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Abstract

This empirical study has provided interpretive outcome from a univariate forecast using Box-Jenkins ARIMA methodology. The HCPI_SA seasonally adjusted data for Sierra Leone shows a robust model outcome with three months ahead prediction based on the STATIC method result. Test results like Autocorrelation and also comparative values for MAPE and the Inverted Root values have indicated that the model is a good fit. Despite better choice of outcome from the STATIC result in comparison to DYNAMIC forecast, the conclusion a cautious means of advice when using results for policy outcomes and with comparative forecasts highly recommended a way forward in guiding policy makers' decision.

Keywords: *ARIMA, Forecast, Headline Consumer Price Index [HCPI], Sierra Leone*

Jel Classification: *C52; C53*

1. Introduction

Forecasting is a highly topical discourse in both the academia and also practice-base environment across the world; the process itself is not necessarily the best in terms of decisions taken by policy makers, but it serve as a guide in enabling objective decisions to be made, given the possibility of margin of errors in the final forecast outcomes (Ericsson, 2016). The use of forecasting is becoming more predominant in research-based institutions across the world, particularly in central banks to address core objective(s) of price stability, as in the case with the Bank of Sierra Leone.

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The methodology of forecasting can incorporate the use of both univariate (as seen in the case with this study) and also complex multivariate use of variables in ARIMAX, VAR and DSGE models (Etuk et al, 2013 and Giacomini, 2014).

Forecasting in economic sciences study would always adhere to strict scientific means empirical outcomes which is mostly done using robust Poperian style methodological approach(es) as a way of proving its scientific existence (Jackson, 2016). Mostly for institutions like central banks, the process of forecast is normally done using high end aggregation of data connection with Inflation, Gross Domestic Product and in some cases, disaggregated level where comparison is likely to be made between sectors of an economy or institutional performances. The precision of forecast as a means of making judgment about (economic) performances is one that has come under great scrutiny lately by professionals across the world (Friedman, 2013 and Batchelor, 2000).

1.1. Stylise Facts about HCPI in Sierra Leone (Post-2017 Data)

Headline Consumer Price Index (HCPI), a proxy for Inflation is very topical 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 (Jackson et al, forthcoming). As seen in Figure 1 below, the chart provide high frequency data for HCPI since 2007M01 to 2017M09; this is a representation of composite of all items in the basket which are weighted by the Central Statistical Office in Freetown. Prior to 2007, HCPI data were disaggregated for those in the capital city and the provincial towns. As seen, the highly time series data (normal and seasonally adjusted) shows upward / deterministic trend in inflation and this is as a result of the predominance of tradable influence of the CPI basket driven by the country's reliance on the importation of basic commodity goods needed for consumption in the country. In order to keep track of the bank's objective of monitoring price stability, staff in the research department would normally (quarterly) make use of econometric applications like EVIEWS to carry empirical study on simple methodology like the Box-Jenkins Autoregressive Moving Average and Autoregressive Integrated Moving Average [ARIMA] to forecast inflation dynamics which is fed into policy judgment for rates fixing in the country.

 Figure 1: Graph Showing Plot of HCPI and HCPI_SA
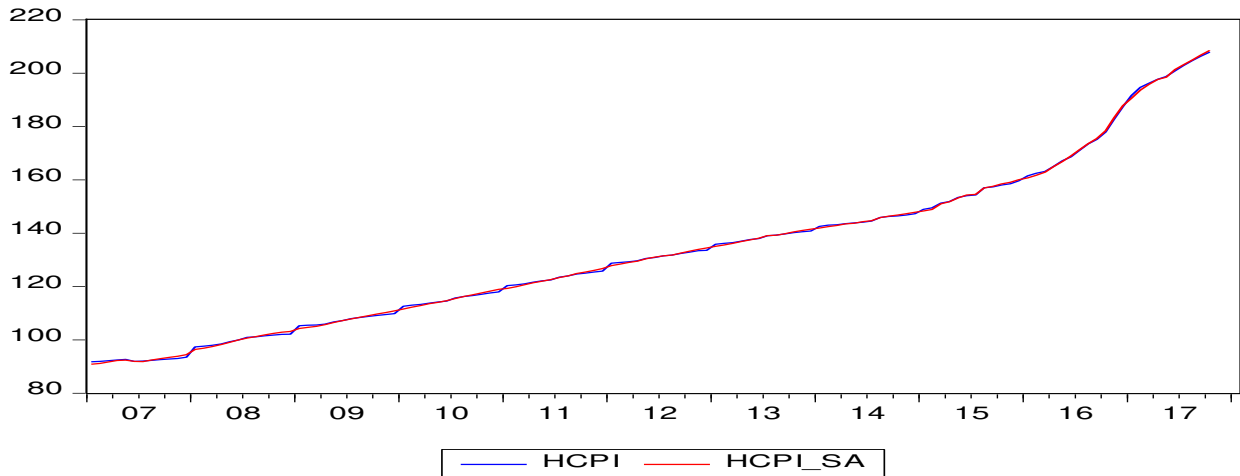
1.2. Hypothetical Question and Objective

The main question that is set to be answered here is: ***Does STATIC forecast provide a better results than that of DYNAMIC forecast in ARIMA model***? In this vein, the main objective here is to investigate the accuracy of the **out-of-sample** forecast for both Static and Dynamic approaches using HCPI variable.

In addition to the aforementioned introduction, the rest of the paper is structure as follows: Section two present the Theoretical Framework and Methodology, which is also sub-divided into Time series models, Methodology, test description, and Data usage. Section three addresses the Empirical Results and discussion, while section four provide conclusion on the outcome and with some suggestions for policy makers in terms of a country's peculiarity.

2. Theoretical Framework and Methodology

2.1. Time Series Model Literature

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 Wold (1938) as expressed in the following equation:

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_3 e_{t-3} - \ldots\ldots\ldots - \theta_q e_{t-q} \tag{1}$$

Such a series is referred to as a moving average of order **q**, with the nomenclature **MA(q)**; where Y_t 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: $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \ldots\ldots\ldots + \phi_p Y_{t-p} + e_t$ [2]

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

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:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \ldots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \ldots - \theta_p e_{t-p} \tag{3}$$

Where, Y_t is the original series, for every t, we assume that is independent of:

$Y_{t-1}, Y_{t-2}, Y_{t-3}, \ldots, Y_{t-p}$.

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

i. *Preliminary analysis:* Data at hand should conform to a stationary stochastic process.

ii. *Identification:* specify the orders p, d, q of the ARIMA model so that it is clear the number of parameters to estimate and also recognition of the importance of autocorrelation functions in the model.

iii. *Estimate:* efficient, consistent, sufficient estimate of the parameters of the ARIMA model (maximum likelihood estimator).

iv. *Diagnostics:* Model to be checked for appropriateness using tests on the parameters and residuals of the model. Even when the model is rejected, still this is a very useful step to obtain information to improve the model.

v. *Usage of the model:* Once tests outcomes are sufficiently passed or satisfies specification, it can then be used to interpret a phenomenon based on forecast outcome(s).

Other procedures worth using and more so, applied in this study include the following:

- Check normality assumption, proceed to the "Jarque-Bera" test, which measure goodness of fit from normality, based on the sample Kurtosis and skewness.

- The "Ljung-Box" test can also be applied under the hypothesis that there is no autocorrelation in the residuals.
- Autocorrelation Function [ACF] and Partial Autocorrelation Function [PAC] can also be used to detect the order of difference of Stationarity conditions.
- Use of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for model selection criterion.

2.2. Empirical Literature

Chatfield (2001: 11), defined time series as an observed sequential data computed over a period of time; in many cases, such observation may be done for a single (univariate) or many (multi-variate) variables. For the purpose of this study, emphasis is paid to univariate time-series observation / analysis. In this vein, a univariate time-series refers to an observation that consists of single observations recorded sequentially through time, for example, the monthly unemployment rate (Klose, Pircher and Sharma, 2004).

In many cases, there is an underlying assumption when doing a time-series analysis, which is to do with the regularities expected of data as in the case with multivariate study. Klose et al (2004) carried sound univariate study as applied in the case with Austria; in this, they made use of Auto-integrated Moving Average [ARIMA] model which proved to be a more robust means for forecast in comparison to a singular study on VAR model. They also provided some limitations, but on the whole, ARIMA was concluded to be a suitable choice of model.

Kelikume and Salami (2014) carried out independent investigation of inflation rate in Nigeria using VAR and ARIMA. They made use of CPI data obtained from the National Bureau of Statistics and the Central Bank Nigeria (CBN) during 2003 to 2012 to predict movements in the general price level. The study highlighted limitations in terms of its reliance on univariate analysis, but also brought to the fore some positive outcomes of using ARIMA model. It also outlined the limitation of using a single variable which may not necessarily have anything to compare with unless based on its past values.

Bokhari and Feridun (2006) also carried out investigation using comparative univariate analysis of VAR and ARIMA to forecast inflation in Pakistan. In their analysis, ARIMA was seen to have

produced a better outcome in the forecast than that of a singular VAR study. Despite the fact that the study was able to unearth some issues around macroeconomic forecasting, it also brought to the fore the implication of such forecast technique for small scale macroeconomic model.

The use of Univariate studies is also found to be very important and applicable in different areas of studies dealing with time series data; Taylor (2008) made use of this using ARIMA to forecast trends associated with intra-day arrivals by operators at a retail bank call centre in the UK. The study confirmed use of methods like "*seasonal ARIMA modelling and AR modelling, an extension of Holt-Winters exponential smoothing for the case of two seasonal cycles, robust exponential smoothing based on exponentially weighted least absolute deviations regression and dynamic harmonic regression, a form of unobserved component state space modeling*". The use of Univariate forecast is quite prominent given its quick response in finding solution to problems, as manifested in Taylor's (2003) research in forecasting short-term electricity demand using double exponential smoothening technique.

Bianchi et al. (1998), in their Univariate study also made use of ARIMA modelling technique in determining seasonal forecasting daily arrivals at a telemarketing call center. In this study, supplemented their technique with intervention analysis as a way of controlling the presence of outliers, for which the resultant forecasts manifested an out-performance of the standard Holt-Winters seasonal exponential smoothing.

In as much as the positive side of using ARIMA model for forecasting univariate study is considered soundly echoed in modeling time series data, it was shown in Meyler, Kenny and Quinn (1998) study that ARIMA perform poorly compared to stand-alone VAR when applied to volatile and high frequency data. On a more positive note, Ho and Xie (1998) complemented ARIMA to be a more viable alternative model in terms of predicting performances.

2.3. Data

Data used were extracted from the Statistics Sierra Leone database source for HCPI from 2007M1 to 2017M10. In order to smoothen out the series, data were seasonally using EVIEWS to remove issues of seasonality.

3. Empirical Results and Discussion

The process commenced with a test of Stationarity for HCPI_SA using Phillips-Perron at 1st level as shown in ***Table 1***; with the application of absolute value concept, the result indicate that ARIMA is the appropriate methodology to be applied as opposed to ARMA.

3.1. Table1: Unit Root Result for Headline Consumer Price Index D(HCPI_SA)

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.580481	0.0000
Test critical values:	1% level	-4.031899	
	5% level	-3.445590	
	10% level	-3.147710	

This is an indication of the method to be proceeded by determining the order of the AR and MA processes and the suitability of best model that will bring about the best forecast outcome given the nature of data used. At first level, the variable is highly significant with its probability value equal to 0.

3.2.Selection and Iteration for Best Model Estimation

Using the automated ARIMA forecast process, EVIEWS have made the best model selection of (6,0)(0,0) as shown in ***Figure 2***.

Figure 2: Automatic ARIMA Model Estimation Choice
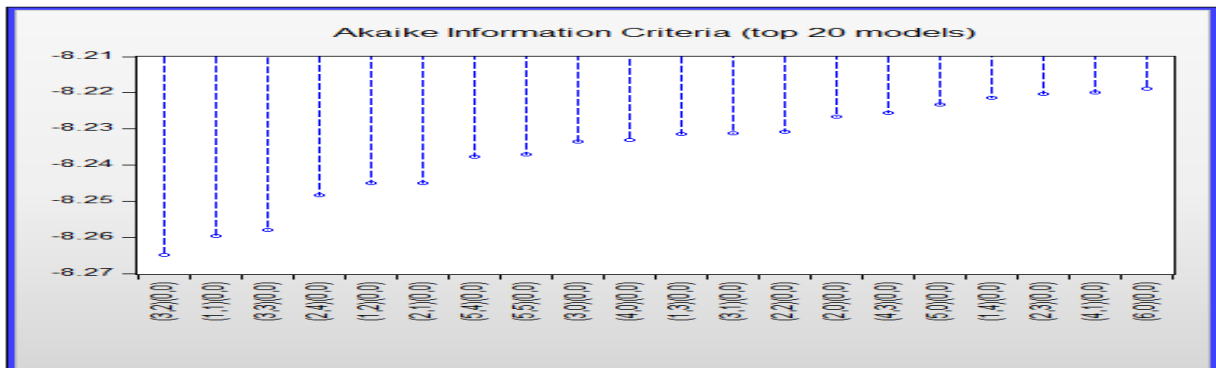
This is based on the use of a single variable, which is HCPI and for which the lag of it is used to determine future occurrences. The estimation output below (4,1,0) in ***Table 2*** is considered the best after series of iterations, with the lowest AIC value and an Inverted AR Root value <1. In other words, there is a four AR processes integrated to first difference as shown in the Phillip Perrons unit root and with Zero MA process. The R^2 value also show high level of significance of the univariate HCPI_SA variable and with the Inverted AR Roots for AR showing roots falling inside the circle or indicating model stability.

Table 2: Model Estimation
Dependent Variable: D(HCPI_SA)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/13/17   Time: 08:29
Sample: 2007M01 2017M10
Included observations: 129
Convergence achieved after 36 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.931163	0.382374	2.435216	0.0163
AR(4)	0.125753	0.057098	2.202419	0.0295
AR(2)	0.254703	0.078015	3.264784	0.0014
AR(1)	0.472282	0.053113	8.892047	0.0000
SIGMASQ	0.245527	0.018674	13.14840	0.0000

R-squared	0.601837	Mean dependent var	0.911797
Adjusted R-squared	0.588993	S.D. dependent var	0.788332
S.E. of regression	0.505398	Akaike info criterion	1.519361
Sum squared resid	31.67295	Schwarz criterion	1.630206
Log likelihood	-92.99877	Hannan-Quinn criter.	1.564400
F-statistic	46.85761	Durbin-Watson stat	2.046465
Prob(F-statistic)	0.000000		

Inverted AR Roots	.91	.07-.48i	.07+.48i	-.59

The Autocorrelation Chart below (Table 3) shows information for the results of the residuals and with the probability indicating the model is a perfect outcome for the proposed forecast.
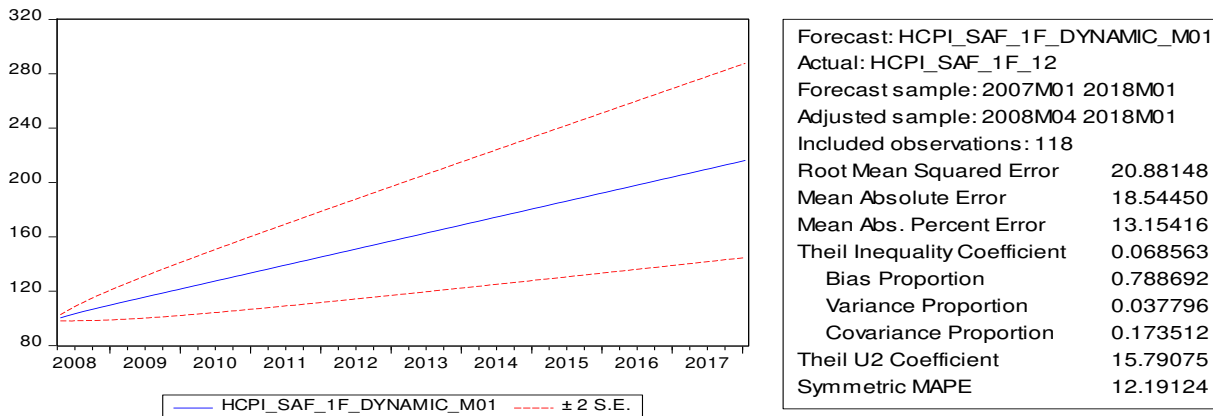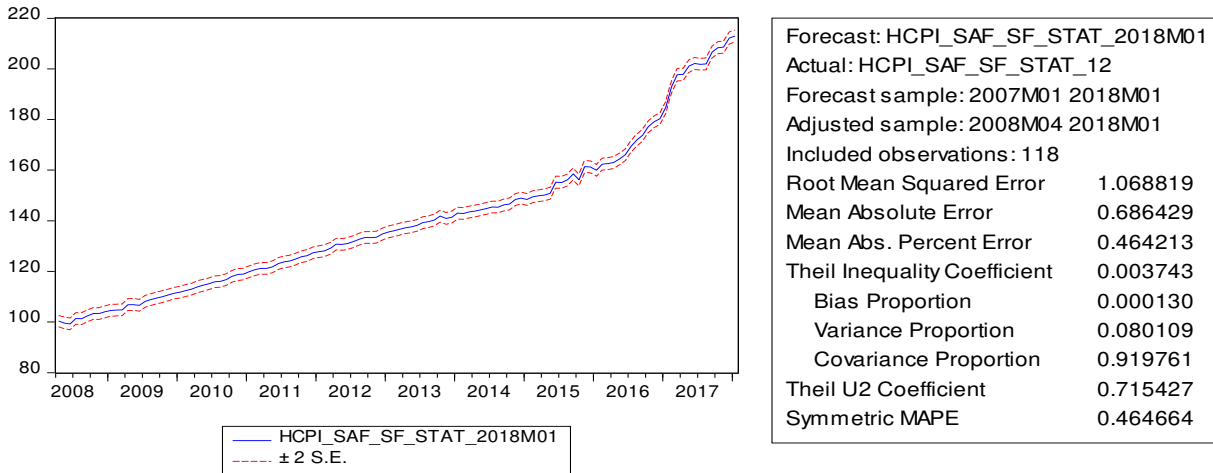
Table 3: Autocorrelation Chart

Date: 01/03/18   Time: 04:48
Sample: 2007M01 2018M01
Included observations: 129
Q-statistic probabilities adjusted for 3 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.027	-0.027	0.0973	
.|. |	.|. |	2	-0.036	-0.037	0.2714	
.|. |	.|. |	3	0.048	0.046	0.5854	
.|. |	.|. |	4	-0.027	-0.025	0.6811	0.409
.|. |	.|. |	5	0.004	0.006	0.6830	0.711
.|. |	*|. |	6	-0.064	-0.068	1.2448	0.742
.|* |	.|* |	7	0.126	0.127	3.4614	0.484
.|. |	.|. |	8	0.057	0.058	3.9185	0.561
.|. |	.|. |	9	0.008	0.027	3.9272	0.687
*|. |	*|. |	10	-0.083	-0.097	4.9021	0.672
.|. |	.|. |	11	-0.053	-0.056	5.3011	0.725
.|. |	.|. |	12	0.009	-0.004	5.3121	0.806
.|. |	.|. |	13	-0.065	-0.042	5.9239	0.822
.|. |	.|. |	14	0.066	0.058	6.5731	0.833
.|. |	.|. |	15	0.072	0.059	7.3521	0.833
.|. |	.|. |	16	0.041	0.040	7.6078	0.868
.|. |	.|. |	17	-0.041	-0.033	7.8624	0.896
.|* |	.|* |	18	0.094	0.120	9.2014	0.867
*|. |	*|. |	19	-0.073	-0.075	10.011	0.866
.|* |	.|* |	20	0.128	0.164	12.539	0.766
.|. |	.|. |	21	-0.006	-0.041	12.545	0.818
.|* |	.|* |	22	0.079	0.100	13.521	0.811
.|. |	*|. |	23	-0.033	-0.108	13.690	0.846
*|. |	*|. |	24	-0.131	-0.092	16.469	0.743
.|. |	.|. |	25	0.033	-0.012	16.642	0.783
*|. |	*|. |	26	-0.105	-0.071	18.445	0.733
.|* |	.|* |	27	0.127	0.129	21.111	0.632
.|. |	.|. |	28	0.003	-0.001	21.112	0.686
.|. |	.|. |	29	-0.032	-0.029	21.284	0.727
.|. |	.|. |	30	0.023	-0.020	21.373	0.768
.|. |	.|. |	31	-0.023	0.055	21.464	0.805
.|. |	.|. |	32	-0.037	-0.058	21.701	0.832
.|. |	.|. |	33	-0.044	0.026	22.047	0.852
.|. |	.|. |	34	0.027	-0.065	22.180	0.877
.|. |	.|. |	35	-0.010	-0.016	22.197	0.902
.|. |	.|. |	36	0.011	-0.060	22.221	0.923

In order to check the robustness of the forecast, both Static and Dynamic outcomes have been produced to help in term of providing constructive judgment about which forecast method is to be used for policy consideration. Based on the outcome on *Figure 3*, it is clear that the use of STATIC forecast is more appropriate in terms of results within the actual HCPI_SA data. In comparison, the DYNAMIC forecast shows marked diversion from the actual HCPI_SA data and with very high margin of errors as shown in the *Root Mean Squared Error*, *Mean Absolute Error* and *Mean Absolute Percentage Error* values in comparison to that of the STATIC forecast.

3.3. Figure 3: Forecast Comparison Graphs [Static and Dynamic]

Forecast: HCPI_SAF_SF_STAT_2018M01	
Actual: HCPI_SAF_SF_STAT_12	
Forecast sample: 2007M01 2018M01	
Adjusted sample: 2008M04 2018M01	
Included observations: 118	
Root Mean Squared Error	1.068819
Mean Absolute Error	0.686429
Mean Abs. Percent Error	0.464213
Theil Inequality Coefficient	0.003743
Bias Proportion	0.000130
Variance Proportion	0.080109
Covariance Proportion	0.919761
Theil U2 Coefficient	0.715427
Symmetric MAPE	0.464664

Forecast: HCPI_SAF_1F_DYNAMIC_M01	
Actual: HCPI_SAF_1F_12	
Forecast sample: 2007M01 2018M01	
Adjusted sample: 2008M04 2018M01	
Included observations: 118	
Root Mean Squared Error	20.88148
Mean Absolute Error	18.54450
Mean Abs. Percent Error	13.15416
Theil Inequality Coefficient	0.068563
Bias Proportion	0.788692
Variance Proportion	0.037796
Covariance Proportion	0.173512
Theil U2 Coefficient	15.79075
Symmetric MAPE	12.19124

4. Conclusion

The above forecast outcome shows that STATIC forecast results is a better prediction of future inflation trend when compared to DYNAMIC forecast. Supposedly, STATIC forecast allow results

of previous forecast to be done singly as a predictor of future inflation outcomes and this is very well tracked as the margin of error is quite small when compared to DYNAMIC forecast outcomes. The DYNAMC forecast on the other hand, forecast outcomes based on series of projected period, as in this case, three monthly periods (2017M10 – 2018M01).

To say that STATIC forecast method is generally the best can sometimes be an over-statement as some researchers have proved that DYNAMIC forecast can be a better choice, even though the former have embedded some economic theory justification (Ericsson, 2016).

To wrap it up, the use of either STATIC or DYNAMIC forecast as a means for economic policy decision must be treated with caution given the experiences of realities from the opposite of dogmatic forecast outcomes, which on the whole can be detrimental for business confidence and also economic realities. In this situation, it will be advisable that the peculiarity of the economy is taken seriously into consideration when using forecast results as a means of policy decisions. In addition, the use of comparative forecasts may also seem a good way of supporting policy makers' decisions, for example, the use of multivariate means of forecast results using methodologies like ARIMAX, VAR and even in an open-economy DSGE model.

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