Inflation dynamics in Jamaica: Evidence from the ARMA methodology

NYONI, THABANI

University of Zimbabwe

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Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This research uses annual time series data on inflation rates in Jamaica from 1968 to 2017, to model and forecast inflation using ARMA models. Diagnostic tests indicate that JINF is I(0). The study presents the ARMA (1, 0, 0) model, which is the same as an AR (1) process. The diagnostic tests further imply that the presented optimal ARMA (1, 0, 0) model is stable and acceptable for forecasting inflation rates in Jamaica. The results of the study apparently show that JINF will be approximately 11.42% by 2020. Policy makers in Jamaica are expected to the take the necessary action with regards to maintaining a low and stable inflation rate over the next decade and even beyond.

Key Words: Forecasting, Inflation, Jamaica

JEL Codes: C53, E31, E37, E47

INTRODUCTION

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). An increase in the general price level causes a reduction in the purchasing power of money. Inflation reflects a reduction in the purchasing power per unit of money – a loss o real value in the medium of exchange and unit of account within the economy (Walgenbach *et al*, 1973). Inflation exerts a constraining effect on the key drivers of growth. The price increase reduces consumption and therefore production and employment. It exerts an inhibitory effect on investment, due to the rise of the nominal wages and the prices of raw materials, both in local and foreign currency. Inflation also contributes to the deterioration of the trade balance when the prices of domestic goods and services rise more than those of foreign competitors. To this are added its negative effects on social activity because of the deterioration of the purchasing power (Fenira, 2014).

It is now generally accepted that keeping low and stable rates of inflation is the primary objective of central banks (Hector & Valle, 2002). 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). Maintaining price stability while ensuring an adequate expansion of credit to assist economic growth have been the primary goals of monetary policy in Jamaica (Whyte, 2011). This study seeks to model and forecast annual rates of inflation in Jamaica based on ARMA models.

LITERATURE REVIEW

Stovicek (2007) investigated inflation in Slovenia using ARMA models with a data set ranging from January 1994 to June 2006 and revealed that in terms of forecast ability ARMA models outperform AR models, when allowing for the same degrees of freedom. Osarumwense & Waziri (2013) investigated monthly inflation rate volatility using GARCH models with a data set ranging over the period January 1995 to December 2011 and found out that the GARCH (1, 0) + ARMA (1, 0) model is appropriate for forecasting inflation in Nigeria. Popoola *et al* (2017) investigated inflation rate in Nigeria using Box-Jenkins ARIMA models with a data set ranging over the period January 2006 to December 2015 and established that the ARIMA (0, 1, 1) model was the best model for forecasting inflation rate in Nigeria. 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) studied 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; investigated 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. In the case of Jamaica, Whyte (2011); analyzed inflation using the ARDL framework and employed a data set ranging over the period $1997Q_1$ – $2011Q_1$ and found out that monetary indicators are useful to predict inflation, especially if the forecasting equations are based on the growth in money supply (M_3).

MATERIALS & METHODS

ARMA Models

For the purpose of forecasting rates of inflation in Jamaica, ARMA models were specified and estimated. A generalized ARMA (p, q) model can be specified as follows:

$$JINF_t = c + \sum_{i=1}^{p} \emptyset_i JINF_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma^2) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . [1]$$

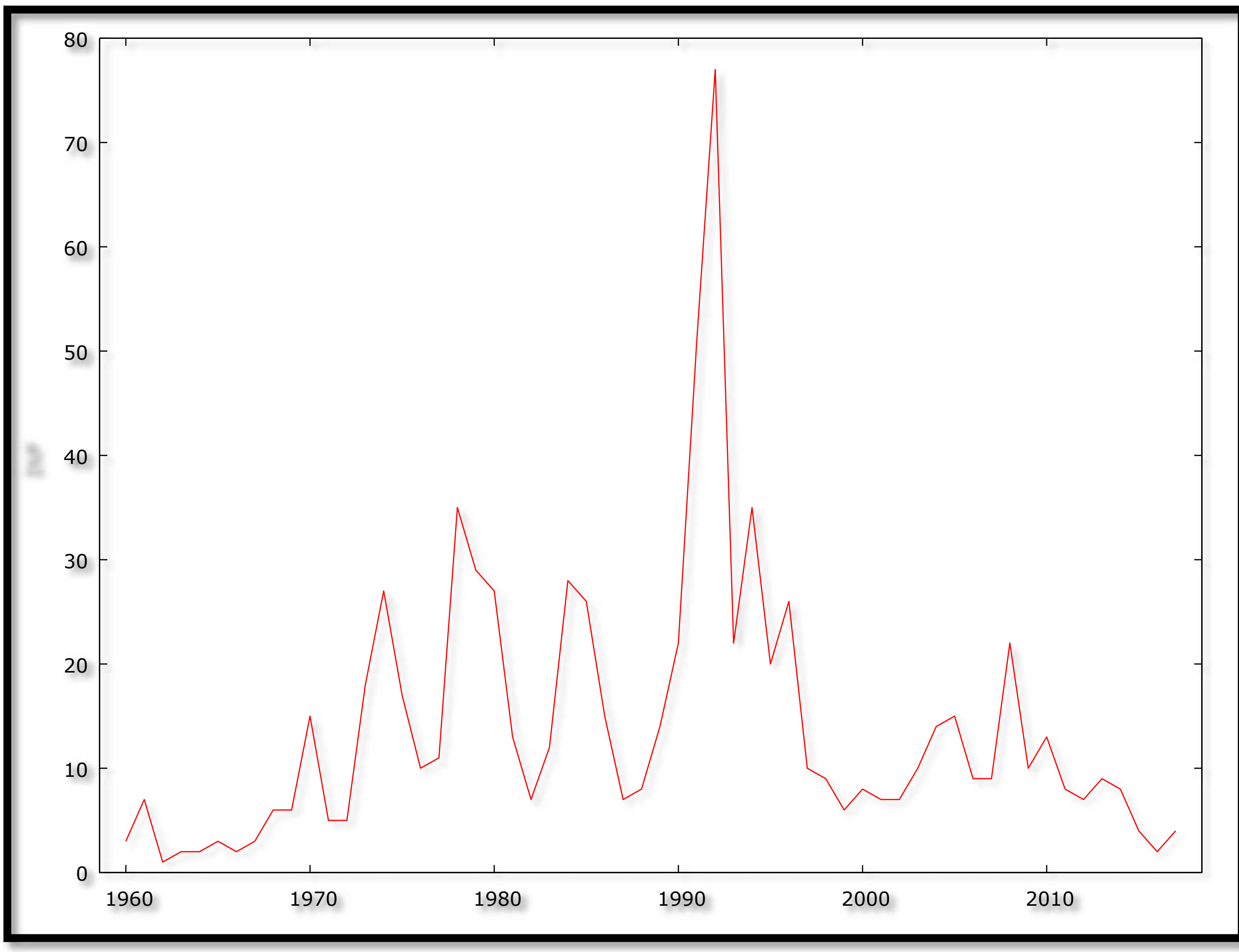
Data Collection

This study is based on a data set of annual rates of inflation in Jamaica (JINF) ranging over the period 1968 – 2017. All the data was gathered from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
JINF	-3.716579	0.0063	-3.550396	@1%	Stationary

			-2.913549	@5%	Stationary
			-2.594521	@10%	Stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
JINF	-3.659060	0.0335	-4.127338	@1%	Non-stationary
			-3.490662	@5%	Stationary
			-3.173943	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
JINF	-2.380248	0.0180	-2.606163	@1%	Non-stationary
			-1.946654	@5%	Stationary
			-1.613122	@10%	Stationary

Figure 1 and tables 1 – 3 show that JINF is an I (0) variable.

Evaluation of ARMA models (with a constant)

Table 4

Model	AIC	ME	MAE	RMSE	MAPE
ARMA (1, 0, 1)	444.6265	0.10795	6.9958	10.427	83.401
ARMA (2, 0, 2)	447.3242	0.077114	6.7648	10.307	83.745
ARMA (1, 0, 0)	**442.6269**	0.10731	6.9964	10.427	83.465
ARMA (0, 0, 1)	450.5226	0.040713	7.7233	11.164	109.27
ARMA (0, 0, 2)	444.0175	0.049559	6.7916	10.369	89.169
ARMA (1, 0, 2)	445.9036	0.057653	6.791	10.36	86.923
ARMA (2, 0, 1)	445.2491	0.11942	6.9049	10.294	82.498
ARMA (0, 0, 3)	445.9656	0.052144	6.7923	10.365	88.312

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will consider the AIC in order to choose the best model for modeling and forecasting inflation rates in Jamaica. Therefore, the ARMA (1, 0, 0) model is carefully selected for modeling and forecasting inflation rates in Jamaica.

Residual & Stability Tests

ADF Tests of the Residuals of the ARMA (1, 0, 0) Model

Table 5: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.355622	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 6: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.291151	0.0000	-4.130526	@1%	Stationary

			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

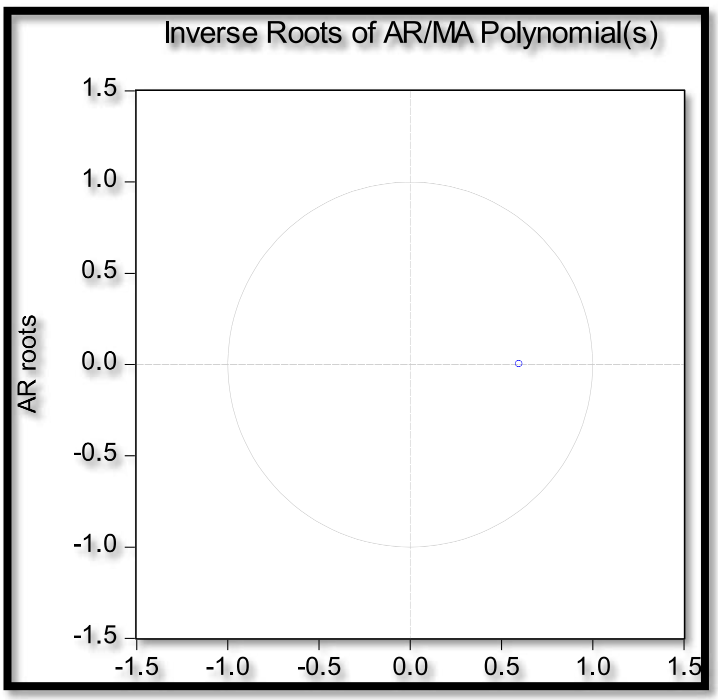
Table 7: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.423474	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Tables 5, 6 and 7 clearly show that the residuals of the ARMA (1, 0, 0) model are stationary.

Stability Test of the ARMA (1, 0, 0) Model

Figure 2



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it clearly illustrates that the chosen ARMA (1, 0, 0) model is indeed stable.

FINDINGS

Descriptive Statistics

Table 8

Description	Statistic
Mean	13.931
Median	9.5
Minimum	1
Maximum	77

Standard deviation	13.113
Skewness	2.4741
Excess kurtosis	8.1856

As shown above, the mean is positive, i.e. 13.931%. The minimum is 1% and the maximum is 77%. The skewness is 2.4741 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis is 8.1856; showing that the inflation series is not normally distributed.

Results Presentation[1]

Table 9

ARMA (1, 0, 0) Model:

$$JINF_t = 13.4238 + 0.597154JINF_{t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots [2]$$

P: (0.0000) (0.0000)
S. E: (3.25068) (0.10552)

Variable	Coefficient	Standard Error	z	p-value
Constant	13.4238	3.25068	4.13	0.0000***
AR (1)	0.597154	0.10552	5.659	0.0000***

Predicted Annual Inflation

Table 10

Year	Prediction	Std. Error	95% Confidence Interval
2018	7.80	10.395	-12.58 - 28.17
2019	10.06	12.107	-13.67 - 33.79
2020	11.42	12.662	-13.40 - 36.23
2021	12.23	12.854	-12.97 - 37.42
2022	12.71	12.921	-12.62 - 38.03
2023	13.00	12.945	-12.38 - 38.37
2024	13.17	12.954	-12.22 - 38.56
2025	13.27	12.957	-12.12 - 38.67
2026	13.33	12.958	-12.06 - 38.73
2027	13.37	12.959	-12.03 - 38.77

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

Table 10, with a forecast range of 10 years clearly shows that inflation rates in Jamaica will likely exceed the single-digit threshold within the next 10 years, ceteris paribus. With a 95% confidence interval of -13.4% to 36.23% and a predicted annual inflation rate of 11.42% by 2020, the chosen ARMA (1, 0, 0) model is giving a warning signal of a likely increase in inflation in Jamaica by 2020 and even beyond. Inflation rates that are beyond a single-digit figure, i.e., beyond 9%; are not generally healthy for the economy. Healthy inflation ought to hover somewhere between 0% - 9% per annum, anything below or beyond that is generally not good for the economy.

CONCLUSION

Accurate forecasting is useful for effective policy planning (Jesmy, 2010). The main objective of this research was to select the optimal ARMA model for modeling and forecasting inflation in Jamaica and the optimal model was selected based model identification statistics shown in table 4 above. As already shown, the optimal model is the ARMA (1, 0, 0) model and this model is envisaged to serve as an early warning signal to policy makers and investors in Jamaica so that they prepare themselves for the anticipated new environment and to take feasible actions in their business activities. The Central Bank of Jamaica must take action towards tightening the monetary policy of Jamaica in order to control inflationary pressures in the Jamaican economy.

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