

Projecting Insurance Penetration Rate in Nigeria: An ARIMA Approach

Usman Ahmed Hafiz¹; Fauzilah Salleh^{2*}; Murtala Garba³; Norfadzilah Rashid⁴

¹Universiti Sultan Zainal Abidin, Terengganu, Malaysia.
Abubakar Tafawa Balewa University, Bauchi, Nigeria.

¹fauzilah@unisza.edu.my

^{2*}Universiti Sultan Zainal Abidin, Terengganu, Malaysia.

³Universiti Sultan Zainal Abidin, Terengganu, Malaysia.
Abubakar Tafawa Balewa University, Bauchi, Nigeria.

³mourgab79@gmail.com

⁴Universiti Sultan Zainal Abidin, Terengganu, Malaysia.

⁴nikmfadzilah@unisza.edu.my

Abstract

Insurance industries' market penetration level is revealed by the premiums paid as a proportion to overall economic output. Nigeria's insurance penetration rate is 0.33 per cent despite its population advantage of about 200 million people. This rate is far below the average African rate of 2.98 per cent, and the lowest compared to some Sub-Sahara African countries like Kenya, Zimbabwe, Namibia and South Africa. The paper uses annual data on insurance penetration (IP) for the period 1981 to 2018. Autoregressive Integrated Moving Average (ARIMA) model was used to projects the insurance penetration rate for 12 years (2019 to 2030). The result shows that the insurance penetration rate keeps decreasing but at a slower rate. The paper recommends that the national regulatory bodies of insurance such as National Insurance Commission of Nigeria (NAICOM) should innovate and implement policies. This action will pave ways for the insurers to design insurance coverage, which will meet the specific needs of heterogeneous societies in order to spur insurance penetration rates.

Keywords- ARIMA Modelling, Forecasting, Premiums, Insurance Penetration.

JEL Classification: G22

1. Introduction

Businesses and individual households are susceptible to uncertainties surrounding our environment in pursuance of their daily endeavours. Insurance is one of the systematic risk mitigation strategies available to guard against the severity of loss that may result from the exposure to

uncertainty. Salleh, Kassim, Yazid, and Rashid (2018) assert that valuable coverage is provided to clients by insurance which significantly reduces their financial risks exposure. In their different contributions, Clarke and Dercon (2016) and Janzen, Carter, and Ikegami (2020) argue that insurance is not only limited to the mitigation of financial losses, but it reduces exposure to poverty and incentivises investment. At the same time, Mrówczyńska-Kamińska and Standar (2016) added that insurance promotes economic stability.

Regarding the insurance contract structure, it typically involves the insured on one part and the insurer on the other side. Okonkwo and Okeke (2019) stated that in this arrangement, the insured pays a premium to the insurer who undertakes to pay the sum insured or its equivalent if the insured suffers a loss within the terms and conditions of the contract. Indeed, insurance helps to reinstate the policyholders back to their original positions before the occurrence of the loss. Hence, penetration of insurance products and the rate at which the populace subscribe to these products can stimulate economic performance.

Insurance penetration refers to the proportion of premiums paid to the Gross domestic product (GDP). It is among the essential indicators of the country's financial development (Houa & Cheng, 2017). The level of insurance penetration in the domestic economy demonstrates its relative size and importance (Olayungbo & Akinlo, 2016). However, the available record shows that in Sub-Saharan Africa (SSA), except for South Africa and Namibia, insurance uptake is below 5 per cent (Swiss Re, 2019) Similarly, insurance penetration status of Nigeria is less than 1 per cent as captured in the same report, which is a distance away from the 2018 revised National Financial Inclusion Strategy (NFIS) target of 25%. According to Weingartner, Simonet, and Caravani (2017), low insurance penetration means weak resilience to catastrophe, low productivity and macroeconomic downturn.

Consequently, the study was based on the premise that predicting the insurance uptake's potential prospects would offer useful facts to stakeholders in the decision-making process. Indeed, the essence of forecasting is to figure out the probable future outcome with a view to forestal aberration from the set targets. Balli and Elsamadisy (2012) point out that forecasting enables regulators to plan for efficient economic activity management, thereby resulting in higher growth. Outcomes from forecast could serve as a wake-up call for the need to re-strategise at the right time. Consequently, determining the future pattern of insurance penetration will lead to the corrective measure required now that will shoot the number of insured in the future. Hence, this study seeks to achieve the objectives of projecting future insurance penetration values in Nigeria and validates the forecasts model's accuracy. To achieve these objectives, we applied the ARIMA forecasting model using Eviews version 10 statistical software

The study has enriched the existing literature from two outlooks. First, there is little attention given to the prediction of insurance uptake in Sub Saharan Africa (SSA). The study furthers the empirical evidence on forecasting economic activities from the perspectives of risks protection growth potential in Nigeria being one the largest economy in the SSA. Secondly, the analysis uses a more extended period than prior studies, thus gives room for long term evaluation of future uptake of insurance in line with the financial inclusion of the sustainable development goals.

2. Literature Review

Financial studies on forecasting have used standard techniques that served as a black box to stakeholders (Matyjaszek, Fernández, Krzemień, Wodarski, & Valverde, 2019). Uncomplicated forecasting techniques are desirable through which instability of the future can be handled effectively (Kriechbaumer, Angus, Parsons, & Rivas Casado, 2014). Hence, ARIMA is the most commonly used technique (Mishra, Sahanaa, & Manikandan, 2019). El-Bassiouni and El-Habashi (1991) found the Box-Jenkins methodology useful for forecasting Kuwait's motor vehicles' compulsory insurance scheme based on monthly claims data, instead of the traditional linear regression approach.

In the United States of America, Bortner, Pulliam, and Yam (2014) conducted a trend analysis on quarterly insurance time series. Although Insurance companies mostly created forecast models using linear regression. This study used time series analysis to determine the reliable model. From the outcome, ARIMA exhibits reliable estimate than the linear regression. To forecast the growth pattern of claims payment, Nwolley-Kwasi (2015) applies the ARIMA approach. The researchers analysed time-series data from January 2010 to November 2014 with the fitted the Suitable Box-Jenkins model. The result shows that ARIMA(1,1,0) model was the best for forecasting claims payment.

From the Middle East and North Africa (MENA), Taha (2017) conducted a study to determine the accurate time series forecasting model in Misr insurance Egypt to predict fire segment loss ratio. The researcher used the Box-Jenkins method on the real reported loss ratios data for 1980 to -2014. The study revealed that ARMA(1,1) is the best forecasting model. Namaweje and Geoffrey (2020) forecast life insurance premiums and insurance penetration rates using the annual data from 2000 to 2018. ARIMA (0, 1, 0) was the optimal model used. The results indicate a slightly increasing trend of between 0.9 per cent to 1.19 per cent for the forecasted period favouring individual life premiums. In contrast, deposit administration, as well as group life premiums, remained constant.

In Asia, Selvakumar, Satpathi, Kumar, and Haragopal (2020) used the annual time series historical claim data for 34 years period to assess the forecasting power of ARIMA, the linear

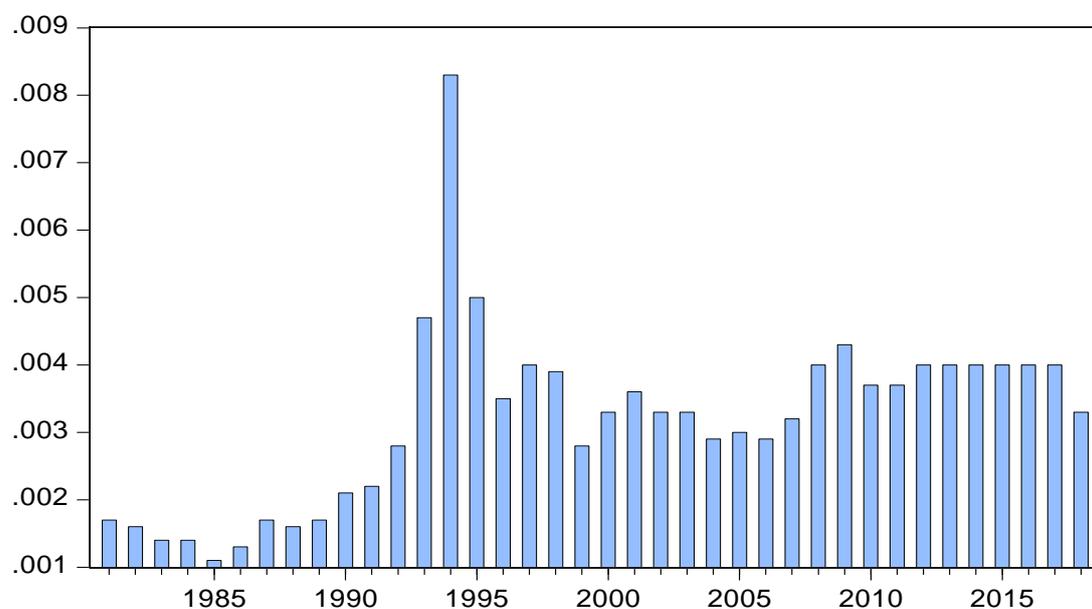
regression model, artificial neural network (ANN), exponential smoothing model and hybrid ARIMA-ANN models through prediction of the third party claim amount of motor insurance data in India. The results indicate within the context of traditional time series modelling, and the ARIMA Model outclasses the traditional models such as Linear Regression and Exponential Smoothing. However, because of the substantial disparity in residuals displayed by ARIMA, the researcher compared a hybrid model against the other models, the results show that ANN model can outperform them.

The previous review reveals that despite some drawbacks of ARIMA modelling, insurance penetration forecasting can be improved by its methodology (Mishra et al., 2019). Similarly, forecasting has been conducted relating to the insurance penetration rate and a few other variables (Selvakumar et al., 2020; Taha, 2017; Bortner et al., 2014). However, there seems to exist a gap in modelling ARIMA from one of the largest potential markets for insurance growth in the SSA countries (Namawajje & Geoffrey, 2020; Nwolley-Kwasi, 2015). In this paper, we extend the knowledge base by forecasting the insurance penetration in Nigeria, which researchers ignored despite its large population's advantage.

3. Data and Methodology

Figure 1 - Insurance Penetration Rate 1981-2018

IP



Source: EViews output (2020)

The current study was based on the secondary data analysis of insurance penetration (IP) of Nigeria between 1981 and 2018 as shown in figure 1, collected from the Statistical Bulletin of Central Bank of Nigeria, 2019 and Okwonwko & Eche (2019). For the analysis (forecast), the ARIMA approach developed by Box and Jenkins in the 1960s was used to forecast a time series variable.

In an ARIMA (p, d, q) model, p determines the AR, d specifies difference and q describes the MA. To be more precise, the p stands for lags of variables in the Autoregressive model, d stands for differencing times to make the data stationary, and q stands for the number of error terms in the model (Arifin & Habibie, 2020).

Yermal and Balasubramanian (2017) listed out the steps involved in Box Jenkins ARIMA forecasting model. The steps are identification, model estimation, diagnostic test and forecasting. Moreover, stationarity, invertibility and parsimony are the three most essential factors in identification, estimation, and diagnostic checking of an ARIMA model (Asteriou and Hall, 2015) outlined.

4. Results and Discussion

The model's identification is the process of checking the stationarity of the time-series data. There are numbers of methods available, and the common ones are Augmented Dickey-Fuller (ADF) test, graph/time plot assessment and plotting of correlogram of the autocorrelation function (ACF) and partial autocorrelation function (PACF).

The ADF was used to test the stationary of the series. The criterion for ADF depends on the value of t-stats (Challa, Malepati & Kolusu, 2018). If the t-stats value exceeds the critical value (CV), the null hypothesis is rejected, and the alternate hypothesis is accepted, otherwise reverse the case. The null hypothesis states the absence of stationarity in the series, whereas the alternate posits stationarity in the series under consideration. Table 1 depicts the result of the ADF test. The result shows that the t-stats value of -4.9755 is higher than the CV of -2.9810. This indicates that the IP is stationary at a 5% significance level. Hence, the null hypothesis is rejected (Challa, Malepati & Kolusu, 2018).

Table 1 - ADF Test

Series	t-stats	5 % CV	Analysis	Stationarity
IP	-4.9755	-2.9810	t-stats >5% cv	Stationary

Source: EViews (2020)

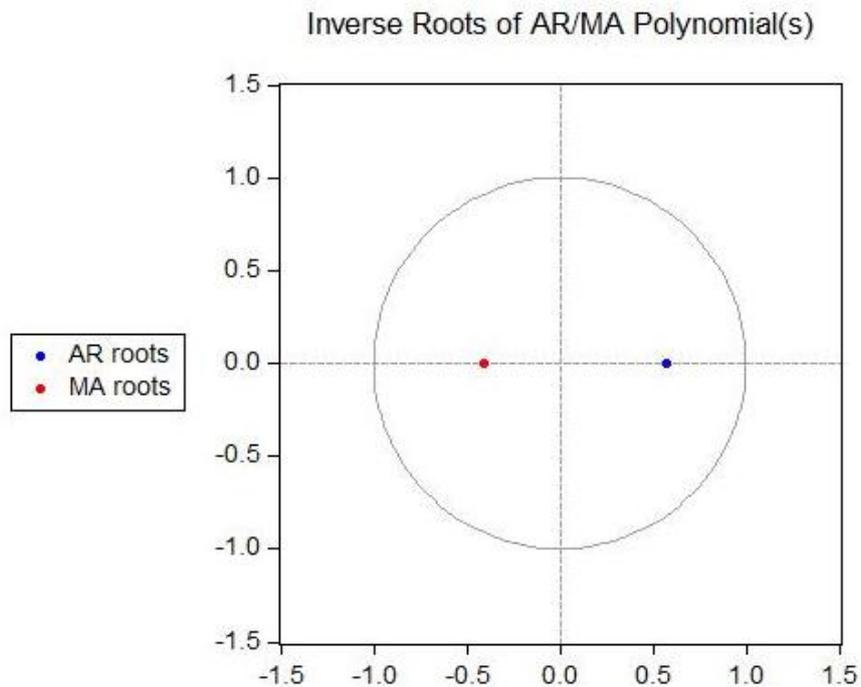
The process of identification is preceded by the model estimation using the default least squares method. The ideal model is selected among the estimated combinations of different p and q for AR and MA, respectively, and d for the integrated seasonality. Hence, the criterion for the selection of the most appropriate combination of ARIMA (p,d,q) is based on parsimonious considerations, such as highest number of significant coefficients, lowest Akaike Criterion Information (AIC), lowest Bayesian Criterion Information (BIC) and highest adjusted R^2 (Balli & Elsamadisy, 2012; Mishra et al., 2019).

Stability Test

The stability test examines AR/MA polynomial(s) inverse roots, which should lie within the unit circle (Nyoni & Nathaniel, 2018).

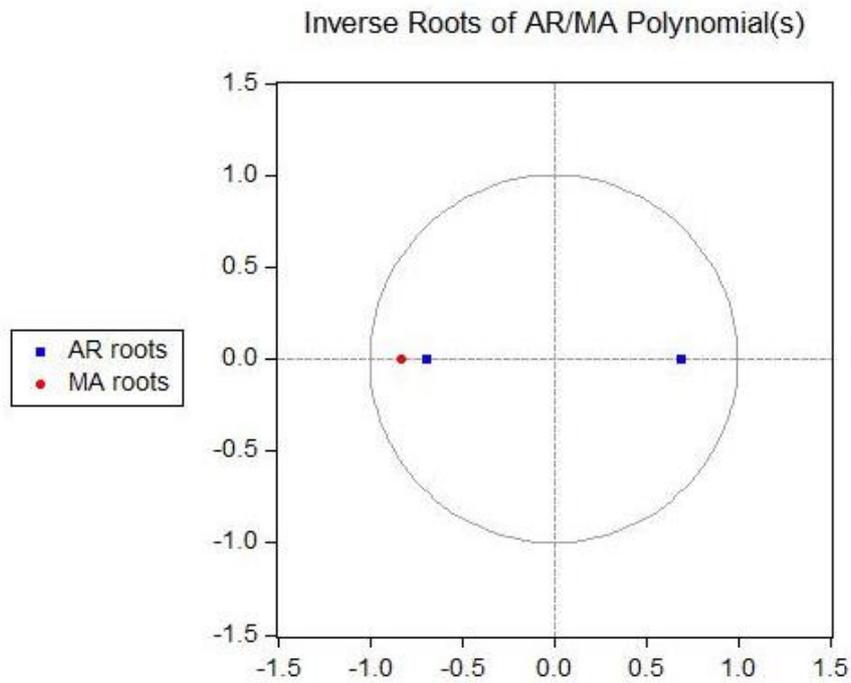
The figure 2 below shows that the ARMA (1, 0, 1) model is stable since the corresponding inverse roots of the characteristic polynomial is found in the unit circle.

Figure 2 - ARMA (1, 0, 1) Stability Test



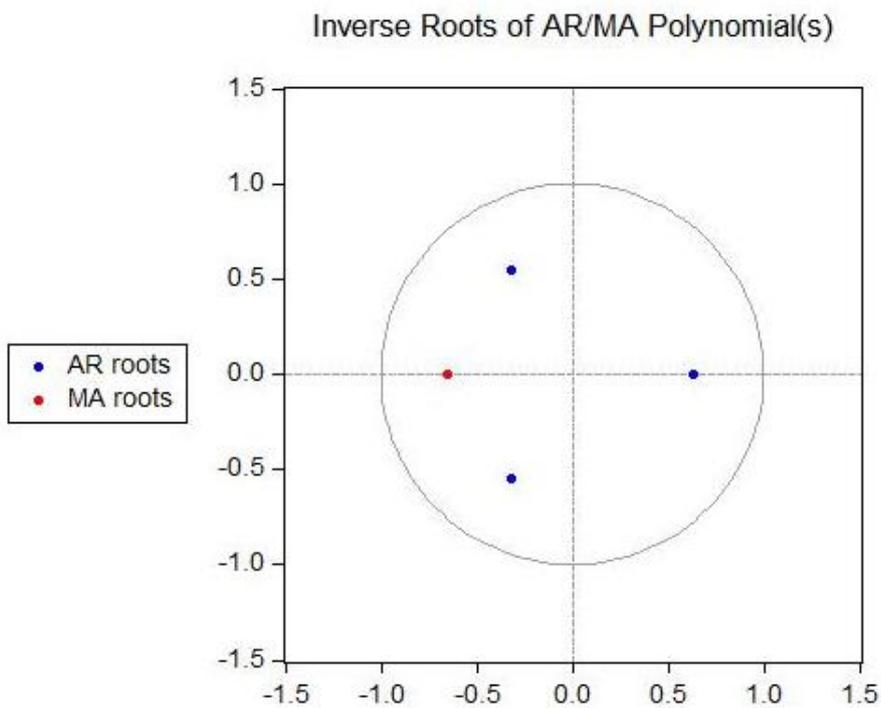
The figure 3 below shows that the ARMA (2, 0, 1) model is stable since the corresponding inverse roots of the characteristic polynomials are in the unit circle.

Figure 3 - ARMA (2, 0, 1) Stability Test



The figure 4 below shows that the ARMA (3, 0, 1) model is stable since the corresponding inverse roots of the characteristic polynomials are in the unit circle.

Figure 4 - ARMA (3, 0, 1) Stability Test



The estimates in Table 2 suggests the ARIMA (2,0,1) model fits best in comparison with the other models, i.e. ARIMA (1,0,1) and ARIMA (3,0,1). Its possession informed the ARIMA (2,0,1) model of the highest significant coefficients, and the second-largest adjusted R² value among the estimates. However, AIC estimates suggest ARIMA (3,0,1) is the most desirable model, followed by ARIMA (2,0,1), while ARIMA (1,0,1) has the highest AIC value. Hence, among the three estimates, ARIMA (2,0,1) model is considered the best in-sample performing model.

Table 2 - Models Estimation

IP	ARIMA(1,0,1)	ARIMA(2,0,1)	ARIMA(3,0,1)
Most Significant Coefficient	00	02	01
Adjusted R ²	0.5396	0.5299	0.4530
AIC	-11.0177	-10.9993	-10.8495
Durbin Watson (DW) stat	2.000	1.954	1.41745
RMSE	2.227	2.428	2.879

4.1. Model Specifications

In accordance with the model estimation as depicted on table 2, the following models have been specified as:

ARIMA(1,0,1) Model

$$IP_t = c + \beta_1 IP_{t-1} + \alpha_1 \mu_{t-1} + \mu_t \quad (1)$$

ARIMA(2,0,1) Model

$$IP_t = c + \beta_2 IP_{t-2} + \alpha_2 \mu_{t-2} + \alpha_1 \mu_{t-1} + \mu_t \quad (2)$$

ARIMA(3,0,1) Model

$$IP_t = c + \beta_3 IP_{t-3} + \alpha_3 \mu_{t-3} + \alpha_1 \mu_{t-1} + \mu_t \quad (3)$$

Succeeding the estimation process is the model proving stage. This process is essential to ensure that no information in the series is left uncaptured. Hence, the stage involves plotting the correlogram of the residuals of ACF and PACF, the lags structure of the ideal model should lie within the 95% confidence interval of the standard error limits.

Therefore, to check the ideal model's fitness, correlogram of the residuals was plotted against the lag lengths. Figure 5 portrays 12 lags of correlogram of the residuals and its associated statistical values.

Figure 5 - Residuals Correlogram of ARIMA (2, 0, 1)

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
		1 0.067	0.067	0.1862	
		2 -0.103	-0.108	0.6309	
		3 0.025	0.041	0.6591	0.417
		4 0.171	0.158	1.9711	0.373
		5 -0.183	-0.209	3.5069	0.320
		6 -0.015	0.055	3.5183	0.475
		7 0.060	0.014	3.6956	0.594
		8 -0.022	-0.055	3.7204	0.714
		9 -0.138	-0.060	4.7223	0.694
		10 -0.103	-0.146	5.2936	0.726
		11 -0.071	-0.080	5.5811	0.781
		12 -0.135	-0.128	6.6533	0.758

Source: EViews output (2020)

The standard error (SE) limits can be seen in the ACF and PACF as the dotted lines. ACF and PACF do not differ statistically from nonexistent at the significance level of 5% if both are under the SE limits (Challa et al., 2018). The correlogram is flat, implying that there is no SE sign as evidently shown by the spikes. Besides the residuals check's correlogram, DW-stat value of 1.9540, which is very close to the threshold value of 2, as shown in Table 2, confirms the absence of autocorrelation (Uyanto, 2020). Therefore the model is ideal for the forecasts.

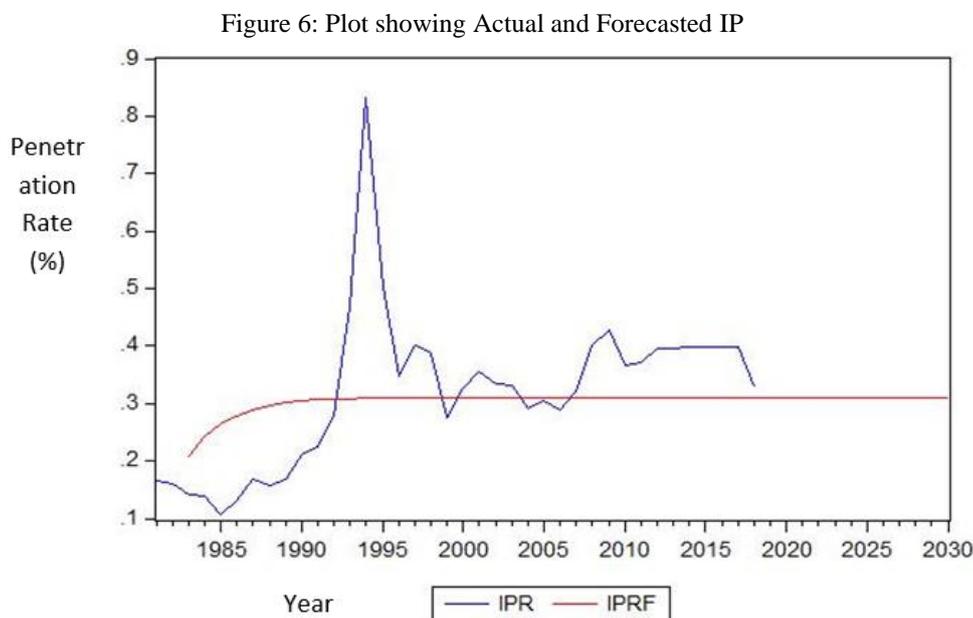
The forecasts from Table 3 show that the penetration rate will be 0.3116 % in 2030, which shows the future insurance rate in Nigeria will decrease from 0.333% in 2018 to about 0.312% by 2030. The declining trend of the insurance uptake could likely trace to cultural limitations, vulnerable households' income and the low-risk mitigation literacy (PWC, 2015).

Table 3 - Forecasts of Insurance Penetration Rate from 2019-2030

Year	IPF
2019	0.3172
2020	0.3201
2021	0.3141
2022	0.3155
2023	0.3127
2024	0.3134
2025	0.3120
2026	0.3123
2027	0.3117
2028	0.3119
2029	0.3116
2030	0.3116

Source: compiled by Authors (2020)

Similarly, Figure 6 (with a 12-year projection range, i.e. 2019-2030) plots the actual against the forecast rates of insurance penetration in Nigeria. The blue line depicts the actual values (IP), while the red line (IPF) indicates the forecast rates. Moreover, the figure reveals that Nigeria's insurance penetration is likely to remain very low, floating around a predicted rate of 0.31 per cent, which is marginally lower than the benchmark rate of 0.33 per cent recorded in 2018. The most revealing aspect of this estimate is that insurance penetration in Nigeria is likely to stay very poor over the projected period. This low penetration may not be unconnected with inadequate distribution frontiers, weak institutional arrangement, products inadequacy and illiteracy, among other things (Inyang, & Bassey, 2019). However, low insurance penetration is unfavourable to economic development. Ul Din, Abu-Bakar and Regupathi (2017) argued that in addition to mitigating excessive uncertainty, insurance facilitates ingenuity, invention, investment, and commerce essential to sustainable economic development.



Source: EViews output (2020)

Concerning the model accuracy validation, many indicators are available for determining the accuracy of the forecasts. These include the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), and Root of Mean Squared Error (RMSE). Regarding the check of accuracy, MAPE is favoured because it accounts for the errors in the percentage of between 0 and 1 (Matyjaszek et al., 2019; Namaweje & Geoffrey, 2020). The forecasted model's MAPE value is

10.352%; this implies that the model is about 89.648% accurate in forecasting the 12 years of future values of IP.

5. Conclusion

Insurance penetration is one of the essential determinants of the nation's financial development. Forecasting helps stakeholders to project future events with a view of supporting the decision making process with facts. In this context, the ARIMA model used to forecasts the insurance penetration rates of Nigeria. The post estimation check shows that ACF & PACF of the residuals were within the SE bounds. The MAPE was about 10.35%, implying that the model is approximately 89.65 % accurate. This rate underlines the reliability of ARIMA in predicting future values. A critical finding of this paper is the decreasing rate of insurance penetration in Nigeria. The consequences of low insurance penetration are weak economic resilience among the uninsured. However, the result will likely flash the stakeholders in advance to remedy the unwanted trend. Therefore government policymakers and insurance managers shall, subject to further empirical investigation use the projection as a roadmap to define monetary and fiscal measures and prepare expected operational activities, respectively that will enhance insurance uptake. Similarly, there is a need for the national regulatory bodies of insurance such as National Insurance Commission of Nigeria (NAICOM) to innovate and implement policies that would accelerate insurance uptake, bearing in mind the socio-cultural differences of Nigeria's heterogeneous population.

Future Study

Studies in the future should explore the reasons behind the likely end downward trend of insurance penetration. Use of different insurance penetration proxies and forecasting techniques to check the robustness of the findings is worth exploring.

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