ISSN 2250-3153

Forecasting Life Insurance Premiums and Insurance Penetration Rate in Uganda

Hellen Namawejje[*], Katamba Geofrey[**]

[*]Lecturer, Department of Statistical Methods and Actuarial Sciences, Makerere University

[**]Master Student, Department of Planning and Applied Statistics, Makerere University

DOI: 10.29322/IJSRP.10.05.2020.p10181
http://dx.doi.org/10.29322/IJSRP.10.05.2020.p10181

Abstract- Uganda still has the lowest insurance penetration rate compared to its neighboring countries Kenya, Rwanda, and Tanzania in the East African region. This paper forecasts life insurance premiums and insurance penetration rates using the ARIMA model on annual data from 2000 to 2018. ARIMA (0, 1, 0) is the optimal model used with the least Akaike information criteria derived from Auto. Arima function in r. The forecast for life insurance premiums and the insurance penetration rate is done for 10 years (2019 to 2028). Results show that among the life insurance premiums only life individual premiums will keep increasing while group life premiums and deposit administration plans will keep constant. Also, the insurance penetration rate keeps increasing but at a lower rate of 0.9% to 1.19%. The paper recommends that the Insurance Regulatory Authority should focus on innovative measures that enable insurance companies to design insurance products suitable for the characteristics of Ugandans to increase life insurance premiums and insurance penetration rates.

Keywords- ARIMA model, Premiums, Insurance, Forecasting.

1. INTRODUCTION

The report by KPMG, 2017 shows that the insurance market in East Africa remains untapped with a population of 340 million people with the penetration of insurance being between 0.4% and 4.0% and this rate works out to the small amount of GDP. Uganda penetration increased from 0.8% in 2017 to 0.84% in 2018, noting that life insurance accounted for 25.34% in 2018 compared to 22.86% in 2017. (IRA Report, 2019).

In Uganda, Life insurance written premiums grow by 28.6% from 168 billion to 216.9 billion in 2018 which is still very low when compared to the growing population in Uganda. Uganda currently has 36 insurance companies put off which 9 are life, 21 non-life, and 2 are insurance brokers with 1996 insurance agents, IRA report. (2019). The growth of insurance may have a direct bearing on economic development, creating value, and sustainability for all stakeholders in the insurance business (Ghosh, 2013; Akinlu & Apansile, 2014; Kramaric & Galctic, 2013).

Many scholars (Rupiny, 2018; PWC, 2020; Opeba, 2020; Alhassan & Biekpe, 2016) have studied why Uganda's insurance penetration rate is still below 1%. Some of the reasons include; insurance companies dodge paying claims and even if they do, they take their time, insurance costs are high, fear of unknown, attitude, and trust towards insurance among others. This study intends to forecast life insurance premiums and Insurance Penetration Rate (IPR) in Uganda. The life insurance premiums are; Life Individual Premiums (LIP), Group Life Premiums (GLP), and Deposit Administration Plans (DAP).

II. LITERATURE REVIEW

According to Ludkovski, Bortner, Pulliam, and Yam, (2020), in their research, "Trend Analysis for Quarterly Insurance Time Series" insurance companies mainly use linear regression to create forecast models, they used time series analysis to create a more reliable model to the data. Their results show some characteristics of seasonality and trend and the ARIMA model shows better results of predicting the data than the linear regression model.

Bing et al., (2016) they constructed an ARIMA model to predict China's gross domestic product. Their results showed that China's GDP reached 72,407.76 billion yuan in 2016 and 77,331.48 billion Yuan in 2017 using ARIMA (2, 4, 2) model derived from Eviews 6.0. They further projected the GDP for the next two years which was also showing a rising trend and this was because China had a changing economic growth strategy at that time of transition from investment-driven to innovation-driven approach.

According to Langat et al., (2017), the insurance sector covers a major role in the life of humanity. They established the influence of consumer behavior on the uptake of insurance services in the Cooperative Insurance Company (CIC), Kericho branch in Kenya. They used structured self-administered questionnaires to determine demographic, social, economic factors that influence consumer behavior in insurance uptake. The study recommended that insurance companies should profile their clients according to the economic and demographic characteristics and develop unique products and marketing strategies for each segment.

III. METHODOLOGY

A. Data sources

The data sample employed annual data for life insurance premiums and insurance penetration rates for the period from 2000 to 2018. Secondary data used is obtained from the Insurance Regulatory Authority (IRA) website.

B. Method

According to Gujarati, 2003, the ARIMA model technique is used to forecast observations. ARIMA represents Autoregressive Integrated Moving Average, sometimes written as ARIMA(p, d, q), where p stands for lags of variables itself in the Autoregressive model, d stands for times of differencing done to make the data stationary, q stands for the number of error terms we need to include in the model from the moving average model hence ARIMA. p, d, and q are determined automatically using the Auto. Arima function in r. This function derives the optimal model that fits the data with the least AIC. The ACF and PACF plots were plotted to check if the lags lie within the significant bounds. The residuals for the fitted model were computed to determine zero autocorrelation in the residuals and the diagnostics tests were done using the Ljung-Box test. In case the p-values were greater than 0.05 level of significance we rejected the null hypothesis: there is no autocorrelation otherwise we accepted the alternative. The ARIMA model is used to forecast observations depending on the given lags. The forecasted models were tested for accuracy metrics using Mean Absolute Percentage Error (MAPE), Mean Error (ME), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Root Mean Squared Error (RMSE), Autocorrelation of Error Lag 1 (ACF1), which shows the relationship between the observed and the future data (corr) and min-max Error (min-max). The MAPE, corr, and min-max provide varying values between 0 and 1 enabling easy judging of how good the forecast model since they have no units involved while other error metrics are quantities. In this study we used the MAPE to determine the accuracy of the ARIMA fitted models.

IV. RESULTS

A. Time Series Nature of Life Insurance Premiums and Insurance Penetration Rate

Our data shows repeated measurements are observed over time. The data is checked to see if there is any time series component associated with it, that is, trend, seasonality, and irregularity.

Distribution of Insurance Penetration Rate and Life Individual Premiums

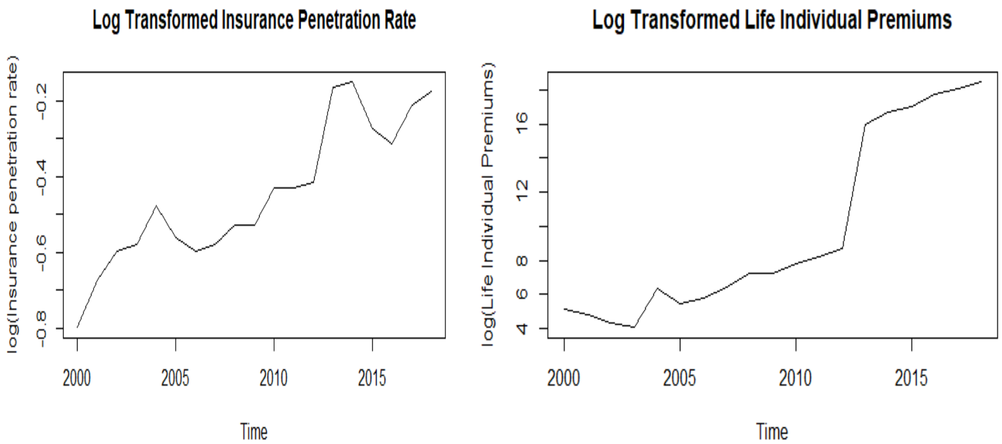

Figure 1: Upward trend of Insurance Penetration rate and Life Individual Premiums

Distribution of Group Life Premiums and Deposit Administration Plans

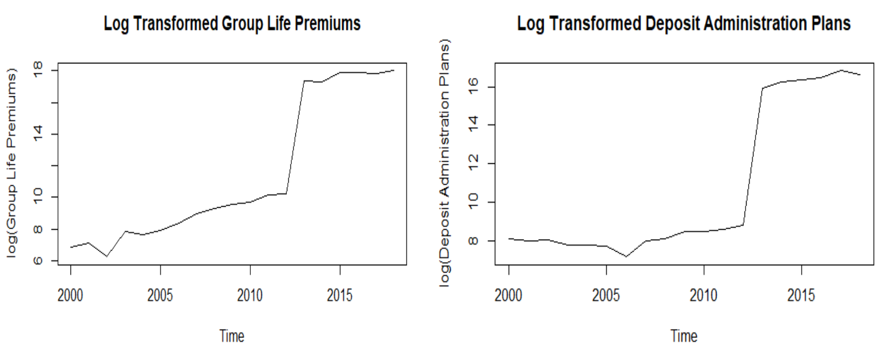

Figure 2: Upward trend of Group Life Premiums and Deposit Administration Plans

B. Optimal ARIMA Model and Model Fitting

The distribution of variables in subsection A shows that the data is non-stationary. The ARIMA technique is used to describe the necessary degree of differencing and when applied makes the data stationary. The auto.arima function in R derived the optimal ARIMA models for IPR, LIP, GLP, and DAP as well as the lowest Akaike Information Criteria (AIC) which gives the best model.

Table 1: Optimal ARIMA models for Life Insurance Premiums and Insurance Penetration Rate

Variable	Optimal model	Coefficient/drift	Standard Error	AIC
IPR	ARIMA(0,1,0)	0.0347	0.020	-34.430
LIP	ARIMA(0,1,0)	0.7405	0.407	74.700
GLP	ARIMA(0,1,0)	Numeric(0)	1.766	73.560
DAP	ARIMA(0,1,0)	Numeric(0)	1.706	72.320

Where IPR represents Insurance Penetration Rate; LIP is Life Insurance Premiums, GLP is Group Life Premiums and DAP is Deposit Administration Plans. Table 1, shows optimal ARIMA models that were fitted for the life insurance premiums and insurance penetration rate. All the models that we fitted used ARIMA (0, 1, 0) model as the best model with the least AIC.

C. Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) of Variables

Autocorrelation is computed to a correlation of time series given data with values at previous time points. A plot of correlation coefficients against lags gives an autocorrelation function.

ACF and PACF for Insurance Penetration Rate

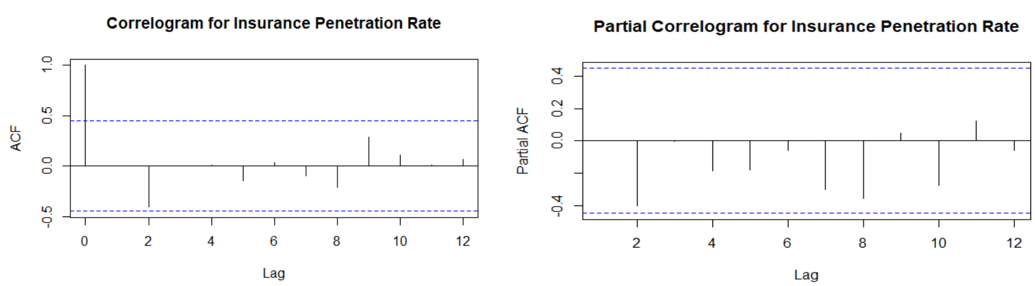

Figure 3: ACF and PACF of Insurance Penetration rate.

Apart from lag zero =1 in the ACF plot, which is expected, all the lags lie within the blue dotted lines which are the significant bounds and thus the autocorrelation for sample forecast do not exceed the significant bounds for lags between 0 and 12, then same is seen in Figure 4, Figure 5 and Figure 6. All the lags have autocorrelation equal to zero

ACF and PACF for Life Insurance Premiums

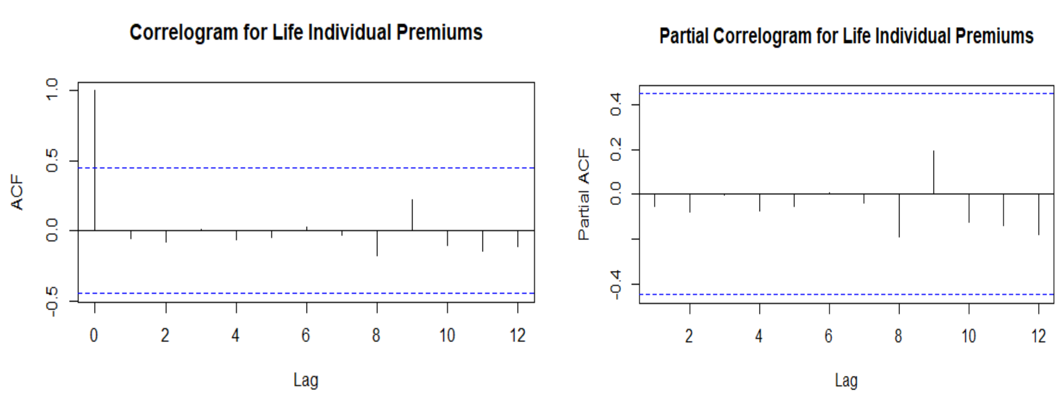

Figure 4: ACF and PACF for Life Insurance Premiums

http://dx.doi.org/10.29322/IJSRP.10.05.2020.p10181 www.ijsrp.org

ACF and PACF for Group Life Premiums

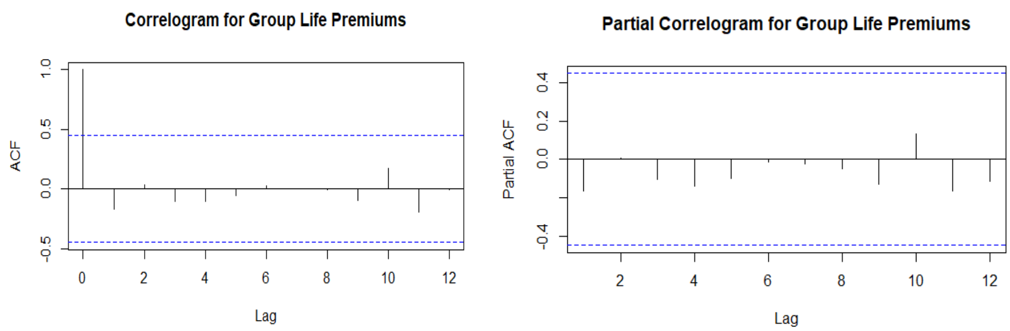

Figure 5: ACF and PACF for Group Life Premiums

ACF and PACF for Deposit Administration Plans

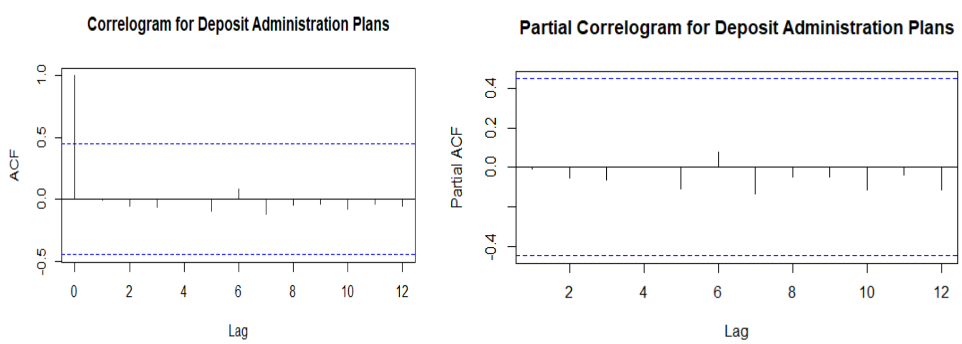

Figure 6: ACF and PACF for Deposit Administration Plans

V. RESIDUAL DIAGNOSTIC TESTING USING THE LJUNG-BOX TEST

The residuals for the fitted models under Section IV subsection B were computed and a diagnostic test using the Ljung-Box test was used to further confirm that the residuals have no autocorrelation and the models fit the data very well.

Table 2: Ljung-Box Test on fitted ARIMA models

Variable	x-squared	df	p-values
IPR	10.154	10	0.427
LIP	3.906	10	0.952
GLP	2.983	10	0.982
DAP	1.558	10	0.999

From Table 2, since all our p-values are greater than 0.05 we cannot reject the null hypothesis hence we confirm that our models are a good fit to forecast IPR, LIP, GLP, and DAP.

VI. FORECASTING OF IPR, LIP, GLP, AND DAP

Using the fitted models in Section IV subsection B, we forecasted the next 10 years of IPR, LIP, GLP, and DAP. The models use lagged observations of time series to forecast observations.

Forecasting for Insurance Penetration Rate and Life Individual Premiums

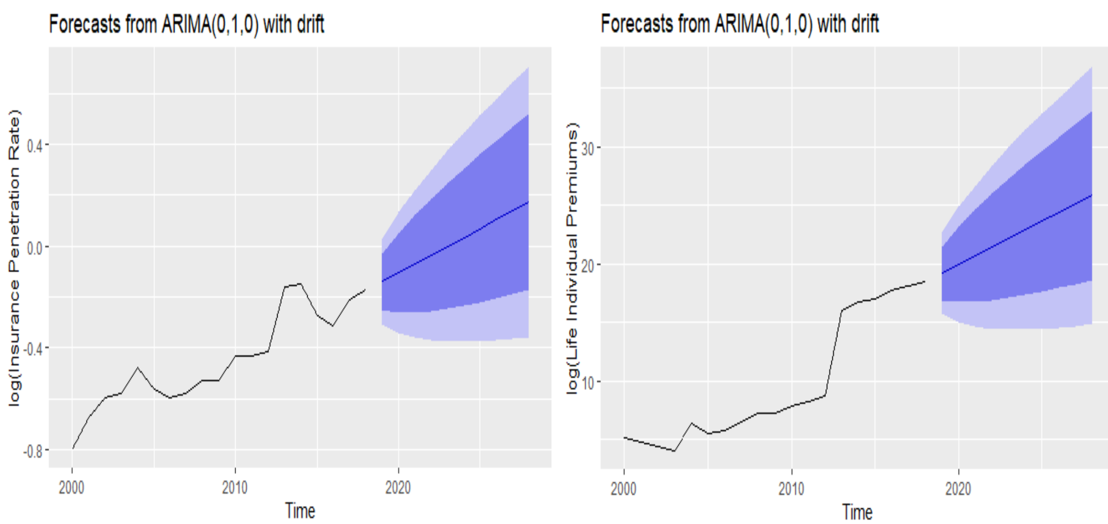

Figure 7: A plot showing forecasted IPR (left) and LIP (right), with deep blue showing 80% Confidence Interval and lighter blue showing a 95% confidence interval. The confidence intervals get bigger as years of prediction increase due to the uncertainty of other unknown factors that may influence the model. In both cases, the figure shows that both IPR and LIP will increase in the next 10 years.

Forecasting for General Life Premiums and Deposit Administration Plans

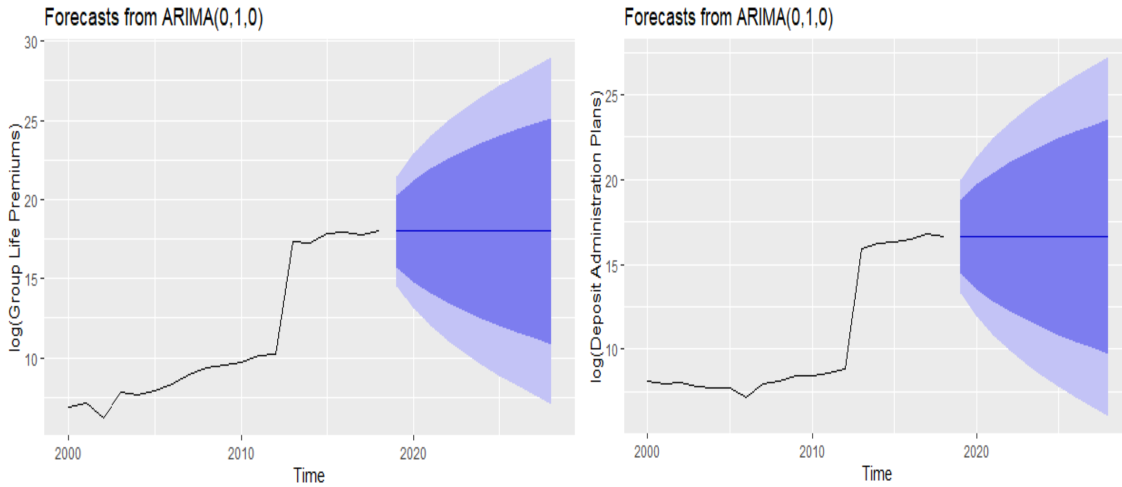

Figure 8: A plot showing forecasted GLP (left) and DAP (right), with deep blue showing 80% Confidence Interval and lighter blue showing a 95% confidence interval. Again the confidence intervals get bigger as the time of prediction increases due to uncertainties that may affect the model. However, from both figures, we see that both the GLP and DAP will remain constant in the next 10 years.

VII. SUMMARY PREDICTION OF INSURANCE PENETRATION RATE

Table 3: Predicted values of Insurance Penetration Rate only

	Last two previous values		Predicted values for Insurance Penetration Rate for the next 10 years in percentage (%)									
Year	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028
Values	0.81	0.84	0.87	0.90	0.93	0.96	1.00	1.03	1.07	1.11	1.15	1.19

Table 3, shows the predicted values of the insurance penetration rate for the next 10 years. Results show that the penetration will keep increasing but at a lower rate of 0.90% to 1.19%.

VIII. ACCURACY OF MODEL FORECASTING

Many accuracy metrics can be used to judge if the forecast is good or not. Among them include; ME, MAE, MPE, MAPE, RMSE, ACF1, corr, and min-max.

Table 4: Accuracy of Fitted Model

Variable	ME	RMSE	MAPE	ACF1	Degree of Accuracy (%)
IPR	$-4.39\text{x}10^{-5}$	0.081	19.738	0.000	80.262
LIP	$2.30\text{x}10^{-4}$	1.679	10.873	-0.051	89.127
GLP	0.587	1.719	6.128	-0.166	93.872
DAP	0.451	1.661	4.563	-0.006	95.437

From Table 4, we considered only the MAPE because it gives percentage errors between 0 and 1. This makes easy it to conclude if the ARIMA model used is a good forecast for the time series data. Other measures are not used because there error metrics are in quantities.

Considering IPR, the MAPE is 19.738%, this implies that the model is about 80.262% accurate in forecasting the next 10 years or observations. LIP has MAPE as 10.873%, this means that the model is about 89.127% accurate in predicting the next 10 years while the MAPE for GLP and DAP are 6.128% and 4.563% respectively, this shows that the GLP and DAP models are about 93.872% and 96.437% accurate in predicting the next 10 years respectively.

IX. DISCUSSION AND CONCLUSION

According to Ludkovski, Bortner, Pulliam, and Yam (2020) in their paper "Trend Analysis for Quarterly Insurance Time Series" they explore whether the time-series analysis applies to calculate future pure premium costs. They used three predictive models, that is, loess smoothing, exponential weighted moving average (EWMA) and ARIMA. With the ARIMA model, they used Auto. Arima function in r to determine the optimal ARIMA. Their results show that ARIMA (0, 1, 0) and ARIMA (0, 0, 2) as the two optimal models. In this current study, our optimal model is ARIMA (0, 1, 0) which was obtained using the Auto. Arima functions as there study. Further, the ARIMA (0, 1, 0) model is also a well-known model in forecasting time series data known as a random walk with drift.

Again, the current research shows that the degree of accuracy of the fitted models, that is, for IPR is 80.26%, LIP is 89.13%, GLP is 93.87% and DAP is 95.44% which show that the ARIMA models used were the best fit. These results conquer with Ludkovski et al., 2020, were also in the result, from the three predictive models used, the ARIMA model had the best accuracy compared to other models. Hence ARIMA modeling best forecasts the insurance premiums.

Bing et al., (2016) used the ARIMA model in the prediction of gross domestic product. The use of annual data from 1978 to 2014 and the ARIMA (2, 4, 2) model was established by applying Eviews 6.0 software. Their results showed an effective forecast of GDP in the short term and the only GDP of the next year was forecasted. In this paper, we also use similar annual data from 2000 to 2018 for IPR, LIP, GLP, and DAP considering four variables, and using Auto. Arima function in r to determine the optimal model with the least AIC. Our results not only support results for the next year like in their work, this research forecast ten years which can help policymakers and implementers to develop policies that support insurance development and economic development.

Kulabako, (2019) in her article, states that Uganda's insurance penetration is still far below that of Sub-Saharan Africa even though seen to increase slowly as years go by. Stakeholders are optimistic that the penetration rate will at least hit 2% by 2022. The results in this work show that the projected penetration rate will be 0.96% by 2022 based on the ARIMA model instead of the projected 2%. Economic, demographic, and other factors such as product knowledge, awareness, consumer behavior claim settlement, and attitude contribute to the low insurance penetration rate (Langat et al., 2017).

The life insurance premiums and insurance penetration rate in Uganda from 2000 to 2018 are forecasted using ARIMA (0, 1, 0) model. This paper recommends that i) insurance companies should design and sell products that are affordable for all income class of people (low, middle and high level) in the society, ii) future research can be done with a more lengthy-time period to give insight on big data if results produced are the same, iii) many other factors affect the insurance penetration rate apart from only life insurance premiums and they can as well be studied to improve the insurance sector.

ACKNOWLEDGMENT

Makerere University, College of Business and Management Sciences (CoBAMS) research fund from the principal's office.

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AUTHORS

First Author- Hellen Namawejje, Lecturer, Makerere University, hnamawejje@gmail.com or hnamawejje2@bams.mak.ac.ug

Second Author- Katamba Geofrey, Master Student, Makerere University, gkatamba@uapoldmutual.com

Correspondence Author: Hellen Namawejje, hnamawejje@gmail.com or hnamawejje2@bams.mak.ac.ug, +256775070000.