Seasonal Autoregressive Integrated Moving Average (SARIMA) Modelling and Forecasting of Inflation Rates in Nigerian (2003-2016)

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Abstract
The study applied Seasonal autoregressive integrated moving average (SARIMA) in modelling inflation rate in Nigeria from 2003-2016. The time plot of the series showed Seasonality but not obvious trend. The raw data is non-stationary at critical level (1%, 5% and 10%). Time plot of the seasonal differencing of inflation rate at lag12 (SDINF) showed a seasonal series. The ADF test statistics is the grater that the critical values at 1%, 5% and 10% this means that the series is non- stationary. Non-seasonal differencing of seasonal differencing of inflation rates (DSDFLA) in Nigeria produced a correlogram with spike of ACF and PACF at lag 12 showing a seasonal component. The ADF test statistics (DSDINF) is less than the critical values at 1% 5% and 10%. Five model were estimated and the best model is the model that minimise the Akaike information criterion (AIC) (SARIMA (001)(211)$_{12}$) with AIC of (3.320166). The plot of the residual correlogram shown adequacy of the model. A one-year (12 months) forecast from January 2017 to December 2017 is based on the best fitted model.*

***Key Word**: Forecasting Inflation rate, Seasonal ARIMA Model.*

Introduction

Inflation has been a problem facing many countries of the world especially unindustrialized countries. It started during the early 60s, which results to the incorporation of economic policies as measures to reduce the effect of inflation in the societies. Most of these measures taken by developing countries to check the problem of inflation are in the form of the use of central bank instruments of credit control. This is aimed at reducing the volume of money in circulation and sustaining it to ensure low cost of living. Nigeria as a developing country is also faced with the problem of inflation. In Nigeria inflation is a problem for policy makers since 1990s, and ever since then till date the rate of inflation is on the increase. Inflation is neither new to the Nigerian economy system of Nigeria nor the world at large. Evidence has shown that inflation persist both in the advanced countries and unindustrialized countries, with difference in magnitude or rates. The rates of inflation in developing countries are more than those in the developed countries. Inflation may be defined as process of continuous increase in price of goods and services as result of: large volume of money in circulation used in the exchange of few goods and services. High price of imported goods arising from increase in foreign price and instability of international exchange rate, sub-charge from port congestion, storage facilities, marketing arrangements plus the distribution network. There has been an increase in the price of oil since the removal of subsidy and this led to increase in price of most items, and increase in transportation fare is a living example at hared (Dewett and Navalur (2010).

Box-Jenkins Seasonal ARIMA Model

In time series analysis, Box and Jenkins modelling procedure, named after the statisticians Box and Jenkins (1970), defines stationary time series as once with constant means and variances. Autoregressive moving average ARMA or autoregressive integrated moving average ARIMA models is use to find the best fitted model to series. The past values of the series is use to make forecasts of present values. Univariate series is analysing using Box-Jenkins techniques. It is basically a linear statistical techniques and most powerful for modelling univariate data. The SARIMA model is combination of seasonal, non-seasonal autoregressive, moving average and integrating parameter. The autoregressive models AR (p) base their forecasts of the past values of the series X_t of order *(p)* of past values of series and a random disturbance W_t. The moving average models MA (*q*) generate forecasts of the past error W_t of order *(q)* of past disturbances terms of variable predicted errors.

W_1, W_2………..,.W_q. A combination of the autoregressive AR of order (p) and moving average MA of order(*q*) generates more flexible models named ARMA *(p, q)* models. The stationary of the data is required for the implementation of all these models. Box and Jenkins (1976) proposed the mathematical conversion of the non-stationary time series into stationary time series by a process of differencing, defined by an order of integration parameter *d*. This converts ARMA (*p*, *q*) models to ARIMA (*p*, *d*, *q*) models, Autoregressive Integrated Moving Average models.

The ARIMA Model Building Approach Includes:

1. Model identification
2. Estimation
3. Diagnosis
4. Forecasting

Identification of method may be accomplished on the basis of the series pattern, time plot and using correlogram to identified the model. Estimation, the parameters are estimated and tested for statistical significance after identifying the tentative model. If the parameter estimates do not meet the stationary condition, then a new model should be identified and its parameters are estimated and tested. In the diagnosis process, the correlogram of the residuals from the estimated model should be a white noise process. If the residuals remain significantly correlated among themselves, a new model should be identified and diagnosed. Once the model is selected is used for forecast. Time series analysis delivers great chances to detecting, describing and modelling series. Ultimately, to understand, planning and decision making process, it is important to study the temporal characteristic of inflation rate and predict the future inflation rate in Nigeria. This can be completed by recognising the best model using Box and Jenkins Seasonal ARIMA modelling methods.

Autoregressive (AR) Models

An autoregressive model is a model in which one uses the statistical properties of the past values of the series to predict the future values. The general representation of an autoregressive model of order p, AR (p) is

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_1 Y_{t-3} + \ldots\ldots\ldots\ldots\ldots + \beta_p Y_{t-p} + W_t \qquad 1.1$$

Where the term W_t is the error term and is called white noise. β_1, β_2 and β_p are unknown parameters relating Y_t ,Y_{t-1} ,Y_{t-2} and Y_{t-p}.

Moving average models of order (q)

A moving average term in a time series models is past error multiplied by the co-efficient. The notation MA (q) also refers to the moving average of order q. the general representation of a moving average model of order (q) $Yt = \mu + \Phi_1 W_{t-1} + \Phi_2 W_{t-2} + \cdots + \Phi q\, W_{t-q} + W_t$ 1.2

Where the $\Phi 1, \ldots, \Phi_q$ are the parameters of the model, μ is the expectation of Y_t (often assumed to equal to 0), and the $W_t, W_{t-1}, \ldots W_{t-q}$ are white noise terms.

Autoregressive-Moving-Average Models (ARMA)

We have seen from above that the AR model includes lagged terms on the series itself, and that the MA model includes lagged terms on the error term. By including both lagged terms, we arrive at ARMA model. Therefore ARMA (p,q), where p is the order of autoregressive term and q the order of the moving-average term, these can generally be represented as

$Y_t - \beta_1 Y_{t-1} - \beta_2 Y_{t-2} - \beta_1 Y_{t-3} + \ldots \beta p Y_{t-p} = \mu + \Phi_1 W_{t-1} + \Phi_2 W_{t-2} + \cdots + \Phi_q W_{t-q} + W_t$ 1.3

A time series {Yt} is said to follow an autoregressive moving average model *of orders p and q*, designated as ARMA (p, q), where β_p and Φ_q are constants such that the model is stationary as well as invertible and {Wt} is a white noise process.

Equation (1.3) can be written as:

A (B) Xt = B(L)Wt 1.4

A (B) = 1 - β1L - β2B2 - ... – βpBp 1.5

$B(L) = 1 + \Phi_1 B_1 + \Phi_2 B_2 + \ldots + \Phi_q B_q$ 1.6

B is the backshift operator defined by

$B^k{}_k Xt = Xt-k.$ 1.7

Arima Model with Differencing

Many time series are non-stationary. For a non-stationary time series $\{Y_t\}$ Box and Jenkins (1976) proposed that differencing up to an appropriate order is needed to make the series stationary. Suppose d is the minimum order of differencing necessary for stationary to be attained. The d^{th} difference of $\{Y_t\}$ is denoted by $\{\Delta^d Y_t\}$ where Δ^d is the difference operator defined by $\Delta^d = 1 - B$. If the series $\{\Delta^d Y_t\}$ follows the model (3), then $\{Y_t\}$ is said to follow an autoregressive integrated moving average model of order p, d and q, ARIMA (p, d, q).

Seasonal Autoregressive Integrated Moving Average Model of Order (p d q)

Seasonality usually causes the series to be non-stationary because the average values at some particular times within the seasonal span (months, for example) may be different from the average values at other times. The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is SARIMA $(p, d, q) \times (P, D, Q)_S$

Where p = non-seasonal AR of order (p), d = non-seasonal differencing, q = non-seasonal MA of order (p), P = seasonal AR of order (P), D = seasonal differencing, Q = seasonal MA of order (Q), and S = time span of repeated seasonal pattern. Without differencing operations, the model could be written more formally as

$\Phi(BS)\varphi(B)(Y_t - \mu) = \Theta(B^s)\theta(B)W_t$ 1.8

The non-seasonal components are:

AR: $\varphi(B) = 1 - \varphi_t B - \ldots - \varphi_p B_p$ 1.9

MA: $\theta(B) = 1 + \theta_1 B + \ldots + \theta_q B_q$ 1.10

The seasonal components are: Seasonal

AR: $\Phi(BS) = 1 - \Phi_1 B^s - \ldots - \Phi_p B^{sp}$ 1.11

MA: $\Theta;\text{'}k(B^s) = 1 + \Theta_1 B^s + \ldots + \Theta_Q B^{SQ}$ 1.12

Seasonal differencing is defined as a difference between a value and a value with lag that is a multiple of S. With $S = 12$, which may occur with monthly data, a seasonal difference is
$(1\text{-}B_{12})Y_t = Y_t - Y_{t12}$ 1.13

The differences (from the previous year) may be about the same for each month of the year giving us a stationary series. Seasonal differencing removes seasonal trend and can also get rid of a seasonal random walk type of non-stationary. Non-seasonal differencing: If trend is present in the data, we may also need non-seasonal differencing. Often a first non-seasonal difference will "de-trend" the data.

Objective of Study

The purpose of this research is to Model and forecast inflation rate using SARIMA model

To achieve this goal, the following objectives are in focus.

Conduct a preliminary check on the data obtained the trend and seasonal components of inflation.

i. Conduct test for stationality on the series using the Augmented Dickey Fuller test.
ii. Establish best the fitted model for the observations
iii. Forecast inflation rate for 12 months using the best fit model

Statement of the Hypothesis

H_O: There is significant difference in inflation rates in Nigerian.

H_O: The pattern of inflation rates in Nigeria is not regular from year to year

Significance of Study

The significance of the study lies on the fact that seasonal modelling of inflation rate in Nigeria, will give a more realistic outlook on how the population as a whole is being affected during increase in prices of goods and services. It is believed that a study of this nature will expose the suffering of masses, policy makers, corporate bodies etc. through its findings, for formulating of most effective plans on how they can cope with inflation and better life for every citizen. This research will be of immense importance for students in statistics as a basis for further research work, assist the planning of unit of government through the provision of more efficient information on the effectiveness of their anti-inflationary policies. It will help individuals and corporations in the planning of their marketing, inflation fluctuation and trends are of great interest to economist as well as agriculturists in view of the important role of prices in the market Etuk et al, (2012).

Scope of the Study

Seasonal ARIMA modelling and forecasting of inflation rate in Nigerian and for effective coverage, the data for this work are inflation rate obtained from Central Bank of Nigeria website (http://www.centralbank.org).

Limitations of the Study

As already stated in the purpose of study, this research is specifically carried out to model and forecast inflation rate in Nigeria, however the work is only limited to fourteen years

(2003-2016). Hence the expected precision may not be so much. This is because the larger the number of observation, the greater the efficiency of the estimate made from the statistical data. Another limitation is on data collection. Data collection is not an easy task to carry out as a result of the confidentiality of data. This scope of this research has been limited to lack of adequate and relevant information from the central bank of Nigeria (cbn), financial constraint, and photocopy of some relevant material and to browse for more information on the internet. There is also the inadequate of materials in the libraries that deals or discuss more on the topic. Lastly, the time limit or duration also constituted considerable limitation because the work was being done at the time normal lectures were going on. Seasonal ARIMA modelling and forecasting of inflation rate in Nigerian and for effective coverage, the data for this work are inflation rate obtained from Central Bank of Nigeria website (http://www.centralbank.org).

Review Related Literature

Etuket et al, (2012) "Forecasting Nigerian inflation rate by seasonal ARIMA mode" from 2003-2011. In his discussion, the time plot show a secular trend but nor seasonality and the seasonal differencing show a seasonality but not trend. The no seasonal differencing produce no trend in the series and no clear seasonality. The plot of the ACF shows a negative spike at lag 12 showing seasonal MA component. The plot of the PACF shows no spike at the beginning suggesting a non -seasonal MA component. In his analysis, the adequate model for inflation rate in Nigeria follow a SARIMA $(011)*(011)_{12}$ model.

Etuk, Azubuike and Uchendu.(2015) "A forecasting model for monthly Nigerian treasury bill rates by Box-Jankins techniques" from January 2006 to December 2014. The time plot of data shows a downward movement from 2006 to 2009 and upward movement to 2013. The 12 month seasonal differencing produces a horizontal trend and no seasonality. The test for stationary show that the monthly Treasury bill rate is stationary. The plot of the ACF shows a negative spike at lag 12, this indicates seasonality. The acceptable model for Treasury bill rates is SARIMA $(011)*(011)_{12}$ model.

Etuk and Amadi (2014) "A model for the forecasting of South African Rand and Nigerian Naira Exchange rate" from 20th march 2014 to 15th September 2014. The time plot of the series show negative secular trend. A 7 point seasonal differencing show a little negative trend and seasonality of period 7 in days. The test for stationary show that the series is non-stationary. The estimated model South African Rand and Nigerian Naira exchange rate is SARIMA $(111)*(111)_7$ and $(011)*(211)_7$.

Etuk (2013) "multiplicative SARIMA modelling of daily Naira-Euro exchange rates" from 8th December 2012 to 30th march 3013. In his discussion, the time plot of the exchange rates show upward and downward trend from December 2012 to early February 2013 and there is a downward trend from that time to late march. Seasonality is not clear but the seasonal differencing and non-seasonal differencing show a negative trend but no clear seasonality in the exchange rates of Naira to Euro. The plot of the ACF shows a negative spike at lag 7 which show seasonality at period 7. In his conclusion the exchange rates of Naira to Euro follow a SARIMA $(011)*(011)_7$ model.

Abdul-Aziz, Anokye, Kwame, munyakazi and Nuamah. (2013) "Modelling and forecasting rainfall pattern in Ghana as a seasonal ARIMA process" from 1974 to 2010 using the Box-Jenkins method. The time plot shows seasonality and trend. The test shows that the series is non-stationary. The twelfth month seasonal differencing makes the series stationary. The ACF and PACF show a spike at lag 12 which indicate seasonality. Four model was estimated for the series but the adequate model was choose base on the lest BIC, which is estimated as SARIMA $(0,0,0)*(2,1,0)_{12.}$

Etuk (2013) studied the seasonal ARIMA model of Nigerian monthly Crude Oil price in U$$ from 2006-2011. ARIMA was used for identification and estimation. Eview Software was use. The seasonality was revealed by time plot and autocorrelation or correlogram. The result of the time plot of the series reveals a peak in 2008 and a digression in 2009. Twelve month differencing still yields a peak in 2008 and a deep trough in 2009. Seasonality is not clear from the time plot. Correlogram revealed an autocorrelation suggested the SARIMA $(0,1,1)*(1,1,1)_{12}$

Material and Method

The relevant data needed for the work is monthly data on inflation rate (2013-2016). These data were obtained from Central Bank of Nigeria website (http://www.centralbank.org)

Model Identification

Identification of model consists of specifying the appropriate structure (AR, MA or ARMA) and order of model. Models can also be identified by looking at plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF). Thus making sure that the variables are stationary, identifying seasonality in the series is done by using the time plots of the ACF and PACF series, to decide if autoregressive or moving average component should be used in the model (Box -Jenkins (1970).

Estimation of Parameters

Coefficients of the models can be estimated by maximum likelihood estimation or non-linear least-squares estimation methods. Estimation of parameters of AR and MA and ARMA models usually requires a more complicated iteration procedure Box-Jenkins, (1970) and Chatfield (2004).

Model Diagnostic Check

Two important elements of checking are to ensure that the residuals of the model are random, and to ensure that the estimated parameters are statistically significant. Plotting the mean and variance of residuals over time and performing a Ljung-Box test or plotting autocorrelation and partial autocorrelation of the residuals are also helpful to identify misspecification.

Result and Discussion

The time plot of the series is shown in figure (1). The plot show many data point, since inflation is a seasonal phenomenon the data shown Seasonality but not obvious trend. The present of Seasonality in the Data will make it not to be stationary (A stationary series, is a series that has constant mean and variance). The correlogram of raw data is in figure (2), showing that the series is seasonal with a spike at lag 1, 12 etc. and a tapering pattern on the ACF and a spike at lag 1 and 13 on the PACF show a non-seasonal behaviour.

Test for Stationarity

Augmented Dickey Fuller test (unit root test) is used. The result of the (ADF) is show in figure (3).The value of ADF test statistics (-1.996533) is greater than -3.472813, -2.880088 and -2.576739 at 1%, 5% and 10%. The raw data is non-stationary at critical level (1%, 5%

and 10%).

Seasonal Differencing

The Augmented Dickey Fuller test (ADF) for seasonal and differencing (SDINFLATION) is show in figure (4).Since the ADF test statistics is the grater that the critical values at 1% 5% and 10% it means that the data is non- stationary.

Non-Seasonal Differencing of Seasonal Differences

The Augmented Dickey Fuller test (ADF) for non-seasonal and differencing (DSDINFLATION) is show in figure (5). Since the ADF test statistics is less than the critical values at 1% 5% and 10%. The non-seasonal differencing makes the series stationary.

Model Selection

Five models were estimated and the values of the Akaike Information Criterion are show below, calculated using Eviews software.

S/N	MODEL	AIC
1	SARIMA(111)*$(111)_{12}$	3.647788
2	SARIMA(011)*$(111)_{12}$	3.922079
3	SARIMA(011)*$(011)_{12}$	4.255401
4	SARIMA(111)*$(011)_{12}$	4.241093
5	SARIMA(011)*$(211)_{12}$	3.320160

The best model is the model that minimise the information criterion (SARIMA (001)*$(211)_{12}$) with AIC (3.320166)

FITTED MODEL SARIMA (011)*$(211)_{12}$

The output is in figure (6), the parameter of the model

$\Phi(Bs)\, \nabla sYt = \Theta(Bs)\theta(B)Wt$ 1.14

$DSDINFLATION_t = \Phi_1 DSDInflationt_{-12} + \Phi_2\, DSDInflationt_{-24} + \theta_1 W_{t-1} + \Theta_i Wt\text{-}_{12} + \Theta_1\theta_1 W_{t-13}$ 1.15

$DSDInflation_t = (-0.629924)DSDInflation_{t-12} + (-0.295980)DSDInflation_{t-24} + (0.235627)W_{t-1} + (-0.162842)W_{t-12} + (0.601357)W_{t-13} + W_t$ 1.16

Diagnostic Test

The analysis of the residual is used for goodness of fit model. The plot of the residual correlogram shows adequacy of the model in figure (7). The model is adequate since there is no spike that cut the level of the correlogram and the histogram of the residual is normally distributed with probability values (0.000026) is in figure(8)

Forecast

From the model at time t+k we have

$DSD\ INFLATION_{t+K} = \Phi_1\ DSDInflationt_{+K-12} + \Phi_2\ DSDInflationt_{+K-24} + \theta_1 W_{t+K-1} + \Theta_i Wt\text{-}12 + \Theta_1\ \theta_1 W_{t+K-13} + W_{t+K}$ 1.17

Where

K =1, 2 1.18.

The forecasting using the estimated model

$DSDINFLATION_{t+K}$ = (-0.629924)$DSDInflation_{t+K-12}$ + (-0.295980) $DSDInflation_{t+K-24}$ + (0.235627)W_{t+K-1} + (-0.162848)Wt-12 + (0.601357)W_{t+K}

And $W_{t+K} = 0$

The conditional expectations given the series up to time t,

When k = 1

$DSDINFLATION_{t+1}$=(-0.629924)$DSDInflation_{t-11}$+(-0.295980)$DSDInflation_{t-23}$ +(0.235627)W_t+ (-0.162848)Wt-11+(0.601357)W_{t-12} 1.19

When k=2

$DSDINFLATION_{t+2}$ = (-0.629924)$DSDInflation_{t-10}$ + (-0.295980)$DSDInflation_{t-22}$ + (-0.162848)W_{t-10}+(0.601357)W_{t-11}…….5.6

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When k = 12

$DSDINFLATION_{t+12}$ = (-0.629924)$DSDInflation_t$ + (-0.295980)$DSDInflation_{t-12}$ + (-0.162848)Wt +(0.601357)W_{t-1} 2.10

The estimated values of DSDinflation is show in figure (8) and the predicted inflation rate for 2017 in figure (9)

Conclusions

It may be concluded that inflation rate in Nigeria follows the SARIMA (0,1,1) x $(2,1,1)_{12}$ model. This model is adequate since it has the minimise information criterion (AIC) of (3.320166).

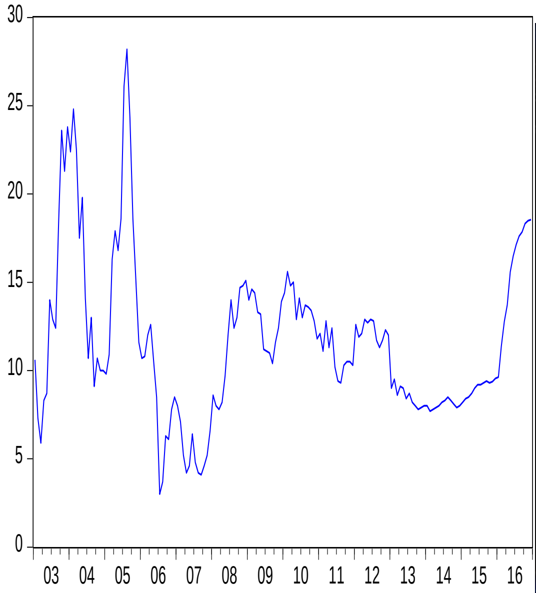
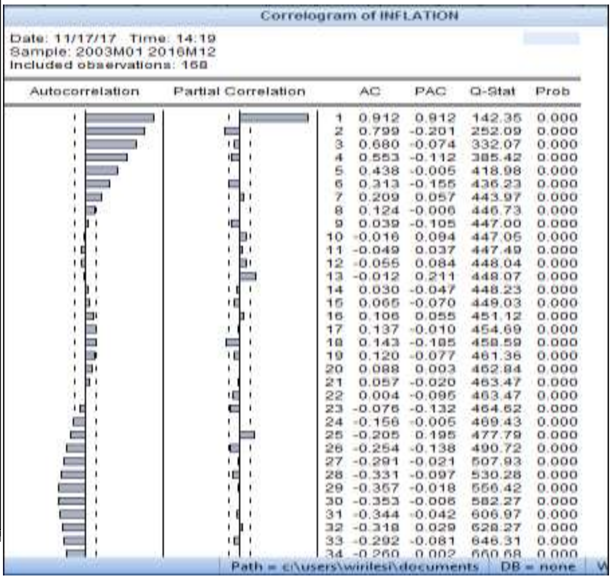


Figure (1)



	AC	PAC	Q-Stat	Prob
1	0.912	0.912	142.35	0.000
2	0.799	-0.201	252.09	0.000
3	0.680	-0.074	332.07	0.000
4	0.553	-0.112	385.42	0.000
5	0.438	-0.005	418.98	0.000
6	0.313	-0.155	436.23	0.000
7	0.209	0.057	443.97	0.000
8	0.124	-0.006	446.73	0.000
9	0.039	-0.105	447.00	0.000
10	-0.016	0.094	447.05	0.000
11	-0.049	0.037	447.49	0.000
12	-0.056	0.084	448.04	0.000
13	-0.012	0.211	448.07	0.000
14	0.030	-0.047	448.23	0.000
15	0.065	-0.070	449.03	0.000
16	0.106	0.055	451.12	0.000
17	0.137	-0.010	454.69	0.000
18	0.143	-0.185	458.59	0.000
19	0.120	-0.077	461.36	0.000
20	0.088	0.003	462.84	0.000
21	0.057	-0.020	463.47	0.000
22	0.004	-0.095	463.47	0.000
23	-0.076	-0.132	464.62	0.000
24	-0.156	-0.005	469.43	0.000
25	-0.205	0.195	477.79	0.000
26	-0.254	-0.138	490.72	0.000
27	-0.291	-0.021	507.93	0.000
28	-0.331	-0.097	530.28	0.000
29	-0.357	-0.018	556.42	0.000
30	-0.353	-0.006	582.27	0.000
31	-0.344	-0.042	606.97	0.000
32	-0.318	0.029	628.27	0.000
33	-0.292	-0.081	646.31	0.000
34	-0.260	0.002	660.68	0.000

Figure (2)

Table 1: Unit Root Test of Inflation Rate

Null Hypothesis: unit root test of inflation
Exogenous: Constant
Lag Length: 12 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.996533	0.2882
Test critical values:	1% level	-3.472813	
	5% level	-2.880088	
	10% level	-2.576739	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TIMEPLOT)
Method: Least Squares
Date: 02/10/17 Time: 10:38
Sample (adjusted): 2004M02 2016M12
Included observations: 155 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TIMEPLOT(-1)	-0.080617	0.040379	-1.996533	0.0478
D(TIMEPLOT(-1))	0.210856	0.081189	2.597121	0.0104
D(TIMEPLOT(-2))	0.002144	0.082171	0.026096	0.9792
D(TIMEPLOT(-3))	-0.014312	0.078490	-0.182341	0.8556
D(TIMEPLOT(-4))	-0.031693	0.074790	-0.423758	0.6724
D(TIMEPLOT(-5))	0.130610	0.073945	1.766308	0.0795
D(TIMEPLOT(-6))	-0.189016	0.074289	-2.544327	0.0120
D(TIMEPLOT(-7))	0.068963	0.072570	0.950294	0.3436
D(TIMEPLOT(-8))	0.101279	0.070593	1.434698	0.1536
D(TIMEPLOT(-9))	-0.118223	0.070451	-1.678088	0.0955
D(TIMEPLOT(-10))	-0.043927	0.070930	-0.619300	0.5367
D(TIMEPLOT(-11))	-0.039452	0.070870	-0.556687	0.5786
D(TIMEPLOT(-12))	-0.261825	0.069727	-3.754980	0.0003
C	0.903491	0.475811	1.898845	0.0596

R-squared	0.280727	Mean dependent var	-0.024839
Adjusted R-squared	0.214411	S.D. dependent var	1.682659
S.E. of regression	1.491399	Akaike info criterion	3.723286
Sum squared resid	313.6221	Schwarz criterion	3.998176
Log likelihood	-274.5547	Hannan-Quinn criter.	3.834940
F-statistic	4.233178	Durbin-Watson stat	1.930402
Prob(F-statistic)	0.000006		

Table 2: Seasonal Differencing of Inflation rate

Null Hypothesis: SINFLATION has a unit root
Exogenous: Constant
Lag Length: 12 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.346136	0.6069
Test critical values:	1% level	-3.476472	
	5% level	-2.881685	
	10% level	-2.577591	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SINFLATION)
Method: Least Squares
Date: 02/10/17 Time: 11:09
Sample (adjusted): 2005M02 2016M12
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SINFLATION(-1)	-0.076371	0.056734	-1.346136	0.1806
D(SINFLATION(-1))	0.196148	0.082858	2.367268	0.0194
D(SINFLATION(-2))	-0.022554	0.083679	-0.269525	0.7880
D(SINFLATION(-3))	-0.085487	0.081245	-1.052211	0.2947
D(SINFLATION(-4))	0.063681	0.077870	0.817790	0.4150
D(SINFLATION(-5))	-0.033990	0.075585	-0.449691	0.6537
D(SINFLATION(-6))	-0.160165	0.073462	-2.180248	0.0311
D(SINFLATION(-7))	0.032633	0.071913	0.453776	0.6508
D(SINFLATION(-8))	0.091642	0.068961	1.328896	0.1862
D(SINFLATION(-9))	-0.077124	0.067877	-1.136221	0.2580
D(SINFLATION(-10))	-0.075521	0.067095	-1.125573	0.2624
D(SINFLATION(-11))	-0.042060	0.066585	-0.631680	0.5287
D(SINFLATION(-12))	-0.423594	0.066244	-6.394427	0.0000
C	0.094328	0.174065	0.541911	0.5888

R-squared	0.435610	Mean dependent var	0.151049
Adjusted R-squared	0.378733	S.D. dependent var	2.609812
S.E. of regression	2.057066	Akaike info criterion	4.373211
Sum squared resid	545.8663	Schwarz criterion	4.663279
Log likelihood	-298.6846	Hannan-Quinn criter.	4.491081
F-statistic	7.658865	Durbin-Watson stat	1.875656
Prob(F-statistic)	0.000000		

Table 3:Non-Seasonal Differencing of Seasonal Differencing of Inflarion Rate
Null Hypothesis: DSINFLATION has a unit root
Exogenous: Constant
Lag Length: 12 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.430211	0.0000
Test critical values:	1% level	-3.476805	
	5% level	-2.881830	
	10% level	-2.577668	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DSINFLATION)
Method: Least Squares
Date: 02/10/17 Time: 11:11
Sample (adjusted): 2005M03 2016M12
Included observations: 142 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSINFLATION(-1)	-1.777369	0.276409	-6.430211	0.0000
D(DSINFLATION(-1))	0.975148	0.231197	4.217816	0.0000
D(DSINFLATION(-2))	0.910381	0.215968	4.215352	0.0000
D(DSINFLATION(-3))	0.785160	0.200129	3.923274	0.0001
D(DSINFLATION(-4))	0.832075	0.182283	4.564739	0.0000
D(DSINFLATION(-5))	0.752703	0.175446	4.290232	0.0000
D(DSINFLATION(-6))	0.558049	0.160758	3.471363	0.0007
D(DSINFLATION(-7))	0.575530	0.141560	4.065625	0.0001
D(DSINFLATION(-8))	0.644519	0.130089	4.954444	0.0000
D(DSINFLATION(-9))	0.540727	0.121343	4.456188	0.0000
D(DSINFLATION(-10))	0.438576	0.111672	3.927365	0.0001
D(DSINFLATION(-11))	0.378663	0.094276	4.016527	0.0001
D(DSINFLATION(-12))	-0.082084	0.074841	-1.096783	0.2748
C	0.105515	0.174755	0.603788	0.5471

R-squared	0.610537	Mean dependent var	0.008380
Adjusted R-squared	0.570982	S.D. dependent var	3.156877
S.E. of regression	2.067738	Akaike info criterion	4.384174
Sum squared resid	547.2690	Schwarz criterion	4.675593
Log likelihood	-297.2763	Hannan-Quinn criter.	4.502595
F-statistic	15.43519	Durbin-Watson stat	2.004537
Prob(F-statistic)	0.000000		

Table 4: Estimation of SARIMA(011)*(211)

Dependent Variable: DSDINFLATION
Method: Least Squares
Date: 03/28/17 Time: 11:02
Sample (adjusted): 2006M02 2016M12
Included observations: 131 after adjustments
Failure to improve SSR after 20 iterations
MA Backcast: 2005M01 2006M01

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.062870	0.092674	0.678401	0.4988
AR(12)	-0.629924	0.062470	-10.08368	0.0000
AR(24)	-0.295980	0.047128	-6.280283	0.0000
MA(1)	0.235627	0.064728	3.640264	0.0004
MA(12)	-0.162848	0.067226	-2.422384	0.0169
MA(13)	0.601357	0.068558	8.771481	0.0000

R-squared	0.679903	Mean dependent var	0.061832
Adjusted R-squared	0.667099	S.D. dependent var	2.157047
S.E. of regression	1.244563	Akaike info criterion	3.320166
Sum squared resid	193.6172	Schwarz criterion	3.451854
Log likelihood	-211.4708	Hannan-Quinn criter.	3.373676
F-statistic	53.10137	Durbin-Watson stat	1.794553
Prob(F-statistic)	0.000000		

Inverted AR Roots	.93-.17i	.93+.17i	.90-.32i	.90+.32i
	.72-.62i	.72+.62i	.62+.72i	.62-.72i
	.32+.90i	.32-.90i	.17+.93i	.17-.93i
	-.17+.93i	-.17-.93i	-.32+.90i	-.32-.90i
	-.62-.72i	-.62+.72i	-.72+.62i	-.72-.62i
	-.90+.32i	-.90-.32i	-.93-.17i	-.93+.17i
Inverted MA Roots	.90-.22i	.90+.22i	.70+.62i	.70-.62i
	.34-.89i	.34+.89i	-.12+.96i	-.12-.96i
	-.56+.81i	-.56-.81i	-.88-.46i	-.88+.46i
	-1.00			

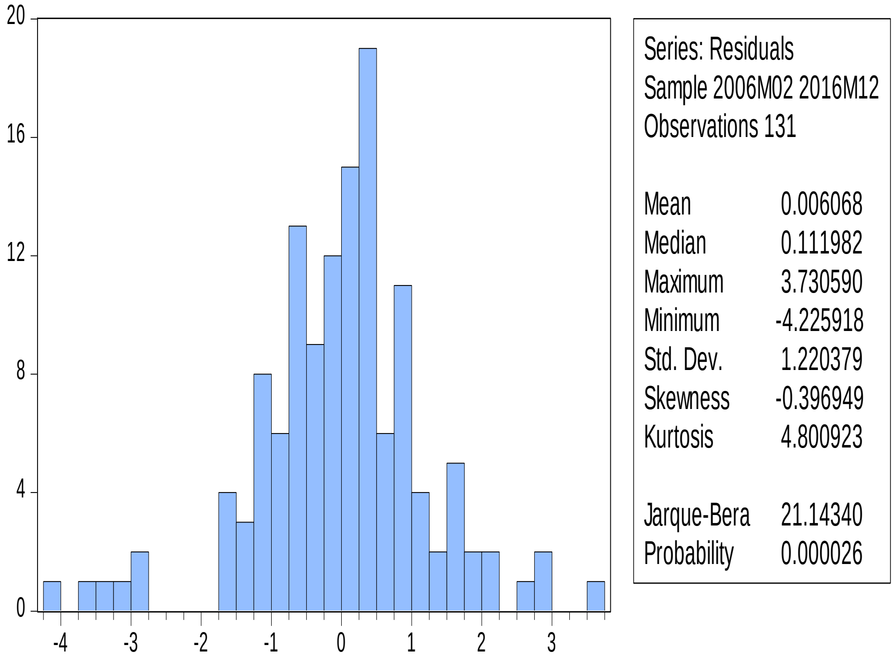


Figure 3:

Table 5: Forecast Value of Inflation from January 2017 to December 2017

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
18.735	18.705	19.75	20.533	21.533	22.935	23.549	23.629	24.229	24.269	24.324	24.761

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