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ARIMA Modeling and Forecasting of Inflation in Egypt (1960 – 2017)

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ABSTRACT

This research uses annual time series data on inflation rates in Egypt from 1960 to 2017, to model and forecast inflation using ARIMA models. Diagnostic tests indicate that E is $I(1)$. The study presents the ARIMA (0, 1, 1). The diagnostic tests further imply that the presented optimal ARIMA (0, 1, 1) model is stable and acceptable for predicting inflation in Egypt. The results of the study apparently show that E will be approximately 23.3% over the out-of-sample forecast period. The CBE is expected to continue tightening Egypt's monetary policy in order to restore price stability.

Key Words: Egypt , Forecasting, Inflation

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 monetary policy objective of the Central Bank of Egypt (CBE) is achieving low rates of inflation essential for sustaining high investment and growth rates as well as maintaining confidence in the Egyptian economy (Hosny, 2016). Low inflation is a key for macroeconomic stability as evidenced by many country experiences, since high inflation in general hurt macroeconomic stability mainly through lower domestic savings by deeply negative real interest rates, lower capital accumulation due to increased uncertainty, and real appreciation of the exchange rate reflecting widened inflation differentials against trade partners (Moriyama, 2011). 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). 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 Egypt using ARIMA models. The study is envisaged to assist the CBE in restoring macroeconomic stability in Egypt.

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. Once gain, 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 Egypt, ARIMA models were specified and estimated. If the sequence $\Delta^d E_t$ satisfies an ARMA (p, q) process; then the sequence of E_t also satisfies the ARIMA (p, d, q) process such that:

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

which we can also re – write as:

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

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, 2018).

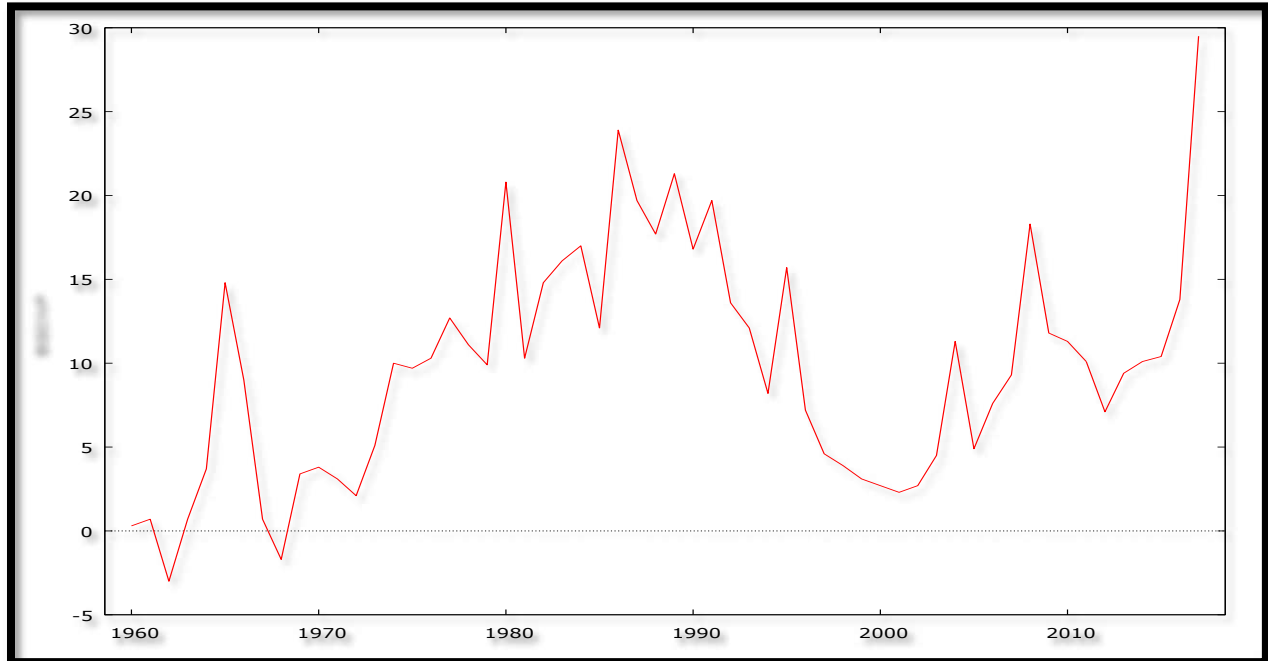
Data Collection

This study is based on a data set of annual rates of inflation in Egypt (EGINF or simply E) ranging over the period 1960 – 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 EGINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF	PACF	Q-stat. [p-value]
1	0.6277 ***	0.6277 ***	24.0568 [0.000]
2	0.5140 ***	0.1979	40.4727 [0.000]
3	0.4140 ***	0.0532	51.3153 [0.000]
4	0.3773 ***	0.0894	60.4890 [0.000]
5	0.2621 **	-0.0824	64.9984 [0.000]
6	0.2714 **	0.1022	69.9277 [0.000]
7	0.1747	-0.0881	72.0102 [0.000]
8	0.1007	-0.0821	72.7167 [0.000]
9	0.1318	0.1293	73.9496 [0.000]

10 -0.0852 -0.3795 *** 74.4762 [0.000]

11 -0.1246 0.0165 75.6259 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-1.910422	0.3253	-3.552666	@ 1%	Non-stationary
			-2.914517	@ 5%	Non-stationary
			-2.595033	@ 10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-2.091735	0.5389	-4.130526	@ 1%	Non-stationary
			-3.492149	@ 5%	Non-stationary
			-3.174802	@ 10%	Non-stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-0.244355	0.5937	-2.606911	@ 1%	Non-stationary
			-1.946764	@ 5%	Non-stationary
			-1.613062	@ 10%	Non-stationary

Figure 1 and tables 1 – 4 show that E is non-stationary in levels.

The Correlogram (at 1st Differences)

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

Table 5

LAG	ACF	PACF	Q-stat. [p-value]
1	-0.2563 *	-0.2563 *	3.9442 [0.047]
2	-0.0077	-0.0785	3.9478 [0.139]
3	-0.0898	-0.1207	4.4501 [0.217]
4	0.1661	0.1187	6.1999 [0.185]
5	-0.1207	-0.0606	7.1419 [0.210]
6	0.1119	0.0825	7.9681 [0.240]
7	-0.1137	-0.0597	8.8378 [0.265]
8	-0.2156	-0.3121 **	12.0274 [0.150]

9 0.3828 *** 0.3410 ** 22.2938 [0.008]
 10 -0.1994 -0.1748 25.1383 [0.005]
 11 0.0999 0.1291 25.8684 [0.007]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-9.161287	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-9.074184	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

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

Variable	ADF Statistic	Probability	Critical Values		Conclusion
E	-9.149124	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Tables 5 – 8 indicate that E is an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	349.0688	0.64775	3.604	4.9003	69.153
ARIMA (1, 1, 0)	348.1304	0.58136	3.6678	4.948	73.893
ARIMA (0, 1, 1)	347.1563	0.63494	3.6045	4.9039	70.442
ARIMA (2, 1, 1)	351.0679	0.64696	3.6032	4.9002	69.09
ARIMA (1, 1, 2)	351.0686	0.64757	3.6038	4.9002	69.137
ARIMA (2, 1, 2)	352.7305	0.65367	3.6047	4.8856	69.81
ARIMA (2, 1, 0)	349.5113	0.61087	3.6302	4.9202	71.413
ARIMA (0, 1, 2)	349.0724	0.64609	3.6031	4.9004	69.179

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 Egypt and therefore, the ARIMA (0, 1, 1) model is eventually selected.

Residual & Stability Tests

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

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.516748	0.0000	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.426933	0.0000	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

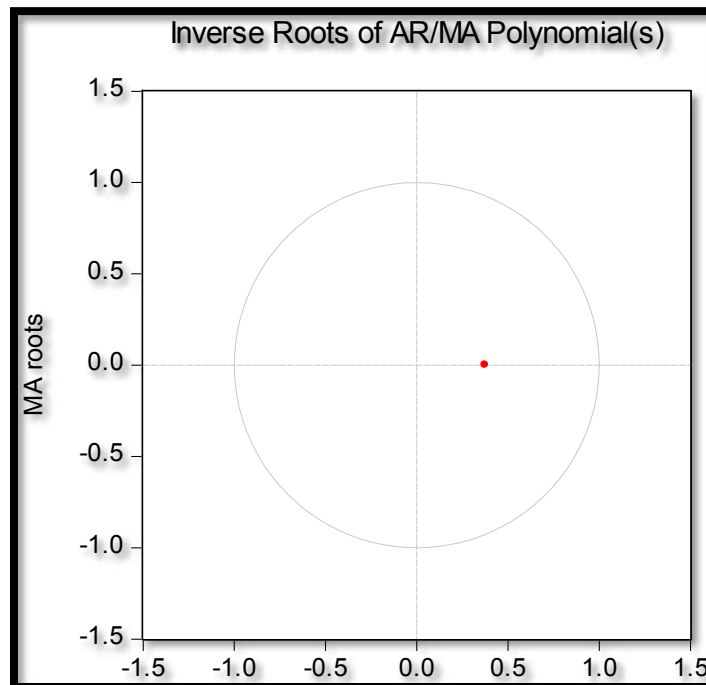
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.465937	0.0000	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

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

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

Figure 2



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

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	9.6914
Median	9.95
Minimum	-3
Maximum	29.5
Standard deviation	6.8439
Skewness	0.46478
Excess kurtosis	-0.063052

As shown above, the mean is positive, i.e. 9.6914%. The minimum is -3% and the maximum is 29.5%. The skewness is 0.46478 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 -0.063052; implying that the inflation series is not normally distributed.

Results Presentation¹

Table 14

ARIMA (0, 1, 1) Model:				
$\Delta E_{t-1} = -0.364872\mu_{t-1} \dots \dots \dots [3]$				
P: (0.0107)				
S. E: (0.1429)				
Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.364872	0.142939	-2.553	0.0107**

Predicted Annual Inflation in Egypt

Table 15

Year	Prediction	Std. Error	95% Confidence Interval
2018	23.3	4.90	13.7 - 32.9
2019	23.3	5.81	11.9 - 34.7
2020	23.3	6.59	10.4 - 36.2

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

2021	23.3	7.29	9.0 -	37.6
2022	23.3	7.93	7.7 -	38.8
2023	23.3	8.52	6.6 -	40.0
2024	23.3	9.07	5.5 -	41.1
2025	23.3	9.59	4.5 -	42.1
2026	23.3	10.08	3.5 -	43.0
2027	23.3	10.55	2.6 -	44.0

After the Egyptian pound's floatation in November 2016, the Central Bank of Egypt (CBE) drastically tightened its monetary policy (BNP PARIBAS, 2018) and this move is also justified by Table 15 above; which clearly shows that inflation in Egypt is projected to be hovering around 23.3% in the next 10 years. This could be attributed to import prices as well as the energy subsidy reform that was recently implemented in Egypt. It is also important to note that monetary factors such as an increase in portfolio investment inflows and the return of foreign currency liquidity into the banking system also played a pivotal role in inflating the economy. This is very bad for the Egyptian economy and the urgent need to control inflation cannot be ruled out.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Egypt from 1960 to 2017. The study planned to forecast inflation in Egypt for the upcoming period from 2018 to 2027 and the best fitting model was carefully selected based on the minimum AIC value. The ARIMA (0, 1, 1) model is stable and most suitable model to forecast inflation in Egypt for the next ten years. Based on the results, policy makers in Egypt should continue to engage proper economic policies in order to fight against persistent inflationary pressures in the economy. In this regard, the CBE is encouraged to continue tightening up its monetary policy in line with its inflation-targeting regime in order to restore macroeconomic stability in the country.

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