Modeling and forecasting CPI in Mauritius

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ABSTRACT

This paper uses annual time series data on CPI in Mauritius from 1963 to 2017, to model and forecast CPI using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the Z series is I (2). The study presents the ARIMA (0, 2, 3) model for predicting CPI in Mauritius. The diagnostic tests further imply that the presented optimal model is actually stable and acceptable for predicting CPI in Mauritius. The results of the study apparently show that CPI in Mauritius is likely to continue on a very sharp upwards trajectory in the next decade. The study basically encourages policy makers to make use of tight monetary and fiscal policy measures in order to control inflation in Mauritius.

Key Words: Forecasting, Inflation, Mauritius

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 Mauritius. This paper seeks to model and forecast CPI in Mauritius using ARIMA models.

LITERATURE REVIEW

Alvarez-Diaz & Gupta (2015) investigated 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 Mauritius, ARIMA models were specified and estimated. If the sequence $\Delta^d Z_t$ satisfies an ARMA (p, q) process; then the sequence of Z_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

where Δ 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 Z) in Mauritius; ranging over the period 1963 – 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
Z	2.630333	1.0000	-3.560019	@1%	Non-stationary
			-2.917650	@5%	Non-stationary
			-2.596689	@10%	Non-stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-1.367648	0.8593	-4.137279	@1%	Non-stationary
			-3.495295	@5%	Non-stationary
			-3.176618	@10%	Non-stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	3.346626	0.9997	-2.609324	@1%	Non-stationary
			-1.947119	@5%	Non-stationary
			-1.612867	@10%	Non-stationary

Table 4: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-3.470802	0.0127	-3.560019	@1%	Non-stationary
			-2.917650	@5%	Stationary
			-2.596689	@10%	Stationary

Table 5: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-5.254367	0.0004	-4.140858	@1%	Stationary
			-3.496960	@5%	Stationary
			-3.177579	@10%	Stationary

Table 6: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-0.736018	0.3928	-2.611094	@1%	Non-stationary
			-1.947381	@5%	Non-stationary
			-1.612725	@10%	Non-stationary

Table 7: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-9.070332	0.0000	-3.565430	@1%	Stationary
			-2.919952	@5%	Stationary
			-2.597905	@10%	Stationary

Table 8: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-9.008322	0.0000	-4.148465	@1%	Stationary
			-3.500495	@5%	Stationary
			-3.179617	@10%	Stationary

Table 9: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
Z	-9.131400	0.0000	-2.611094	@1%	Stationary
			-1.947381	@5%	Stationary
			-1.612725	@10%	Stationary

Tables 1 – 6 reveal that Z is neither I (0) nor I (1). Tables 7 – 9 show that Z is an I (2) variable.

Evaluation of ARIMA models (without a constant)

Table 10

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 2, 2)	198.757	0.74187	0.24956	1.0806	1.482	4.0564
ARI MA (2, 2, 0)	197.361	0.75049	0.10008	1.0243	1.4639	4.1867
ARIMA (1, 2, 0)	208.2451	0.7844	0.080253	1.1751	1.6608	4.4177
ARIMA (0, 2, 1)	198.609	0.74457	0.18248	1.1058	1.5085	4.1465
ARIMA (2, 2, 1)	197.3609	0.71547	0.15153	1.0142	1.4343	3.9549
ARIMA (0, 2, 3)	**196.3941**	0.74237	0.18873	0.98813	1.4196	4.0263
ARIMA (0, 2, 2)	196.4769	0.74226	0.26605	1.0443	1.4496	4.0328

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 best model. Therefore, the ARIMA (0, 2, 3) model is carefully selected.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 2, 3) Model

Table 11: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion

R_t	-7.262581	0.0000	-3.562669	@1%	Stationary
			-2.918778	@5%	Stationary
			-2.597285	@10%	Stationary

Table 12: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.238407	0.0000	-4.144584	@1%	Stationary
			-3.498692	@5%	Stationary
			-3.178578	@10%	Stationary

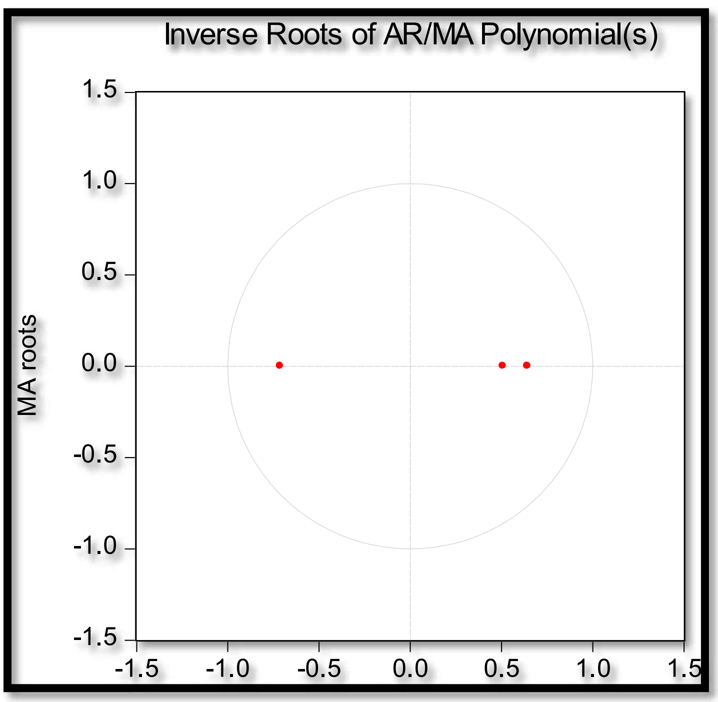
Table 13: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.181313	0.0000	-2.610192	@1%	Stationary
			-1.947248	@5%	Stationary
			-1.612797	@10%	Stationary

Tables 11, 12 and 13 demonstrate that the residuals of the ARIMA (0, 2, 3) model are stationary.

Stability Test of the ARIMA (0, 2, 3) Model

Figure 1



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (0, 2, 3) model is indeed stable and suitable for predicting CPI in Mauritius over the period under study.

FINDINGS

Descriptive Statistics

Table 14

Description	Statistic
Mean	42.855
Median	30
Minimum	3
Maximum	125
Standard deviation	39.518
Skewness	0.75173
Excess kurtosis	-0.76409

As shown above, the mean is positive, i.e. 42.855. The minimum is 3 while the maximum is 125. The skewness is 0.75173 and the most striking characteristic is that it is positive, indicating that the Z series is positively skewed and non-symmetric. Excess kurtosis is -0.76409; showing that the Z series is not normally distributed.

Results Presentation[1]

Table 15

ARIMA (0, 2, 3) Model:

$$\Delta^2 Z_{t-1} = -439059\mu_{t-1} - 0456598\mu_{t-2} + 0.216189\mu_{t-3} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots [3]$$

P: (0.0013) (0.0015) (0.1374)

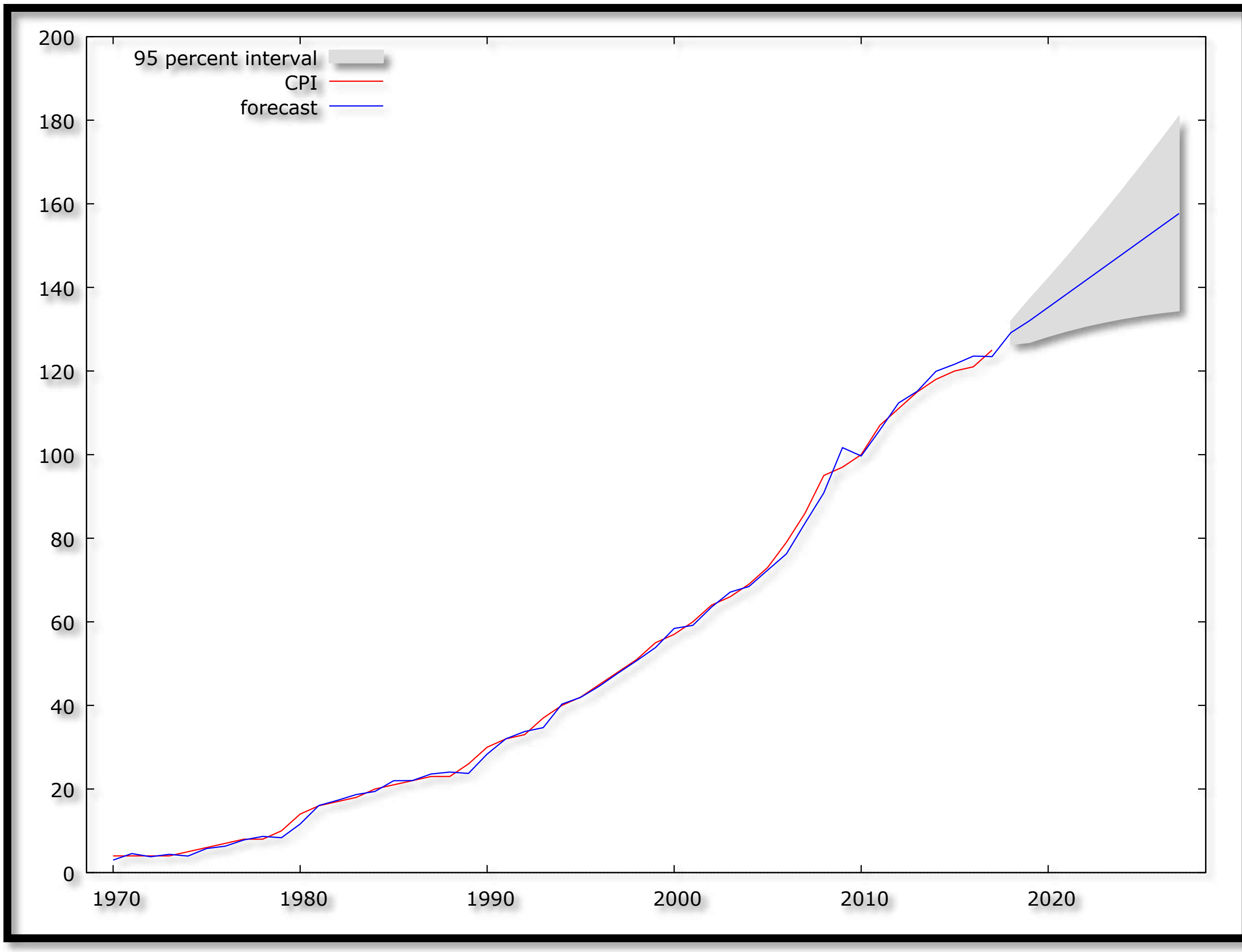
S. E: (0.136358) (0.143797) (0.145538)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.439059	0.136358	-3.22	0.0013***
MA (2)	-0.456598	0.143797	-3.175	0.0015***
MA (3)	0.216189	0.145538	1.485	0.1374

Forecast Graph

Figure 2

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*



Predicted Annual CPI in Mauritius

Table 16

Year	Prediction	Std. Error	95% Confidence Interval
2018	129.14	1.419	126.35 - 131.92
2019	132.01	2.631	126.85 - 137.17
2020	135.22	3.537	128.29 - 142.15
2021	138.43	4.523	129.57 - 147.30
2022	141.64	5.583	130.70 - 152.58
2023	144.85	6.714	131.69 - 158.01
2024	148.06	7.911	132.56 - 163.57
2025	151.27	9.171	133.30 - 169.25

2026	154.48	10.490	133.92 - 175.04
2027	157.69	11.867	134.43 - 180.95

Figure 2 (with a forecast range from 2018 – 2027) and table 16, clearly show that CPI in Mauritius 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 Mauritius from 1960 to 2017. The study mostly planned to forecast the annual CPI in Mauritius 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 (0, 2, 3) is not only stable but also the most suitable model to forecast the CPI of Mauritius for the next decade. In general, CPI in Mauritius; showed an upwards trend over the forecasted period. Based on the results, policy makers in Mauritius should engage more proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. Thus, monetary and fiscal authorities in Mauritius are encouraged to engage on a contractionary monetary policy regime, which should be complimented by a tight fiscal policy stance.

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