Modeling and forecasting inflation in Lesotho using Box-Jenkins ARIMA models

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25 February 2019

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ABSTRACT

This research uses annual time series data on inflation rates in Lesotho from 1974 to 2017, to model and forecast inflation using ARIMA models. Diagnostic tests indicate that L is I(1). The study presents the ARIMA (0, 1, 2). The diagnostic tests further imply that the presented optimal ARIMA (0, 1, 2) model is stable and acceptable for predicting inflation in Lesotho. The results of the study apparently show that L will be approximately 5.2% over the out-of-sample forecast period. The CBL is expected to tighten Lesotho's monetary policy in order to maintain price stability.

Key Words: Forecasting, Inflation

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is an important indicator of the health of an economy (Central Bank of Lesotho, 2012). Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). 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). That is why countries implement monetary policy to maintain price stability and keep inflation at low levels (Central Bank of Lesotho, 2012). 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). In Lesotho, price stability is maintained through the fixed exchange rate regime through which Lesotho's currency, the loti is pegged at par to the South African currency, the rand. The exchange rate peg results in lower inflation by constraining the scope for excessive monetary expansion (Central Bank of Lesotho, 2012). It is almost unnecessary to reiterate the importance of inflation forecasting to the Central Bank of Lesotho (CBL), especially with regards to maintaining price stability. Indeed, the CBL must be fully aware of the inflation path in order to engineer a successful monetary policy framework. Hence, the need for this study.

To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012). 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). In this study, we seek to model and forecast inflation in Lesotho using ARIMA models.

LITERATURE REVIEW

Nyoni (2018) 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 (2018) 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 inflation rate in Lesotho, ARIMA models were specified and estimated. If the sequence $\Delta^d L_t$ satisfies an ARMA (p, q) process; then the sequence of L_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d L_t = \sum_{i=1}^{p} \beta_i \Delta^d L_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

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, 2018).

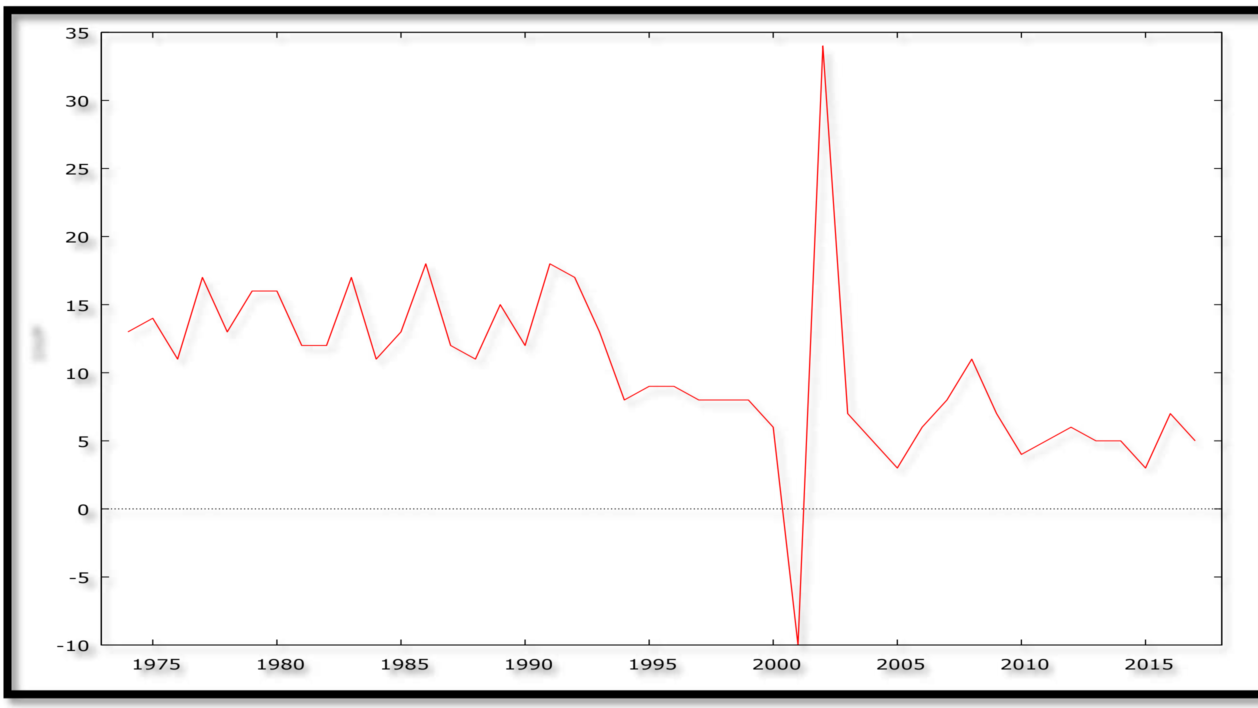
Data Collection

This study is based on a data set of annual rates of inflation in Lesotho (INF or simply L) ranging over the period 1974 – 2017. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for INF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF	PACF	Q-stat. [p-value]
1	0.0531	0.0531	0.1325 [0.716]
2	0.2087	0.2064	2.2309 [0.328]
3	0.2227	0.2126	4.6790 [0.197]
4	0.2403	0.2065	7.6019 [0.107]

5	0.2277	0.1701	10.2933 [0.067]
6	0.2820 *	0.2080	14.5292 [0.024]
7	0.1226	0.0129	15.3517 [0.032]
8	0.0326	-0.1695	15.4114 [0.052]
9	0.1147	-0.1067	16.1727 [0.063]
10	0.1471	-0.0027	17.4608 [0.065]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-6.032287	0.0000	-3.592462	@1%	Stationary
			-2.931404	@5%	Stationary
			-2.603944	@10%	Stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-8.618390	0.0000	-4.186481	@1%	Stationary
			-3.518090	@5%	Stationary
			-3.189732	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-1.395	0.1489	-2.627238	@1%	Non-stationary
			-1.949856	@5%	Non-stationary
			-1.611469	@10%	Non-stationary

Figure 1 and tables 1 – 4 reveal that L is non-stationary.

The Correlogram (at 1st Differences)

Autocorrelation function for d_INF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG	ACF	PACF	Q-stat. [p-value]
1	-0.5867 ***	-0.5867 ***	15.8561 [0.000]
2	0.0714	-0.4159 ***	16.0968 [0.000]
3	-0.0046	-0.3489 **	16.0978 [0.001]
4	0.0191	-0.2933 *	16.1159 [0.003]
5	-0.0373	-0.3392 **	16.1867 [0.006]

6	0.1118	-0.1736	16.8406 [0.010]
7	-0.0357	0.0277	16.9092 [0.018]
8	-0.0876	0.0128	17.3334 [0.027]
9	0.0281	-0.0537	17.3785 [0.043]
10	0.0039	-0.1553	17.3794 [0.066]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-5.889230	0.0000	-3.615588	@1%	Stationary
			-2.941145	@5%	Stationary
			-2.609066	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-5.803128	0.0001	-4.219126	@1%	Stationary
			-3.533083	@5%	Stationary
			-3.198312	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
L	-7.057411	0.0000	-2.624057	@1%	Stationary
			-1.949319	@5%	Stationary
			-1.611711	@10%	Stationary

Tables 5 – 8 show that L is an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	280.5772	0.89455	-1.1455	3.8066	5.8016	45.093
ARIMA (1, 1, 0)	295.2952	0.97835	-0.26611	3.9329	7.1253	41.325
ARIMA (0, 1, 1)	281.4450	0.88424	-1.1595	3.8189	6.0146	43.72
ARIMA (2, 1, 1)	281.5187	0.90655	-1.135	3.7166	5.7241	43.98
ARIMA (1, 1, 2)	280.213	0.84974	-1.0215	3.6664	5.6283	41.203
ARIMA (2, 1, 2)	282.1614	0.85423	-1.0195	3.6514	5.6254	40.86
ARIMA (2, 1, 0)	289.6051	0.97802	-0.3967	3.6749	6.491	43.979
ARIMA (0, 1, 2)	**278.987**	0.88833	-1.0938	3.8087	5.6795	44.729
ARIMA (3, 1, 0)	286.5683	0.9994	-0.53972	3.784	6.1014	42.387
ARIMA (3, 1, 1)	282.6314	0.89887	-1.1213	3.7545	5.6602	42.271
ARIMA (0, 1, 3)	280.2068	0.857	-1.025	3.6613	5.6281	41.187

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

95% Confidence Ellipse & 95% 95% Marginal Intervals

Figure 2 [MA (1) & MA (2) components]

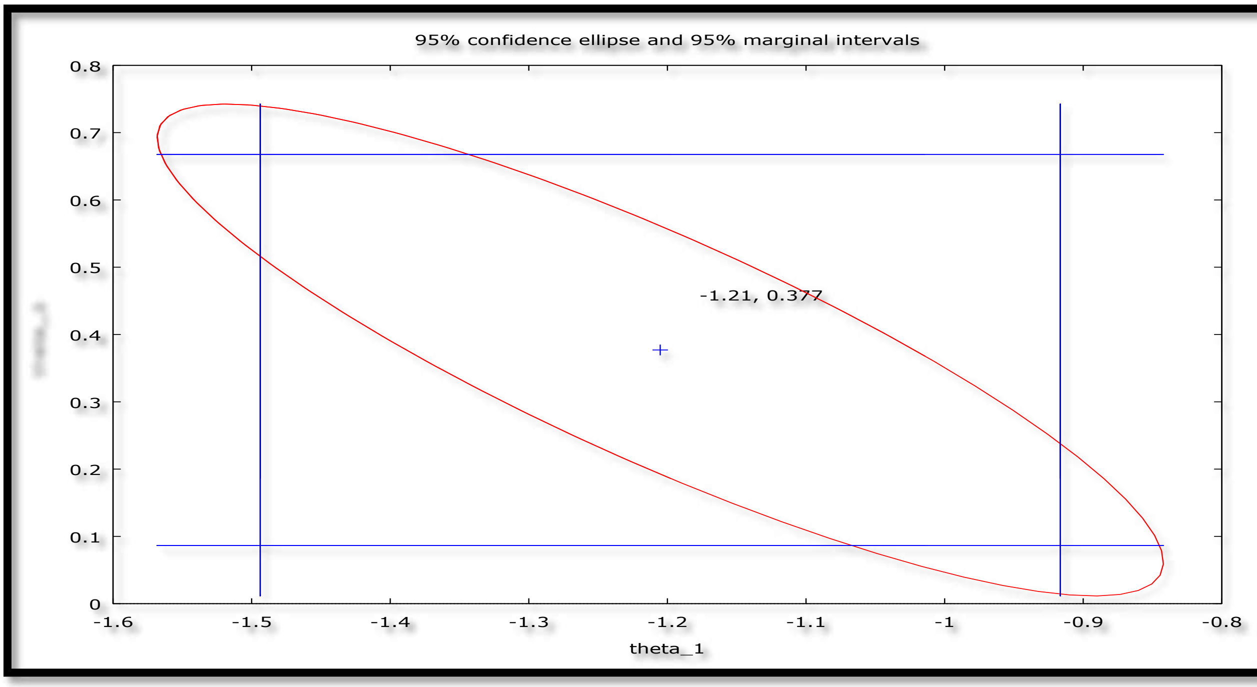


Figure 2 above apparently indicates that the accuracy of our forecast is satisfactory since it falls within the 95% confidence interval.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 1, 2) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.216731	0.0000	-3.596616	@1%	Stationary
			-2.933158	@5%	Stationary
			-2.604867	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.207556	0.0000	-4.192337	@1%	Stationary
			-3.520787	@5%	Stationary
			-3.191277	@10%	Stationary

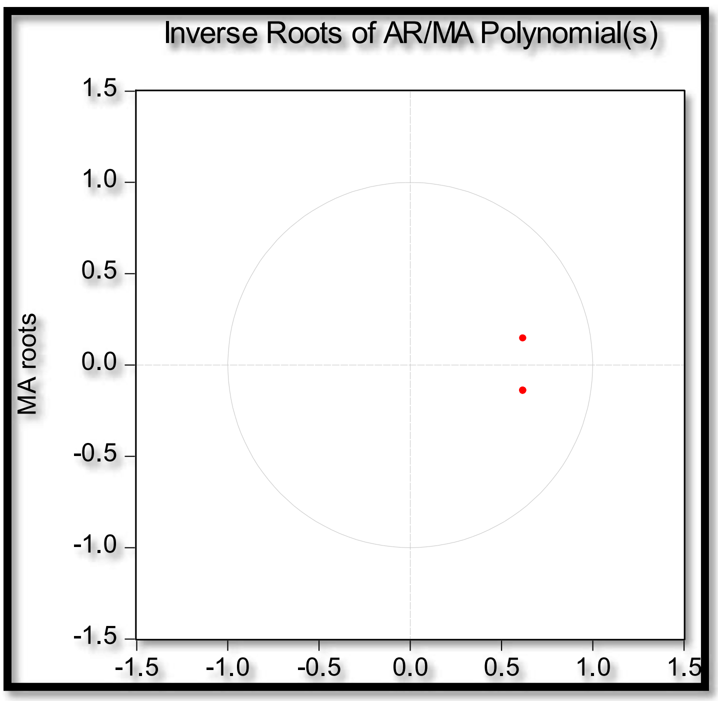
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.004449	0.0000	-2.621185	@1%	Stationary
			-1.948886	@5%	Stationary
			-1.611932	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (0, 1, 2) model are stationary and hence the ARIMA (0, 1, 2) model is suitable for forecasting inflation in Lesotho.

Stability Test of the ARIMA (0, 1, 2) Model

Figure 3



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (0, 1, 2) model is stable and suitable for predicting inflation in Lesotho over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	10.182
Median	10
Minimum	-10
Maximum	34

Standard deviation	6.4241
Skewness	0.51749
Excess kurtosis	4.2205

As shown above, the mean is positive, i.e. 10.182%. The minimum is -10% and the maximum is 34%. The skewness is 0.51749 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 4.2205; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

ARIMA (0, 1, 2) Model:

$$\Delta L_{t-1} = -1.20518\mu_{t-1} + 0.377009\mu_{t-2} \ldots \ldots \ldots \ldots [3]$$

P: (0.0000) (0.0088)

S. E: (0.1429) (0.1439)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	-1.20518	0.142938	-8.432	0.0000***
MA (2)	0.377009	0.143916	2.62	0.0088***

Predicted Annual Inflation in Lesotho

Table 15

Year	Prediction	Std. Error	95% Confidence Interval
2018	5.17	5.668	-5.93 - 16.28
2019	5.20	5.786	-6.14 - 16.54
2020	5.20	5.868	-6.30 - 16.70
2021	5.20	5.948	-6.45 - 16.86
2022	5.20	6.027	-6.61 - 17.02
2023	5.20	6.105	-6.76 - 17.17
2024	5.20	6.183	-6.91 - 17.32
2025	5.20	6.259	-7.06 - 17.47
2026	5.20	6.334	-7.21 - 17.62
2027	5.20	6.409	-7.36 - 17.76

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

Table 15, with a forecast range from 2018 – 2027; clearly show that inflation in Lesotho is projected to be hovering around 5.2% in the next 10 years. Our confidence intervals also generally indicate that inflation in Lesotho could potentially grow to as high as 17%. Major contributors to inflation in Lesotho continue to be food and non-alchoholic beverages, followed by other things such as housing, water, gas etc. This implies that there is need to control inflation in Lesotho.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Lesotho from 1974 to 2017. The study planned to forecast inflation in Lesotho for the upcoming period from 2018 to 2027. The ARIMA (0, 1, 2) model is stable and most suitable model to forecast inflation in Lesotho for the next ten years. Based on the results, policy makers in Lesotho should continue to engage prudent economic policies in order to fight against persistent inflationary pressures in the economy. In this case, the CBL is encouraged to tighten its monetary policy in order to foster macroeconomic stability in Lesotho.

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