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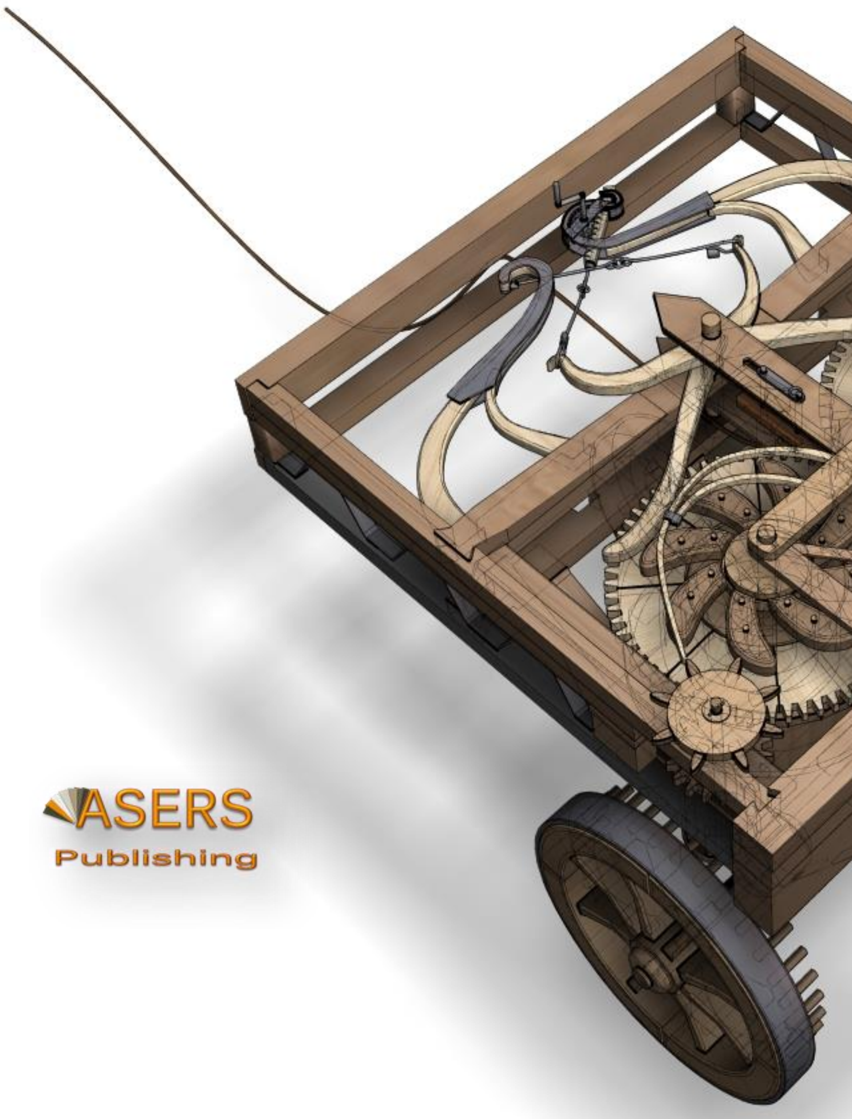
Theoretical and Practical Research in Economic Fields



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Contents:

1	**Tourism Demand and Exogenous Exchange Rate in Cambodia: A Stochastic Seasonal ARIMAX Approach** Theara CHHORN	…5
2	**Wage Inequality and Innovative Intelligence-Biased Technological Change** Taiji HARASHIMA	…17
3	**Technical Trading Rules and Trading Signals in the Black Market for Foreign Exchange in Sudan** Ibrahim A. ONOUR	…25
4	**Assessing the Impact of Integration on Economic Growth and Food Security in ECOWAS** Almame Abdoulganiour TINTA, Daniel Bruce SARPONG, Idrissa Mohamed OUEDRAOGO, Ramatu Al HASSAN, Akwasi Mensah-BONSU, Edward Ebo ONUMAH	…32
5	**Aggregation with a Non-Convex Labour Supply Decision, Unobservable Effort, and Reciprocity (“Gift Exchange”) in Labor Relations** Aleksandar VASILEV	…45
6	**The Credit Channel Transmission of Monetary Policy in Tunisia** Ali MNA, Moheddine YOUNSI	…49
7	**Forecasting Inflation in Sierra Leone Using ARIMA and ARIMAX: A Comparative Evaluation. Model Building and Analysis Team** Edmund TAMUKE, Emerson Abraham JACKSON, Abdulai SILLAH	…63
8	**Monetary Policy of Georgia in XI-XII Centuries and Its Influence on the International Financial and Economic Relations** George ABUSELIDZE	…75
9	**Creative Economy Development Based on Triple Helix in Indonesia** Rudy BADRUDIN, Baldric SIREGAR	…82
10	**Investment Attraction, Competition and Growth; Theoretical Perspective in the Context of Africa** Emmanuel Tweneboah SENZU	…92
11	**Evolution of International Trade in Romania between 2016 - 2018 with Forecasts for 2019-2021** Octavian Dan RĂDESCU	…103
12	**The Link Between Migration, Remittances and Economic Growth: Empirical Evidence from Romania** Ramona PIRVU, Roxana BADARCEA, Alina MANTA, Nicoleta FLOREA	…109

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Volume IX, Issue 2(18), Winter 2018
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FORECASTING INFLATION IN SIERRA LEONE USING ARIMA AND ARIMAX: A COMPARATIVE EVALUATION. MODEL BUILDING AND ANALYSIS TEAM[4]

Edmund TAMUKE
Research Department, Bank of Sierra Leone

Emerson Abraham JACKSON
Research Department, Bank of Sierra Leone
emersonjackson69@gmail.com

Abdulai SILLAH
Research Department, Bank of Sierra Leone

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Abstract

The study has provided empirical investigation of both ARIMA and ARIMAX methodology as a way of providing forecast of Headline Consumer Price Index (HCPI) for Sierra Leone based on data collected from the Sierra Leone Statistical Office and the Bank of Sierra Leone. In this, the main research question of addressing outcomes from in and out-of-sample forecast were provided using the Static technique and this shows that both methodologies were proved to have tracked past and future occurrences of HCPI with minimal margin of error as indicated in the MAPE results. In a similar note, the key objective of identifying whether the ARIMAX methodology or the ARIMA methodology is a better predictor of forecasting future trends in HCPI. However, on the whole, both ARIMA and ARIMAX seem to have provided very good outcome in predicting future events of HCPI, particularly when Static technique is used as the option for forecasting outcomes, with the ARIMAX marginally coming out as the preferred choice on the basis of its evaluation outcomes.

Keywords: ARIMA; ARIMAX; Box-Jenkins; HCPI; NEXR; Sierra Leone

JEL Classification: C32; C52; C53.

Introduction

Inflation and its dynamics is a topical concept in Sierra Leone and more so, a primary objective of the central bank in maintaining stability to general prices of goods and services in the country. In this situation, it is part of the culture by senior management to continuously track dynamics of inflation [Year-on-Year and Month-on-Month], both as a univariate element and jointly with some explanatory variables which are key in influencing inflation movement in the country as a whole. Given the emphasis on the need to monitor inflation dynamics, staff in the Model Building and Analysis Section [MBAS] are regularly assigned the responsibility of using appropriate methodologies and for which Box-Jenkins Autoregressive Moving Average and Autoregressive Integrated Moving

[4] **Disclaimer**: Views expressed in this article are those of the authors and nothing to do with the named institution.

Average [ARIMA] seemed popular in forecasting inflation dynamics relevant for short-term policy formulation at the Bank of Sierra Leone [BSL].

The graphs below provide a snapshot of key variables like HCPI [normally used as a proxy for inflation in Sierra Leone] and Nominal Exchange Rate [NEXR] as an explanatory component in forming part of the model forecast for this study.

Figure 1. Graph Showing Seasonal Adjusted HCPI and NEXR Trends

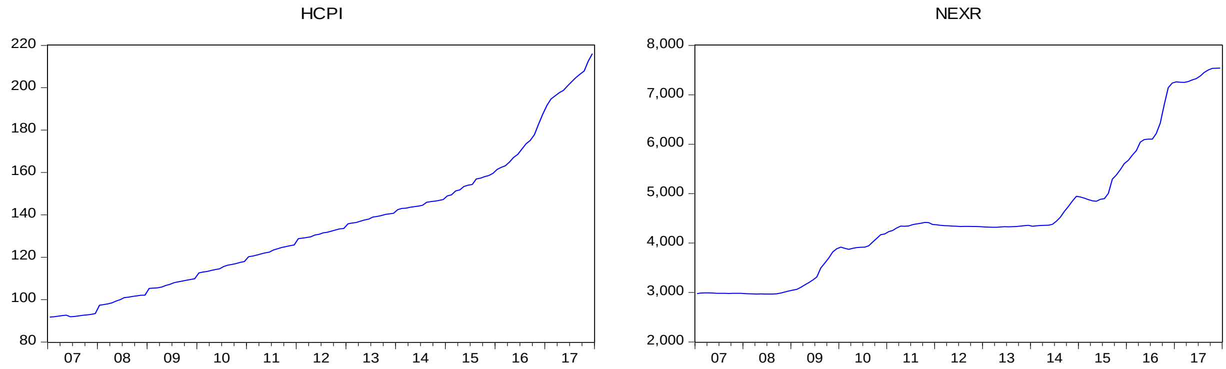


Figure 1 above shows the seasonally adjusted trends for both HCPI and NEXR over monthly periods from 2007M1 to 2017M12. The pattern for HCPI seemed more deterministic, while that of NEXR seem quite interesting in terms of break pattern, more so around 2008. Some researchers like Theil (1954), Grunfeld and Griliches (1960) and more lately, Hubrich (2005) are convinced in some way about the efficiency of the use of both models, but more so when an explanatory variable is used as dictated by the quality of data.

The main question that is set to be answered here is: ***Does ARIMAX provide a better forecast outcome than that of a normal ARIMA model***? In this vein, the main objective here is to investigate the accuracy of in-sample and out-of-sample forecast for both ARIMAX and ARIMA approaches using HCPI for the ARIMA and NEXR as an explanatory variable for the ARIMAX.

The rest of the paper is structure as follows: Section two present the Literature Review, which is further divided into Theoretical and Empirical review. Section three addresses the Methodological Framework and Data Collection, also sub-divided by looking at details of Time series models for both ARIMA and ARIMAX approaches, Methodology and Data usage. Section four addresses the Empirical Analysis and Discussion, section five discuss the interpretation for the Sierra Leone economy, while section six provide conclusion on the outcome, with some salient points for policy recommendation in terms of model evaluation.

1. Literature Review

This section addresses both theoretical and empirical literature on works carried out on both ARIMA and ARIMAX output by various authors.

1.1. Theoretical Literature Review of ARIMA Modelling

The use of ARIMA and ARIMAX seemed to be quite popular given the fact that as time series data, their future predictability can be easily determined through their past occurrences (Paul *et al*. 2013 and Dash, 2017). In her master's thesis, Green (2011) used the ARIMA models with attention focused on Box-Jenkins Approach - in this, she found out that ARIMA model is the most appropriate for classifications of time series data sets on the basis of their behavior.

While ARIMA only looks at the Univariate component of past events of the same variable, its counterpart, ARIMAX make it possible to track moment or shocks to the variable with independent predictor(s). According to Kravchuk (2017), the ARIMAX model is considered to be a form of multivariate regression model which allows to take advantage of autocorrelation that may be present in residuals of the regression to improve the accuracy of a forecast.

As emphasised by Nosedal (2016), univariate forecasting methods (including ARIMA methods) are based on the same logic - firstly, the expected value of the time series process is calculated, while secondly, the expected value is extrapolated into the future. In this case, with the current time series observation being Y_t, our forecast model equation for predicting future events can be expressed as $Y_{t+1}, Y_{t+2}, \ldots, Y_{t+n}$.

1.2. Empirical Literature Review of ARIMA Modelling.

As a way of finding out best practice on the output of empirical study on ARIMA, Jackson *et al.* (2018) carried out an investigation on the Box-Jenkins ARIMA methodology using univariate HCPI data. This study provided evidence on which the use of Static approach to the methodology was seen as the best outcome, with MAPE and other statistical evidences showing very close outcome for both the within and out-of-sample forecast results. In the same token, another more specific output was provided by Jackson (forthcoming) in which the Static output coming out as one of the best means of forecast when compared to that of the Dynamic technique. In this, the author stressed the fact that both techniques (Static and Dynamic) can be very good, but the best judgment for policy outcome can be more determined when various forecasting methodologies are applied.

Kongcharoen and Kruangpradit (2013) provided an investigation on the use of ARIMA(X) studies where they showed that the forecast with exogenous exports to countries like China, European Union and the USA provided a better forecast outcome than that of a normal univariate outcome. Their outcome, more so that of the Out-of-Sample result was considered more like a policy response to relevant ministries. On a similar note of methodological investigation, empirical findings produced by Andrews *et al*. (2013) demonstrated that both autoregressive integrated moving average (ARIMA) and autoregressive integrated moving average with exogenous variables (ARIMAX) methodologies have the ability to produce accurate four-quarter forecasts. This was perceived as a way of forecasting outcomes of disability insurance based on the past occurrences of disability data and backed by exogenous variable / components.

Adebiyi *et al.* (2014) examines the forecasting performance of ARIMA and artificial neural networks model with published stock data obtained from New York Stock Exchange as against model like GARCH. Their empirical findings revealed that superiority of neural networks model over ARIMA model - this also resolved and clarify contradictory opinions reported in literature over some level of superiority of neural networks and ARIMA model and vice versa.

Peter and Silvia (2012) pursued studies to compare ARIMA models with ARIMAX models, and in order to facilitate the comparison, they took GDP per capita, considered as a more popular macroeconomic variable. The modelling of time series data set made use of both ARIMA and ARIMAX, and on the basis of the results of the study, they were able to conclude that ARIMA is a better model choice than ARIMAX. This shows that exogenous variable influence did not play much of an impact in deciding best choice of model, for which it is mostly expected that ARIMAX would come out as a better option.

Williams (2001) carried out model forecast using ARIMA and also an extension of exogenous factor to determine external influences on traffic flow in France. The results show that ARIMAX models exhibit better forecast performance over its univariate counterpart which is the ARIMA models. Most importantly on this study, Williams also, provide outline of issues that needs addressing prior to carrying out ARIMAX models for intelligent transportation system (ITS) forecasts. Such issues as highlighted include increased complexity of model specification, estimation, and maintenance; model consistency; model robustness in the face of interruptions in the upstream data series; and variability in the cross-correlation between upstream and downstream observations. It is worth noting the importance of the last issue because ARIMAX models assume constant transfer function parameters, while the correlation between upstream and downstream observations vary with prevailing traffic conditions, especially traffic stream speed. In such a case, Williams (2001) suggested the need for further research to investigate model extensions and refinements as a way of enabling outcome of generalizable, self-tuning multivariate forecasting model which can be implemented than cognizance of varying upstream to downstream correlations.

2. Time Series Basics, Methodological Framework and Data Source

2.1. Time Series Basic

Time series model is more common in using past movement of variable as a way of predicting future values/events. Unlike structural models which relates to the model at hand to forecast, time series models are not necessarily rooted on economic theory, while the reliability of the estimated equation is normally based on out-of-sample forecast performance as first observed by Stock and Watson (2003).

Times series are mostly expressed by Autoregressive Moving Average (ARMA) models which was first produced by Slutsky (1927) and Wald (1938) as expressed in the following equation:

$$\mathbf{Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \ldots\ldots\ldots - \theta_q e_{t-q}} \quad (1)$$

Such a series is referred to as a moving average of order **q**, with the nomenclature **MA(q)**; where Yt is the original series and e_t as error term in the series. As Yule (1926) suggested, the autoregressive process of the moving average series can be expressed as:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \varphi_3 Y_{t-3} + \ldots\ldots\ldots\ldots + \varphi_p Y_{t-p} + e_t \,. \tag{2}$$

It is assumed that t, is independent of Y_{t-1}, Y_{t-2}, Y_{t-3}, ... Y_{t-q} .

In this model, we are trying to fit the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model, which is the generalised model of the non-stationary ARMA model represented by ARMA(p,q) and this can be written as:

$$Y_t = \varphi_1 Y_{t-1} + \varphi 2 Y_{t-2} + \varphi_3 Y_{t-3} + \ldots + \varphi_p Y_{t-p} + e_t - \boldsymbol{\theta_1 e_{t-1}} - \boldsymbol{\theta_2 e_{t-2}} \ldots\ldots - - \boldsymbol{\theta_p e_{t-p}} \tag{3}$$

where, Y_t is the original series, for every t, we assume that is independent of Y_{t-1}, Y_{t-2}, Y_{t-3}, …, Y_{t-p} .

Autoregressive Integrated Moving Average with an External Regressor [ARIMAX] Model

An ARIMA model with external regressor, that is, ARIMAX model with d=1 can be written as:

$$\mathbf{W_t = \varphi_1 W_{t-1} + \varphi_2 W_{t-2} \ldots\ldots + \varphi_p W_{t-p} + e_t - \theta_1 e_{t-1} \ldots\ldots - \theta_p e_{t-p} + \beta_1 X_{t-1} + \ldots\ldots + \beta_r X_{t-r}} \tag{4}$$

where X’s are regressor variables and β’s are the coefficients of regressor variable.

According to Hamjah (2014, 170-171), the following steps are worth considering when auctioning the Box and Jenkins approach to ARIMA[X] forecasting:

- *Preliminary analysis:* create conditions such that the data at hand can be considered as the realization of a stationary stochastic process.
- *Identification:* specify the orders p, d, q of the ARIMA model so that it is clear the number of parameters to estimate. Recognizing the behavior of empirical autocorrelation functions plays an extremely important role.
- *Estimate:* efficient, consistent, sufficient estimate of the parameters of the ARIMA model (maximum likelihood estimator).
- *Diagnostics:* check if the model is a good one using tests on the parameters and residuals of the model. Note that also when the model is rejected, still this is a very useful step to obtain information to improve the model.
- *Usage of the model:* if the model passes the diagnostics step, then it can be used to interpret a phenomenon, forecast.

2.2. Methodology

The research approach for this study is modelled on the Box–Jenkins methodology (Box and Jenkins 1976), which is normally attributed to short-run forecasting of time series events. It is a form of algebraic model, usually used in forecasting outcomes of events, with an ascribed name of Autoregressive Integrated Moving Average (ARIMA) model; the model seems to have enjoyed great successes in academic research, and particularly in discourses pertaining to methodological preferences for time series studies (Bigovic 2012; Coshall 2005; Huang and Min 2002; Kulendran and Witt 2001 and Law 2004).

The ARIMA and ARIMAX models applied in this study are expressed in equations 3 and 4 above in the expressed time series specifications identified as (*p*,*d*,*q*); where *p* is the order of the autoregressive (A.R.) process, *d* is the number of differences or integrations and *q* is the order of the moving average (M.A.) process, with short-run estimations characterised by annual, quarterly, monthly, weekly, daily and hourly data usage.

2.3 Data Usage and Source

Data used were extracted from the Statistics Sierra Leone database source for HCPI and also the methodical calculation of NEXR based on other data sources like the World Bank Data source from 2007M1 to 2017M12. In order to smoothen out data series, the de-seasonalised process was used for only the HCPI variable but not for the NEXR variable. When the NEXR variable was de-seasonalised, its model was not good because of its high AIC, the inverted AR and MA roots lies outside the unit circle and also the MAPE for the forecast was also large. The EVIEWS application package has been used throughout to estimate values and carrying out test procedures.

3. Empirical Analysis and Discussion

The objective here is to present model comparison that accurately predict both the within and out-of-sample forecast for ARIMA and ARIMAX methodologies. The research is based on the available data provided by the

Central Statistical Office [CSO] and the Bank of Sierra Leone [BSL] of HCPI and NEXR data respectively between the period 2007M1 – 2017M12. In order to carry out the analysis, the EVIEWS 9.0 application was used with and with initial diagnostic test of Unit Root produced to assess stationarity of the variables concerned and this was done after the Hcpi variable has been de-seasonalised.

Table 1. Augmented Dickey-Fuller [ADF]

Variable	Augmented Dickey-Fuller [ADF]		Phillips-Perron [PP]	
	Level	**1st Difference**	**Level**	**1st Difference**
HCPI	1.871934 (0.9998)	0.233398 (0.9737)	-5.370101 (1.0000)	-6.890669*** (0.0000)
NEXR	0.636092 (0.9902)	-4.570829*** (0.0002)	1.859240 (0.9998)	-4.346651*** (0.0006)

Note: *** = 1% significance, ** = 5% significance, * = 10% significance [with no trend and Intercepts]
Source: Own Estimates

From the above (Table 1), variables in the parenthesis are the probabilities of both HCPI and NEXR which depict their level of significance when the test Unit Root was conducted. This indicate that the PP test is the best for both HCPI and NEXR at 1st Difference. Using the PP test, both the HCPI and NEXR do not appear to be significant at Level but are significant at1st difference which means that ARMA is not possible and the option is to resort to ARIMA model estimation.

Figure 2. Automatic ARIMA Estimation

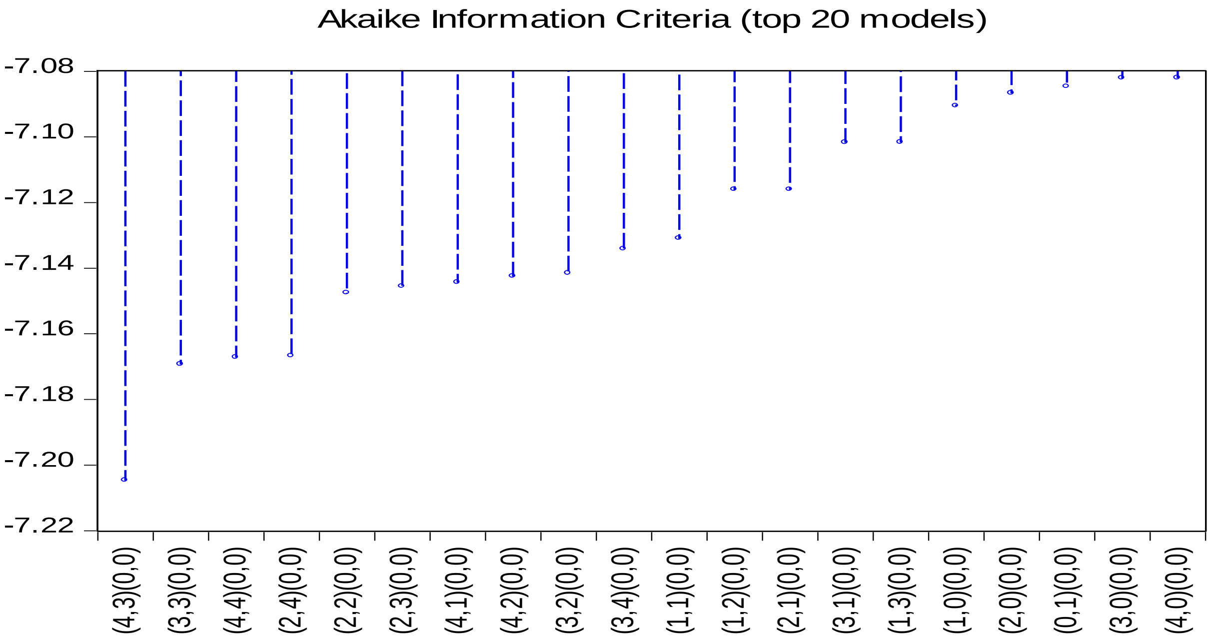


Figure 2 above shows the outcome of an automatic forecast process that was used to decide on the best model outcome for estimating the model. Based on the table, it shows that (4,0) (0,0) is the best out of series of models which then gives use the mandate now to proceed by determining the order of the AR and MA processes and the suitability of best model iteration that will bring about the best forecast outcome given the nature of data used.

The estimation was divided into ARIMA with HCPI as the only variable used and the second is based on the ARIMAX process but utilizing NEXR as an explanatory to help determine the outcome of the best estimation, particularly in relation to both within and out-of-sample forecast [see steps as provided below in sections *4.1.1 and 4.1.2*].

3.1. Model Estimation Outcomes: ARIMA and ARIMAX

3.1.1. ARIMA OUTCOMES

This is based on the use of a single variable, which is HCPI and for which the lag of it is used to determine future occurrences. The estimation output below is considered the best with the lowest AIC value and an Inverted AR Root value <1. Using the automated ARIMA forecast process, EVIEWS have made the best model selection of (4,0)(0,0).

Figure 3. Model Estimation Outcome for ARIMA

Dependent Variable: D(HCPI_SA)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 02/15/18 Time: 16:31
Sample: 2007M02 2017M12
Included observations: 131
Convergence achieved after 34 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.231242	0.834946	1.474637	0.1428
AR(1)	1.248852	0.119903	10.41556	0.0000
AR(3)	-0.256953	0.107329	-2.394056	0.0181
MA(1)	-0.838229	0.124104	-6.754264	0.0000
SIGMASQ	0.241332	0.018841	12.80888	0.0000

R-squared	0.651898	Mean dependent var	0.953822
Adjusted R-squared	0.640847	S.D. dependent var	0.835831
S.E. of regression	0.500908	Akaike info criterion	1.506380
Sum squared resid	31.61449	Schwarz criterion	1.616121
Log likelihood	-93.66791	Hannan-Quinn criter.	1.550973
F-statistic	58.99080	Durbin-Watson stat	1.972399
Prob(F-statistic)	0.000000		

Inverted AR Roots	.98	.66	-.40
Inverted MA Roots	.84		

Given the process involved in iteration as shown in Figure 3 for the best model that will support theoretical principles where the Inverted AR and MA roots are within a define range, that is less than ONE or within the root circle and also satisfying the condition of the probability values been significant.

Table 2. Correlogram for ARIMA

Date: 02/19/18 Time: 20:03
Sample: 2007M01 2018M01
Included observations: 131
Q-statistic probabilities adjusted for 3 ARMA terms

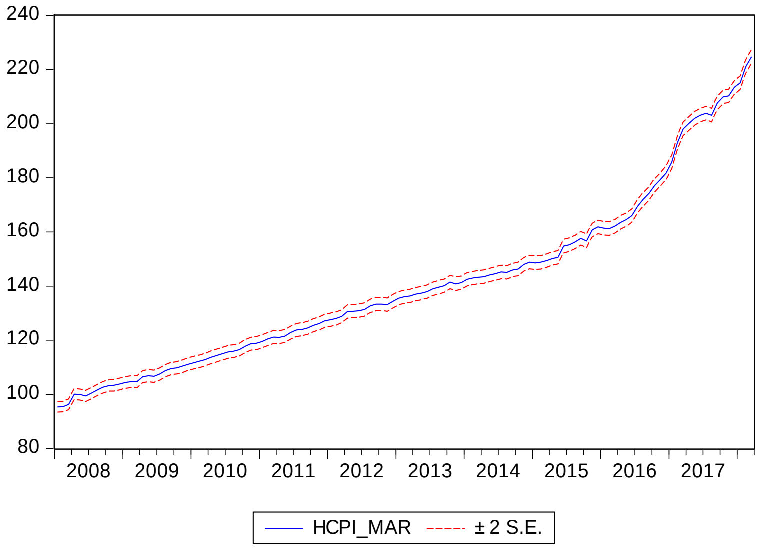
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.006	0.006	0.0045	
.|. |	.|. |	2	0.002	0.002	0.0054	
.|. |	.|. |	3	0.020	0.020	0.0576	
*|. |	*|. |	4	-0.068	-0.068	0.6874	0.407
.|* |	.|* |	5	0.138	0.139	3.3128	0.191
*|. |	*|. |	6	-0.171	-0.179	7.4117	0.060
.|. |	.|. |	7	0.006	0.019	7.4167	0.115
.|. |	.|. |	8	-0.045	-0.062	7.7096	0.173
.|. |	.|. |	9	-0.019	0.013	7.7636	0.256
*|. |	*|. |	10	-0.092	-0.147	8.9772	0.254

Date: 02/19/18 Time: 20:03
Sample: 2007M01 2018M01
Included observations: 131
Q-statistic probabilities adjusted for 3 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	11	-0.041	0.026	9.2230	0.324
.|* |	.|. |	12	0.076	0.030	10.073	0.345
.|. |	.|. |	13	0.021	0.047	10.137	0.429
.|* |	.|. |	14	0.084	0.050	11.182	0.428
.|. |	.|* |	15	0.049	0.082	11.540	0.483
.|. |	.|. |	16	0.038	0.002	11.755	0.548
.|. |	.|. |	17	0.063	0.053	12.366	0.577
.|* |	.|* |	18	0.098	0.109	13.842	0.538
.|. |	.|. |	19	-0.009	-0.020	13.854	0.610
.|* |	.|* |	20	0.108	0.125	15.675	0.547
.|. |	.|. |	21	0.005	0.011	15.680	0.615
.|* |	.|* |	22	0.136	0.198	18.615	0.482
.|. |	*|. |	23	-0.052	-0.090	19.047	0.519
*|. |	*|. |	24	-0.176	-0.082	24.063	0.290
.|. |	.|. |	25	0.004	-0.039	24.065	0.344
*|. |	*|. |	26	-0.129	-0.068	26.844	0.263
.|** |	.|* |	27	0.223	0.207	35.185	0.066
*|. |	.|. |	28	-0.069	-0.034	35.986	0.072
.|. |	.|. |	29	-0.038	-0.008	36.229	0.088
.|. |	.|. |	30	0.056	-0.016	36.779	0.099
.|. |	.|. |	31	-0.060	-0.007	37.396	0.110
.|. |	*|. |	32	0.043	-0.089	37.726	0.129
.|. |	.|. |	33	-0.035	0.026	37.938	0.151
.|. |	*|. |	34	0.031	-0.087	38.114	0.177
.|. |	.|. |	35	-0.005	-0.023	38.118	0.211
.|. |	.|. |	36	0.006	-0.037	38.125	0.248

The efficiency of this process is also tested against the sample autocorrelation function [shown in Table 2], as depicted in the Correlogram values of either one of AC, PAC, Q-Stat or Prob values; in this case the outcome was judged using the Prob values which clearly satisfies the condition of the model consistency.

Figure 4. Forecast Estimation output for ARIMA



Forecast: HCPI_MAR
Actual: HCPI_FEB
Forecast sample: 2007M01 2018M03
Adjusted sample: 2008M01 2018M03
Included observations: 122

Root Mean Squared Error	0.925004
Mean Absolute Error	0.585098
Mean Abs. Percent Error	0.395167
Theil Inequality Coefficient	0.003224
Bias Proportion	0.001103
Variance Proportion	0.036088
Covariance Proportion	0.962809

Figure 4 above presents the forecast graph of the estimation of the ARIMA models of HCPI in Sierra Leone for the period 2007M1 – 2018M03. The diagram clearly shows that the ARIMA specification produced closely track the actual values of the time series, both for the within and out-of-sample forecast performance

Table 3. Evaluation Outcome for ARIMA

The Arima Forecast			
Year	**Linear Model**		
	Forecast HCPI	**Forecast Y-O-Y [%]**	**Monthly Change**
Jan. 2018	218.8628	14.23498	0.01273
Feb. 2018	221.8779	13.99985	0.01377
Mar. 2018	224.7666	14.58914	0.01301
R^2	0.651		
MAPE	0.395		

The accuracy of the model prediction can be determined through analysis of information provided in Table 3 for HCPI during the period Jan – Mar. 2018. This shows an increase for the three months forecasted for the Hcpi variable. In a similar note, the percentage forecast for Year-on-Year [Y-O-Y] in the three months for Sierra Leone indicate both decrease an increase, which from an economic interpretation shows that the value of people's potential of living standard is fluctuating and economically unstable. The specifics of the model evaluation can also be determined through comparative information provided for R^2 and also the Mean Absolute Percentage Error [MAPE] values. The high R^2 shows that the model is very good and fit for purpose, with a rather small MAPE value.

3.1.2. ARIMAX Outcomes

With this, NEXR is incorporated as an explanatory variable to help track future processes of inflation, given the high dependency rate of the Sierra Leone economy on the importation of goods, which also add a lot of pressure on exchange rate hike in the country.

Figure 5. Estimation outcome for ARIMAX with NEXR as Exogenous variable

Dependent Variable: D(HCPI_SA)
Method: Two-Stage Least Squares
Date: 02/16/18 Time: 16:07
Sample (adjusted): 2007M05 2017M12
Included observations: 128 after adjustments
Convergence achieved after 36 iterations
MA Backcast: 2007M04
Instrument specification: D(NEXR)
Constant added to instrument list
Lagged dependent variable & regressors added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.888623	2.261696	0.835048	0.4053
AR(1)	1.128064	0.246710	4.572422	0.0000
AR(3)	-0.143428	0.219193	-0.654347	0.5141
MA(1)	-0.698270	0.314996	-2.216755	0.0285

R-squared	0.652592	Mean dependent var	0.965739
Adjusted R-squared	0.644187	S.D. dependent var	0.841745
S.E. of regression	0.502101	Sum squared resid	31.26113
Durbin-Watson stat	2.015281	J-statistic	8.282272
Instrument rank	5	Prob(J-statistic)	0.004003

Inverted AR Roots	.98	.47	-.32
Inverted MA Roots	.70		

The outcome from Figure 5 shows that after iteration from the automatic estimation that was given as a starting point [(4,0)(0,0)] now leaves the model with AR(1), AR(3) and MA(1) and with an indication of a clearly stable Inverted Roots value which typically fall under ONE, indicating that the model is stable.

Table 4: Correlogram Output for ARIMAX

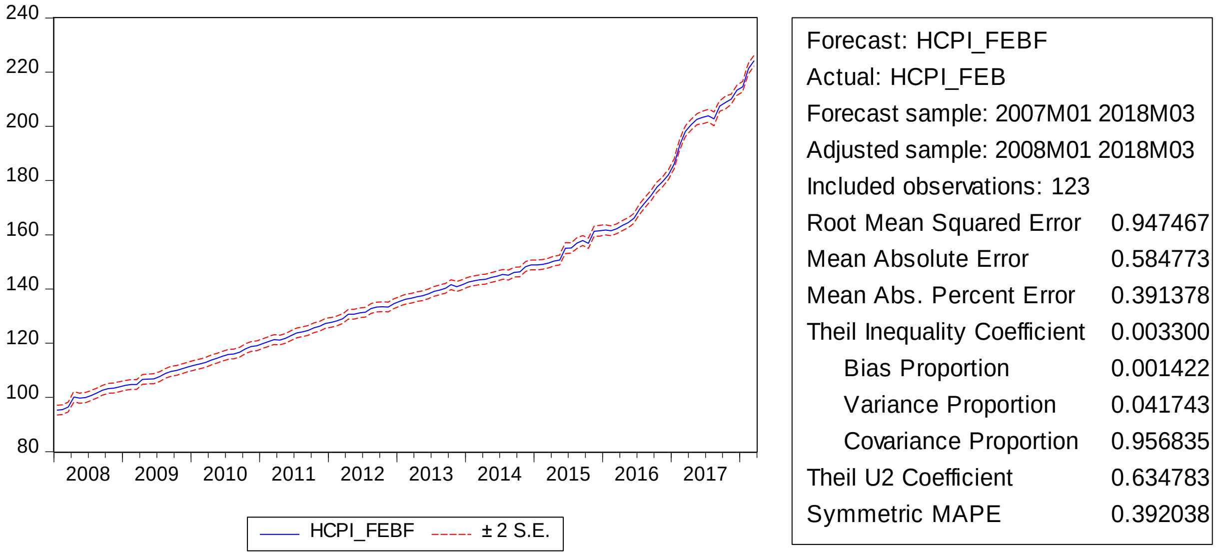
Date: 02/19/18 Time: 20:06
Sample: 2007M01 2018M03
Included observations: 120
Q-statistic probabilities adjusted for 3 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|.	.|.	1	0.007	0.007	0.0055	
.|.	.|.	2	0.001	0.001	0.0058	
.|.	.|.	3	0.016	0.016	0.0387	
*|.	*|.	4	-0.128	-0.128	2.1013	0.147
.|.	.|.	5	0.012	0.014	2.1192	0.347
*|.	*|.	6	-0.079	-0.081	2.9296	0.403
.|*	.|*	7	0.151	0.160	5.8676	0.209
.|.	.|.	8	0.025	0.002	5.9471	0.311
.|.	.|.	9	0.017	0.027	5.9839	0.425
.|.	*|.	10	-0.053	-0.088	6.3584	0.499
.|.	.|.	11	-0.051	-0.006	6.7128	0.568
.|.	*|.	12	-0.053	-0.067	7.0960	0.627
.|.	.|.	13	-0.041	-0.002	7.3270	0.694
.|*	.|.	14	0.083	0.046	8.2750	0.688
.|.	.|.	15	0.065	0.066	8.8708	0.714
.|.	.|.	16	0.026	-0.007	8.9639	0.776
.|.	.|.	17	0.026	0.035	9.0600	0.827
.|*	.|*	18	0.081	0.097	10.007	0.819
*|.	.|.	19	-0.075	-0.052	10.817	0.821
.|*	.|*	20	0.111	0.141	12.614	0.762
.|.	.|.	21	-0.024	-0.050	12.695	0.809
.|*	.|*	22	0.140	0.169	15.632	0.682
.|.	*|.	23	-0.045	-0.118	15.935	0.721
*|.	*|.	24	-0.187	-0.131	21.248	0.444
.|.	.|.	25	0.033	-0.029	21.418	0.495
*|.	.|.	26	-0.125	-0.039	23.846	0.412
.|*	.|*	27	0.167	0.157	28.259	0.249
.|.	.|.	28	-0.007	-0.020	28.267	0.296
.|.	*|.	29	-0.029	-0.073	28.398	0.339
.|.	.|.	30	0.050	0.019	28.800	0.371
.|.	.|.	31	-0.029	0.061	28.940	0.416
.|.	*|.	32	-0.061	-0.082	29.562	0.436
.|.	.|.	33	-0.039	0.027	29.823	0.475
.|.	.|.	34	0.031	-0.056	29.982	0.518
.|.	.|.	35	-0.018	-0.021	30.039	0.566
.|.	.|.	36	0.020	-0.058	30.106	0.612

*Probabilities may not be valid for this equation specification.

The efficiency of the model estimation for ARIMAX was also tested through outcomes from the Correlogram data and for which effort is dedicated to the Prob (Table 4). Values which clearly shows that the model is a perfect choice for forecasting outcomes for HCPI, with NEXR as the exogenous variable.

Figure 6. Estimation Outcome of ARIMAX [Based on Static Forecast]



The estimation outcome for ARIMAX in Figure 6 clearly shows that the model is a good choice which perfectly tracks both the within and out-of-sample forecast result for HCPI, where NEXR is used as exogenous variable.

Table 5. Evaluation Outcome for ARIMAX

Year	LINEAR MODEL		
	HCPI Forecast	Y-O-Y [%] Forecast	Monthly Change
Jan 2018	218.8010	14.20272	0.01245
Feb 2018	221.6423	13.87881	0.01298
Mar 2018	224.1955	14.29799	0.01151
R^2	0.652		
MAPE	0.391		

The efficiency of the models is determined through evaluative outcomes as shown in Table 5 above, where monthly inflation for the periods Jan – Mar. 2018 have shown continual increase in the Hcpi forecast. The Y-O-Y percentage forecast seem to show some levels of fluctuation where it fell from Jan to Feb. 2018 and rose again from Feb. to Mar. 2018.

4. The Interpretation for the Sierra Leone Economy

This section outlined both the upside and downside risk to the inflation forecast values in this paper and also, emerging circumstances that might cause these forecast values to be different from the actual inflation.

4.1. Identified Upside Risk to the Forecast

Given the time of the empirical study was carried out, it is with the view that economic agents' expectations around the election period would heightened worries and which may resulting in a hike in general price level of (essential) goods and services, mostly due to people's tendency hoard items and also backed by anticipated fear in the minds of people about international organizations withholding donor funds.

In addition, given the state of the country's finances which is tied to external donor funds from the IMF, there is fear that adherence to removal of fuel subsidy will also prompt some level of price increase at fuel-pump after the general elections, which is likely to have a pass-through effect to consumers, and eventually an upward trend in inflation. Finally, restructuring of the import duty on rice and other essential imported commodities during post-elections may also be a catalyst to inflationary pressure.

4.2 Anticipated Downside Risk to the Forecast

Over considerable period of time, exchange rate tends to have direct correlation with inflation and given its relatively stable state over the past months, there is the tendency that the outcome from this (inflation) forecast might not be feasible during the first quarter of 2018. In other words, continued stability of the foreign exchange rate, amidst tight monetary policy stance will likely witness a downward trend on inflation. In a similarly token, continued tightness in monetary policy rate by the Bank of Sierra Leone (currently at 14.5%, up from 15% for February 2018) will also witness downward inflationary pressure, holding all other factors constant. If aggregate demand continues to be low, it is then likely that inflationary pressures will take a downward trend.

Evaluation of Model Forecast Results and Conclusion

Both ARIMA and its extension ARIMAX have been proved to be good forecast for future occurrences when the univariate variable is used as a predictor for future events, particularly for time series data. The difference in the results did not show significant variance between ARIMA and ARIMAX, which actually means that both are reasonably accurate in predicting future state of inflation in the country.

In view of the forecast outcomes for both ARIMA and ARIMAX (Reference to Tables 3 and 5), it seems very obvious that ARIMAX is a better choice of model given its relatively low values of monthly HCPI results and also, the Year-on-Year (Y-O-Y) forecast for the three given months [Jan - March 2018]. Evaluation of the models result for MAPE, Mean Absolute Error [MAE], Thiel Inequality Coefficient [TIC] and Bias Proportion [BP] seem to prove that ARIMAX is a better choice of model outcome than the ARIMA model. In the same vain, the ARIMAX model has a slightly higher R^2 value than that of the ARIMA and also lower MAPE than of the ARIMA based on comparison between Tables 3 and 5 above. This actually shows that the chosen exogenous variable also has great influence in determining the state of inflation in an economy as shown in the case when NEXR is used.

The outcome of the result shows that both the '***within and out-of-sample***' forecast for static forecast technique provide low level of error margin in the forecast results [Figures 4 and 6]. In as much as outcome from ARIMAX model seem to have shown a higher percentage of R^2 than that of the ARIMA (as identified in the research question), it is not a certainty that this will the case for all forecast results in future occurrences / model specification. The way forward is to ensure effort is used to provide trials with different suite of models, for example, the case with VAR and more so as part of the long-term objective with DSGE model.

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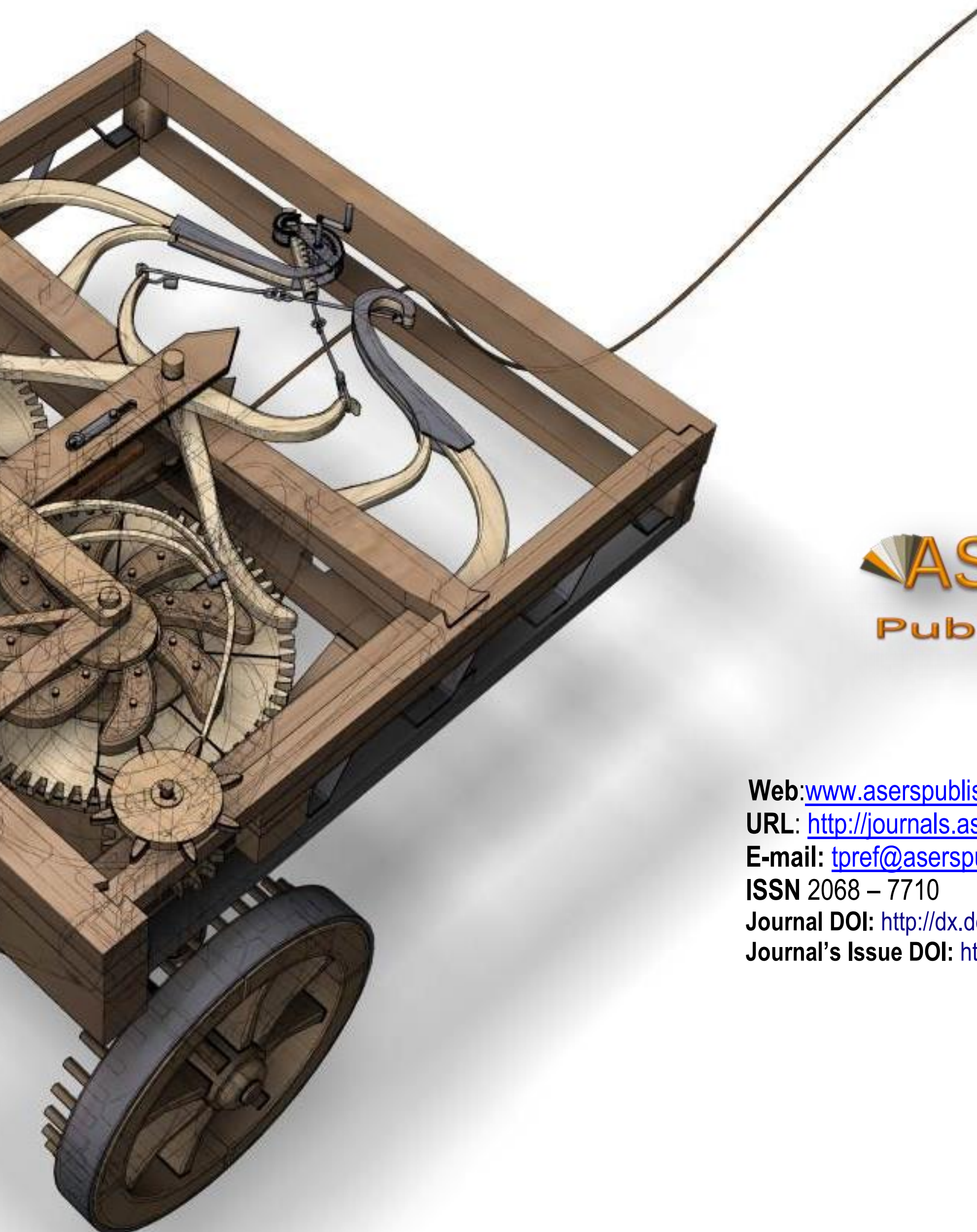

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