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Original Research

Forecasting Inflation in Egypt (2019-2022) by using AutoRegressive Integrated Moving Average (ARIMA) Models

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Abstract

The AutoRegressive Integrated Moving Average (ARIMA) model was employed to investigate annual inflation rates in Egypt from 2018 to 2022. The study planned to forecast inflation in Egypt for the upcoming period from August till December of 2022, and the best fitting model was carefully selected based on the minimum AIC value. ARIMA model was applied using EViews10. It is made up of three processes: the Autoregressive process (AR), the differencing process (d), and the Moving Average Process (MA). The Box–Jenkins methodology for analyzing and modeling time series is characterized by four steps: model identification, parameter estimation, diagnostic checking, and forecasting. This study used Autoregressive Integrated Moving Average (ARIMA) model to estimate and forecast the inflation rates for the year 2018-2022 using the univariate historical data of inflation rate. The ARIMA (1, 1, 1) model is stable and most suitable model to forecast inflation in Egypt for the next five months. The percent value of the inflation in August is (11.4±4.20); September (10.6±4.13); October (10.0±4.03); November (9.5±4.23) and December (9.2±4.11). In order to reduce inflation and increase macroeconomic stability in Egypt, policymakers should continue to implement sound economic policies.

KEYWORDS
Inflation Rate, AutoRegressive Integrated Moving Average (ARIMA), Egypt.

INTRODUCTION

A sustained rise in the average level of goods and services over time is referred to as inflation. (Blanchard, 2000). The Central Bank of Egypt's (CBE) monetary policy goal is to achieve low inflation rates, which are necessary for sustaining strong investment and growth rates as well as for preserving public confidence in the Egyptian economy (Hosny, 2016.).

According to numerous country experiences, low inflation is essential for macroeconomic stability because high inflation generally undermines it through lower domestic savings caused by real interest rates that are profoundly negative, lower capital accumulation because of increased uncertainty, and real exchange rate appreciation due to widening inflation differentials with trading partners (Moriyama, 2011).

The literature on economics has frequently and unfavourably analyzed the issue of inflation, which is crucial for both developing and in dustrialised nations (Justine *et al.*, 2017). As a particular issue for this country and a local one, inflation refers to the long-term rise in average prices for goods, services, and commodities across the whole economy caused by a decline of the value of a nation's currency (Chua, 2015).

If the inflation rate is low, price stability is shown; if it's high, it's not (Ngpilipinas, 2018). Food price increases, increases in overseas pricing, and an increase in the federal funds rate are just a few of the factors that contribute to inflation (Mariano, 1985), Inflation is an important gauge of how well central banks are doing.

Forecasts of inflation are therefore viewed as crucial factors on which monetary policy choices are based (Yap, 1996).

In the national macroeconomic policy debate, it is one of the most-discussed topics in addition to being a crucial variable for monetary policy decision-making (Moser *et al.*, 2004). In economic and technological literature, there is a wide variety of methods for predicting and determining inflation. One of the key components of econometric modelling is forecasting, and it comes in two types. One is the well-known statistical forecasting that can be based on historical data, and the other is economic forecasting that can be based on multivariate models. These two types of forecasting are known as linear regression and multivariate models, respectively (Zafar *et al.*, 2015). Over the past few decades, analysis of inflation has increased steadily, opening new opportunities for knowledge extraction from it from many angles. Data mining is a well-known technique for finding intriguing patterns and information in data (Rajalakshmi *et al.*, 2015; Zanetti *et al.*, 2018).

In fields involving business intelligence, sciences, finance, government, economics, and marketing, data mining analytics

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such as neural networks, classification, clustering, decision trees, and more have become widespread.

In general, social sciences and humanities will be impacted by the usage of such methodologies (Cagas *et al*., 2019)

There is a substantial amount of academic and empirical literature on inflation and studies related to inflation. A study by Kitchin (2014) employed an appropriate autoregressive-moving average (ARMA) model to evaluate the behaviour of month-over-month (m-o-m) inflation.

Findings demonstrated that the BSP's inflation targeting strategy was successful in anchoring inflation because, at the time of introduction, its rate was considered to be mean-stationary. In addition, the ARIMA (1, 2, 1) model was employed to forecast inflation rates in Sudan. Based on the historical data examined, which spans the years 1970–2016, the result showed that Sudan's inflation is expected to rise in the years 2017–2026. (Medalla and Fermo, 2013).

Additionally, a study that forecasts Nigerian inflation rates for 2017 was carried out using the ARIMA (1, 2, 1) model because it was determined to be the best model based on the AIC, AICc, and BIC statistical criteria. Following the 95% confidence interval, the forecasted number showed that an increase in the inflation rate in Nigeria is expected. (Abdulrahman *et al*., 2018).

This paper implemented the traditional ARIMA methodology, a type of time series simple data of yearly inflation. Various ARIMA models were observed, and the best model that will be used in predicting the inflation rate is selected from it.

MATERIALS AND METHODS

Data Collection

The data set used for this analysis includes annual rates of inflation in Egypt for the years 2019 through 2022. The World Bank was used to source all the data. The goal was to demonstrate the accuracy of an ARIMA model for analysing and predicting inflation rate series Box- Jenkins's (Box *et al*., 1994). EViews10 was used to implement the ARIMA model. It is composed of the Moving Average Process (MAP), the Autoregressive Process (AR), and the Differencing Process (d) (MA) (Adubisi *et al*., 2018). Using simple historical data on inflation rates, this study employed the Autoregressive Integrated Moving Average (ARIMA) model to estimate and predict the inflation rates for the years 2018–2022.

Model description

ARIMA modeling (Urrutia *et al*., 1992; Box *et al*., 1994; Chua, 2015). Depending on the kind of data, an ARIMA model is split into three parts:

The Autoregressive (AR) Model The following is an AR(p).

$$Y_t = B_0 + B_1Y_{t-1} + B_2Y_{t-2} +,\dots, B_pY_{t-p} + u_t$$

Where u_t denotes a white noise error term.

The dependent variable (i.e., the variable of interest) is forecasted in the context of future observations using an autoregressive (AR) time series model, which is the first component.

The Moving Average (MA) Model

The second component is the moving average (MA) models, which estimate upcoming observations of the dependent variable by including historical data from the white noise process (i.e., historical forecast errors). The following is a representation of the first-order MA model (MA (1). The MA(q) model, a weighted or moving average of the present and previous white noise error components, can also be used to simulate Y_t:

$$Y_t = C_0 + C_1u_t + C_2u_{t-1} +,\dots, C_ju_{t-q}$$

The ARMA (p, q) model combines AR and MA

The stationary ARMA model is created by combining the two stationary models, MA and AR. In the event that the inputted data are nonstationary, a third component is utilised to transform the inputted data into stationarity by differencing (integrating (I)) original series, which according to (Rohrbach and kiriwaggulu, 2001) and (Nau, 2018) is represented as:

$$y'_t = y_t - y_{t-1}$$

where y'_t is the anticipated consumption, y_t and y_{t-1} are original series and lagged original series, respectively. The three first-order models combined produce models that can be utilized for estimation.

Stages in ARIMA model building

The Box-Jenkins method of time series analysis and modeling (Box *et al*., 1994) is (model identification, parameter estimates, diagnostic verification, and forecasting) are comprised of these four processes.

Model identification

The data used in creating time series models should be stationary.

When non-stationary data are incorporated into a model, the conclusions could point to an unreliable link. (Chua, 2015) Time series data must therefore be checked for stationary pattern before choosing the model.

Data that are stationary have statistical characteristics that do not fluctuate over time. (Nau, 2018). Formally, a time series is considered stationary if it exhibits constant mean and variance as well as an autocovariance that is independent of time.) (Adubisi *et al*., 2018). The data are deemed nonstationary if any of these conditions are not satisfied.

To identify this issue, the data will be subjected to the autocorrelation function (ACF).

The data are nonstationary if the ACF plot is positive and has a very slow linear decline trend.

If this nonstationary issue is brought on by the mean or model transformation, or if it is brought on by variance, proper data differencing can be applied to fix it. (Ramasubramanian, 2016; Adubisi *et al*., 2018; Nau, 2018). Establishing the starting values for the seasonality and non seasonality orders is the next step (p and q).

The ACF and partial ACF (PACF) are the main analytical methods employed in this step.

We compute correlation between Y_t and Y_{t-k} over the n-k pairs in the data set to determine the autocorrelation of lag k, which is one hallmark of stationary data.

$$ACF(k) = \frac{\sum(Y_t - \mu)(Y_{t-k} - \mu)}{\sum(Y_t - \mu)^2} = \frac{Cov(Y_t, Y_{t-k},)}{Var(Y_t)}$$

Where Y_t stands to the original set, Y_{t-k} is a lagged version of original series and μ is the mean. The linear correlation between Y_t and Y_{t-k}, compensating for any potential effects of linear connections between values at intermediate lags, is referred to as the PACF.

Although the second order can be calculated as follows, the first order partial is equivalent to the first order autocorrelation.

$$PACF = \frac{Cov(Y_t, Y_{t-2} \backslash Y_{t-1})}{\sqrt{(VarY_t \backslash Y_{t-1})(VarY_{t-2} \backslash Y_{t-1})}}$$

While the PACF issues the order of MA(q), the ACF issues the order of AR (p)

Parameter estimation

Using least squares, as outlined by Box and Jenkins, we attempt to discover precise estimates of the model's parameters after determining an appropriate order for ARIMA (p,d,q). Maximum likelihood, which is asymptotically accurate for time series, is used to determine the parameters

.

Diagnostic verification

Produces diagnostic results to assess the model's suitability. Test the significance of the parameters shows whether certain model parameters can be eliminated. Other if the residual series contains extra information that can be useful to attempt a different model, then repeat the estimate and diagnostic testing step. Tests used to decide on fit model test residuals follow white noise if it was not in this case.

Forecasting

In order to produce confidence ranges for these projections, we utilized the final model to forecast upcoming values of the time series addition.

The key indicator of an ARIMA model's success is how well it forecasts both during and outside of the sample period.

RESULTS AND DISCUSSION

Step One: Model identification: Testing for stationarity

If a change in time does not result in a change in the distribution's shape, a time series is said to be stationary.

Unit roots are one reason for non-stationarity; fundamental distributional features like the mean, variance, and covariance are constant throughout time.

Figures (1) and (2) illustrate Egyptian inflation is not steady for this period, according to the initial content's time charts. A stochastic trend in a time series known as a unit root, also known as a unit root process or a difference stationary process, is frequently referred to as a "random walk with drift." If a time series has a unit root, it displays an unpredictable systematic pattern. Tests for stationarity in a time series are known as unit root tests. The statistical power of these tests is notoriously low. There are numerous tests since none stand out as having the most power. Among the tests is the Augmented Dickey-Fuller (ADF) (Fuller, 1976), a linear regression-based test.

Serial correlation can be problematic, as seen in table 1, in which case the Augmented Dickey-Fuller (ADF) test might be applied. Larger and more complicated models are handled by the ADF. Its rather high Type I error rate is a drawback. The Augmented Dickey Fuller Test (ADF) is a stationarity unit root test. In the analysis of time series, unit roots might lead to unexpected outcomes. These models include lag differences.

- No constant, no trend: $\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant, no trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$
- Constant and trend: $\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$

Figures 1, 2 and 3, illustrates the nonstationarity of the data in terms of variance or mean.

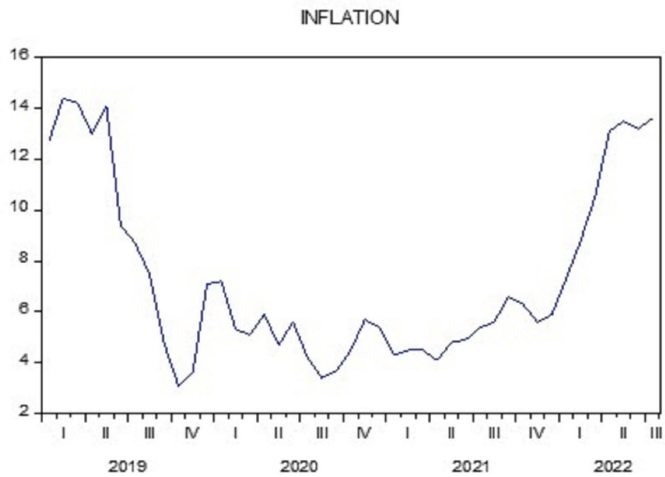


Figure 1. The time plots of the initial data indicate that Egyptian inflation is not a stationary for this series.

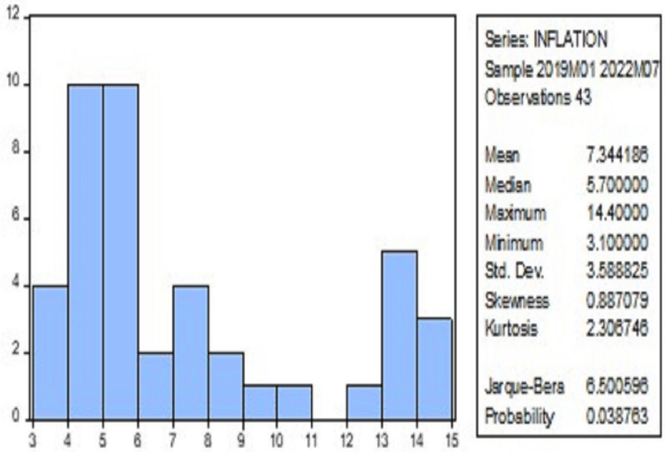


Figure 2. Histogram and Stats of the initial data indicate that Egyptian inflation is not a stationary for this series.

A logarithmic expression also demonstrates non-stationary behaviour of the data. Mathematical transformations like natural logarithm figures can be used to address instability in variance. In addition, the Augmented Dickey-Fuller (ADF) (Fuller, 1976), Table (1)'s null and alternatives for the unit root test are: Ho: time series have a unit root (non-stationary); if the p-value from ADF >0.05, H0 is accepted.

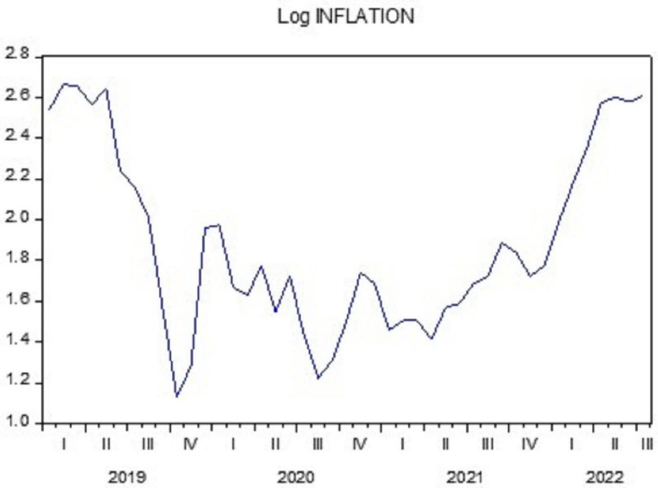


Figure 3. A logarithmic expression also show Non- stationary behavior of the data.

ADF in Table 1 indicates that the time series is not stationary at the data level and that differencing, as utilized in the creation of ARIMA models, must be performed to achieve stationarity. Ha: time series do not follow unit root (stationary).

Hence, using the series is steady because of the first-order difference, In inflation I (1) (Table 2).

Step Two: Model estimation

The PACF and ACF values are used to determine the values of the other two ARIMA model parameters, p and q. The Correlogram (at 1" Differences) at Figure (4) that help us to choose a lag length to execute the test.

The lag duration should be selected to prevent serial correlation of the residuals. The many models are utilized to determine the worth of Figures 5 and 6 respectively (in contrast to PACF at all other lags) reveal that the initial lag value of PACF is statistically significant, offering a potential model for Egypt's inflation

Table 1. Unit root test by The Augmented Dickey-Fuller test statistic (ADF) Test.

1. The test	The Augmented Dickey-Fuller test statistic (ADF) in Levels-intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-3.59)	Non-stationary
		5% level (-2.93)	Non-stationary
Inflation rate	-1.128 (0.69)	10% level (-2,60)	Non-stationary
2. The test	The Augmented Dickey-Fuller test statistic (ADF) in Levels-Trend and intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-4.19)	Non-stationary
		5% level (-3.52)	Non-stationary
Inflation rate	- 0.88 (0.94)	10% level (-3.19)	Non-stationary
3. The test	The Augmented Dickey-Fuller test statistic (ADF) Non Levels- trend and intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-2.62)	Non-stationary
		5% level (-1.94)	Non-stationary
Inflation rate	-0.39 (0.53	10% level (-1.6)	Non-stationary

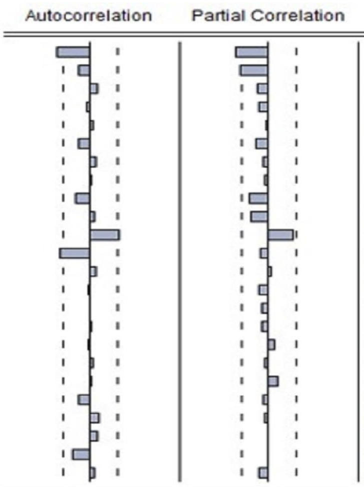
Table 2. Unit Root test at the first difference by The Augmented Dickey-Fuller statistic (ADF) Test.

1. The test	The Augmented Dickey-Fuller test statistic (ADF) in Levels-intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-3.60)	Stationary
		5% level (-2.93)	Stationary
Inflation rate	-3.92 (0.004)	10% level (-2.60)	Stationary
2. The test	The Augmented Dickey-Fuller test statistic (ADF) in Levels-Trend and intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
		1% level (-4.20)	Stationary
		5% level (-3.52)	Stationary
Inflation rate	-5.09 (0.000)	10% level (-3.19)	Stationary
3. The test	The Augmented Dickey-Fuller test statistic (ADF) Non Levels- trend and intercept		
Variable	ADF Statistic and probability	Critical Values	Conclusion
Inflation rate	-5.32 (0.000)		

Table 3. The forecast inflation value in Egypt for the upcoming period from August till December of 2022.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Year
						2019							2019
Inflation	12.7	14.4	14.2	13	14.1	9.4	8.7	7.5	4.8	3.1	3.6	7.1	9.4
predicted	12.7	14.4	14.2	13	14.1	9.4	8.7	7.5	4.8	3.1	3.6	7.1	9.4
						2020							2020
Inflation	7.2	5.3	5.1	5.9	4.7	5.6	4.2	3.4	3.7	4.5	5.7	5.4	5.1
predicted	7.2	5.3	5.1	5.9	4.7	5.6	4.2	3.4	3.7	4.5	5.7	5.4	5.1
						2021							2021
Inflation	4.3	4.5	4.5	4.1	4.8	4.9	5.4	5.6	6.6	6.3	5.6	5.9	5.2
predicted	4.3	4.5	4.5	4.1	4.8	4.9	5.4	5.6	6.6	6.3	5.6	5.9	5.2
						2022							2022
Inflation	7.3	8.8	10.5	13.1	13.5	13.2	13.6	--	--	--	--	--	11.4
predicted	7.3	8.8	10.5	13.1	13.5	13.2	12.3	11.4	10.6	10	9.5	9.2	10.8

series. The dependent variable (i.e., the variable of interest) is forecasted based on prior data in the autoregressive (AR) (1) time series model. (Anderson, *et al.*, 2001).



	AC	PAC	Q-Stat	Prob
1	-0.383	-0.383	6.4611	0.011
2	-0.139	-0.334	7.3286	0.026
3	0.096	-0.136	7.7541	0.051
4	-0.028	-0.111	7.7906	0.100
5	0.037	-0.008	7.8559	0.164
6	-0.116	-0.147	8.5382	0.201
7	0.070	-0.052	8.7952	0.268
8	0.019	-0.035	8.8142	0.358
9	-0.171	-0.218	10.433	0.317
10	0.055	-0.195	10.605	0.389
11	0.338	0.295	17.337	0.098
12	-0.344	-0.088	24.529	0.017
13	0.081	0.033	24.939	0.024
14	-0.010	-0.099	24.946	0.035
15	0.001	-0.069	24.946	0.051
16	0.018	-0.074	24.968	0.070
17	-0.013	0.077	24.980	0.095
18	0.028	-0.048	25.042	0.124
19	0.017	0.104	25.066	0.158
20	-0.121	-0.052	26.294	0.156
21	0.101	-0.035	27.188	0.165
22	0.092	-0.006	27.975	0.177
23	-0.189	0.008	31.489	0.111
24	0.052	-0.112	31.765	0.133

Figure 4. A lag length for PACF and ACF of the first order of Augmented Dickey-Fuller (ADF).

Dependent Variable: LOG(DDD)
Method: ARMA Maximum Likelihood (BFGS)
Date: 09/12/22 Time: 04:45
Sample: 2019M01 2022M07
Included observations: 43
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.020538	0.252621	7.998306	0.0000
AR(1)	0.831924	0.107547	7.735469	0.0000
MA(1)	0.428994	0.121392	3.533971	0.0011
SIGMASQ	0.036633	0.008862	4.133807	0.0002

R-squared	0.818601	Mean dependent var	1.888310
Adjusted R-squared	0.804648	S.D. dependent var	0.454705
S.E. of regression	0.200974	Akaike info criterion	-0.236559
Sum squared resid	1.575225	Schwarz criterion	-0.072726
Log likelihood	9.086010	Hannan-Quinn criter.	-0.176142
F-statistic	58.66534	Durbin-Watson stat	1.970751
Prob(F-statistic)	0.000000		

Inverted AR Roots	.83
Inverted MA Roots	-.43

Figure 5. TheAutoamtic equations for ARIMA model out put for the log inflation data for egypt 2019-2022.

For the Egyptian inflation rate series. The model that fits the data the best is ARIMA (1, 1, 1). Figure 5 shows the statistical significance of the first lag value of PACF, whereas none of the other lags are. This implies a potential AR (1) model for series. Since only the first lag of the ACF is statistically significant and all other subsequent autocorrelations are not, MA (1) is the suggested moving average. Following the first order, ARIMA is the model that fits the Egyptian inflation rate series the best (1, 1, 1). Therefore, it is clear from figure 5 that all of the output's values are significant. Consequently, forecasting is done using this approach. It is vital to validate assumptions first before forecasting (Studenmund, 2016).

Included observations: 43

Model	LogL	AIC*	BIC	HQ
(1,1)(0,0)	9.086010	-0.236559	-0.072726	-0.176142
(2,4)(0,0)	12.820888	-0.224227	0.103438	-0.103395
(4,2)(0,0)	12.249437	-0.197648	0.130017	-0.076815
(3,0)(0,0)	9.228503	-0.196675	0.008116	-0.121154
(2,0)(0,0)	8.189555	-0.194863	-0.031030	-0.134447
(1,2)(0,0)	9.152122	-0.193122	0.011669	-0.117601
(2,1)(0,0)	9.125336	-0.191876	0.012915	-0.116356
(4,1)(0,0)	10.963939	-0.184369	0.102338	-0.078641
(2,3)(0,0)	10.520495	-0.163744	0.122963	-0.058015
(1,0)(0,0)	6.420237	-0.159081	-0.036206	-0.113769
(4,0)(0,0)	9.395355	-0.157923	0.087825	-0.067299
(3,1)(0,0)	9.331026	-0.154931	0.090817	-0.064307
(1,3)(0,0)	9.294389	-0.153227	0.092521	-0.062603
(2,2)(0,0)	9.187367	-0.148250	0.097499	-0.057625
(3,3)(0,0)	10.663318	-0.123875	0.203790	-0.003042
(1,4)(0,0)	9.487177	-0.115683	0.171024	-0.009954
(3,2)(0,0)	9.428947	-0.112974	0.173733	-0.007246
(3,4)(0,0)	11.053534	-0.095513	0.273110	0.040424
(4,3)(0,0)	10.921358	-0.089366	0.279258	0.046571
(0,4)(0,0)	7.655077	-0.076980	0.168769	0.013644
(4,4)(0,0)	11.132649	-0.052681	0.356900	0.098360
(0,3)(0,0)	5.233009	-0.010838	0.193953	0.064683
(0,2)(0,0)	2.735442	0.058817	0.222649	0.119233
(0,1)(0,0)	-6.231848	0.429388	0.552263	0.474701
(0,0)(0,0)	-26.619861	1.331156	1.413073	1.361365

Figure 6. The Autoregressives (AR)(p) and the Moving Average (MA)(q) for ARIMA models out put for the inflation

Step Three: Diagnostic Checking

In Figure (7), the quality of a collection of statistical models is compared using Akaike's information criterion (AIC) (Akaike, 1973). Each model was ranked by the AIC from best to worst. The model that was neither under-fitting nor over-fitting is considered the "best."

Additionally, Figure (8), Correlogram-Q-Statistics shows that there isn't a lag with a probability value of less than 0.05. Therefore, it can be said that there is no autocorrelation in the residual.

Figure (9) reports the inverse roots of the AR and MA characteristics (Chua, 2015). If all roots have a modulus of less than one and are located inside the unit circle, the predicted AR and MA are stable (stationary).

Step four: Forecastin

In the forecast stage, we project future time series addition values using the final model in order to produce confidence intervals or standard errors for these projections. The key indicator of an ARIMA model's success is how well it forecasts both during and outside of the sample period. The percentage value of inflation for the following five months of the year 2022 (Nau, 2018) is shown in Table (3) and Figure (10).

For the next five months, the most reliable model to predict inflation in Egypt is the ARIMA (1, 1, 1) model since it is stable. That applies to the initial difference with p = 1 and q = 1. The percent value of the inflation in August is (11.4±4.20); September (10.6±4.13); October (10±4.03); November (9.5±4.23) and December (9.2±4.11).

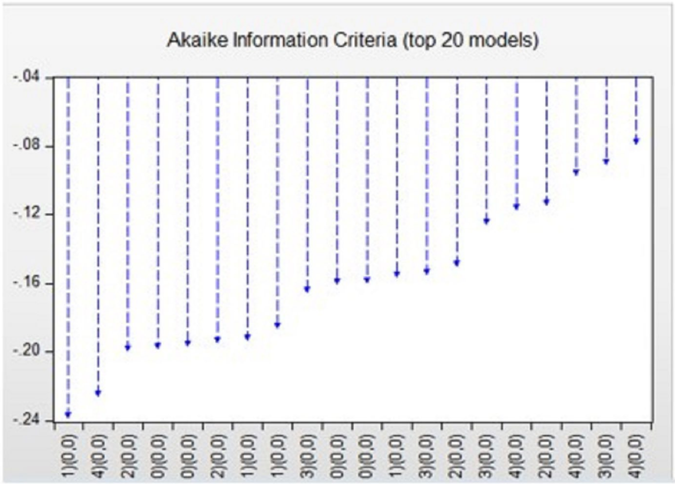
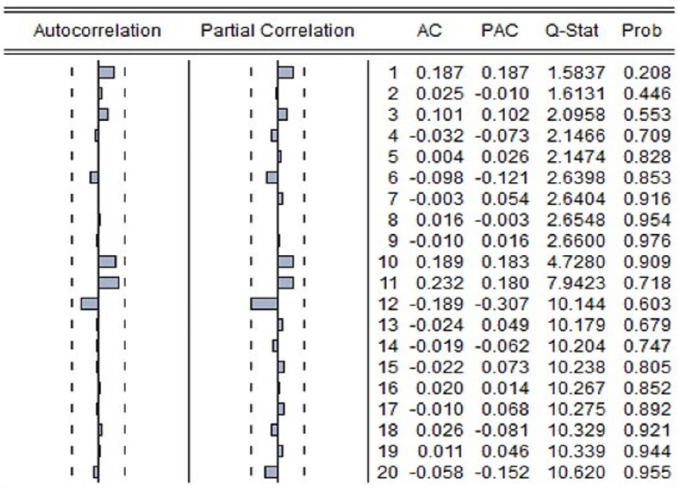


Figure 7. Akaike's information criterion (AIC) compares the quality of a set of statistical models (20) to each other.



	AC	PAC	Q-Stat	Prob
1	0.187	0.187	1.5837	0.208
2	0.025	-0.010	1.6131	0.446
3	0.101	0.102	2.0958	0.553
4	-0.032	-0.073	2.1466	0.709
5	0.004	0.026	2.1474	0.828
6	-0.098	-0.121	2.6398	0.853
7	-0.003	0.054	2.6404	0.916
8	0.016	-0.003	2.6548	0.954
9	-0.010	0.016	2.6600	0.976
10	0.189	0.183	4.7280	0.909
11	0.232	0.180	7.9423	0.718
12	-0.189	-0.307	10.144	0.603
13	-0.024	0.049	10.179	0.679
14	-0.019	-0.062	10.204	0.747
15	-0.022	0.073	10.238	0.805
16	0.020	0.014	10.267	0.852
17	-0.010	0.068	10.275	0.892
18	0.026	-0.081	10.329	0.921
19	0.011	0.046	10.339	0.944
20	-0.058	-0.152	10.620	0.955

Figure 8. Correlogram-Q-Statistics based on the correlogram above, it can be seen that there is no lag that has a probability value of <0.05. So, it can be concluded that the residual does not contain autocorrelation.

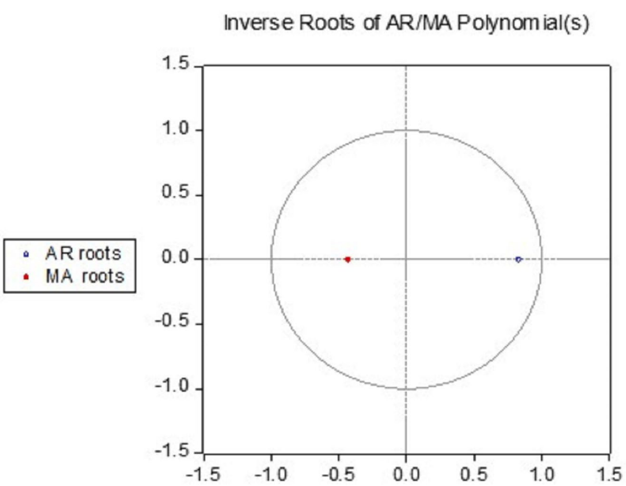


Figure 9. The estimated inverse roots of AR and MA is stable (stationary) if all roots have modulus less than one and lie inside the unit circle.

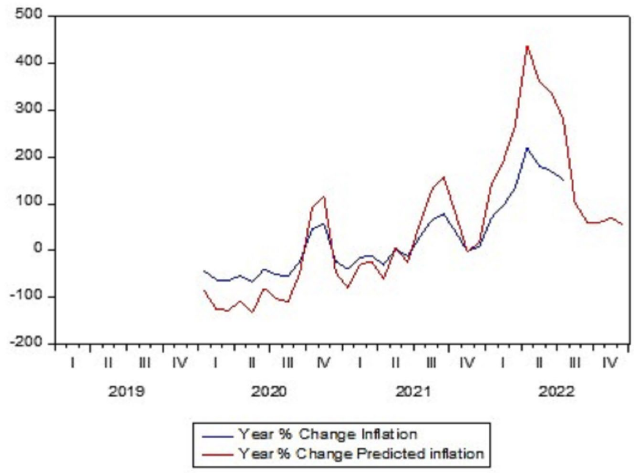


Figure 10. The Forecasting results of the inflation rate for the next five months (August till December) of 2022.

CONCLUSION

The ARIMA (1, 1, 1) model is stable and most suitable model to forecast inflation in Egypt for the next five months. The percent value of the inflation in August is (11.4±4.20); September (10.6±4.13); October (10.0±4.03); November (9.5±4.23) and December (9.2±4.11) with average standard error based on the results. In order to reduce inflation and increase macroeconomic stability in Egypt, policymakers should continue to implement sound economic policies.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

REFERENCES

Abdulrahman, B.M.A., Ahmed, A.Y., Yahia, A.A., Abdellah, E., 2018. Forecasting of Sudan Inflation Rates using ARIMA Model. Int. J. Econ. Financ. Issues 8, 17-22.

Adubisi, O.D., David, 1.J., James, F.E., Awa, U.E., Terna, A.J., 2018. A predictive Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Inflation Rates. Res. J. Bus. Econ. Manag. 1, 1—8.

Akaike, H., 1973. Information theory and an extension of the maximum likelihood principle. In: Petran, B.N., and Csa`aki, F., editors. International symposium on information theory. Second edition. Akade`emiai Kiadi, Budapest, Hungary. pp. 267–281

Anderson, D.R., Burnham, K.P., Lubow, B.C., Thomas, L., Corn, P.S., Medica, P.A., Marlow, R.W., 2001. Field trials of line transect methods applied to estimation of desert tortoise abundance. Journal of Wildlife Management 65, 583–597

Blanchard, O., 2000. Macroeconomics. 2nd Edition Prentice Hall, New York.

Box, G.E.P., Jenkins, G.M., Reinsel, G.C., 1994. Time series analysis; Forecasting and control. 3rd edition. Prentice Hall, Englewood Cliff, New Jersey.

Cagas,U. O., Delima, A.J.P., Toledo, T.L., 2019. Predictability of Faculty Instructional Performance through Hybrid Prediction Model. Int. J. Innov. Technol. Explor. Eng. 8, 22-25.

Chua, K.C., 2015. The effect of U.S. Inflation on the Philippines. South East Asia J. Contemp. Business, Econ. Law 7, 16-22.

Fuller, W.A., 1976. Introduction to Statistical Time Series. New York: John Wiley and Sons. ISBN 0-471-28715-6.

Hosny, S., 2016. What is the Central Bank of Egypt's implicit inflation target?. International Journal of Applied Economics 13, 43- 56.

Justine, W.Y.M., Lim, Y.T., Loke, H.Y., Tai, J.J., 2017. Effect of Macroeconomic Variables Toward inflation in Malaysia's economy. http://eprints.utar.edu.my/2692/1/fyp_BF_2017_TJJ_-_1300477.pdf

Kitchin, R., 2014. Big Data, new epistemologies and paradigm shifts. Big Data Soc. 1, 1—12.

Mariano R.S., 1985. Forecasting Monthly Inflation in the Philippines. Monograph, no. 10, 1—26.

Medalla, F.M., Fermo, L.B., 2013. A Univariate Time Series Analysis of Philippine Inflation During the Inflation Targeting Period. in Bangko Sentral Review, pp. 18-36.

Moriyama K., 2011. Inflation inertia in Egypt and its policy implications Middle East and Central Asia Department. IMF Working Paper, WP/11/160.

Moser, G., Rumler, F., Scharler, J., 2004. Forecasting Austrian Inflation. In: Macroeconomic Models and Forecast for Austria. workshop no. 5, pp. 275-319.

Nau R., 2018. ARIMA models for time series forecasting. Retrieved: https://people.duke.edu/~rnau/ mDep. Evon.Res., 411arim.htm.

Ngpilipinas, B.S., 2018. The BSP and Price Stability. Dep. Evon. Res. pp.1-20

Rajalakshmi, K., Dhenakaran, S.S., Roobini, N., 2015. Comparative Analysis of K-Means Algorithm in Disease Prediction. Int. J. Sci. Eng. Technol. Res. 4, 2697-2699.

Ramasubramanian V., 2016. Time Series Analysis. IA.S.R.I., Library Avenue, Pusa, New Delhi – 110 012.

Rohrbach, D., kiriwaggulu A.J., 2001. Commercialization prospects for sorghum and pearl millet in Tanzania. Working Paper Series no, 7, Bulawayo Zimbabwe/Socioeconomic and Policy, Programme, ICRISAT.

Studenmund, A.H., 2016. Using econometrics: A practical guide (4th ed.) Pearson, USA. ISBN 10: 013418274-X.

Urrutia, J.D.F., Mingo, L.T., Balmaceda, C.N.M., 1992. Forecasting Income Tax Revenue of the Philippines Using Autoregressive Integrated Moving Average (Arima) Modeling: a Time Series Analysis. Am. Res. Thoughts 1, 1938-2015.

Yap, J.T., 1996. Inflation and Economic Growth in the Philippines. no. 96, pp. 1-26.

Zafar, R., Qayyum, F.A., Pervaiz, S.G., 2015. Forecasting Inflation using Functional Time Series Analysis, Munich Pers. RePEc Arch. pp. 1—26.

Zanetti, M.A., Tedesco, D.C., Schneider, T., 2018. Economic losses associated with wooden breast and white striping in broilers," Semina: Ciˆencias Agra´rias 39, 887–892.