Determining the Better Approach for Short-Term Forecasting of Ghana's Inflation: Seasonal-ARIMA vs. Holt-Winters

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Abstract

In this paper, we examine the most appropriate short-term forecasting method for Ghana's inflation. A monthly inflation data which spans from January 1971 to October 2012 was obtained from Ghana Statistical Service. The data was divided into two sets: the first set was used for modelling and forecasting, whiles the second was used as test set. Seasonal-ARIMA and Holt-Winters approaches were used to achieve short-term out-of-sample forecast. The accuracy of the out-of-sample forecast was measured using MAE, RMSE, MAPE and MASE. Empirical results from the study indicate that the Seasonal-ARIMA forecast from ARIMA(2,1,1)(0,0,1)$_{12}$ recorded MAE, RMSE, MAPE and MASE of 0.1787, 0.2104, 1.9123 and 0.0073 respectively; that of the Seasonal Additive HW was 1.8329, 2.0176, 19.996, 0.0745; and the Seasonal Multiplicative HW forecast recorded 2.2305, 2.4274, 24.000, 0.0911 respectively. Based on these results, we conclude by proposing the Seasonal-ARIMA process as the most appropriate short-term forecasting method for Ghana's inflation

Keywords: inflation, Holt-Winters, Seasonal- ARIMA, forecasting accuracy, Ghana

1. Introduction

The need for forecasting is in recent times increasing, as administrators and managers of various economies attempts to decrease their over-dependence on chance and instead become more scientific in dealing with issues (Makridakis *et al*., 1998). To obtain a more accurate and reliable future forecast for economic variables such as inflation, several time series approaches have been used by analysts in different economies around the world. One of the most frequently used time series approaches for forecasting inflation is that from the Box-Jenkins ARIMA models (see, Meyler *et al.*, 1998; Faisal, 2012; Olajide *et al.*, 2012). Moreover, Pufnik and Kunovac (2006) obtained short-term forecast of inflation in Croatia, by using Seasonal ARIMA processes. An extended version of the Seasonal ARIMA, known as the Driftless Extended Seasonal ARIMA (DESARIMA) was introduced in a study by Puncheira and Medel (2012) to forecast inflation across 12 countries. Also, Barros and Gil-Alana (2012) employed a fractional approach (Autoregressive Fractionally Integrated Moving Average) to forecast inflation in Angola. In a new direction, the forecast performance of a Vector Autoregressive (VAR) model in forecasting inflation was compared to an ARIMA forecast model (see, Hector, 2000; Bohkari and Feridun, 2006). Similar to this, Suhartono (2005) compared the forecasting accuracies of three (3) approaches used in forecasting Indonesian inflation (Neural Networks, ARIMA and ARIMAX). In his study, the forecast from the Neural Network approach outperformed the two other approaches. Recently, He *et al*., (2012) also investigated into the most appropriate methods for inflation forecasting.

The researchers considered the following methods: Neural Network, ARIMA, ARIMA-GARCH, Exponential Smoothing and other traditional methods. Their study selected the ARIMA-GARCH as the most appropriate method for their inflation data.

In Ghana, not much work has been done with respect to modelling and forecasting inflation. However, Atta-Mensah and Bawumia (2003) presented a vector-error-correction forecasting model (VECFM), based on broad money to forecast some selected Ghanaian macroeconomic variables: money, growth, inflation, output growth, Treasury-bill rate and exchange rate. The out-of-sample experiments from their study reveals that the VECFM approach performs well around the turning points. Also, Ocran (2007) identified inflation inertia, changes in money, Treasury bill rates and exchange rate as key determinants of inflation in the short run using Johansen cointegration test and an error correction model. In a different study, Alnaa and Abdul-Mumuni (2005) forecasted Ghana's inflation using ARIMA and VAR models. Based on the Root Mean Square Error, the VAR model was found to have been more efficient than the ARIMA forecasting model. Contrast to this, Alnaa and Ahiakpor (2011) built an ARIMA model to predict inflation in Ghana. From their study, they claimed, the ARIMA forecasting model is much efficient for forecasting Ghana's inflation. To a more current study, Suleman and Sarpong (2012) identified and used a Seasonal Autoregressive Moving Average model (SARIMA) as appropriate approach for forecasting inflation in Ghana. Moreover, in an unpublished thesis, Aidoo (2011) examined the forecast performance between SARIMA and SETAR models as applied to Ghana's inflation rate. He revealed that the SETAR forecasting model outperforms that of the SARIMA's.

From the review, no study has been conducted in Ghana to forecast inflation using Holt-Winters' approach. This study then contributes to the existing literature by focusing on two time series approaches (Seasonal-ARIMA and Holt-Winters) for inflation forecasting. In the study, a forecast from the Seasonal-ARIMA approach was compared to that of the Holt-Winters'. The objective of the study is to examine the optimal forecast approach for obtaining short-term out-of-sample forecast for Ghana's monthly inflation. The study also seeks to verify whether the appropriate Seasonal-ARIMA forecast model, based on the Akaike Information Criterion (AIC), necessarily produces the most optimal forecast accuracy for the inflation series being considered.

The entire paper has been organised as follows: the current section has reviewed existing time series approaches for forecasting inflation in Ghana, and in some other countries. The second section presents data and methods used for the study. Empirical results and analysis are given in section three. A summary of findings from the study is lastly presented in section four of the paper.

2. Data and Methods

The "Year-on-Year" Consumer Price Index (CPI) data used for this study was obtained from Ghana Statistical Service. It covers a total of 502 data points, spanning from January 1971 to October 2012. The average inflation rate for this period is estimated at 33.2 and ranges from 1.1 to 174.1. The Inflation data was specifically used to investigate the most appropriate short-term out-of-sample forecast, using the Box-Jenkins Seasonal Autoregressive Integrated Moving Average and the Holt-Winters forecasting approaches.

2.1 Specifying the Seasonal-ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model was put forward and made popular by Box and Jenkins in the 1970s. The two renowned scholars combined the Autoregressive (AR) and Moving Average (MA) models with an integrated term (I), which removes time series patterns that usually renders the series to be non-stationary. There are two forms of the model based on the kind of pattern the series exhibits. A Seasonal Autoregressive Integrated Moving Average (Seasonal-ARIMA) model is basically used when the time series shows clear seasonal patterns. In the absence of seasonal patterns, a non-seasonal Autoregressive Integrated Moving Average model may be used to represent the series. In notation, a non-seasonal ARIMA model is expressed as ARIMA(p, d, q), where p represents the Autoregressive term which places much weight on past values of the series for forecasting future values; d denotes the number of times the series is differenced to achieve stationarity; and q is the Moving Average term which relies on past forecasting errors of the series for obtaining future forecast values.

In an extension to the non-seasonal model, the Seasonal-ARIMA model may be expressed in a multiplicative way as ARIMA(p, d, q)(P, D, Q)$_s$, where (p, d, q) represents the non-seasonal part of the model, (P, D, Q)$_s$ shows the seasonal component of the model and s is the number of periods per season. In the seasonal component, P represents the Seasonal Autoregressive (SAR) term, D is the number of seasonal difference(s) performed and Q denotes the Seasonal Moving Average (SMA) term. The general notational form of a fit from the Seasonal-ARIMA model may be written as;

$$(1-B)^d(1-B)^D Y_t = \mu + \frac{\theta(B)\Theta(B^s)}{\phi(B)\Phi(B^s)}\varepsilon_t \tag{1}$$

where, B is a backward shift operator and Φ, Θ are the Seasonal Moving Average (SMA) and the Seasonal Autoregressive (SAR) polynomials of order P and Q respectively.

2.1.1 Specification of the Holt-Winters' Models

The Holt-Winters' (HW) method of smoothing is a generalization of the Holt's linear method. The technique was proposed in 1960 by Holt and Winters, and was later named after the inventors. Its largely extend the Holt's linear equations to directly capture seasonality. The Holt-Winters method is widely used on time series which exhibit patterns of increasing or decreasing trend with presence of seasonality. It basically has three (3) smoothing equations. Each smoothing equation is designed to capture either the presence of level, trend or seasonality in the series. It can be used for forecasting time series in the short-, medium-, and long-term periods. The technique is different from other forecasting methods in the sense that it does not depend on the fit from any statistical modelling technique. Instead, it uses iterative steps to produce forecast values.

Generally, there are two versions of the Holt-Winters smoothing method, depending whether the seasonal pattern in the series is modelled in an additive or multiplicative process. The seasonal multiplicative HW is not applicable if the time series has null or negative values. Its equations are as follows;

$$\text{Level}: \quad L_t = \alpha\frac{y_t}{S_{t-s}} + (1-\alpha)(L_{t-1}+b_{t-1}) \tag{2}$$

$$\text{Trend}: \quad b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{3}$$

$$\text{Seasonal}: \quad s_t = \gamma\frac{y_t}{L_t} + (1-\gamma)s_{t-s} \tag{4}$$

$$\text{forecast}: \quad f_{t+m} = (L_t + b_t m)s_{t-s+m} \tag{5}$$

where, y_t is the observed series, s is the length of the seasonal cycle, L_t gives the level of the series, b_t represents the trend, $0 \le \alpha \le 1$, $0 \le \beta \le 1$, $0 \le \gamma \le 1$ and f_{t+m} presents forecast for m-periods ahead.

Unlike the Seasonal Multiplicative HW, the Seasonal Additive HW equations differ in terms of the smoothing and forecast processes. The Seasonal Additive HW equations are given as;

$$\text{Level}: \quad L_t = \alpha(y_t - s_{t-s}) + (1-\alpha)(L_{t-1}+b_{t-1}) \tag{6}$$

$$\text{Trend}: \quad b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{7}$$

$$\text{Seasonal}: \quad s_t = \gamma(y_t - L_t) + (1-\gamma)s_{t-s} \tag{8}$$

$$\text{forecast}: \quad f_{t+m} = L_t + b_t m + s_{t-s+m} \tag{9}$$

where, as explained earlier, y_t is the observed series, s is the length of the seasonal cycle, L_t gives the level of the series, b_t represents the trend, f_{t+m} is the forecast for m-periods into the future and α, β and γ are probability values.

2.1.2 Measures of Out-of-Sample Forecast Accuracy

A comparison of short-term forecasting accuracy between the Seasonal-ARIMA and the Holt-Winters forecasting approaches have been drawn in this study. To set the platform for the comparison, the inflation data was separated into two set. The first set which spans from January 1971 to January 2012 was used to model and forecast for the near future. The next nine (9) data points were used as test set or holdout set for the out-of-sample forecast accuracy of the competing forecasting methods.

Two (2) scaled-dependent measures: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used for comparing the forecast performances between the forecast methods. According to Hyndman and Koehler (2005), these measures are useful when comparing different methods of the same set of data, but they strongly advised researchers against their use when comparing across data sets that have different scales. In notation, the MAE and the RMSE are given as;

$$Mean\ \ Absolute\ \ Error(MAE) = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{10}$$

$$Root\ \ Mean\ \ Square\ \ Error(RMSE) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(e_t)^2} \tag{11}$$

The study again employed a forecast accuracy measure based on percentage errors. The percentage error is expressed as $P_t = 100e_t/y_t$. It is a scaled-independent measure. The Mean Absolute Percentage Error (MAPE) is one of the percentage errors that have been consistently used for comparing forecast accuracy. It is calculated as;

$$Mean\ \ Absolute\ \ Percent\ \ Error(MAPE) = \frac{1}{n}\sum_{t=1}^{n}|P_t| \tag{12}$$

Another accuracy measure statistic used in this study is the Mean Absolute Square Error (MASE). It was first proposed by Hyndman and Koehler (2005), as scale-free error metric. It is less sensitive to outliers and can be used to compare forecast methods on a single series, as well as forecast accuracy between series. In the presence of trend, seasonal or both patterns, the MASE is applicable and does not give infinite or undefined values.

MASE is recommended to be a standard measure for the comparison of forecasting accuracies (Hyndman, 2006). It is computed as;

$$Mean\ \ Absolute\ \ Square\ \ Error(MASE) = \frac{1}{n}\sum_{t=1}^{n}|q_t| \tag{13}$$

where, $q_t = \dfrac{e_t}{\frac{1}{n}\sum_{i=2}^{n}|Y_i - Y_{i-1}|}$

In general, the smaller the value of the forecast accuracy measure, the better the forecast. However, there is no specific threshold for these measures. Instead, a smaller value produced by these accuracy statistics foretells the best forecasting methods among severally competing methods.

3. Empirical Results and Analysis

This section basically presents the forecast results from the Seasonal-ARIMA and the Holt-Winters forecasting methods. The R statistical software (with version 2.14.1) was used to obtain all the results under this study. The R software codes used for the results can be obtained from the authors upon official request.

3.1 Seasonal-ARIMA Forecasting Results

In modelling and forecasting any time series data, it is always advisable to plot and observe the unique pattern(s) exhibited by the series. This helps analysts to choose the appropriate modelling approach which adequately captures such identified pattern(s). In line with this, the "Year-on-Year" inflation series used in this study was first plotted to examine its pattern(s). Figure 1 shows Ghana's inflation series from January 1971 to January 2012. The figure also gives the sample Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the original series. From the figure, it could be observe that, the series exhibit a continually increasing and decreasing trend. The trendy nature of the series is also characterised by some few seasonal patterns. Ghana recorded high level of inflation from the late 1970s to the mid of 1980. The situation was entirely different during the 1990s, through to the 2000s. This period experienced swift increases and decreases in the pattern of the series. Critical observation of the sample ACF and PACF of the original inflation series, shown in Figure 1, could lead one to classify the series as non-stationary. The spikes of the ACF starts at a higher point and do not decay to zero, whiles the PACF has its first spike almost close to 1. This condition gives a clear indication of a non-stationary series.

To forecast the inflation series in Figure 1, there is a need to make the series stationary. A forecast from a non-stationary series may results to spurious forecast values which would be inconsistent and cannot be reliable, in terms of making decisions to meet future occurrences. Due to these circumstances, a non-seasonal first difference was taken to make the series look reasonably stationary. This can be seen through the movement of the spikes in Figure 2. From the figure, the spikes of the series oscillate around a common mean. This shows a series which is stationary in the mean. We further used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test to verify the stationarity or otherwise of the original and the differenced inflation series respectively, based on 5% significance level. The results of the KPSS test in Table 1 confirm the earlier observation made on the series. From Table 1, the KPSS test conferred a non-stationary series (with p-value of 0.010) on the original inflation series. In the same table, the non-seasonally differenced inflation series was found to have exhibited both level and trend stationary.

After achieving stationarity in the series, candidate models were selected based on the sample ACF and PACF of the non-seasonally differenced series. From Figure 2, the ACF recorded two (2) non-seasonal significant spikes and one (1) seasonal significant spike at lag 12. In the PACF of the same figure, there were three (3) non-seasonal significant spikes and one (1) seasonal significant spike at lag 12 only. There were no recorded significant seasonal spikes at lag 24 and 36 in the sample ACF and PACF. Based on the behaviour of the spikes, we settled on a Multiplicative Seasonal-ARIMA model: ARIMA(3, 1, 2)$(1, 0, 1)_{12}$. Other candidate models were also selected to compete with the earlier model. These latter models include; ARIMA(2,1,2)$(0,0,1)_{12,}$ ARIMA(2,1,2)$(1,0,0)_{12,}$ and ARIMA(3,1,4)$(0,0,1)_{12.}$ The adequacies of all these candidate models were examined using significant parameters and the behaviour of the residuals, through the Ljung-Box test and the Akaike Information Criterion (AIC).

The maximum likelihood estimates of each competing Seasonal-ARIMA model are presented in Table 2, 3, 4 and 5. The AIC penalty function statistic was used to compare the fit from the four models. A model which records the smallest AIC value is believed to possess well-behaved residuals. The residuals of each model were verified to ascertain whether they follow or depart from a white noise process. From Table 2, both coefficients of the seasonal components of ARIMA(3, 1, 2)$(1, 0, 1)_{12}$, (sar1 and sma1) were found to be non-significant (based on the t-statistic test). The non-seasonal AR part (ar3) of the same model also recorded another non-significant coefficient. However, all the coefficients of the other three competing seasonal models were found to have recorded significant coefficients. In terms of the residuals, all four models passed the Ljung-Box residual test (with p-values far above 0.05 significant levels). This obviously suggests that the residuals of the selected Seasonal-ARIMA models follow a white noise process. With respect to the penalty statistic, ARIMA (3, 1, 4)$(0, 0, 1)_{12}$ had the lowest AIC value (3500.57). It simply means, the residuals of ARIMA (3, 1, 4)$(0, 0, 1)_{12}$ are much well-behaved, compared to the other candidate models. By using the AIC, the most appropriate model which best fit the inflation series is that of ARIMA (3, 1, 4)$(0, 0, 1)_{12}$. However, available literature has well documented that, models with best AIC values does not always turn out to be the best forecast model. To optimize the forecasting values for the inflation series, we considered all the four competing models, since all these models had proven to have shown well-behaved residuals (from the Ljung-Box test).

In furtherance, the selected Seasonal-ARIMA models were then used to obtain out-of-sample forecast for the inflation series. A nine (9) month out-of-sample forecast results from each of the Seasonal-ARIMA models and the actual inflation values (test set) for that period are presented in Table 6. Critical observation from the table indicates that, almost all the four candidate models forecast the inflation series with less error margins. Yet, the MAE, RMSE, MAPE and MASE were best used to assess the performances of each forecast model.

3.1.1 Holt-Winters Forecasting Results

Table 7 presents the level, trend and seasonal components, as well as the smoothing parameters for the Seasonal Additive and Multiplicative Holt-Winters. The alpha, beta and gamma smoothing parameters were used for estimating the level, trend and seasonal components. From the table, the estimated values for alpha, beta and gamma are 0.9546, 0.0000 and 1.0000 for the Seasonal Additive HW and 0.3000, 0.1000 and 0.1000 for the Seasonal Multiplicative HW respectively. The smoothing parameters do have values between 0 and 1. Values close to zero (0) means relatively little weight is placed on the most recent observations when making forecasts of future values. On the contrary, values closer to one (1) signify that much weight is put on observations in the far distant past to obtain future forecast values.

However, the estimated beta value of 0.0000 indicates that the estimate of the slope *b* of the trend component of the Seasonal Additive HW is not updated over the time series, but rather set equal to its initial value.

Results from Table 8 then give a nine (9) month out-of-sample forecast for the Seasonal Additive and the Seasonal Multiplicative Holt-Winters models. The table also presents the test set for the nine (9) months period. A comparison between the actual data (test set) and the forecasts mainly shows that the forecast values from the Seasonal Additive HW and the Seasonal Multiplicative HW are not quite good with respect to the error margins. Meanwhile, the forecast accuracy for the two models was later assessed using four accuracy measure statistics.

3.1.2 Forecasting Accuracy: Seasonal-ARIMA vs. Holt-Winters

The fit performance from each competing forecast model was compared to the original inflation series. Figure 3 shows how best the fit of each model performs with the series. From the figure, the black line represents the original inflation series; the red, dark green, blue, and grey line colours indicate a fit from ARIMA(3,1,2)$(1,0,1)_{12}$, ARIMA(2,1,2)$(0,0,1)_{12}$, ARIMA(2,1,2)$(1,0,0)_{12}$ and ARIMA(3,1,4)$(0,0,1)_{12}$ respectively; the light green shows that of the Seasonal Additive HW, whiles the pink represents a fit from the Seasonal Multiplicative HW. A close observation from Figure 3 clearly indicates that all the competing models, with the exception of the Seasonal Multiplicative HW fit the original inflation series quite better.

From Table 9, the out-of-sample forecast performances of the Seasonal-ARIMA models and that of the Holt-Winters' were ranked using accuracy measure statistics: MAE, RMSE, MAPE and MASE. Unanimously, ARIMA(2,1,2)$(0,0,1)_{12}$ was adjudged the best model for obtaining a much accurate short-term out-of-sample forecast for Ghana's inflation. This was followed by ARIMA(3,1,2)$(1,0,1)_{12}$, ARIMA(2,1,2)$(1,0,0)_{12}$ and ARIMA(3,1,4)$(0,0,1)_{12}$ in that order respectively. The last ranked models were the Seasonal Additive HW and the Seasonal Multiplicative HW respectively. From the rankings, it is obviously clear that all the selected Seasonal-ARIMA models forecast Ghana's inflation with greater precision, compared to the two Holt-Winters models.

4. Conclusion

In this study, we investigated into the most appropriate method for obtaining short-term out-of-sample forecast for Ghana's "Year-on-Year" inflation series, using the Seasonal-ARIMA and the Holt-Winters forecasting methods. The out-of-sample forecast accuracies of four Seasonal-ARIMA models and the two Holt-Winters forecasting approaches were assessed using accuracy measure statistics: MAE, RMSE, MAPE and MASE. The forecast accuracies were ranked based on these statistics.

The four Seasonal-ARIMA forecast models; ARIMA(2,1,2)$(0,0,1)_{12}$, ARIMA(3,1,2)$(1,0,1)_{12}$, ARIMA (2,1,2) $(1,0,0)_{12}$ and ARIMA(3,1,4)$(0,0,1)_{12}$ took the first, second, third and fourth positions respectively. The Seasonal Additive HW became fifth, whiles the Seasonal Multiplicative HW occupied the last position. This indicates that, an out-of-sample forecast from a Seasonal-ARIMA approach far supersedes any of the Holt-Winters' approach with respect to forecast accuracy or precision. We again realised that, the best AIC model, did not give the most optimal forecast performance.

In conclusion, we propose Seasonal-ARIMA as the most appropriate method for obtaining short-term out-of-sample forecast for Ghana's monthly inflation.

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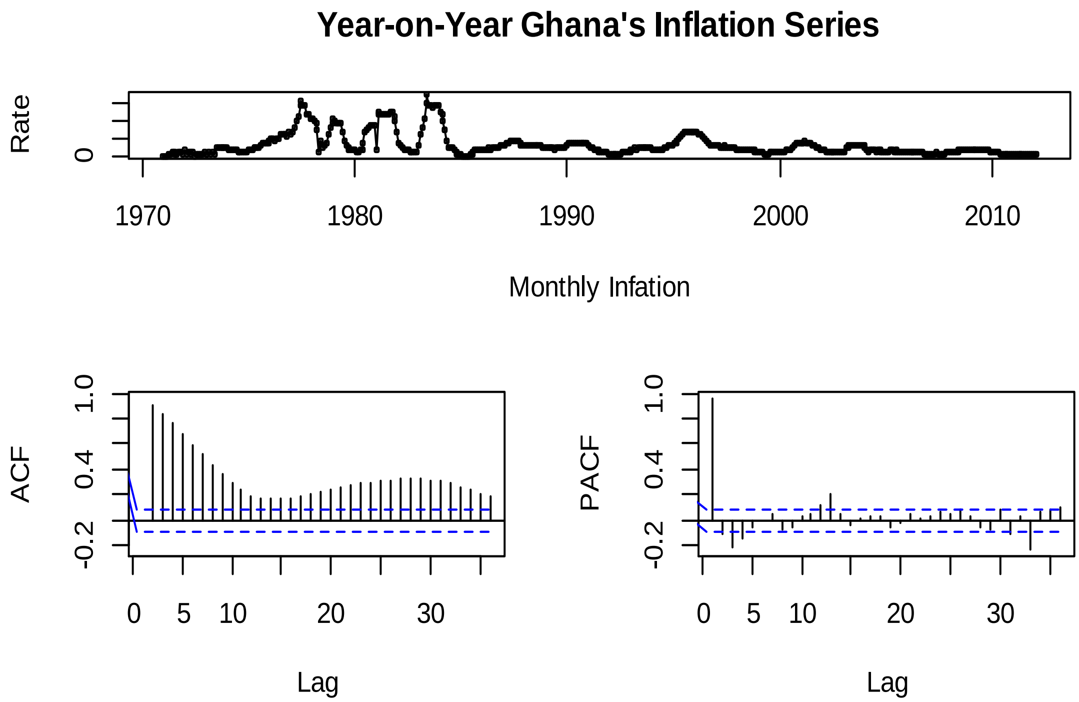

Figure 1: Original "Year-on-Year" Ghana's Inflation Series from Jan 1971 to Jan 2012

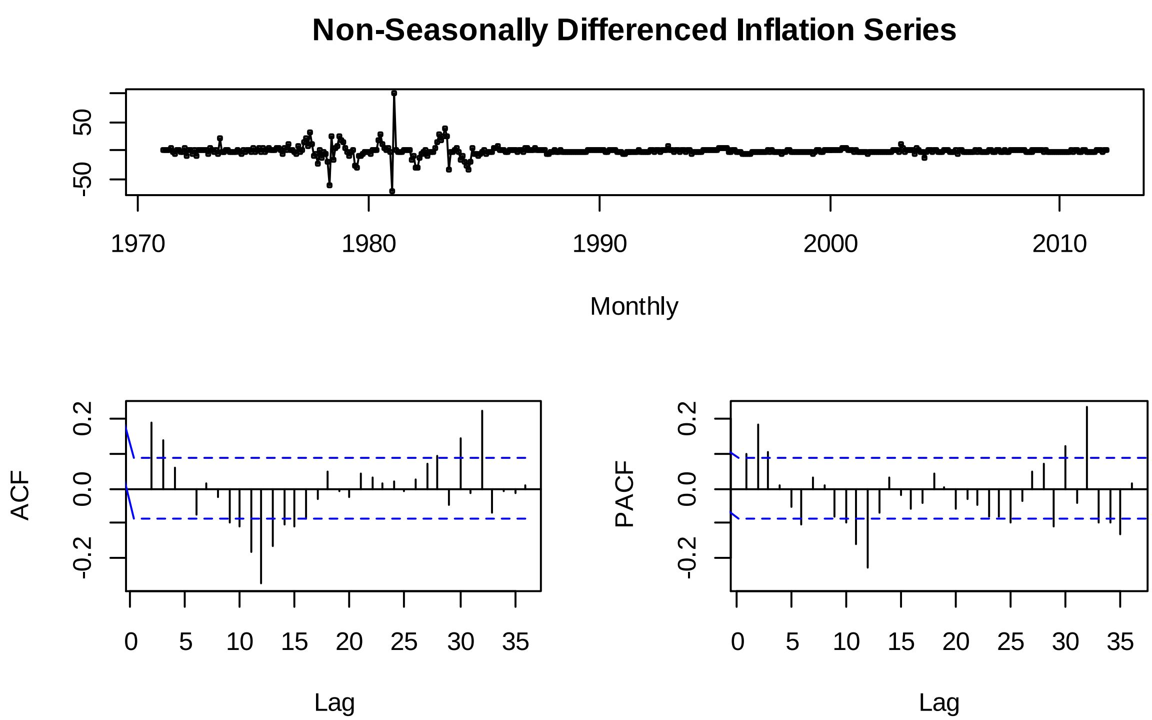

Figure 2: Non-Seasonal First Difference with Sample ACF and PACF

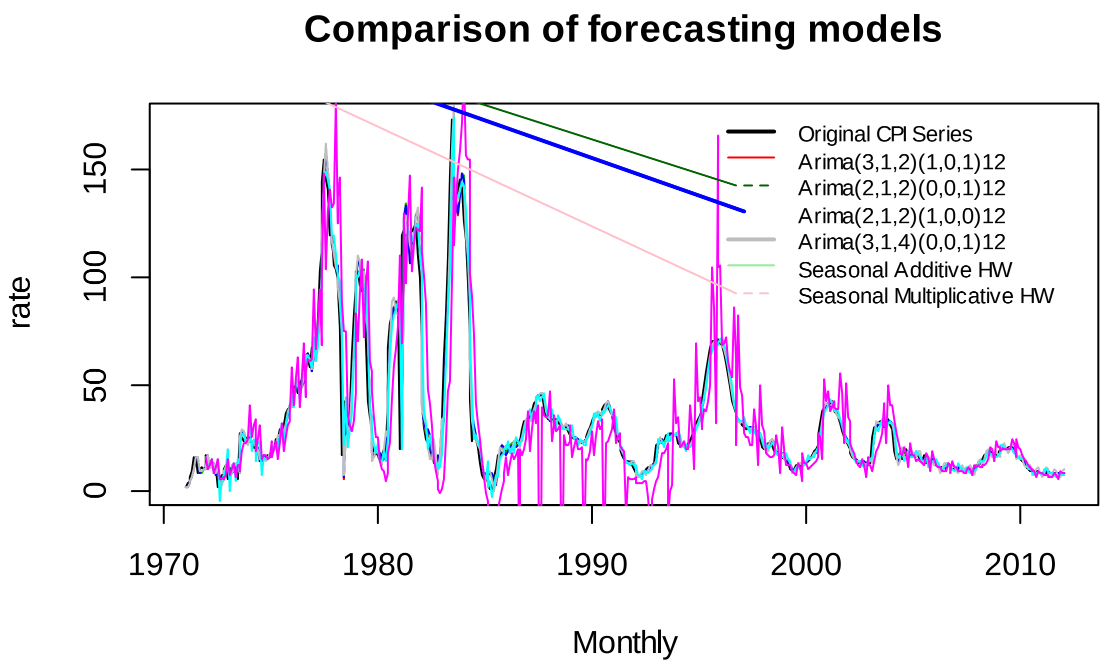

Figure 3: Performance of forecast models with original series

Table 1: Stationarity Test

KPSS Test for Trend/Level Stationarity				
	Original Inflation Series		**Non-Seasonal Differenced Inflation Series**	
	Test Statistic	P-value	Test Statistic	P-value
Level	1.5344	0.010	0.0281	0.100
Trend	0.2485	0.010	0.0160	0.100

Table 2: Parameter Estimate of Arima $(3,1,2)(1,0,1)_{12}$

Variable	**ar1**	**ar2**	**ar3**	**ma1**	**ma2**	**sar1**	**sma1**
Estimate	0.7473	-0.5867	0.0310	-0.7556	0.7456	-0.0170	-0.2292
Std. Error	0.1679	0.1497	0.0608	0.1556	0.1279	0.1668	0.1630
t-statistic	4.4509	-3.9192	0.5099	-4.8560	5.8300	0.1019	-1.4061
			Chi-square		P-Val		
	Ljung-Box Test		17.1529		0.1439		
			AIC = 3513.24				

Table 3: Parameter Estimate of Arima $(2,1,2)(0,0,1)_{12}$

Variable	**ar1**	**ar2**	**ma1**	**ma2**	**sma1**
Estimate	0.7771	-0.5939	-0.7969	0.7681	-0.2453
Std. Error	0.1306	0.1554	0.1082	0.1252	0.0482
t-statistic	5.9502	-3.8218	-7.3651	6.1350	5.0892
			Chi-square		P-Val
	Ljung-Box Test		18.2582		0.1081
		AIC = 3509.54			

Table 4: Parameter Estimate of Arima (2,1,2)(0,0,1)

Variable	**ar1**	**ar2**	**ma1**	**ma2**	**sma1**
Estimate	0.8345	-0.6510	-0.8436	0.8096	-0.2253
Std. Error	0.1389	0.2115	0.1234	0.1712	0.0480
t-statistic	6.0079	-3.0780	-6.8363	4.7290	4.6938
			Chi-square		P-Val
	Ljung-Box Test		17.8153		0.1214
		AIC = 3511.15			

Table 5: Parameter Estimate of Arima $(3,1,4)(0,0,1)_{12}$

Variable	**ar1**	**ar2**	**ar3**	**ma1**	**ma2**	**ma3**	**ma4**	**sma1**
Estimate	0.8353	-1.1245	0.4031	-0.8611	1.3571	-0.4680	0.1799	-0.2647
Std. Error	0.0607	0.0692	0.1471	0.1588	0.0879	0.1543	0.0360	0.0453
t-statistic	13.761	-16.250	2.7403	-5.4225	15.439	-3.0331	4.9972	5.8433
				Chi-square		P-Val		
		Ljung-Box Test		11.9173		0.4523		
				AIC = 3500.57				

Table 6: Short-Term Forecast of Selected Seasonal-Arima Models

Test Set		**Out-of-Sample Forecast**			
2012 Month	Actual Data	**Arima $(3,1,2)(1,0,1)_{12}$**	**Arima $(2,1,2)(0,0,1)_{12}$**	**Arima $(2,1,2)(1,0,0)_{12}$**	**Arima $(3,1,4)(0,0,1)_{12}$**
Feb	8.60	8.6323	8.6277	8.5887	8.7522
March	8.80	8.7297	8.7360	8.6477	6.9287
April	9.10	8.9055	8.9223	8.7585	6.1430
May	9.30	9.0203	9.0442	8.8309	7.3201
June	9.40	9.1358	9.1609	8.8827	8.6276
July	9.50	9.1605	9.1802	8.8821	8.0723
Aug	9.50	9.1671	9.1834	8.8542	6.7141
Sept	9.40	9.1908	9.2088	8.8607	6.7397
Oct	9.20	9.1599	9.1832	8.8392	8.0073

Table 7: Smoothing parameters with coefficients for level, trend and seasonal components

		Additive HW	Multiplicative HW
Smoothing parameters	alpha	0.9546	0.3000
	beta	0.0000	0.1000
	gamma	1.0000	0.1000
Coefficients	l	10.7049457	6.6067689
	b	-0.08748543	-0.1342983
	S_1	-0.40915640	1.2397302
	S_2	0.96171758	1.2166162
	S_3	1.76119434	1.2116693
	S_4	1.17577296	1.1604408
	S_5	0.95206961	1.1162528
	S_6	1.49650030	1.0939037
	S_7	1.24625242	1.2608108
	S_8	0.25328927	1.2563936
	S_9	-0.54928808	0.9935918
	S_{10}	-1.19864053	1.3109050
	S_{11}	-1.72524672	1.2581399
	S_{12}	-2.00494565	1.3222701

l:level component b:trend component s:seasonal component

Table 8: Short-term forecast from the Holt-Winters Models

Test Set		**Out-of-Sample Forecast**	
2012 Month	Actual Data	Additive HW	Multiplicative HW
Feb	8.60	10.2083	8.0241
March	8.80	11.4917	7.7111
April	9.10	12.2037	7.5170
May	9.30	11.5308	7.0434
June	9.40	11.2196	6.6253
July	9.50	11.6765	6.3457
Aug	9.50	11.3388	7.1446
Sept	9.40	10.2584	6.9509
Oct	9.20	9.36830	5.3635

Table 9: Comparison of Out-of-Sample Forecasting Accuracy

	Summary of Accuracy Measurement Statistics				
	Forecasting Models	**MAE**	**RMSE**	**MAPE**	**MASE**
Seasonal-ARIMA Models	$ARIMA(3,1,2)(1,0,1)_{12}$	0.1959	0.2269	2.0966	0.0080
	$ARIMA(2,1,2)(0,0,1)_{12}$	**0.1787**	**0.2104**	**1.9123**	**0.0073**
	$ARIMA(2,1,2)(1,0,0)_{12}$	0.4061	0.4531	4.3470	0.0166
	$ARIMA(3,1,4)(0,0,1)_{12}$	1.7555	1.9744	18.962	0.0717
Holt-Winters	Seasonal Additive	1.8329	2.0176	19.996	0.0745
	Seasonal Multiplicative	2.2305	2.4274	24.000	0.0911