48	197.83
2/19/2023	177.15	172.66	155.23	190.09	146.01	199.31
2/26/2023	178.78	172.66	154.32	191.00	144.60	200.71
3/5/2023	180.04	172.66	153.44	191.88	143.27	202.05
3/12/2023	175.63	172.66	152.61	192.71	141.99	203.32
3/19/2023	174.70	172.66	151.81	193.51	140.77	204.55

Source: Author's computation using R.

Figure 11. Line Chart of Actual and Forecasted Values for the Insurance Index Plotted Against Time



Source: Author's computation using R.

Table 3 and Figure 11 presents the figures and the line chart of the actual and forecasted values of the index along with the 80% and 95% prediction intervals. Figure 11 shows that all the actual values fall in the 80% and 95% prediction interval.

Evaluation of Forecast Accuracy

Table 4 presents the error measures of the actual and forecasted values of the index.

Table 4. Training and Testing Set Error Measures

	Training set	Test set
ME	-0.1086	4.8226
RMSE	4.4098	5.2107
MAE	2.9576	4.8226
MPE	-0.0905	2.6985
MAPE	1.9479	2.6985

Source: Author's computation using R.

The ARIMA(0,1,7) model works well with the training data, as shown by its low error values. However, when used to predict new data, its accuracy drops, with higher error values indicating that it struggles to adapt to new data.

5.0 Discussion and recommendations

This study forecasted the Nigerian Insurance Index using the ARIMA model, with the Statistical R package employed to determine that ARIMA (0,1,7) was the most appropriate model for the index. This conclusion was validated using the Box-Jenkins methodology. During the identification stage, the ndiffs function indicated that one differencing was necessary to achieve stationarity in the data. The ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) correlograms were also used to help identify potential values for the p and q parameters.

After estimating the proposed models, it was found that ARIMA (0,1,7) was the best-fitting model, as it had the lowest AIC (Akaike Information Criterion) and a higher log-likelihood, indicating a better fit to the data. The model's performance on the training set was evaluated using error metrics, which showed relatively low RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error), demonstrating its competitiveness.

Box-Ljung test diagnostics confirmed that the residuals were white noise which meant there is no autocorrelation in the residuals so the model could be used to predict the index without hesitation.

For predicting the insurance index, ARIMA (0,1,7) models were also applied and their accuracy was evaluated. For the insurance index the actual values did lie consistently in the intervals from 80% to 95% bounds of the forecast which mean the model was performing well over the training data. Still the model appeared to have some troubles in its sensitivity to the new incoming data as shown in the error metrics. This problem could perhaps be explained with the economic conditions of Nigeria at the time of the analysis.

Lastly, the results do indicate that there is indeed a possibility to forecast future stock prices by means of ARIMA models. These findings contradict the Efficient Market Hypothesis (EMH) and Random Walk Theory both holding that stock prices are not predictable. Moreover, the obtained findings are similar to the findings in earlier studies by Adebayo et al. (2014), Adewumi et al. (2014b), and other researchers that also report the ARIMA methodology as a relevant forecasting tool for the Nigerian Stock Exchange.

Hence, in order to improve the effectiveness of the Nigerian stock market and assist the economy, the ARIMA model is accurate in modeling and forecasting the Nigerian Insurance Index on short run basis. The forecasts provide useful information to the insurance companies and investors improving the decision-making processes and risk management. These forecasts could also be used by regulatory agencies as well as the government for purposes of supervision and control of the insurance industry. Also, combining ARIMA with AI techniques in future research could result in better forecasting accuracy. This could provide greater understanding of the forecasting models' results in different market circumstances in determining the best suitable techniques for predicting the Insurance Index.

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