Quest Journals
Journal of Research in Business and Management
Volume 6 ~ Issue 2 (2018) pp: 47-55
ISSN(Online) : 2347-3002
www.questjournals.org

Research Paper

SARIMAModelling of Inflation: The Case of Liberia

Felix Atanga Adongo[a] John Amo Jr. Lewis[b] Richmond Essieku[c] John Boamah[d]
James Chukwubudom Chikelu[e]
Xiamen University, China
Wang – Yanan Institute for Studies in Economics – School of Economics
Corresponding Author:Felix Atanga Adongo

ABSTRACT:*Not being doubtful of the fact that Inflation is one of the most important macroeconomic indicators assessing the economic well-being of a nation, this paper seeks to develop a model to forecastmonthly inflation rate for Liberia using Time Series Econometric tools and concepts. The paper used a monthly data on inflation from January 2005 through May 2018. Part of the data from January 2005 through May 2017 were used to assess the model's in-sample performance. The rest of the data were used to assess the out-of-sample performance of the model. It was realized that running the routinely ARIMA model was restrictive and less informative given the model's inability to capture any seasonality when there exists. Raw plot of log of inflation was stationary with evidence from the ADF, ADF-GLS and the PP testsfor unit root. Nonetheless, seasonal peaks were highly discernible from AC and PAC plots which appear to decay at a very slow rate. Seasonal difference was taken and the paper proposed 8 candidate models intended to slim the likelihood of missing out on a good model. Out of these models,* $ARIMA(1,0,0)(0,1,1)_{12}$ *emerged as the best model. Gross attention for model selection was given to the Information Criteria (AIC and SBIC), Ljung-Box test for serial correlation and significance of model's coefficients.*$ARIMA(1,0,0)(0,1,1)_{12}$*outperforms all other 7 proposed models both in-sample and out-of-sample with a fairly lower forecast error*
.

KEYWORDS:*Inflation, Forecast, Stationarity, Model, Seasonality, Unit Root, Difference, Information, Criteria, Serial, Correlation, In-Sample, Out-of-Sample, Performance, Time Series, Econometrics.*

Abbreviations: ARIMA: Autoregressive Integrated Moving Average ADF: Augmented Dickey-Fuller
ADF-GLS: Augmented Dickey-Fuller Generalized Least Squares PP: Phillips Perron
AIC: Akaike's Information Criterion SBIC: Schwarz Bayesian Information Criterion
AC: Autocorrelation PAC: Partial Autocorrelation

Received 09 July, 2018; **A**ccepted 23 July, 2018 © The author(s) 2018. **P**ublished with open access at **www.questjournals.org**

I. INTRODUCTION

Generally speaking, the practice of forecasting macroeconomic indicators has been considered a pivotal tool in both fiscal and monetary policymaking. Like any other macroeconomic indicator, future forecasts of inflation aids in determining current monetary policy as well helps both buyers and sellers to have an idea about the future outlook prices. The term inflation is defined as the persistent increase in the general prices of goods and services in a particular economy that results into a decline in the purchasing power of money. Inflation is an economic phenomenon that affects the behaviors of economic agents. Inflation can be used to effectively gauge the variation in the prices of the basket of consumable goods and services in a month, quarter or year. In Liberia, inflation is calculated by using Consumer Price Index (CPI).

Inflation is mainly caused by an imbalance between money supply and money demand, increase in taxes on goods or changes in the cost of production and distribution of goods and services. During this time, the value of money tends to fall whenever an economy experience an inflation. In other words, consumers can no longer buy the usual quantity of goods that they used to buy before inflation. The worst effect of inflation can be felt by consumers, especially households that depend on fixed income. The increase in the price of goods and services negatively affect their purchasing power, thereby, inducing them to demand for higher wages. As a result, government strive to keep inflation as low as possible. Even though inflation hurts the poor and fixed income earner, a modest level of inflation is good for an economy. Hence, research has proven that an inflation rate of 2% to 3% is advantageous for an economy given that consumers are encouraged to spend and borrow more because interest rate will tend to be low when inflation is low, hence, both the fiscal and monetary authorities of government always strive to maintain a moderate level of inflation.

Given the current wave of rising inflation in the Liberian economy, forecasting the next twelve months inflation would help buyers and sellers to prepare ahead of the uncertainty that inflation generate when price changes significantly over time. Therefore, in this paper, we use a time series Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast Liberia's monthly inflation rates among numerous models available. ARIMA models have received great criticisms about its failure to include explanatory variables in its modelling other than the past term of the process and past term of the errors. With this notwithstanding, according to Saz (2011),ARIMA models have been touted for the highest level of forecast accuracy compared to other econometric models because of its dynamism. The need therefore to extend such model to the domain of seasonality could be an interested field to explore (see, for example, Litterman 1986; Stockton & Glassman 1987; Nadal-De Simone 2000). Therefore the need to study SARIMA models and its application to macroeconomic data has become increasingly apparent. SARIMA models unlike simple econometric models have gained an appreciable limelight in the area of forecasting as almost every time dependent data contain a negligible to enormous amount of seasonality.

For a univariate time series forecasting, it is worth using quite a lengthy data as a minimum of 50 observations are recommended for a sound performance of model. (Meyler et al. 1998). With monthly inflation data from January 2005through May 2018, the selected model performed well both in-sample and out-of-sample. The paper proposed eight candidate seasonal ARIMA models including a constant model of only seasonal difference. Several criteria were used in carefully eliminating the models. However, the paper is particularly concerned with the out-of-sample performance rather than the in-sample fit. Being apprehensive of a situation where other closely competing models could outperform the selected model in terms of out-of-sample performance, the out-of-sample performances of these models were compared to the initially chosen model and the results were quite striking. There were insignificant to zero differences among the models with the MAE, RMSE and MAPE out-of-sample performance measures but slight differences were in favor of the initially chosen model$\text{ARIMA}(1,0,0)(0,1,1)_{12}$. Our best model in the framework of forecasting inflation in Liberia has by far lower forecast errors compared to the $\text{ARIMA}(0,1,0)(2,0,0)_{12}$ model proposed by (Fannoh et al. 2014) with fairly larger out-of-sample performance values. Therefore with thorough scrutiny of the data's behavior and being fastidious on modelling selection criteria entailing the AC and PAC plots, differencing, information criteria as well as adopting the appropriate tests,the SARIMA model was appropriateand more efficient for forecasting inflation in Liberia.

The rest of the paper is categorized into three sections, section II is concerned with the time series methods adopted in the modelling procedure, section III talks about the data and analysis and section IV presents the discussion of issues arising from data analysis and conclusions.

II. METHODOLOGY

The Time Series Econometrics

Time series models and concepts are fast becoming the most adopted concepts in analyzing and explaining a phenomenon thatis time related or occurs with time. Key among these modelsis the widespread ARMA model which forecasts a phenomenon looking at the past terms and past error terms of the phenomenon. The number of past terms and past error terms to consider depends massively on the data process.

ARMA Model

Generically, the Autoregressive Moving Average (ARMA) modelcan be written with (p)Autoregressive (AR) terms and (q) Moving Average (MA) terms as:

$A(L)(y_t - \mu) = B(L)u_t for\ t = -\infty, \ldots\ldots.., T\ and\ u_t \sim i.i.d(0, \sigma^2)$

$A(L) = 1 - \emptyset_1 L - \emptyset_2 L^2 - \cdots \ldots\ldots. -\emptyset_p L^p\ and\ B(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots \ldots\ldots. +\theta_q L^q$

In the $ARMA(p,q)$ model there are generally$(p + q)$ parameters to estimate $(\emptyset_1, \emptyset_2, \ldots\ldots, \emptyset_p and \theta_1, \theta_2, \ldots\ldots, \theta_q)$. Here, the error terms u_t are independent and identically distributed or are more conveniently called White Noise since independence is rather a stronger assumption. L is the lag operator or (back shift operator) and the equations $A(L) and B(L)$ are the characteristic equations or polynomials of the AR and the MA part respectively.Special cases in the ARMA models are when $\mu = 0$ and$A(L) = B(L) = 1$, then the $ARMA(p,q)$ model is the Independent White Noise process. When $A(L) = 1$, then the $ARMA(p,q)$ model becomes the $MA(q)$ model, when $B(L) = 1$, the $ARMA(p,q)$ model becomes $AR(p)$ model.

Unit Root Process (Random Walk)

Unit root also known as random walk almost always confront econometricians analyzing time series data as it becomes impossible to evade without obtaining spurious outcomes. Aware of this, innovative approaches are constantly sought to find out the possibilities of its occurrence in the data process. Famous and frequently used of these approaches are the Augmented Dickey-Fuller ADF (Dickey and Fuller, 1979), Augmented Dickey-Fuller GLS (Elliott et al. 1992), PP (Phillips and Perron, 1988) tests etc. This paper adopted the ADF test of unit root. The ADF test modifies the customary Dickey-Fuller test in order to account for any serial correlation in the dependent variable. The ADF test runs the following regression:$\Delta(y_t) = \alpha + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + u_t$ under the condition that $\sum_{i=1}^{p} |\gamma_i| < 1$. It tests the hypotheses; $H_0: \theta = 0$ against $H_1: \theta < 0$ where $\theta = \rho - 1$, ρ is the parameter of the process and $-1 \leq \theta < 0$. Under the null hypothesis, $\Delta(y_t)$ is weakly stationary and weakly persistent $AR(p)$ process. Under the alternative hypothesis, y_t is a weakly stationary and weakly persistent $AR(p+1)$ process. If the null hypothesis is not rejected, there will be problems of unit rootsince ρ will be equal to unity and hence non-stationarity. Consequently, under the plausibility of the null hypothesis, the process could then be transformed using the appropriate econometric tools and concepts to attain stationarity.

Integrated ARMA Model (ARIMA)

ARMA processes by default are weakly stationary and weakly dependent if the absolute or square summable of the MA coefficients are finite and the sum of the absolute values of the AR coefficients are less than unity $\{\sum_{i=1}^{q} |\theta_i| < \infty,\ \sum_{i=1}^{q} \theta_i^2 < \infty$ and $\sum_{i=1}^{p} |\emptyset_i| < 1\}$. There could be alarms of unit root (non-stationarity)in the ARMA model if one of the roots of the AR characteristic equation $A(L)$ lies either within or on the boundaries of a unit circle. Box and Jenkins (1976), suggest taking a difference of the process addressing non-stationarity or unit root problems. Taking the first difference of the random walk (unit root) process results in the White Noise process which are basically independent with constant mean and variance.Extending the idea of differencing to ARMA processes, the ARMA model becomes the Autoregressive Integrated Moving Average (ARIMA) model denoted by$A(L)\nabla^d (y_t - \mu) = B(L)u_t$ or $ARIMA(p, d, q)$where d is the order of difference.

Modeling Seasonality

Running a non-seasonal ARIMA model canoften timesbe restrictive given the model's failure to capture any seasonality if there exists. Forecasts from modelsthat fail to account for the presence of seasonality could be severely biased and there is noa better cause to believe these biases would be unsubstantial. Consequently, allowing the model to account for the presence of seasonality is very informative. We can either in the additive sense model seasonality by addinga slowly decaying seasonal component to the model to account for the seasonal dependence or in the multiplicative sense allow the seasonal and non-seasonal effect to interact by multiplying the AR and MA polynomials by seasonal polynomials. Additive seasonal model is given as $y_t = a_1 y_{t-1} + \tilde{a}_s y_{t-s} + u_t + \theta_1 u_{t-1}$, adding a slowly decaying AR seasonal component $\tilde{a}_s y_{t-s}$ to the $ARMA(1,1)$ model to capture seasonality. The multiplicative seasonal models are given as: $A(L)y_t = \left(1 + \tilde{\theta}_s L^s\right)B(L)u_t$ or $(1 - \tilde{a}_s L^s)A(L)y_t = B(L)u_t$ where s is the seasonal component.

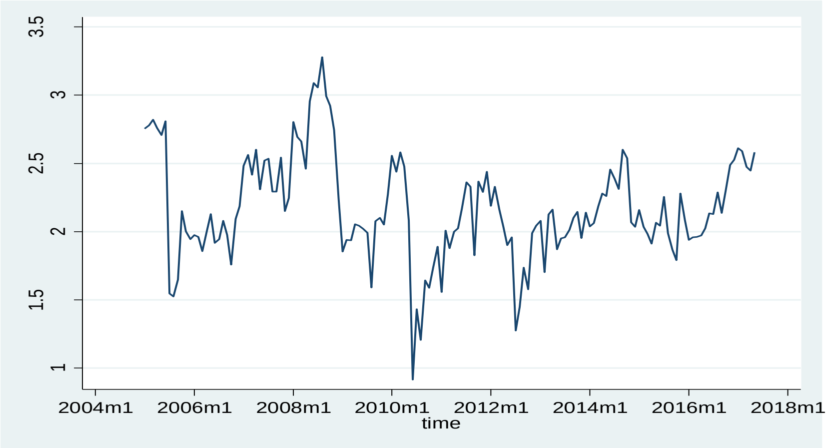
Seasonal Difference and the SARIMA Model

In order to properly handle a noticeable seasonality in the data process, seasonal difference at the s^{th} lag (seasonal lag) is routinely taken. Given a process y_t with seasonality, it is worth noting that $m_t \equiv (1 - L^s)y_t$ is the best option, and m_t is the deseasonalized process. Seasonal difference is necessary when the autocorrelation at the seasonal lags appear not to decay at a rapid rate, then seasonal difference is taken. It is interesting to learn that seasonal difference does not stimulate unit root, by contrast, it strengthens the stationarity of the process as evidenced by unit root tests. In order to forecast using deseasonalized data, it is thus appropriate to reseasonalize the data to obtain raw forecasts.Multiplicative seasonal ARIMAor SARIMA models are generally written in the form $ARIMA(p, d, q)(P, D, Q)_s$ where $p$and q are non-seasonal ARMA coefficients, d is the number of non-seasonal differences, P is the number of multiplicative seasonal AR coefficients, D is the number of seasonal differences, Q is the number of multiplicative MA coefficients and s is the seasonal period. The most commonly used and efficient SARIMA models are the ones with fewer seasonal and non-seasonal AR and MA terms such as $ARIMA(1,1,0)(0,1,1)_s$ and $ARIMA(0,1,1)(0,1,1)_s$ because the entertain parsimony pretty well.

III. DATA AND ANALYSIS

In order to realize the objective of this paper, we applied the econometric methods discussed in section II on monthly time series data in this section. The data used in the paper is a monthly data on inflation for

Liberia from January 2005 through May 2018. The paper divided the data intotwo unequal parts with one part from January 2005 through May 2017. The second partis from June 2017 through May 2018. The first part of the data will be used to assess the in-sample performance of the model (assessing how well the model fits the data). The second part of the data will be used to assess the out-of-sample performance of the model (assessing how well the model predicts the data outside of the sample).



From the plot of the raw data of log of inflation, naively, we observe stationarity inferring from the fact that the plot does not trend with time. However the absence of either an upward or downward trend by a mere observation of plots could sometimes lead to false conclusions regarding stationarity. The Dickey-Fuller tests for unit root is conservative in testing for stationarity. In order to capture any time dependence in the data, change in the log of inflation ($\Delta \ln(Inflation)_t$) is regressed on time trend t and first lagged term of the log of inflation ($ln(Inflation)_{t-1}$). In order to guard against issues of serial correlation in the error terms of ($\Delta \ln(Inflation)_t$), the test included 4 differencedlagged terms of ($ln(Inflation)_{t-1}$). The approach is widely adopted by researchers in stationarity check called the Augmented Dickey-Fuller (ADF) test for unit root (Random Walk). From the test, we can infer from the test statistic -4.052 that, since the absolute value of the test statistic is greater than the absolute values for the tests at 1%, 5% and 10%level of significance each, then, we can reject the null hypothesis of unit root in the alternative's favor. The MacKinnon p-value of 0.0074 for the test suggest even a stronger evidence against unit root. Other convincing tests for unit root were performed on this data including the Augmented Dickey-Fuller GLS and the Phillips Peron tests and the results likewiseprovided evidence against the null hypothesis of unit root. Therefore the raw data of the log of Inflation is a stationary data. Syntax for Augmented Dickey-Fuller test in Stata is;***dfuller depvar, trend regress lags(k)*** where k is the number of lags.

Output of the Augmented Dickey-Fuller test is shown below(regression output not shown):

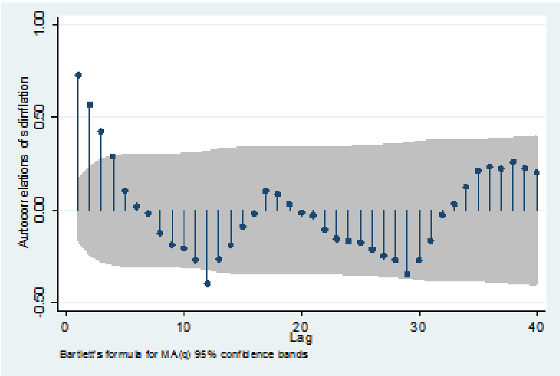
```
Augmented Dickey-Fuller test for unit root          Number of obs   =       144

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.052            -4.025            -3.444            -3.144
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0074
```

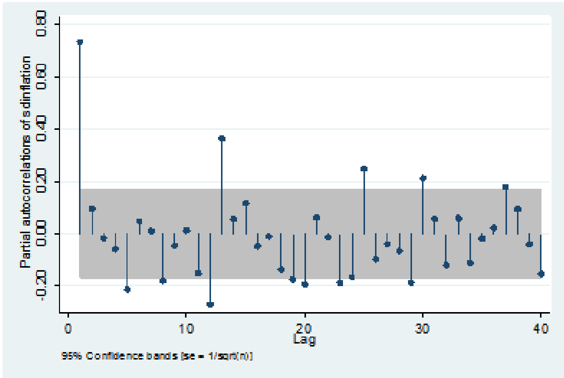
Guaranteed thus about the stationarity of the data, yet, we couldrun into issues of seasonality given the monthly report of data on Inflation. First seasonal difference was taken in an attempt to sidestep the issue of seasonal fluctuations or high peaks which appear persistent and repeats periodically at a regular interval. The best guess of a type of model for this kind of data process would be a model (not specifying AR and MA terms) with a seasonal difference and zero non-seasonal difference so to speak. After the seasonal difference, the ADF, ADF-GLS and the Phillips Peron tests for unit root even revealed an overwhelming evidence against the null

hypothesis of unit root. MacKinnon's p-value for the test (output not shown) is 0.0020 indicating no concern of random walk.
Box Jenkins Conventional Approach

Identifying and estimating the Seasonal and Non-seasonal terms

The autocorrelation (AC) and partial autocorrelation (PAC) plots are used here in determining both seasonal and non-seasonal AR and MA terms of the prospective model. The AC and PAC plots of the first seasonal difference of the log of inflation are shown below.





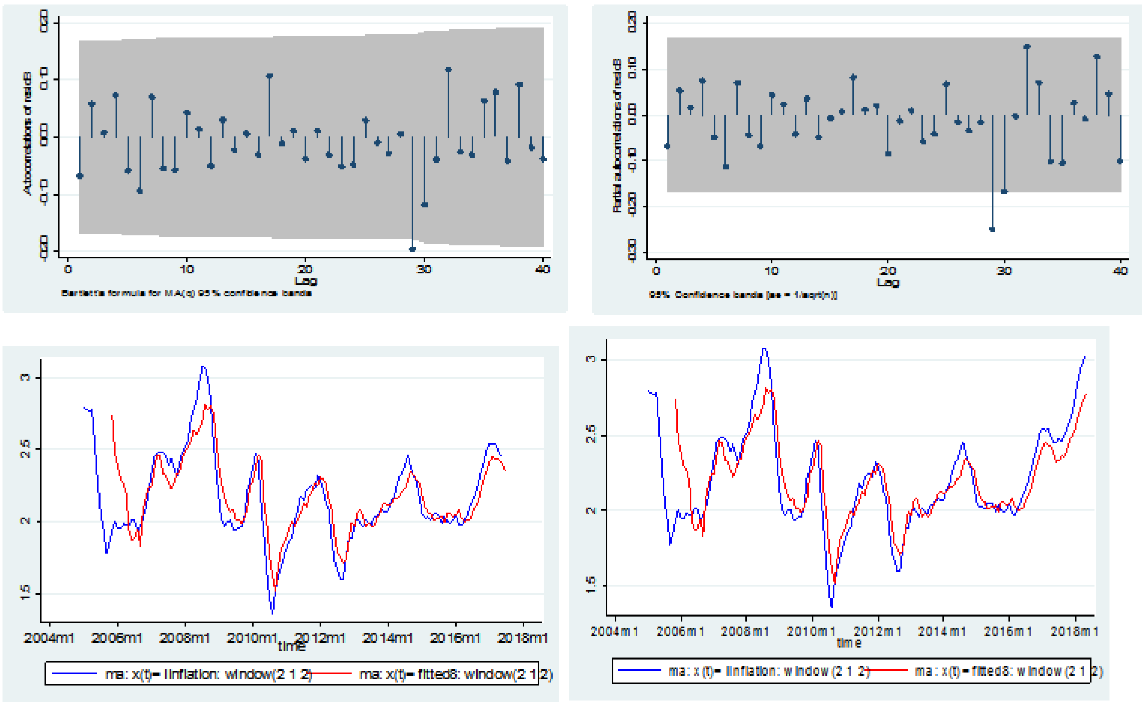
Deducing from the correlograms, the AC plot on the left is not very educational as it shows relatively quite a considerable number of lags beyond the Bartlett 95% confidence region. This suggests including either 3 seasonal or 3 non-seasonal MA terms which is counterintuitive and hostile to addressing concerns of parsimony. Conversely, the PAC plot on the right shows a first significant lag and subsequently noticeable significant lags appear to be seasonal (multiple of 12 or roughly 12) indicating a very strong seasonal AR term (seasonal AR term of a unit order). The AC and PAC plots of log of inflation free of seasonal difference show a similar pattern (plots not shown). This further logically suggests fitting a model with seasonal and non-seasonal AR terms of a unit order each. With this notwithstanding, the study identified and estimated 8 possible seasonal ARIMA models including a constant model (model with the first seasonal difference without AR, MA, SAR and SMA terms). This is done to slim the likelihood of missing outon a good fitting model observing the correlograms alone. These models were compared based on their Akaike (1974) Information Criterion (AIC), Schwarz (1978) Bayesian Information Criterion (SBIC), significance of the models' estimated coefficients and the Ljung Box test for serial correlation (a.k.a. Portmanteau test for white noise). Gross attention was however given to the Information Criteria, AC and PAC plot of models' residuals while entertaining frugality in fitting model parameters. The table below shows the diagnostic checks of the proposed models estimated in Stata with the ***`arima depvar, arima(p,d,q) sarima(P,D,Q,S)`*** command and the ***`vce(robust)`*** option to address potential issues of heteroskedasticity.

Model	Information Criteria		Diagnostic Check	
			Portmanteau Test (16 Lags)	
	AIC	BIC	Q-Statistic	p-value
1. ARIMA(0,0,0)(0,1,0)$_{12}$	230.3255	236.1655	230.4270	0.0000
2. ARIMA(1,0,0)(1,1,0)$_{12}$	90.4653	102.1452	10.8940	0.8160
3. ARIMA(0,0,1)(1,1,0)$_{12}$	142.2758	153.9557	92.1401	0.0000
4. ARIMA(1,0,1)(1,1,0)$_{12}$	91.1572	105.7571	9.0251	0.9124
5. ARIMA(2,0,1)(1,1,0)$_{12}$	92.7063	110.2262	9.0438	0.9116
6. ARIMA(1,0,2)(1,1,0)$_{12}$	92.6755	110.1954	8.6819	0.9259
7. ARIMA(1,0,1)(1,1,1)$_{12}$	50.9888	68.5087	4.8969	0.9962
8. ARIMA(1,0,0)(0,1,1)$_{12}$	50.6203	62.3002	6.5699	0.9807

The constant model ARIMA(0,0,0)(0,1,0)$_{12}$ and ARIMA(0,0,1)(1,1,0)$_{12}$inferring from the table above are not good models at all given their relatively large AIC and BIC values and Q-Statistic of the Portmanteau test. Moreover, the p-values of the test for white noise are not significantly different than zero. This implies an overwhelming evidence against the null hypothesis which posits that the errors are white noise against the alternative hypothesis of serially correlated errors. The null hypothesis in this fashion is not a plausible statement. Models 1 and 3 therefore have issues of poor fitting and appreciable evidence of serial correlation among the error terms. The remaining 6 models fit the data pretty well observing the lines plots (not shown) of actual and predicted log of inflation. Not forgetting, we must entertain parsimony pretty well while looking at goodness of fit. As we fit a seasonal ARIMA model with higher parameters to be estimated, the reliability or significance of the estimates could be adulterated and may severely affect the precision of the modelfrom the angle of forecasting. A victim of this is the$\text{ARIMA}(2,0,1)(1,1,0)_{12}$ model where none except seasonal AR term of the estimates was found to be significant despite joint significance.Also, amidst joint significance, the $\text{ARIMA}(1,0,2)(1,1,0)_{12}$ model has only the seasonal and non-seasonal AR terms significant at the expense of the 2 non-seasonal MA terms. These are utterly attributed to over fitting or a case I call the parsimony breach. Their AIC and BIC are fairly large as well.

$\text{ARIMA}(1,0,1)(1,1,0)_{12}$ estimates three parameters with significant AR terms and an overall significance. Not dwelling solely on AIC and BIC for the smallest possible values, $\text{ARIMA}(1,0,1)(1,1,1)_{12}$ estimates 4 parameters with again significant autoregressive terms at the expense of seasonal and non-seasonal MA terms. The models $\text{ARIMA}(1,0,0)(1,1,0)_{12}$ and $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ are both estimating two parameters and estimates are both significant at the 1% level. Now comparing the AIC and BIC values of these two parsimonious models, we will unhesitatingly choose $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ given its relatively smaller AIC and BIC values. So the best possible model now in our setting is $\text{ARIMA}(1,0,0)(0,1,1)_{12}$, anAR term with a seasonal MA term. A model which is jointly significant with the lowest AIC and BIC and more parsimonious. Later on in this section, we will compare the out-of-sample performance of our selected model $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ to $\text{ARIMA}(1,0,0)(1,1,0)_{12}$ and $\text{ARIMA}(1,0,1)(1,1,1)_{12}$ using the Mean Absolute Forecast Error (MAFE), the Root Mean Square Forecast Error (RMSFE) and the Mean Absolute Percentage Forecast Error (MAPFE)

Graphical Representation of $\mathbf{ARIMA(1,0,0)(0,1,1)_{12}}$ ***Performance (Further Diagnostic Checks)***



The AC and PAC plots of the residuals of our selected model$\text{ARIMA}(1,0,0)(0,1,1)_{12}$ confirm the smaller Q-Statistic and a bigger p-value for the Portmanteau test of white noise. Roughly 98% of lags from AC and PAC plots are within the confidence regions indicating an overwhelming possibility of having serially uncorrelated errors for the $\text{ARIMA}(1,0,0)(0,1,1)_{12}$model. Essentially, the line graphs beneath AC and PAC plots were smoothened using the moving average method of two lags and two leads so to differentiate the signal from the noise using the ***tssmooth ma newname = varname, window(2,1,2)***Stata command.Thegraph on the left is the fitted and true values of log of inflation using the $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ model with data through May 2017. The graph on the right is the fitted and the true values of log of inflation with the same model using data through May 2018. The fitted values from June 2017 through May 2018 on the right are out-of-sample forecasts. From the line graphs, we can obviously say that, the model has good in and out-of-sample performance.The motivation behind every time series forecasting is to minimize the loss function. This can be achieved by minimizing the forecast error so that predicted values (forecasts) will always go closer to the realized values. The common statistics used in assessing the out-of-sample performance are the MAFE, RMSFE and MAPFE mentioned earlier.

Date	Log of Inflation (Realized)	Log of Inflation (Forecasted)	Forecast Error
June 2017	2.381974	2.437996	-.0560212
July 2017	2.348729	2.218437	.1302918
August 2017	2.510719	2.221353	.2893659
September 2017	2.570459	2.424552	.1459068
October 2017	2.473851	2.509969	-.0361185
November 2017	2.569608	2.387816	.1817915
December 2017	2.631469	2.477067	.1544024
January 2018	2.737488	2.530545	.2069433
February 2018	2.881157	2.597584	.2835728
March 2018	2.971609	2.702623	.2689858
April 2018	3.063391	2.782496	.2808952
May 2018	3.057080	2.828655	.2284243

From the table above, MAFE for the model is 0.189, RMSFE is 0.206 and MAPFE is 6.883.The selected model seems not disappointing in forecasting the data out-of-sample. But how could we justify it is really the best among the 2 other closely contended models? Now returning to the equally parsimonious multiplicative Autoregressive model $\text{ARIMA}(1,0,0)(1,1,0)_{12}$ with two highly individual significant AR coefficients and the model with comparatively smaller AIC and BIC values,$\text{ARIMA}(1,0,1)(1,1,1)_{12}$, we can make comparisons of how these models are performing out-of-sample with our selected model$\text{ARIMA}(1,0,0)(0,1,1)_{12}$.Below is the tabulated results for the forecast performances of the three models.

Model	Forecast Performance Measure		
	MAE	RMSE	MAPE
1. $\text{ARIMA}(1,0,0)(0,1,1)_{12}$	0.189	0.206	6.883
2. $\text{ARIMA}(1,0,1)(1,1,1)_{12}$	0.190	0.212	6.915
3. $\text{ARIMA}(1,0,0)(1,1,0)_{12}$	0.189	0.208	6.907

The parsimonious models $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ and $\text{ARIMA}(1,0,0)(1,1,0)_{12}$ have roughly an identical MAFE but a very slight difference in RMSFE and MAPFE in favor of $\text{ARIMA}(1,0,0)(0,1,1)_{12}$ indicating a better out-of-sample performance of the initial selected model over the other competing two models.$\text{ARIMA}(1,0,0)(0,1,1)_{12}$ minimizes the loss function than any of the closely contended models given the lower forecast errors. However in a broader spectrum, any of these three competing models could be used in forecasting inflation given the slight differences among the models in assessing forecast performances.But the best model in our context is $\text{ARIMA}(1,0,0)(0,1,1)_{12}$. In a much simplified form the selected model can equivalently be written as: $\ln(Inflation)_t = \alpha_0 + \emptyset_1 \ln(Inflation)_{t-1} + \epsilon_t + \theta_{12}\epsilon_{t-12}$, where α_0 is the intercept, $\emptyset_1$ is the non-seasonal AR coefficient, θ_{12} is the seasonal MA coefficient and ϵ_t is the error term. The other two competing models can equally be written as:

$$\ln(Inflation)_t = \alpha_0 + (1 + \emptyset_1 L)(1 + \emptyset_{12} L^{12}) \ln(Inflation)_{t-1} + \epsilon_t$$

$$\ln(Inflation)_t = \alpha_0 + \emptyset_1 \ln(Inflation)_{t-1} + \theta_1\epsilon_{t-1} + \epsilon_t + \emptyset_{12} \ln(Inflation)_{t-12} + \theta_{12}\epsilon_{t-12}$$

IV. DISCUSSION AND CONCLUSIONS

In effect, this paper explicitly scrutinizes the data and identified 8 candidate models based on the pattern of lags on correlograms whiles being mindful of the goodness of fit parsimony trade off. Generally, 6 models seem to fit the data well given their 0.0000 p-value for the test of an overall model fit or joint significance. Per the PAC plots of log of inflation and the deseasonalized log of inflation, incorporating an autoregressiveterm is key given a significant lag in both plots. The AC plots of similar data was not very instructive as we found rather quite a substantial number of significant lags with a great decayof lags thereafter, an incident suggesting none or a maximum of one moving average termin the model prioritizing parsimony. The AC plot alternatively suggests that, moving average terms could be nuisance to the model. Despite the moderately larger AIC and BIC values of $\text{ARIMA}(1,0,0)(1,1,0)_{12}$, its terms perfectly align with the PAC plots which clearly evidencedthe presence of AR terms both seasonal and non-seasonal.$\text{ARIMA}(1,0,0)(0,1,1)_{12}$ and $\text{ARIMA}(1,0,1)(1,1,1)_{12}$also were found with extremely low AIC and BIC values relative to the other competing models. The differences in values of the Information Criteria between the two models canbe ignored. However, the principle of parsimony would choose the former over the latter.So the paper selected the model based on parsimony, the values of the Information Criteria and the end result was not regrettable.The best model among the numerous models proposed is $\mathrm{ARIMA}(1,0,0)(0,1,1)_{12}$ and the model is thus estimated and shown below and can be used henceforth for forecasting inflation in Liberia:

$$\ln(Inflation)_t = -0.0141621 + 0.7608699 * \ln(Inflation)_{t-1} + \epsilon_t - 0.9999993 * \epsilon_{t-12}$$

However, this forecasts inflation in natural logarithms. Forecast values of realized inflationcan then be obtained by simply exponentiating the logged values of inflation.

Notes: We could not take any first non-seasonal difference because AC and PAC plots did not show any significant lag suggesting a constant model for forecasting inflation which is least to say is less informative. Additional models could be proposed but again, parsimony must be remembered. The ACplots of the residuals and line plots of realized and fitted values of thetwo closely competing models above are shown in the Appendix of this paper. This is done to notify future researchers on modelling inflation about the models' good in and out-of-sample performances in the context of forecasting inflation for Liberia.They could also emerge as best models in forecasting inflation undervariousforms of data transformationsuch as scaling, differencing, smoothing, logging etc.Line plots in Appendix are smoothened with the moving average style including two lags and two leads.

REFERENCE

[1]. Akaike, H., 1974. A New Look at Statistical Model Identification, *IEEETransactions on Automatic Control*, AC-19, pp. 716-723.

[2]. Box, G.E.P., and Jenkins, G.M. 1976. Time Series Analysis, Forecasting and Control. Holden-day.

[3]. Enders, W., Applied Econometric Time Series (Wiley series in probability and statistics), 4th Edition.

[4]. Fannoh, R., Orwa, G. O., Mung'atu, J. K. 2014. Modeling the inflation rate in Liberia SARIMA Approach, International Journal of Science and Research (IJSR). ISSN(Online): 2319 – 7064.

[5]. Litterman, R.B. 1986. Forecasting with Bayesian vector autoregressions- Five years of experience. Journal of Business and Economic Statistics 4, 25-38.

[6]. Meyler, A., Kenny, G., and Quinn, T. 1998, Forecasting Irish Inflation using ARIMA models, Economic Analysis, Research and Publications Department, Central Bank of Ireland, PO Box 559, Dublin 2.

[7]. Nadal-de Simone Franscisco 2000. Forecasting inflation in Chile using State-space and Regime-switching models, IMF Working Papers 00/162, International Monetary Fund.

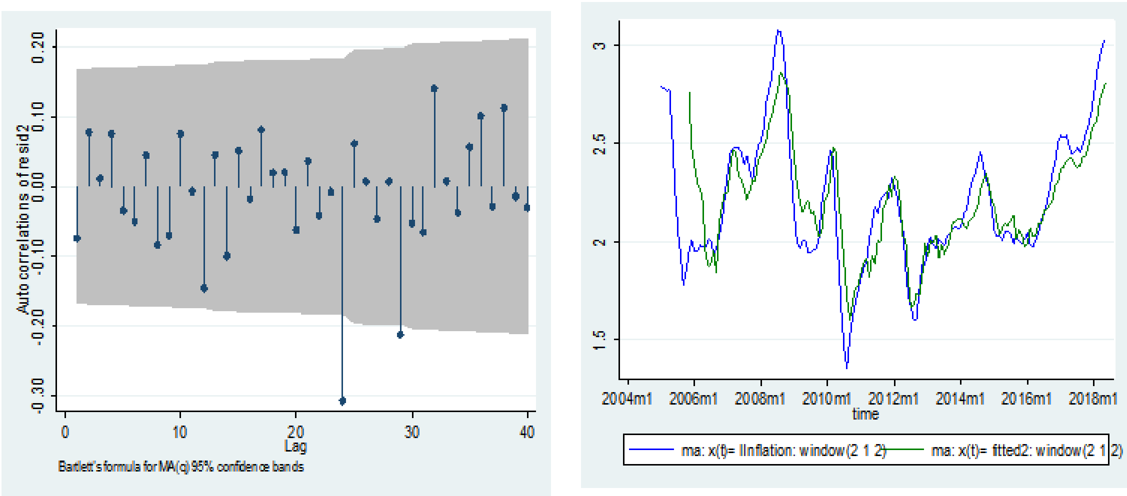
[8]. Otu Archibong Otu, Osuji George A., Opara Jude, Mbachu Hope Ifeyinwa, and Iheagwara Andrew I.Application of SARIMA Models in Modelling and Forecasting Nigeria's Inflation Rates. American Journal of Applied Mathematics and Statistics 2, no. 1(2014): 16-28. doi:10.12691/ajams-2-1-4

[9]. Saz,G. (2011).The efficacy of SARIMA models in forecasting inflation rates in developing countries: The case for Turkey, International Research Journal of Finance and Economics, 62, 111-142.

[10]. Stockton, D., and Glassman, J. 1987. An evaluation of the forecast performance of alternative models of inflation, Review of Economics and Statistics, Vol 69, No 1 , February, pp 108-117

Appendix

Autocorrelation plot of residuals of $\mathrm{ARIMA}(1,0,0)(1,1,0)_{12}$ and line plots of actual and fitted values of log of inflation (both in sample and out-of-sample fit)



Autocorrelation plot of residuals of ARIMA(1,0,1)$(1,1,1)_{12}$ and line plots of actual and fitted values of log inflation (both in sample and out-of-sample fit)