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# Modeling and forecasting CPI in Myanmar: An application of ARIMA models

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# MODELING AND FORECASTING CPI IN MYANMAR: APPLICATION OF ARIMA MODELS

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## ABSTRACT

*This research uses annual time series data on CPI in Myanmar from 1960 to 2017, to model and forecast CPI using the Box − Jenkins ARIMA technique. Diagnostic tests indicate that the M series is I (2). The study presents the ARIMA (2, 2, 1) model for predicting CPI in Myanmar. The diagnostic tests further imply that the presented optimal model is stable and acceptable in modeling CPI in Myanmar. The results of the study apparently show that CPI in Myanmar is likely to continue on an upwards trajectory in the next decade. The study encourages policy makers to make use of tight monetary and fiscal policy measures in order to deal with inflation in Myanmar.*

**Key Words:** Forecasting, Inflation, Myanmar

**JEL Codes:** C53, E31, E37, E47

## INTRODUCTION

Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013). As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). Consumer Price Index (CPI) may be regarded as a summary statistic for frequency distribution of relative prices (Kharimah *et al*, 2015). CPI number measures changes in the general level of prices of a group of commodities. It thus measures changes in the purchasing power of money (Monga, 1977; Subhani & Panjwani, 2009). As it is a prominent reflector of inflationary trends in the economy, it is often treated as a litmus test of the effectiveness of economic policies of the government of the day (Sarangi *et al*, 2018). The CPI program focuses on consumer expenditures on goods and services out of disposable income (Boskin *et al*, 1998). Hence, it excludes non-market activity, broader quality of life issues, and the costs and benefits of most government programs (Kharimah *et al*, 2015). To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). Precisely forecasting the change of CPI is significant to many aspects of economics, some examples include fiscal policy, financial markets and productivity. Also, building a stable and

accurate model to forecast the CPI will have great significance for the public, policy makers and research scholars (Du *et al*, 2014). In this study we use CPI as an indicator of inflation in Myanmar and apparently seek to model and forecast CPI in Myanmar.

## LITERATURE REVIEW

Alvarez-Diaz & Gupta (2015) forecasted US CPI using RW, AR, SARIMA, ANN and GP models with a data set ranging over the period January 1980 to December 2013 and revealed that SARIMA models were the best models to forecast US inflation. Nyoni (2018k) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018n) modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

## MATERIALS & METHODS

### Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting Consumer Price Index (CPI) in Myanmar, ARIMA models were specified and estimated. If the sequence $\Delta^d M_t$ satisfies an ARMA (p, q) process; then the sequence of $M_t$ also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d M_t = \sum_{i=1}^{p} \beta_i \Delta^d M_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [1]$$

which we can also re – write as:

$$\Delta^d M_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i M_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [2]$$

where $\Delta$ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

### The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the

estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

**Data Collection**

This study is based on a data set of annual CPI (denoted as M) in Myanmar ranging over the period 1960 – 2017. All the data was gathered from the World Bank.

**Diagnostic Tests & Model Evaluation**

**Stationarity Tests**

**The ADF Test**

Table 1: Levels-intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 4.899931 | 1.0000 | -3.577723 | @1% | Non-stationary |
| | | | -2.925169 | @5% | Non-stationary |
| | | | -2.600658 | @10% | Non-stationary |

Table 2: Levels-trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 4.391520 | 1.0000 | -4.165756 | @1% | Non-stationary |
| | | | -3.508508 | @5% | Non-stationary |
| | | | -3.184230 | @10% | Non-stationary |

Table 3: without intercept and trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 5.210367 | 1.0000 | -2.615093 | @1% | Non-stationary |
| | | | -1.947975 | @5% | Non-stationary |
| | | | -1.612408 | @10% | Non-stationary |

Table 4: 1$^{st}$ Difference-intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 1.917385 | 0.9998 | -3.581152 | @1% | Non-stationary |
| | | | -2.926622 | @5% | Non-stationary |
| | | | -2.601424 | @10% | Non-stationary |

Table 5: 1$^{st}$ Difference-trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 0.417648 | 0.9987 | -4.170583 | @1% | Non-stationary |
| | | | -3.510740 | @5% | Non-stationary |
| | | | -3.185512 | @10% | Non-stationary |

Table 6: 1$^{st}$ Difference-without intercept and trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | 2.328326 | 0.9945 | -2.616203 | @1% | Non-stationary |
| | | | -1.948140 | @5% | Non-stationary |
| | | | -1.612320 | @10% | Non-stationary |

Table 7: 2$^{nd}$ Difference-intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | -2.107797 | 0.2427 | -3.584743 | @1% | Non-stationary |
| | | | -2.928142 | @5% | Non-stationary |
| | | | -2.602225 | @10% | Non-stationary |

Table 8: 2$^{nd}$ Difference-trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | -4.632539 | 0.0028 | -4.170583 | @1% | Stationary |
| | | | -3.510740 | @5% | Stationary |
| | | | -3.185512 | @10% | Stationary |

Table 9: 2$^{nd}$ Difference-without intercept and trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| M | -1.792614 | 0.0697 | -2.617364 | @1% | Non-stationary |
| | | | -1.948313 | @5% | Non-stationary |
| | | | -1.612229 | @10% | Stationary |

Tables 1 – 7 indicate that the M series is non-stationary while tables 8 and 9 show that M is stationary. Therefore, M is an I (2) variable.

**Evaluation of ARIMA models (without a constant)**

Table 10

| Model | AIC | U | ME | MAE | RMSE | MAPE |
|---|---|---|---|---|---|---|
| ARIMA (1, 2, 1) | 295.7666 | 0.65856 | 0.47943 | 1.5261 | 3.1993 | 7.9146 |
| ARIMA (2, 2, 0) | 297.8175 | 0.60781 | 0.21481 | 1.5137 | 3.2661 | 7.5619 |
| ARIMA (1, 2, 0) | 304.9642 | 0.62184 | 0.13045 | 1.5995 | 3.5542 | 7.5788 |
| ARIMA (0, 2, 1) | 299.6951 | 0.69496 | 0.41395 | 1.6069 | 3.3725 | 8.3515 |
| ARIMA (2, 2, 1) | **292.1876** | 0.63913 | 0.42824 | 1.5315 | 3.0374 | 7.9501 |
| ARIMA (3, 2, 1) | 294.0458 | 0.63883 | 0.41185 | 1.5316 | 3.0332 | 8.0011 |

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). The study will only consider the AIC as the criteria for choosing the most parsimonious model. Therefore, the ARIMA (2, 2, 1) model is carefully selected.

**Residual & Stability Tests**

**ADF Tests of the Residuals of the ARIMA (2, 2, 1) Model**

Table 11: Levels-intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| $R_t$ | -7.412381 | 0.0000 | -3.560019 | @1% | Stationary |
| | | | -2.917650 | @5% | Stationary |
| | | | -2.596698 | @10% | Stationary |

Table 12: Levels-trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| $R_t$ | -4.115595 | 0.0118 | -4.180911 | @1% | Stationary |
| | | | -3.515523 | @5% | Stationary |
| | | | -3.188259 | @10% | Stationary |

Table 13: without intercept and trend & intercept

| Variable | ADF Statistic | Probability | Critical Values | | Conclusion |
|---|---|---|---|---|---|
| $R_t$ | -7.308552 | 0.0000 | -2.609324 | @1% | Stationary |
| | | | -1.947119 | @5% | Stationary |
| | | | -1.612867 | @10% | Stationary |

Tables 11 – 13 demonstrate that the residuals of the ARIMA (2, 2, 1) model are stationary.

**Stability Test of the ARIMA (2, 2, 1) Model**

Figure 1
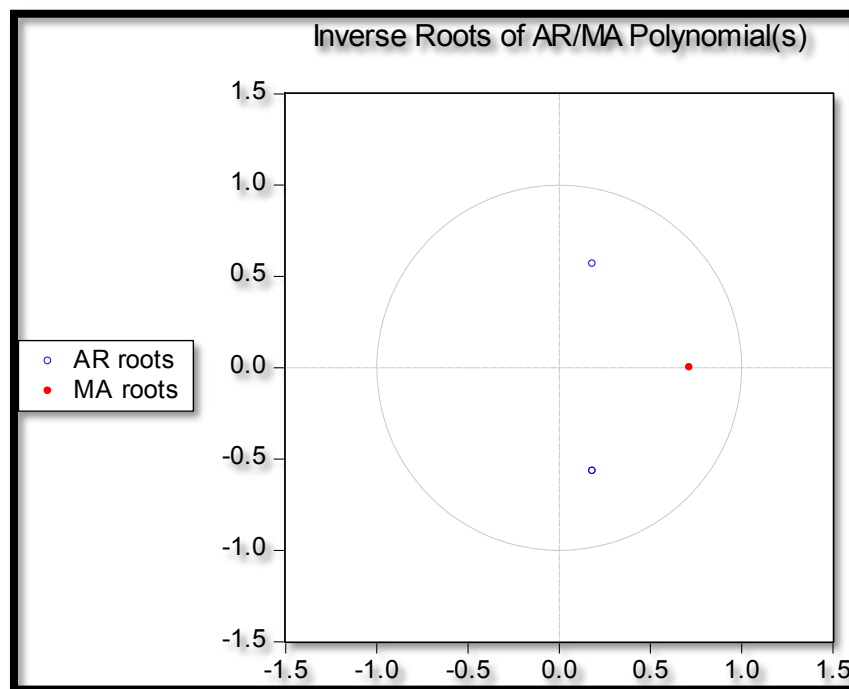


Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (2, 2, 1) model is indeed stable and suitable for predicting CPI in Myanmar over the period under study.

**FINDINGS**

**Descriptive Statistics**

Table 14

| Description | Statistic |
|---|---|
| Mean | 26.32 |
| Median | 1.275 |
| Minimum | 0.15 |
| Maximum | 144.61 |
| Standard deviation | 43.466 |
| Skewness | 1.5195 |
| Excess kurtosis | 0.79383 |

As shown above, the mean is positive, i.e. 26.32. The minimum is 0.15 while the maximum is 144.61. The skewness is 1.5195 and the most striking characteristic is that it is positive, indicating that the M series is positively skewed and non-symmetric. Excess kurtosis is 0.79383; showing that the M series is not normally distributed.

**Results Presentation[1]**

Table 15

**ARIMA (2, 2, 1) Model:**

$$\Delta^2 M_{t-1} = 0.363656\Delta^2 M_{t-1} - 0.342675\Delta^2 M_{t-2} - 0.705199\mu_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

| | | | |
|---|---|---|---|
| P: | (0.0343) | (0.0143) | (0.0000) |
| S. E: | (0.171812) | (0.139945) | (0.15234) |

| Variable | Coefficient | Standard Error | z | p-value |
|---|---|---|---|---|
| AR (1) | 0.363656 | 0.171812 | 2.117 | 0.0343** |
| AR (2) | -0.342675 | 0.139945 | -2.449 | 0.0143** |
| MA (1) | -0.705199 | 0.15234 | -4.629 | 0.0000*** |

*Forecast Graph*

Figure 2

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[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*
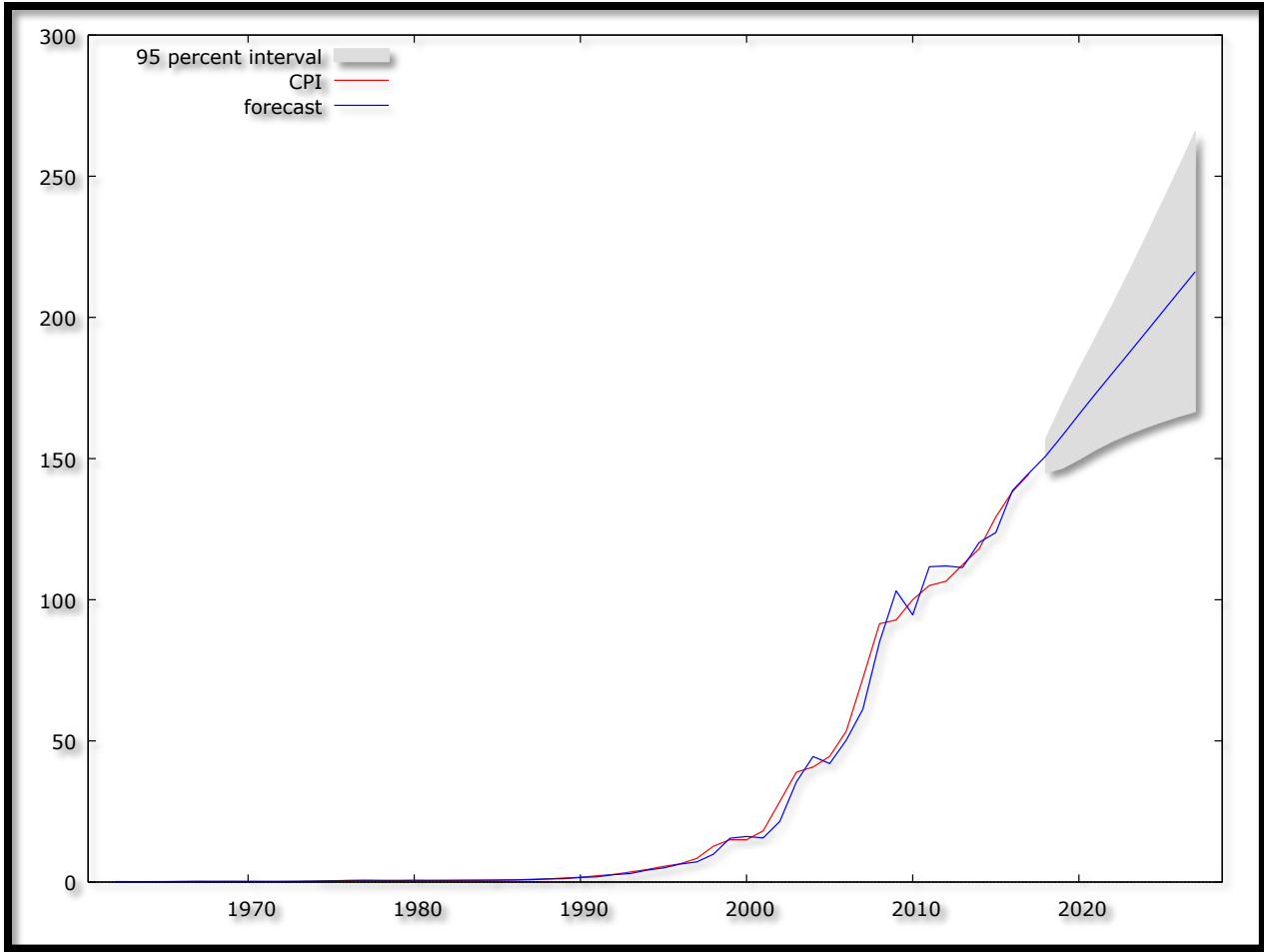
*Predicted Annual CPI in Myanmar*

Table 16

| Year | Prediction | Std. Error | 95% Confidence Interval | |
|------|-----------|-----------|----------|--------|
| 2018 | 150.90 | 3.037 | 144.94 - | 156.85 |
| 2019 | 158.09 | 5.882 | 146.56 - | 169.61 |
| 2020 | 165.61 | 8.135 | 149.67 - | 181.56 |
| 2021 | 172.96 | 10.133 | 153.10 - | 192.82 |
| 2022 | 180.12 | 12.254 | 156.10 - | 204.14 |
| 2023 | 187.28 | 14.607 | 158.65 - | 215.91 |
| 2024 | 194.50 | 17.125 | 160.93 - | 228.06 |
| 2025 | 201.74 | 19.747 | 163.04 - | 240.44 |

| 2026 | 208.97 | 22.466 | 164.94 - 253.00 |
| 2027 | 216.19 | 25.294 | 166.61 - 265.76 |

Figure 2 (with a forecast range from 2018 – 2027) and table 16, clearly show that CPI in Myanmar is indeed set to continue rising sharply, in the next decade.

## POLICY IMPLICATION & CONCLUSION

After performing the Box-Jenkins approach, the ARIMA was engaged to investigate annual CPI of Myanmar from 1960 to 2017. The study mostly planned to forecast the annual CPI in Myanmar for the upcoming period from 2018 to 2027 and the best fitting model was selected based on how well the model captures the stochastic variation in the data. The ARIMA (2, 2, 1) model, as indicated by the AIC statistic; is not only stable but also the most suitable model to forecast the CPI of Myanmar for the next ten years. In general, CPI in Myanmar; showed an upwards trend over the forecasted period. Based on the results, policy makers in Myanmar should engage more proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. Hence, policy creators in Myanmar are encouraged to rely more on tight monetary policy, which should be accompanied by a tight fiscal policy.

## REFERENCES

[1] Alvarez-Diaz, M & Gupta, R (2015). Forecasting the US CPI: Does Nonlinearity Matter? *Department of Economics Working Paper Series*, University of Pretoria.

[2]  Boskin, M. J., Ellen, R. D., Gordon, R. J., Grilliches, Z & Jorgenson, D. W (1998). Consumer Price Index and the Cost of Living, *The Journal of Economic Perspectives*, 12 (1): 3 – 26.

[3] Box, G. E. P & Jenkins, G. M (1976). Time Series Analysis: Forecasting and Control, *Holden Day*, San Francisco.

[4] Brocwell, P. J & Davis, R. A (2002). Introduction to Time Series and Forecasting, *Springer*, New York.

[5] Chatfield, C (2004). The Analysis of Time Series: An Introduction, 6th Edition, *Chapman & Hall*, New York.

[6] Cryer, J. D & Chan, K. S (2008). Time Series Analysis with Application in R, *Springer*, New York.

[7] Du, Y., Cai, Y., Chen, M., Xu, W., Yuan, H & Li, T (2014). A novel divide-and-conquer model for CPI prediction using ARIMA, Gray Model and BPNN, *Procedia Computer Science*, 31 (2014): 842 – 851.

[8] Enke, D & Mehdiyev, N (2014). A Hybrid Neuro-Fuzzy Model to Forecast Inflation, *Procedia Computer Science*, 36 (2014): 254 – 260.

[9] Hurtado, C., Luis, J., Fregoso, C & Hector, J (2013). Forecasting Mexican Inflation Using Neural Networks, *International Conference on Electronics, Communications and Computing*, 2013: 32 – 35.

[10] Kharimah, F., Usman, M., Elfaki, W & Elfaki, F. A. M (2015). Time Series Modelling and Forecasting of the Consumer Price Bandar Lampung, *Sci. Int (Lahore).*, 27 (5): 4119 – 4624.

[11] Manga, G. S (1977). Mathematics and Statistics for Economics, *Vikas Publishing House*, New Delhi.

[12] Mcnelis, P. D & Mcadam, P (2004). Forecasting Inflation with Think Models and Neural Networks, *Working Paper Series*, European Central Bank.

[13] Nyoni, T & Nathaniel, S. P (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 91351.

[14] Nyoni, T (2018k). Modeling and Forecasting Inflation in Zimbabwe: a Generalized Autoregressive Conditionally Heteroskedastic (GARCH) approach, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88132.

[15] Nyoni, T (2018l). Modeling Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.

[16] Nyoni, T (2018n). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6): 16 – 40.

[17] Nyoni, T. (2018i). Box – Jenkins ARIMA Approach to Predicting net FDI inflows in Zimbabwe, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 87737.

[18] Sarangi, P. K., Sinha, D., Sinha, S & Sharma, M (2018). Forecasting Consumer Price Index using Neural Networks models, *Innovative Practices in Operations Management and Information Technology* – Apeejay School of Management, pp: 84 – 93.

[19] Subhani, M. I & Panjwani, K (2009). Relationship between Consumer Price Index (CPI) and Government Bonds, *South Asian Journal of Management Sciences*, 3 (1): 11 – 17.

[20] Wei, W. S (2006). Time Series Analysis: Univariate and Multivariate Methods, 2$^{nd}$ Edition, *Pearson Education Inc*, Canada.