Modelling and Forecasting Claim Payments of Tanzania National Health Insurance Fund

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Abstract
The expenses of medical services are increasing across the globe. As a result, pressure is placed on government and insurance companies' budgets. The amounts of money collected are not enough to cover the claim payments. Therefore, it threatens the sustainability of the health insurance companies due to the mismatch of income and expenditures. This study aimed to model and forecast claim payments for the national health insurance fund (NHIF) in Tanzania. The claim payment data for the period of 2001–2021 from NHIF were used in building the ARIMA model. It was proven that ARIMA (0, 2, 2) is the most accurate model for forecasting the claim payments from 2022 to 2031. Furthermore, numerical results show that the claim payments for NHIF will grow by 68% by 2031.

Keywords: Health insurance; Claim payments; NHIF; ARIMA.

Introduction

Health insurance is a way of paying for some or all of the costs of medical expenses in exchange for premium payments (Dutta 2020). Pitacco (2014) suggested that the unpredictability of healthcare expenses creates risks for individuals, which can be mitigated by transferring them to an insurance firm. Health insurance functions optimally through cross–subsidization when there are sizable risk pools and diverse health risks among the insured population.

A medical claim payment is compensation from an insurer to healthcare providers (Douven et al. 2022). These are bills that a healthcare provider submits to a patient's insurance company. Globally, there is a problem of high costs for health care services (Jiying et al. 2019). Health insurance bills have been dramatically increasing in recent years (Bertsimas et al. 2008, Mashasha et al. 2022). Most countries have reported a significant rise in health care expenses whose growth outpaces their gross domestic product (GDP) growth (Glassman and Zoloa 2014, Jahanmehr et al. 2022). Moreover, Klazoglou and Dritsakis (2018) commented that health care spending increases along with a nation's GDP per capita income. Governments all over the world have formulated several policies to enable wider access to healthcare services for all citizens. Health insurance policies are one of the strategies.

The history of health financing in Tanzania dates back to 1993, when user fees were introduced. Due to escalating medical expenses, the spread of pandemic illnesses like HIV/AIDS, and poor economic performance, the government failed to provide free health care to all of its citizens through tax financing (Quijada and Comfort 2002). This led to the formulation of insurance programs as additional financing mechanisms, such as the national health

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insurance fund (NHIF), community health funds (CHF), tiba kwa kadi (TIKA), as well as private insurance companies (Mtei and Mulligan 2007). Currently, the national social security fund (NSSF) has established a health care benefit package known as social health insurance benefit (SHIB).

NHIF is a social health insurance scheme formulated under the national health insurance fund act of 1999. The NHIF operates under the principles of social solidarity and cross-subsidization, where risks are shared among members. At the present, NHIF pays healthcare providers through a fee-for-service model. However, the increasing costs of healthcare have placed significant strain on health insurance companies, impacting their ability to sustainably maintain their services, as noted by Lee et al. (2018) and Jahanmehr et al. (2022). Also in Tanzania, various studies (Lee et al. 2018, Piatti-Funfkirchen and Ally 2020, Embrey et al. 2021) have reported a rapid increase in health care costs. Nevertheless, Klazoglou and Dritsakis (2018) suggested that this rise is primarily due to factors such as income growth, changes in disease patterns, demographic changes, and advancements in medical technology.

Lee et al. (2018) emphasized the importance of closely monitoring the rapid rise in healthcare costs to properly plan and ensure the sustainability of health insurance funds. In addition, knowing the distribution of benefit payments beforehand is crucial for designing appropriate long-term investment strategies for financial sustainability. Ramezanian et al. (2019) suggested that accurate predictions of health insurance claim payments can provide policymakers with valuable information for decision-making in the future. The accurate forecasting should be done by appropriate economic model. Autoregressive Integrated Moving Average (ARIMA) is one of the successful statistical and econometrics models used for prediction of economic variables.

ARIMA is a statistical approach that predicts future values based on past values of the observed data and the error terms (Shumway and Stoffer 2011). The approach

was discovered by two prominent mathematicians in the 1970s. It is sometimes known as the Box–Jenkins methodology, which involves identifying, estimating, and diagnosing ARIMA models with time series data (Ariyo et al. 2014). Most researchers have been focusing much on using ARIMA models since they have proven simplicity in comprehension and applications (Fattah et al. 2018).

Zheng et al. (2020) used ARIMA models to predict various health expenditures in China, including total health expenditures, government health expenditures, social health expenditures, and out-of-pocket health expenditures, based on 39 years of expenditure records. Also, Ramezanian et al. (2019) focused on predicting health expenditures in Iran using ARIMA models, based on annual expenditure records from 1971 to 2015. The appropriate ARIMA models were chosen for out-of-pocket, public, and total health expenditures and used to generate forecasts for the period of 2016–2020.

Jiao and Zhang (2020) used 20 years of revenue and expenditure records for China's social medical insurance fund to create two ARIMA models. The predictions from the models showed a deficit would start happening in 2024. Mashasha et al. (2022) analysed health insurance claim payment patterns in Zimbabwe using a seasonal ARIMA model based on monthly records from January 2012 to December 2016. The study used Seasonal ARIMA with monthly data but did not show to what extent the results could be trusted.

Also, several studies have been done in Tanzania to analyse different aspects of NHIF. These studies include Embrey et al. (2021) that looked at the relationships between health insurance plans and retail providers in low-and middle-income countries. The study of Piatti-Fünfkirchen and Ally (2020) focused on reviewing the health care expenditure in Tanzania.

Furthermore, Lee et al. (2018) conducted a study that focused on analysis of cost escalation at the national health insurance fund in Tanzania. This study reported that

since 2012/2013 the annual NHIF surplus has been decreasing every year, in which it was revealed that NHIF will begin to run a deficit in 2025. Also, the study by Byaro et al. (2018) reported that the population aged 60 years and older is one of the major factors contributing to the rise in health care expenditures.

Despite several studies done on NHIF, no study has focused on modelling and forecasting claim payments for NHIF. To achieve that, this study has used a non-seasonal ARIMA to model and forecast the annual claim payments of NHIF. In our work, we modelled claim payments for Tanzania NHIF using the ARIMA model and performed an evaluation of forecast accuracy to show to what extent our forecasts can be trusted.

Materials and Methods

In this study, 20 annual benefit payments (2002–2021) from NHIF were used to build the ARIMA model. The benefit payments records were divided into two categories: the records of 15 years (2002–2016) for training the ARIMA model and five records (2017–2021) for testing purposes.

ARIMA model

The study utilized the autoregressive integrated moving average (ARIMA) approach to model claim payments of NHIF. The choice of ARIMA model is due to the fact that our data is a univariate time series with a trend, as suggested by (Brockwell and Davis 2002). The ARIMA or sometimes known as Box-Jenkins approach was proposed by Box and Jenkins (1976), which incorporates autoregressive (AR), moving average (MA), and differencing. The model has three parameters: p for the number of autoregressive terms, d for the number of times the data is differenced, which correspond to I in ARIMA, and q for the number of moving average terms. The $ARIMA\,(p, d, q)$ model is expressed in Equation 1.

$$(1-\alpha_1 B - \alpha_2 B^2 - ... - \alpha_p B^p)(1-B)^d Y_t = (1-\theta_1 B - \theta_2 B^2 - ... - \theta_q B^q)\varepsilon_t$$

$$(1)$$

where the error term ε_t is assumed to be normally distributed with mean zero and some variance σ^2.

Furthermore, the approach involves model identification, estimation of parameters, model testing, and forecasting. The model identification process involves converting non-stationary data into stationary series and identifying the order of the ARIMA model. The stationarity of the data in this study was assessed by the augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979) and autocorrelation function (ACF) plot. The choice of ADF test is due to the fact that our time series is having a trend, and as suggested by Bawdekar et al. (2022) the ADF test is a powerful test for analysing the time series with trend. On the other hand, the identification of the order of the ARIMA model was done with ACF and the Partial Autocorrelation Function (PACF). The Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (BIC) were used to select the best model, by choosing the model with minimum values of AIC and BIC.

After having identified the ARIMA model, the selected corresponding parameters were estimated. The estimation involved determining the significance of the p-parameters for the autoregressive (AR) part and the q-parameters for the moving average (MA) part. The current study used ML method to estimate the parameters of the ARIMA model. The method was chosen due to the act that the selected ARIMA model is having only MA parts, that are suitably estimated using of ML method as suggested by Abonazel and Abd-Elftah (2019).

After estimating the ARIMA model parameters, the next step was to check the adequacy of the model. This involved testing the assumptions of the model, which included uncorrelated and normally distributed residuals with a mean of zero and some variance σ^2.

This study tested the normality assumption using a Q–Q plot and the Shapiro-Wilk test (Shapiro and Wilk 1965).

The use of the Shapiro-Wilk test was due to the fact that our sample size was less than 50 (Mishra et al 2019). The Q-Q plot was chosen because it is the most sensitive graphical approach for normality test as reported by Al-Reqep (2013). Additionally, the independence assumption was assessed using the Ljung-Box test, as suggested by Ljung and Box (1978), and the ACF plot. The Ljung-Box test was selected because it is a powerful test for non–seasonal time series, as noted by Ljung (1986). The selected model, which satisfied the assumptions, was used to make predictions for future claim payments.

Results and Discussions

Figure 1 shows that there was an upward trend in claim payments, implying that the series was non-stationary. To address the non-constant variance, the Box-Cox transformation (Box and Cox 1964) with lambda 0.2352 was utilized. Figure 2 depicts how the data became more stable as a result of this transformation. This outcome aligns with the work by Klazoglou and Dritsakis (2018), Afeef et al. (2018), Jiao and Zhang (2020), Ramezanian et al. (2019), Uddin and Tanzim (2021) that utilized the Box-Cox transformation with varying lambda values to normalize variance and eliminate heteroscedasticity. Nevertheless, despite applying the transformation to claim payments as shown in Figure 2, the data still displayed an upward trend, suggesting that the series lacks stationarity with respect to its mean.

Figure 3 depicts the Box-Cox transformed series with a second-order difference. It was observed that the series fluctuates around zero, and there were roughly no variations in the distribution of the data points over time, suggesting that the series is stationary. However, the Box-Cox transformed with a first-order difference, was found to be non-stationary with the p-value of ADF test being 0.3431. Additionally, Figure 4 presents its ACF plot, which shows a swift decrease in spikes, signifying stationarity. The ADF test results in Table 2 demonstrated a negative test statistic and a p-value of 0.04892, which is below the significance level of 0.05. Based on these findings, we reject the null hypothesis that the time series is non-stationary and conclude that the time series is stationary at second order differencing.

The transformed series in Figure 3 was used to determine the order of the ARIMA model. The ACF in Figure 4 and PACF in Figure 5 of the transformed series suggested the list of ARIMA models as in Table 1. Furthermore, the suitable model should be the one with the lowest values of AIC and BIC. Therefore, the best model is the ARIMA (0, 2, 2) that is having the minimum values of AIC and BIC as shown in Table 1.

Table 1: List of ARIMA models suggested by the ACF and PACF plots

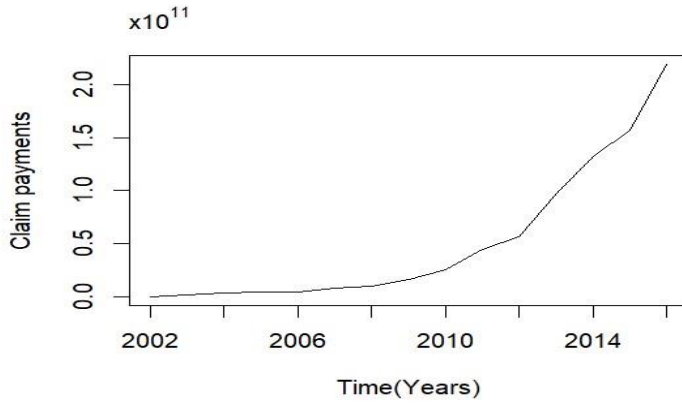| Model	AIC	BIC
$ARIMA(0, 2, 0)$	646.88	647.49
$ARIMA(0, 2, 1)$	647.08	648.21
$ARIMA(0, 2, 2)$	641.95	643.65
$ARIMA(0, 2, 3)$	643.97	646.21
$ARIMA(0, 2, 4)$	645.62	648.44
$ARIMA(1, 2, 0)$	646.58	647.71
$ARIMA(1, 2, 1)$	648.33	650.03
$ARIMA(1, 2, 2)$	643.94	646.20
$ARIMA(1, 2, 3)$	644.31	647.14
$ARIMA(1, 2, 4)$	646.10	649.51

$\times 10^{11}$

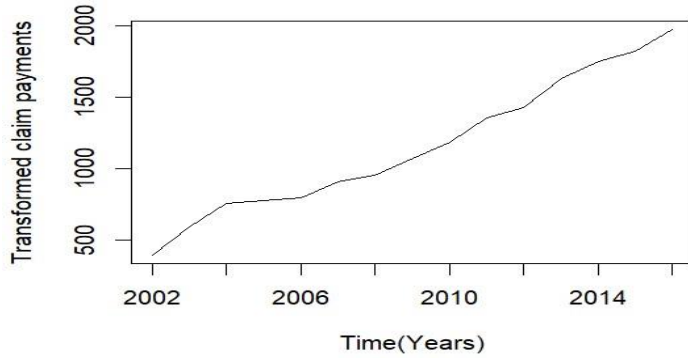**Figure 1:** A time series plot of claim payments.

Figure 2: A plot of Box-Cox transformed claim payments.
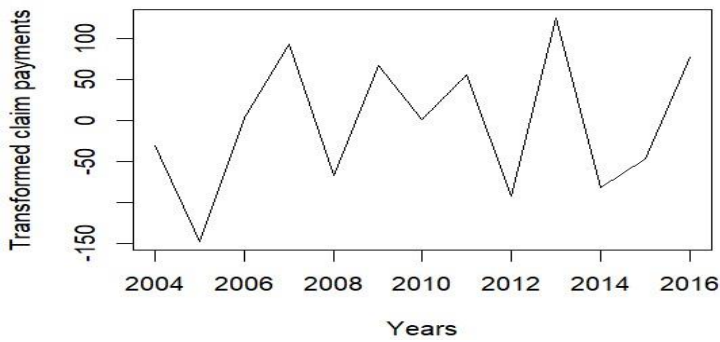

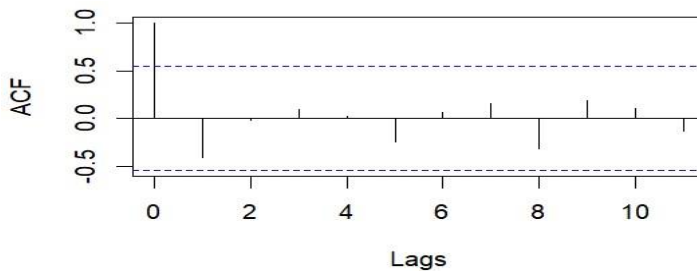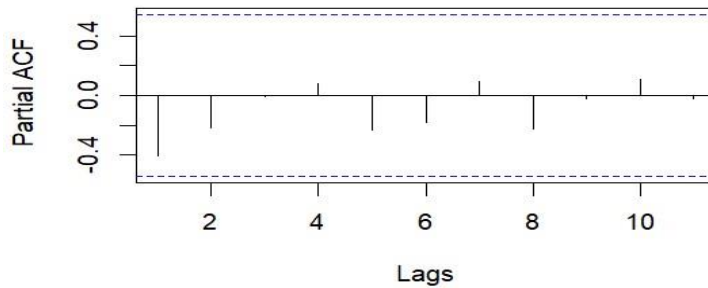**Figure 3:** A plot of Box-Cox and second order differenced claim payments.

Figure 4: ACF plot of second order differenced claim payments.

Figure 5: Partial ACF plot of second order differenced claim payments.

Table 2: ADF test results for Box-Cox transformed series with a second-order difference

Dickey-Fuller	Lag order	p-value
-3.6151	2	0.04892

Estimation of parameters for ARIMA (0, 2, 2) model
The maximum likelihood method was used to estimate the parameters of the ARIMA (0, 2, 2) model using R programming, and the estimated parameters are presented in Table 3, which shows that the p-values of the estimated parameters are less than the significance level of 0.05.

Table 3: Estimated parameters of ARIMA (0, 2, 2) model

Lags	Estimate	Std. Error	z value	P - value
θ_1	-1.01662	0.26581	-3.8247	0.0001309
θ_2	0.99986	0.33710	2.9661	0.0030164

In this case, we reject the null hypothesis that the two parameters θ_1 and θ_2 are not statistically significant, concluding that the estimated parameters are statistically significant. The ARIMA (0, 2, 2) model that describes the behaviours of the benefit payments of NHIF for (2002–2021) is given as follows:

$$(1-B)^2 P_t = (1+1.01662B - 0.99986B^2)\varepsilon_t \qquad (2)$$

where B is the backshift operator, ε_t is the set of error terms and P_t is the claim payments at any time t.

Goodness of fit of the model
The normality assumption was assessed using a Q-Q plot and the Shapiro-Wilk test. On the other hand, the independence assumption was tested using an ACF plot and the Ljung Box test. The Q-Q plot in Figures 6 shows that majority of the quantiles were close to the line, indicating that the normality assumption was reasonably met. The normality of errors was further assessed using the Shapiro-Wilk test, and the p-value obtained as shown in Table 3 was 0.1171, which is greater than 0.05. Therefore, the null hypothesis that the residuals are normally distributed cannot be rejected, and it can be concluded that the residuals are normally distributed.

The ACF of residuals plot in Figure 7 shows that there is no significant spike, meaning that the residuals are not correlated. The Ljung Box test was also used to test for independence, giving a p-value of 0.2073, which is greater than 0.05 (see Table 4). Therefore, the null hypothesis that the residuals are independently distributed cannot be rejected, concluding that the residuals are independently distributed.
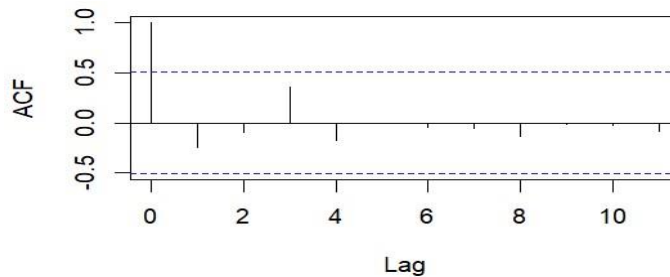
Table 4: Shapiro–Wilk normality test

W	p-value
0.90588	0.1171

Table 5: Ljung-Box test result

Q - statistic	Degree of freedom	p-value
4.5564	3	0.2073
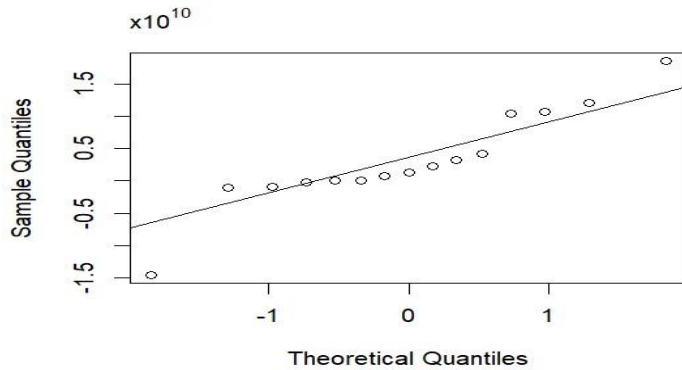
Figure 6: A normal Q-Q plot.

Figure 7: ACF plot of residuals.

Evaluation of forecast accuracy

The forecast accuracy of the model within the sample and out of the sample was assessed by the mean absolute percentage error (MAPE).

In–sample prediction

The fitted model's predictive power was evaluated in-sample, as shown in Figure 8. The observed claim payments are shown in a dashed plot, while the solid plot represents the predictions from the fitted model. The plots are very close, indicating that the model can reproduce data. The accuracy of the model was also evaluated using the MAPE, which yielded a value of 13.8%, indicating that the model's in–sample predictions were in an acceptable range. This result is consistent with prior studies (Lewis 1982, Blasco et al. 2013), which indicated that a MAPE value between 10% and 20% represents good forecasts.

Out-of-sample prediction

As mentioned earlier, benefit payments from 2002 to 2021 were split into two parts for model training and testing. Forecast accuracy was evaluated by comparing predicted values to observed values for the last five years (2017–2021). Results showed that a low MAPE value of 8.95% was obtained, indicating reliable forecasts. This finding is consistent with the works of Lewis (1982), Sumi et al. (2013), Blasco et al. (2013), Cerqueira et al. (2020), Zhao et al. (2022) and Wang et al. (2022).
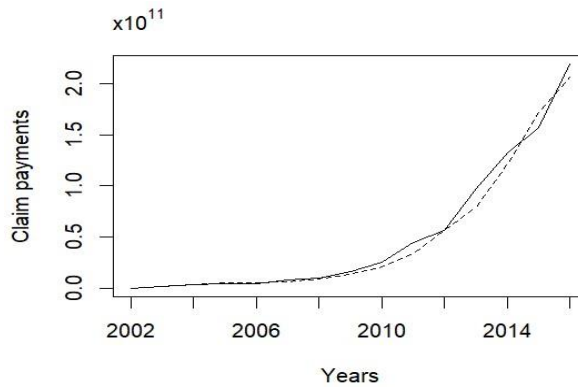
Figure 8: A plot of the model reproducing the training data.

Forecasting future claim payments

The annual benefit payment data of NHIF were well fitted to the non-seasonal ARIMA (0, 2, 2) model. The model in Equation 2 was used to project the distribution of NHIF benefit payments for the next decade, as shown in Figure 9. Moreover, Figure 9 consists of two parts: the first part shows the observed claim payments between 2002 and 2016, while the second part depicts the projected claim payments between 2017 and 2031, with a 95% confidence interval represented by shaded areas. The trend suggests that claim payments will keep on growing almost exponentially, which is expected to grow by 68% in the year 2031 from the year 2021, in which the claims payout in 2031 is expected to be 919.07 billion. This is primarily due to epidemiologic and demographic transitions as well as advancements in biomedical technology as noted by Klazoglou and Dritsakis (2018).
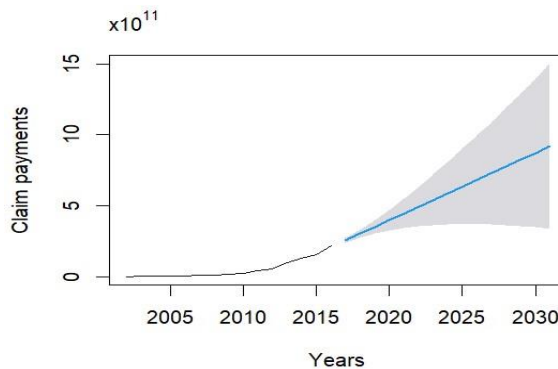
Figure 9: A plot of future claim payments.

Conclusion

Health insurance companies face several financial challenges as a result of the rapid increase in healthcare costs. The increase in these healthcare costs is due to numerous factors that are out of the control of these companies. This necessitates the analysis of the claim payments in order to understand their future distributions. This study has used ARIMA to examine the distribution and future trends of claim payments from the NHIF. The results showed that the claims payments will grow by 68% from 2022 to 2031. This is the fast growth that needs to be well controlled by devising appropriate strategies that will generate enough funds to cope with this rapid growth of claim payments. These findings are expected to assist government and NHIF in devising

appropriate strategies to achieve financial sustainability.

Acknowledgements

Declaration

The authors state that they have no conflicts of interest related to this research work.

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