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Inflation Forecasting in Developing Economies Using SARMA Models: The Case of Ghana

Senanu Kwasi Klutse

Due in part to a weakening link between monetary aggregates and the inflation variable, monetary policy authorities are specifically targeting the price level. This has made it more necessary for inflation forecasting to be considered in the conducting of monetary policy. This paper presents different approaches to forecasting inflation in developing economies using Seasonal Autoregressive Moving Average (SARMA) models. SARMA models were employed because they capture seasonal components of the inflation variable which other univariate (ARMA) models cannot effectively capture.

The analysis showed that the complex approach is good for forecasting inflation in both the short-term (1 year) and the very short-term (2 months). The results further showed that the models can capture policy changes only if they occur in the in-sample period. This feature makes it somewhat suitable for policy authorities who will want to know the direction of the inflation variable after policy decisions have been made, and can help them make future policy decisions.

Keywords: Inflation, Seasonality, Forecasting

1. Introduction

There is a widely held belief among macroeconomists that there is a long-run relationship between the growth rate of money supply and the growth rate of prices (inflation). This belief forms the basis of monetary policy making in most central banks and hence its extraordinary importance for the conduct of public policy. Its importance makes it one of the most commonly tested hypotheses in economics.

Linkages between money and inflation became increasingly important during the recent financial crisis. The long-run relationship between money and inflation is almost surely not linear, and the short-run dynamics may disguise the long-run relationship, confusing tests for this relationship. As these variables involve interaction between various economic variables, it raises the possibility that the correspondence between them may be both non-linear and time varying (Binner et al. 2010).

If indeed there is a dynamic, long run relationship between money supply and increase in prices, then it is a reasonable proposition that the near-term growth of money supply might have a predictive power for inflation. Various studies have explored this relationship. The argument here is that deregulation, financial innovation and other factors have led to recurrent instability in the relationship between various monetary aggregates and other nominal variables – inflation (Binner et al. 2010). With the adoption of the Inflation Targeting (IT) framework, more countries have shifted towards targeting the price level specifically in conducting monetary policy. Some economists have however expressed notes of caution on the importance of money, stating that money will regain an important place in the conversation of economists (Binner et al. 2010).

In order to target the price level effectively, there is the need to properly manage inflation expectations, which includes staying within the inflation target that has been set. This can be achieved in part by effectively forecasting inflation to help monetary authorities set policy rates to guide current inflation to its intended levels.

Inflation forecasting is a very important input in monetary policy making, even though others do not consider forecasting models as a useful guide for monetary policy (Fisher et al. 2002). Apart from providing an input to monetary policy deliberations, inflation forecasts also play a role in the macroeconomic policy debate. By informing the public about likely trends, inflation forecasts can influence expectations and can therefore serve as a nominal anchor in the wage-bargaining process and nominal fixed contracts like rents or interest rates (Moser et al. 2007).

This study adds to the various inflation forecasting models that exist, by taking note of the seasonality that exists in the inflation variable in developing economies, using Ghana as a case study. Since the target variable is the inflation variable, this study adopts the use of univariate models. This was in part achieved by adding a Seasonal Autoregressive (SAR) and a Seasonal Moving Average (SMA) term to produce higher order Autoregressive Moving Average (ARMA) models with non-linear restrictions. This model was then used to forecast inflation using three approaches: a simple (naïve) approach, an intermediate approach and a complex approach. As a control experiment, a normal ARMA model was also used to forecast inflation using the same approaches mentioned earlier.

The analysis showed that the SARMA model had a superior forecasting ability than the normal ARMA model. In the case of the SARMA model, the complex approach provided the best forecast ability, as a combination of the food and non-food component of inflation in Ghana provided the best out of sample result. For the ARMA models the intermediate approach, which uses the forecast values of the overall CPI, provided the best forecast ability. This conclusion was reached by first looking at various pieces of literature on inflation forecasting. Secondly, we delve into the methods of analysis in this study and finally analysed the data using the proposed methods – SARMA and ARMA forecasting.

2. Literature Review

A simple Phillips curve, which uses a single measure of economic slack such as unemployment to predict future inflation, is probably the most common econometric basis of inflation forecasting. The usefulness of the Phillips curve as a means of predicting inflation has, however, been questioned by several authors.

Focusing on the one-year-ahead forecast horizon, Atkeson and Oharian (2001), argue that unemployment – based Phillips curve models and generalized Phillips curve models can do no better than a naïve model which says that inflation over the coming year is expected to be the same as inflation over the past year (Fisher et al. 2002). Cecchetti et al. (2000) considered inflation prediction with individual indicators, including unemployment, and argue that none of these gives reliable inflation forecasts. Stock and Watson (2003, 2004) considered prediction of inflation in each of the G7 countries using a large number of possible models. Each model had a single predictor (plus lagged inflation). They found that most of the models they considered give larger out-of-sample root mean square prediction error than a simple time series forecast based on fitting an auto regression to the inflation variable.

In recent years, researchers have, however, made substantial progress in forecasting inflation using large datasets (i.e., a large number of predictive variables), but where the information in these different variables is combined in a judicious way that avoids the estimation of a large number of unrestricted parameters (Wright, 2009). For instance, Fisher et al. (2002), in accessing 'when we can forecast inflation', focused on the ability to forecast the magnitude of inflation in the CPI, CPI less food and energy component (Core CPI), and the Personal Consumption Expenditures (PCE) deflator over the 1985 to 2000 sample period. They found that the forecasting model based on core PCE, improve forecasting significantly relative to the naïve models (simple univariate) in the 1993–2000 period. However, periods of low inflation volatility and periods after regime shifts favour the naïve model. The relatively poor performance of the Philips curve model reflects its inability to forecast the magnitude of inflation accurately.

Some studies used multivariate models and compared their predictive powers to determine which was better in forecasting inflation (Stock and Watson 1999, 2001). Hassani et al. (2018) used this approach to compare professional forecasts to academic forecasts. They found that professional forecasts are good at short-term forecasts whereas academic forecasts are good at long-term forecasts. They went further to even determine causality between the two. Stock and Watson (2016) had discovered earlier that multivariate estimates of trend inflation are similar to the univariate estimates of trend inflation. They computed trend inflation using core inflation, i.e. inflation excluding food inflation and energy.

Moser et al. (2007) applied factor models proposed by Stock and Watson as well as Vector Auto-Regression (VAR) and Auto-Regression Integrated Moving Average (ARIMA) models to generate 12-month out of sample forecasts of Austrian HICP inflation and its sub-indices. According to them factor models possess the highest predictive accuracy for several sub-indices, and predictive accuracy can be further improved by combining the information contained in factor and VAR models for some indices. They favoured the aggregation of sub-indices forecasts over a forecast of headline inflation itself.

Other studies have also tried to forecast inflation in developing economies. Mohammed et al. (2015), in studying the efficacy of the inflation variable in Nigeria, favoured the use of neural networks to forecast inflation just like Binner et al. (2010). Others also forecasted the inflation variable by using ARIMA, Seasonal Auto-Regression Integrated Moving Average (SARIMA) and Vector Error Correction

Model (VECM), and since the SARIMA model performed better, they concluded that the inflation variable has some level of seasonality.

Some studies also used models new to macroeconomics in forecasting inflation. Binner et al. (2010) used two non-linear techniques, namely recurrent neural networks and Kernel recursive least square regression – techniques that are new to macroeconomics. They then compared the two models to forecasts from naive random walk model. The best models according to them were the non-linear autoregressive models based on kernel methods. Balcilar et al. (2017) also used Vector Autoregressive Fractionally Integrated Moving Average (VARFIMA) and compared it to a standard ARIMA and VAR model. They found that their model outperformed these other models used in inflation forecasting. Other models such as the Moment Estimation Through Aggregation (META) where found to compare favourably with alternative univariate and multivariate models as well as those by professional forecasters (Sbrana et al. 2017).

The conclusion here is that the best predictive performance is obtained by constructing forecasts from a very large number of models and simply averaging these forecast values (Stock and Watson, 2003, 2004, 2008, 2010, Fisher et al. 2002). This gives the best predictive performance of inflation and that it is remarkably consistent across sub periods and across countries. Stock and Watson (2003, 2004) explored other methods for pooling the different forecasts, but found that none does better than simply averaging them, i.e., giving them all equal weights.

The studies above have varying conclusions on whether univariate or multivariate models are superior in terms of predicting the inflation variable. None of the studies above considered seasonality in the inflation variable in their forecasting models, which is a very important characteristic of inflation in developing countries. Those that came close to studying seasonality in the inflation variable – as mentioned above – only used the SARIMA model to test for seasonality based on its forecast performance. Developing countries like Ghana, are predominantly agrarian in nature and rely significantly on rainfall for irrigation. These factors – agriculture and rainfall – are seasonal in nature. As a result, this study will take into consideration the above-mentioned forecasting models to determine the appropriate model for forecasting inflation in developing countries. The focus will be on SARMA models and the aggregation of sub-indices to forecast headline inflation in developing countries (Ghana) considering also the seasonality in the component of the inflation variable.

3. Methodology

If we are in a stable monetary regime and expect the regime to persist, then it makes sense for policy makers to pay attention to inflation forecasting. This study will attempt to forecast inflation using three different methods – a method that focuses on headline inflation (simple model), a method that focuses on the overall (combined) CPI to forecast headline inflation (intermediate model) and a method that will use the CPI of food and non-food inflation to determine a forecast for headline inflation (complex model). The Seasonal Auto Regressive Moving Average (SARMA) model will be used in all cases. As a control, this study will use an Auto Regressive Moving Average (ARMA) model which does not include seasonal components to test the efficiency of the proposed SARMA model.

The simple model will forecast year-on-year headline inflation using a Seasonal Autoregressive Moving Average (SARMA) model. The SARMA model is based on a series of past behaviours only. This model is able to capture rich dynamics, both seasonal and non-seasonal. The forecast model is shown in equation (1) below.

$$f_{t,s} = \sum_{i=1}^{p} a_i f_{t,s-i} + \sum_{j=1}^{q} b_j u_{t+s-j} \quad (1)$$

where $f_{t,s} = Y_{t+s}, s \leq 0; u_{t+s} = 0, s > 0 = u_{t+s}, s \leq 0$ and a_i and b_j are the autoregressive and moving average coefficients respectively. s is the number of steps ahead. For equation (1) above, let $f_{t,s}$ denote the forecast variable and u_{t+s} denote the error term – the AR and the MA process.

Box et. al. (2015) recommended the use of seasonal autoregressive (SAR) and seasonal moving average (SMA) terms for monthly or quarterly data with systematic seasonal movement. Processes with SAR and SMA terms are ARMA models constructed using products of lag polynomials. These products produce higher order ARMA models with nonlinear restrictions on the coefficients. Both the SAR and the SMA are not intended to be used alone.

Since the appropriate reaction of monetary policy to inflationary pressures depends, among other things, on the sources of inflation, it is useful to monitor, analyse, and forecast sub-indices of headline inflation which are defined at the level of product types contained in the CPI (Moser et al. 2007).

The intermediate model will first forecast the CPI of overall inflation (LNCPI_O) and then derive the Year-on-Year Inflation using the equation below:

$$\text{LNINF\_YOY}_t = [(\text{CPI\_O}_t | \text{CPI\_O}_{t-12}) - 1] * 100 \quad (2)$$

Where LNYOY_INF is the Year-on-Year headline inflation; CPI_O_{t-12} and CPI_O_t are the CPI of overall inflation at time $t - 12$ and t.

The complex model will forecast the CPI of both food and non-food inflation using the SARMA model, and then using their respective weights in the consumer basket, the year-on-year headline inflation will be derived.

$$\text{LNINF\_YOY}_t = (1 + r_f) * w_f + (1 + r_{nf}) * w_{nf} \quad (3)$$

Where r_f and r_{nf} are the derived year-on-year food and non-food inflation rates; w_f and w_{nf} are the weights of food and non-food inflation in Ghana's inflation basket, which is the previous month's share of food (43.89959) and non-food (56.10041) CPIs.

The three models will then be compared to each other to see which model better forecasts headline inflation in Ghana. Statistical tests of a model are commonly conducted by splitting a given data set into an in-sample period, used for the initial parameter estimation and model selection, and out-of-sample period, usually used to evaluate forecasting performance. For this study, the in-sample period is from 2012M01 to 2016M02 and the out-of-sample period is from 2016M03 to 2017M02. However, the sample period may be adjusted in order to select the best-forecast model for each variable.

Empirical evidence based on out-of-sample forecast performance is generally considered trust worthier than evidence based on in-sample performance, which can be more sensitive to outliers and data mining. Out-of-sample forecasts also better reflect the information available to the forecaster in real time (Hansen and Timmermann 2012). Forecasters generally agree that forecasting methods should be assessed for accuracy using out-of-sample tests rather than goodness of fit to past data (in-sample tests) (Tashman 2000).

The argument here is that for a given forecasting method, it is possible for one to understate forecasting errors. Method selection and estimation are designed to calibrate a forecasting procedure to its historical data. But the nuances of past history are unlikely to persist into the future, and the nuances of the future may not have revealed themselves in the past. The other variance to this argument is that methods selected by best in-sample fit may not be good at predicting post-sample data. Bartolomei and Sweet (1989) and Pant and Starbuck (1990) provided more convincing evidence on this argument (Tashman 2000).

For this study, the fit period is used to identify and estimate the models while the test period is reserved to assess the model's forecasting accuracy. By withholding all data about events occurring after the end of the fit period, the forecast-accuracy evaluation is structurally identical to the real-world-forecasting environment, in which we stand in the present and forecast the future. However, one was cautious at 'peeking' at the data while selecting the forecasting method since this pollutes the evaluation environment.

As discussed in the literature review, Kernel models have also shown great promise in financial forecasting. However, they typically scale rather unfavourably with the number of training examples, thus pose a degree of freedom problem (Binner et al, 2010). Also based on the argument that the correspondence between the various components of the inflation variable may be both non-linear and time varying (Binner et al. 2010), this study will not use VAR models. This is regardless of the fact that VAR models are major tools for investigating linear relationships between small groups of variables (Duarte–Rua, 2007). As a result, this study will stick to the use of SARMA models to forecast the inflation variables using ARMA models as a control experiment.

4. Data Analysis

Data used for this study was obtained from the website of the Ghana Statistical Service (GSS). The Consumer Price Index (CPI) according to the GSS measures changes over time in the general price level of goods and services that households acquire for the purpose of consumption, with reference to the price level in 2012, the base year, which has an index of 100. The data spans from January 2012 to February 2017 (2012M01 to 2017M02).

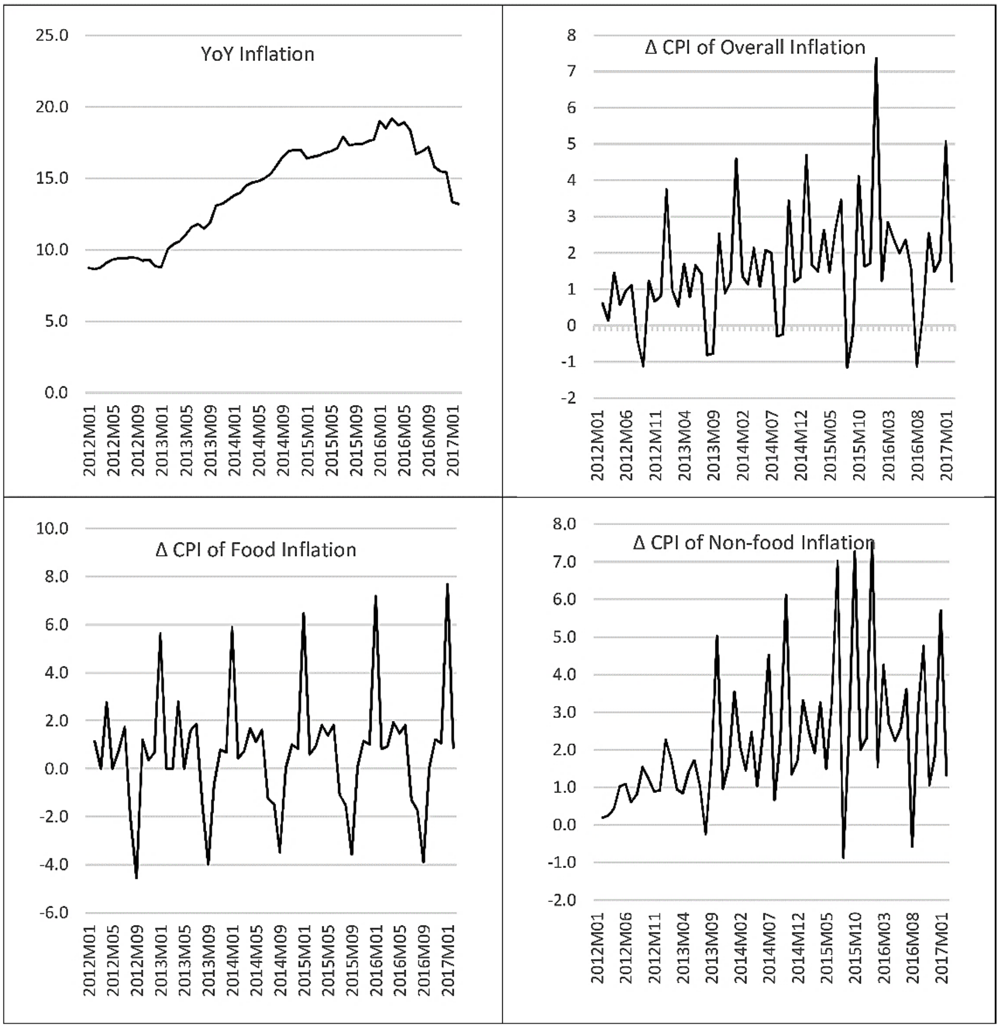
In order to prevent situations where the errors do not have a constant variance (heteroscedasticity) the variables (CPI_F, CPI_NF, CPI_O, and YOY_INF) were transformed into logs (LNCPI_F, LNCPI_NF, LNCPI_O, and LNYOY_INF). The consequences of using OLS in the presence of heteroscedasticity include the possibility that the OLS estimation will still give unbiased coefficient estimates, but that they are no longer BLUE (Best, Linear, Unbiased, Estimator). Also, the standard errors could be inappropriate and hence any inferences we make could be misleading. Also transforming the variables into logs will also prevent specification errors. By this we linearize many previously multiplicative models into additive ones.

There is also the problem of confusing trends in a variable with the presence of seasonality in the variable. For instance, Lütkepohl and Xu (2011), focused explicitly on seasonally unadjusted price series – an interpretation for series with unit roots. They used autoregressive (AR) models which they refer to as seasonal differences (stochastic seasonality models) and models with seasonal dummies for the first differences, called deterministic seasonality models. They found these two models to be more successful in forecasting seasonal time series than models with both first and seasonal differences and models without any differences at all. However, these are normal processes one has to follow when using univariate models for forecasting. In fact, dealing with unit roots cannot be equated to dealing with seasonality. Thus, the dominance of a series by a trend can obscure the presence of seasonal effect in a series, showing it is necessary to de-trend time series data before conducting test for seasonality. The Student t-test and Wilcoxon Signed-Ranks test have been recommended for detection of seasonality but this study uses the graphical method for this purpose as shown in Figure 1 (Nwogu et al. 2016).

A critical examination of the CPIs of the various components of inflation shows an underlying seasonality in Ghana’s inflation data. This seasonality is more visible if a first difference is computed and plotted for the CPIs of the various components of inflation. The seasonality is not very pronounced in the CPI of non-food inflation. This is expected as its components involve goods that are very volatile in nature and are mainly imported products that rely heavily on foreign exchange.

As a result, a seasonal autoregressive (SAR) and seasonal moving average (SMA) terms were introduced (products of lag polynomials). Their addition produces ARMA models of a higher order, referred to in this study as SARMA models with non-linear restrictions on coefficients. For this purpose, we will use the overall CPI to demonstrate how a SARMA model can be generated from an ARMA model.

Figure 1 Year-on-year Inflation Rate and Tests for Seasonality



Source: Author's Construction based on Ghana Statistical Service data (2019)

For instance, the SAR and SMA terms can be added to an ARMA (2.2) model of the log of overall inflation (LNCPI_O) to derive the following:

$$LNCPI\_O_t = \phi_1 LNCPI\_O_{t-1} + \phi_2 LNCPI\_O_{t-2} + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \mu_t \quad (4)$$

Where $\emptyset \ and \ \theta$ are the coefficients of the AR and MA terms denoted by $LNCPI\_O_{t-1,2,3}$ and $\mu_{t-1,2}$.
Using a lag operator L

$$LNCPI\_O_t = (1 - \emptyset_1 L - \emptyset_2 L^2) LNCPI\_O_t + \mu_t (1 + \theta_1 L + \mu_2 L^2) \quad (5)$$

For data on year-on-year inflation, we might wish to add a SAR (12) and a SMA (12) term because we believe that there is a correlation between a year and the previous year.

$$LNCPI\_O_t = (1 - \emptyset_1 L - \emptyset_2 L^2)(1 - \rho_{12} L^{12}) LNCPI\_O_t + \mu_t (1 + \gamma_{12} L^{12})(1 + \theta_1 L + \mu_2 L^2) \tag{6}$$

The parameter $\rho\ and\ \gamma$ are associated with the seasonal part of the process with non-linear restrictions on the coefficients. Thus the current values of the log of the Consumer Price Index (CPI) of the overall component over the study period depends on its own previous two values plus a combination of current and the previous two values of white noise error terms, where $\epsilon(\mu_t) = 0; \epsilon(\mu_t^2) = \sigma^2; \epsilon(\mu_t \mu_s) = 0; t \neq s$

The best SARMA model was estimated and thus selected for the variables (LNCPI_F, LNCPI_NF, LNCPI_O and LNYOY_INF) using the Akaike Information Criterion (AIC). This is meant to determine the type of model that best fits the set of data, and also choose the best model from which to forecast that data. The graphical plots of the autocorrelation function and the partial autocorrelation function were not used to determine the best model because they were difficult to interpret, as there was no clear trend. Information criteria are the most common model selection tool used in econometrics. By using the AIC, the aim is to choose the number of parameters, which minimises the value of the information criterion. It is based on the estimated log-likelihood of the model, the number of parameters in the model and the number of observations.

Since SARMA (a seasonal ARMA) models are non-theoretical (not based on any economic or financial theory) the focus of this study was to determine whether the SARMA model selected describes the log of the Inflation and CPIs in Ghana well and produces accurate forecasts. A year less observations was taken from the full sample to estimate the SARMA model selected in table 1 below. That of the ARMA model is shown in appendix table 1.

Table 1 The Best SARMA Models for Study Variables

CPI	**Adjusted Sample**	**SARMA Model**	**AIC**
LNCPI_F	2014M05 2017M02	(1,0) (12,0)	–6.263680
LNCPI_NF	2014M10 2017M02	(2,1) (12,0)	–6.349343
LNCPI_O	2013M02 2017M02	(2,2) (12,12)	–7.074027
LNINF_YOY	2014M08 2017M02	(4,1) (12,6)	–3.808331

Source: Author’s Construction

The maximum order for both the AR and the MA terms for the alternative ARMA models in appendix table 1 were set at par with that of the SARMA models – with the exception of the model for the log of the overall CPI. That notwithstanding, the SARMA models had a better AIC than the alternative ARMA model in all but one case – the log of non-food CPI.

An out of sample dynamic forecast was then conducted for the period 2016M03 to 2017M02. The forecast function is of the form similar to equation (1) but this time $f_{t,s}$ denote the forecast made using the SARMA (2, 2) (12, 12) model at time t for s steps into the future for Overall CPI in Ghana – the same forecast function was applied to the best models selected for the other variables (Brooks, 2008).

Table 2 Properties of Forecast SARMA Models a One Year Forecast Period

Properties	LNCPI_F	LNCPI_NF	LNCPI_OL	NINF_YOY
Root Mean Squared Error (RMSE)	0.00878	0.01351	0.01745	0.15413
Mean Absolute Error (MAE)	0.00698	0.01228	0.01397	0.11846
Mean Absolute Percentage Error	0.14235	0.22769	0.26759	4.38936
Theil Inequality Coefficient	0.00090	0.00126	0.00168	0.02698
Bias Proportion	0.57094	0.27814	0.35378	0.47153
Variance Proportion	0.10794	0.65805	0.61792	0.50700
Covariance Proportion	0.32113	0.06381	0.02830	0.02147

Source: Author's Estimates

Table 2 above shows the output table of the dynamic forecast for the selected SARMA models. The Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) for the models are fairly small. The criterion for these two statistics is that the smaller the error, the better the forecasting ability of the model. The bias proportion indicates that the mean of the forecast is not far from the mean of the actual series. The gap between the variation of the forecast and the variation of the actual series as shown by the Variance Proportion are also fairly small. The Covariance Proportion shows the remaining unsystematic forecasting errors. The forecast for the various SARMA model for the log of the CPI of food inflation can be said to be accurate, followed by the non-food CPI, the overall CPI and then the year-on-year inflation rate. The result for the Theil Inequality Coefficient is also consistent with the results above. The forecast properties for the SARMA models where better than the ARMA forecast properties for both the log of food CPI and the log of non-food CPI. The same cannot be said of the log of overall CPI and the log of the year-on-year inflation (see appendix table 2).

To test for consistency in the result, we varied the out-of-sample period from one year to two months. By doing this the CPI of food lost its forecast accuracy to the CPI of non-food followed by the CPI of overall. This evaluation was based on the forecast properties shown in table 3 below. Just like the forecast properties with the one year out-of-sample period, the forecast properties of the SARMA models appeared to be good in predicting the CPI of food and non-food inflation. The same could not be said for the year-on-year inflation and the CPI of overall inflation (see appendix table 3). In both tables (2 and 3), the average of the CPI forecast for both food and non-food inflation appeared to have better forecast properties than the CPI forecast of the overall inflation and the year-on-year inflation. This confirms the observations of Stock and Watson (2003, 2004) that the best predictive performance is obtained by simply averaging these forecasts. This applied only to the SARMA models – the ARMA models showed mixed results.

Studies have, however, criticised the use of these forecasting properties for deciding the accuracy of a forecasting model. For instance, Makridakis and Hibon (1995) have argued that some of these properties may be influenced by outliers, and as a result has little intuitive meaning. For this reason, the out-of-sample forecasts were compared to the actual data graphically to determine if the findings noted in the forecast properties above would still hold.

Table 3 Properties of Forecast Models for a Two Months Forecast period

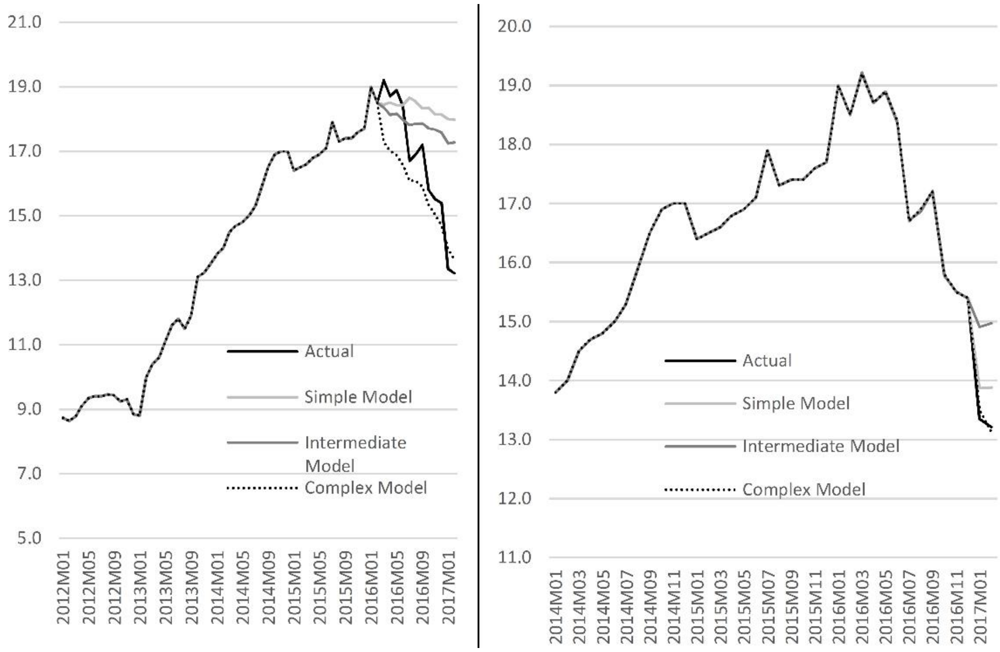
Properties	LNCPI_F	LNCPI_NF	LNCPI_O	LNINF_YOY
Root Mean Squared Error (RMSE)	0.02106	0.00183	0.01443	0.04430
Mean Absolute Error (MAE)	0.02103	0.00167	0.01441	0.04393
Mean Absolute Percentage Error	0.42557	0.03059	0.27439	1.69893
Theil Inequality Coefficient	0.00213	0.00017	0.00137	0.00849
Bias Proportion	0.99770	0.17139	0.99749	0.98334
Variance Proportion	0.00231	0.82862	0.00252	0.01121
Covariance Proportion	0.00000	0.00000	0.00000	0.00545

Source: Author's Estimates

Figure 2 shows that the complex model (the model that uses both the forecast values of both food and the non-food CPI) is close to the actual data followed by either the simple model or the intermediate model, depending on the out of sample period. The graph also shows some deviations from the actual inflation values during the forecast period – the variation was worse for the forecast based on just the ARMA models (see appendix figure 1). This observation is not surprising considering the tight monetary stance taken by the government after the signing the IMF program in April-2015. The monetary policy stance tightened over early 2016. The past tightening, together with the fiscal consolidation under the IMF program contributed to the sharp decline in inflation (IMF, 2017).

This change in policy was not fully captured by the models since the out of sample period started at about the time when inflation was peaking and the policy rate was reduced after it had peaked some months into the out of sample period. This observation confirms the observations of Lucas (1977) that backward-looking forecasting models are not good at predicting future events because of changes in policies. To correct for this, we reduced the out of sample period to two months using the forecast outcome from table 3 above. A graphical representation of this showed the forecast abilities of the models to have improved (figure 2 and appendix figure 1). The complex model appeared to be the most accurate, followed by the simple model and the intermediate model. The complex model predicted inflation values of 13.5 and 13.1 for January 2017 and February 2017 respectively. This compares with 13.3 and 13.2 actually realised for the same period. All the models were able to mimic the movement of the actual inflation data but with some variance.

Figure 2 One year and Two Month Out of Sample Forecast Models Versus Actual



Source: Author's Construction based on Ghana Statistical Service data (2019)

5. Conclusion

The adoption of the IT framework by Ghana and other developing countries, implies that monetary aggregates have lost their relevance as explanatory variables to inflation or the price level. It has thus become imperative for monetary policy to target inflation specifically. In other words, for monetary policy to be effective in doing so, a lot of stall will have to be placed on inflation forecasting. A good forecasting model will help the Monetary Policy Committee (MPC) to know when to tighten or loosen their policy stance in order to achieve the desired inflation rate.

As discussed earlier, the components of inflation in Ghana show some seasonality, which most univariate (ARMA) models ignore. By comparing forecast models of both ARMA and SARMA models, this study showed that SARMA model, as demonstrated by its forecast ability, appears to be the best univariate model for inflation forecasting in developing economies (Ghana) due to its seasonal components. The results also show that the complex approach which uses the forecast values of both food and non-food CPI, is very good at forecasting inflation in Ghana. Its predictability however, is most effective in the very short run e.g. two months. This to some extent corresponds to the work of Moser et al. (2007) who favoured the aggregation of sub-indices forecasts over a forecast of headline inflation itself (simple approach).

The results of this study could help monetary policy authorities determine the path of the inflation variable after they have made their policy decisions. This is because the complex model performs very well when policy decisions are captured in the in-sample period. An avenue for further studies is to estimate the role of expectations and other variables in determining the inflation variable in developing economies, allowing for better forecast models. Also, it would be interesting to compare the approach in this study to multivariate models to confirm if the conclusions arrived at still hold.

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Appendix

Table 1 The Best ARMA Models for Study Variables

CPI	Adjusted Sample	ARMA Model	AIC
LNCPI_F	2012M05 2017M02	(3,3)	–5.030210
LNCPI_NF	2012M05 2017M02	(4,4)	–6.465971
LNCPI_O	2012M11 2017M02	(9,5)	–6.396296
LNINF_YOY	2012M05 2017M02	(4,3)	–3.604795

Source: Author's construction

Table 2 Properties of Forecast Models a One Year Forecast Period (ARMA)

Properties	LNCPI_F	LNCPI_NF	LNCPI_O	LNINF_YOY
Root Mean Squared Error (RMSE)	0.06805	0.03104	0.01475	0.08898
Mean Absolute Error (MAE)	0.06169	0.02692	0.01317	0.06910
Mean Absolute Percentage Error	1.25468	0.49854	0.25295	2.54904
Theil Inequality Coefficient	0.00698	0.00288	0.00142	0.01574
Bias Proportion	0.82167	0.61766	0.04900	0.24765
Variance Proportion	0.01261	0.34787	0.71786	0.70753
Covariance Proportion	0.16572	0.03447	0.23314	0.04483

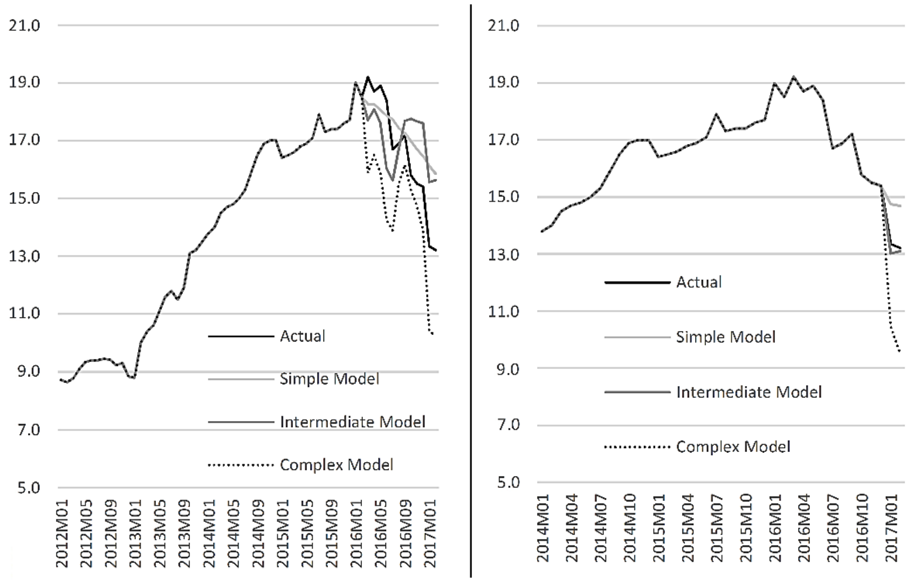
Source: Author's construction

Table 3 Properties of Forecast Models for a Two Months Forecast period (ARMA)

Properties	LNCPI_F	LNCPI_NF	LNCPI_O	LNINF_YOY
Root Mean Squared Error (RMSE)	0.03806	0.01039	0.00226	0.10296
Mean Absolute Error (MAE)	0.03765	0.01000	0.00210	0.10292
Mean Absolute Percentage Error	0.76175	0.18364	0.04005	3.97978
Theil Inequality Coefficient	0.00387	0.00096	0.00022	0.01952
Bias Proportion	0.97867	0.92577	0.86709	0.99920
Variance Proportion	0.00326	0.07423	0.13291	0.00081
Covariance Proportion	0.01808	0.00000	0.00000	0.00000

Source: Author's construction

Figure 1 One year and Two Month Out of Sample Forecast Models Versus Actual (ARMA)



Source: Author's Construction based on Ghana Statistical Service data (2019)