Inflation Forecasting Models and Forecasting Combination Analysis: The Case of Ethiopia

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Abstract
The main objective of this study is to compare different inflation forecasting models and combinations techniques that best fit for Ethiopian inflation forecasting. In particular, the random walk model, ARIMA, ECM, VECM, Phillips curve and BVAR model was employed. Since Ethiopian CPI data does not follow random walk process using statistical analysis Augmented Dickey-Fuller test it was excluded in forecast performance evaluation and forecasting combination analysis. Therefore, in model comparison only five models have been compared using RMSE for both in-sample and pseudo out of sample forecasting. The empirical finding shows that, using both in-sample and pseudo out of sample forecast accuracy ARIMA model performs best than other models. Next to ARIMA model ECM and BVAR model performs best as compared to VECM and Phillips curve. On the other hand VECM performs worst than other models compared up to eight period ahead forecasts. In the study different forecast combination techniques were compared. From those forecasting combination techniques Winsorized Mean, Median and Trimmed Mean respectively performs best than Bats/Granger Method, Equal Weight and OLS. Compared to VECM model forecast combination leads best in a reduction of forecast error, although some of the individual models like ARIMA, ECM and BVAR perform better than forecast combinations.
Key words: Inflation, forecasting, forecast combination, ARIMA, BVAR and VECM, Forecast Evaluation;
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1. Introduction

The monetary policy in most central banks is designed for controlling inflation at low level because inflation has a clear welfare costs. Implementing monetary policy takes time lags depending on the responsiveness of financial markets and real economy to policy interventions. As a central bank National Bank of Ethiopia (NBE) has an objective of achieving and maintaining price stability by achieving single digit inflation rate. Therefore accurate and reliable inflation forecast for the future rate is necessary for the successful realization of NBE objectives.

Inflation forecasting is a fundamental task in setting monetary policy but it a challenging task which involves large number of specification choices. The choice of specification ranges from time series models (both univariate and multivariate) to theoretical models which each model have its own advantages and disadvantages.

Among the possible multivariate time series models Vector Autoregressive (VAR) models are popular tools for forecasting and policy analysis which doesn't suffer from an endogenueity problem but it may lead to a problem of over parameterization which may result inaccurate estimation of parameters. The over parameterization problem of VAR will be solved by using other alternative models like Bayesian Vector Autoregressive (BVAR) which applies shrinkage by explicitly imposing restrictions through prior distributions.

Ogunc (2019) uses BVAR model to compare the forecast performance of including small or many variables able to produce best forecast. The empirical result of Ogunc shows that the forecast accuracy of including small selected variables has high forecast performance than including many variables. On the other hand Papavangjeli (2019) do inflation forecast performance comparison between BVAR, VAR and benchmark univariate and found that BVAR model outperforms best than VAR and bench mark models.

Empirical literatures found that theoretical models are good in forecasting when the economy is weak/economic crises as compared to Autoregressive Integrated Moving Average (ARIMA), VAR and naïve models (Pretorious and Pensburg, 1996; Fisher et al. 2002; Onder, 2004; Dotsey et al. 2011and Buelens, 2012). ARIMA performs better as compared to Naïve and VAR during the period of stable inflation while for the period of high inflation VAR performs better than ARIMA and static models (Mitra and Rashed, 1996). Lee (2012) compares the inflation forecasting power of ARIMA, Naïve and VAR for inflation targeting countries. Lee's empirical result shows that ARIMA model have better inflation forecasting performance than naïve and VAR models for inflation targeting countries which have stable inflation. Phillips curve is more accurate in forecasting inflation when the economy is weak compared with ARIMA, Naïve and VAR models (Pretorious and Pensburg, 1996; Fisher et al. 2002; Onder, 2004; Dotsey et al. 2011; Buelens, 2012) while it performs poorly during periods of stable inflation (fisher et al. 2002).

Different inflation forecast methodologies have different performance on different countries because different countries have unlike economic environments. Empirically there is no consensus that single model fits to all economy for inflation forecasting and there is no single forecast combination that fits to combine inflation

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forecasting from different models.

When we see Ethiopia's experience of inflation forecasting, currently NBE uses ARIMA model as a dominant model to forecast Ethiopian inflation rate which was developed by Chalachew (2011). Even though the forecast performance of existing ARIMA model in forecasting Ethiopian's inflation is good it should be compared with other forecasting models that currently exist in the literature. So the existing literature in Ethiopia shows there is not yet done any Ethiopia inflation forecast combination and forecast comparison analysis for different forecasting methodologies.

Therefore, the general objective of this study was to develop inflation forecasting models and make forecasting combination analysis in the case of Ethiopia. While the specific objectives are; develop different time series and theoretical models and produce inflation rate forecasting using those models, do a forecast comparison between inflation forecasting models by using their forecast accuracy and select the best fitted model for Ethiopian inflation forecast. Finally to identify the best forecast combination techniques using different forecasting combination techniques.

The main significance of this research paper is that it helps to identify the best inflation forecasting models and forecast combination techniques for Ethiopia economy by doing forecast comparison analysis among different models and forecast combination techniques. This study will be used as a reference for top management of National Bank of Ethiopia, academic staffs and government bodies in order to give an empirical insight in forecasting inflation and to provide policy recommendation based on the forecast accuracy of different models and forecast combination techniques. It also will give a motivation to other researchers to conduct a research on forecasting inflation and other macroeconomic variables which are relevant for policy decisions.

In this study time series and theoretical models were compared to select the best forecasting models. Univariate model considers the dependent variable and its past history or the autoregressive or moving average component, the multivariate model considers both the dependent and independent variables, while the Phillips triangle model includes dependent variable and the explanatory variables (output gap, expectation and other control variables which capture cost-push inflation). The forecasting techniques used in this study include ARIMA, ECM, VAR and BVAR and modified Phillips curve model (Gordon's triangle model).

2. Literature Review

2.1. Theoretical Literature Review

Sargent & Wallace (1981) states that the cause of inflation in developed countries is broadly identified as growth of money supply while the causes of inflation in developing countries, in contrast, is not a purely monetary phenomenon. According to Sergent and Wallace in addition to money supply fiscal imbalances and exchange rate depreciation dominate the inflation process.

According to Keynesian theory of demand pull inflation, inflation is caused by further increases in effective demand after full employment is attained. Keynes states that inflation is an excess of aggregate demand over the aggregate supply. If investment is less than saving deflationary gap exists and on the reverse inflationary gap. When the inflationary gap exists inflation increases because investment is more than adequate to fill the gap between income and consumption and Keynes assumes the government must be responsible for closing these gaps by using the policies of manipulating taxes, interest rate and government expenditure (Lin, 1967).

2.2. Empirical Literature Review

Aiol et al, (2010) consider combinations of subjective survey forecasts and model-based forecasts. Survey forecasts reflect individual forecasters' subjective judgment which able to adjust rapidly to changes in the data generating process conversely, forecasts from time-series models can efficiently incorporate past regularities in the data. Their empirical result suggest that a simple equal-weighted average of survey forecasts outperform the best model-based forecasts for a majority of macroeconomic variables and forecast horizons.

Akdogan et al. (2012) produce short term inflation forecasts in Turkey using univariate models, decomposition based approaches, a Phillips curve, motivated time varying parameter model, a BVAR models and dynamic factor models. A forecasting model with a good in-sample fit does not necessarily imply that it will have a good out-of sample performance so to solve this problem they divide total sample period (2003Q1:2011Q2) into training sample(2003Q1: 2009Q3) and the forecasting sample(2009Q4: 2011Q2). Using the training sample to estimate the forecasting models they produce one to four quarters ahead forecasts from their models following recursive window. Based on the forecast errors, models which incorporate more economic information outperform the benchmark random walk model. They further combine their forecasts by means of several weighting schemes and found that forecast combination leads to reduction of forecast errors compared to individual models, although some of the individual models perform alike in certain horizons.

Ajayi (2019) compares alternative inflation forecasting models in the case of OPEC and BRICS countries. Ajayi considers ARIMAX, ARIMA, SARIMA, naïve, VAR and VECM models. The univariate ARIMA model is generally favoured for the BRICS countries except South Africa. However in the case of OPEC countries the results are mixed between univariate and multivariate methods. For OPEC countries that have moderate inflation like Saudi Arabia, ARIMA model outperforms the multivariate model. In contrast, multivariate models generally outperform ARIMA models for countries with high inflation like Angola and Algeria.

Ogunc (2019) applies a BVAR approach for short-term inflation forecasting and compares the forecasting performance of BVAR under alternative specifications. In comparison of forecast performance Ogunc considers modeling in levels or in differences, choice of tightness, estimating BVARs of different model sizes and the accuracy of conditional and unconditional forecasts. The empirical result shows that BVAR forecasts using variables in log-difference outperform than using log-levels of the data. On the other hand when evaluating forecast performance in terms of model size, the lowest forecast errors belong to the models having relatively small number of variables.

Papavangjeli (2019) developes BVAR unconditional mean, random walk, ARIMA models to forecast short-term inflation, and the best performing among them is used as a benchmark to evaluate the forecast performance of the BVAR model. The results show that the BVAR approach, which incorporates more economic information outperforms the benchmark univariate and the unrestricted VAR models in the different time horizons of the forecast sample.

Pretorious and Pensburg (1996) forecast South Africa inflation and compare the forecast performance of theoretical models which includes Philips curve, traditional monetarist and money demand specifications with ARIMA. RMSE and MAE shows theoretical models have better forecasting performance as compared to ARIMA model. Fisher et al. (2002) compare the forecast performance of Phillips curve and naïve models during inflation volatility period in the United States and found that Phillips curve have better performance than naïve models. Atkeson and Ohanian (2001), Fischer et al.(2002), Orphanides and Van alorden(2005) and Stock and Watson(2007) stats that the relationship between unemployment and inflation is not stable because the historical data changes as a result of changes in the economic environment at that time univariate modes have better forecast performance.

Zardi (2017) develops and compares different time series models which include RW, SARIMA, a Time Varying Parameter model, BVAR and Dynamic Factor models in the case of Tunisia's short-term inflation forecast. Zardi two quarter forecast value result shows that models which incorporate more economic information outperform the RW. Zardi uses root mean squared weights method of forecast combination and found that the forecast combination leads best forecast performance than individual models. Timmermann (2004) used forecast combination to produce a better forecsts than best individual forecsting models.

3. Research Methodology

This section tells us about the research design, data type and source, model specification, description of variables and method of data analysis.

3.1. Data Source and Variables

In this paper quarterly time series data which ranges from 1999/2000Q1 to 2021/22Q2 was used. The data was collected from the NBE, Ministry of Planning and Development (MoPD) and Ethiopian Statistics Service (ESS). The variables included in the study are CPI, RGDPA, M2, RGGDPGAP_700[1], Energy Price (EP), official exchange rate (EX), NEER, WTPP[2] and RFEA. The variables used as explanatory for each model specification depend on the model that is specified because there is difference in model specification. In this paper Random Walk (RW), ARIMA, Error Correction Model (ECM), Vector Error Correction Model (VECM), BVAR and Phillips curve models were considered. In the case of RW and ARIMA model lag values of dependent variable, auto regressive and moving average component was used explanatory variable respectively. While ECM consider an additional variable which is used as explanatory variables in addition to its lags, whereas in using VECM and BVAR all variables are used as endogenous. In the case of modified Phillips curve model (Gordon's triangle model, 1988) the dependent variable was CPI and the explanatory variables were output gap, energy price, expectation and official exchange rate. For all the variables incorporated in the model, seasonality has been tested and for those series that show seasonality, seasonality adjustment were made and the adjusted data is used for the analysis, all series were transformed to logarithm form to smooth the data.

3.2. Research Design

The main objective of this study was to develop the best quarterly inflation forecasting models and determining the best forecast combination techniques. To achieve this objective causal research design which helps to predict the future inflation rate was considered.

[1] Scaled by adding 7000 to the output gap to make the negative value positive for making it convenient to do logarithmic transformation
[2] Sudan's CPI was excluding because our trade share with it is around 1.5% and considering its CPI which is more than 1000 for the last years over estimate trading partners CPI and causes misleading of parameter estimation

3.3. Model Specification

3.3.1. Random Walk (RW)

A random walk or no-change model often found to forecast surprisingly well. It has been argued to robust to common forms of structural change (Kapetanios G. et al., 2007). The form of this model is given by

$$Y_t = Y_{t-1} + e_t \qquad (1)$$

Where y_t is Consumer Price Index, the h-step ahead forecast from this models is written as

$$E\left(y_{(t+h)/t}\right) = y_t$$

$$Where \;\; E\left(y_{(t+h)/t}\right) = E\left(y_{(t+h)}/y_t, y_{t-1}, y_{t-2 \ldots\ldots}\right)$$

$$Y_t = Y_{t-1} + e_t \qquad (2)$$

Random Walk model with drift is presented as follows;

$$Y_t = \alpha + Y_{t-1} + e_t \qquad (3)$$

Where; α is a drift parameter

3.3.2. Uni-variate ARIMA Model

Box and Jenkins time series modeling techniques is used to model and forecast inflation. The general notation of Box and Jenkins ARIMA model for non-seasonal component is given by a combination of three parts: Autoregressive (AR) order p, Moving Average (MA) order q, and the degree of Integration order d, ARIMA (p, d, q). Suppose there are N observations for a given univariate time series at given time t, say Y_1, Y_2,….. Y_t. Then, the Box-Jenkins ARIMA model for non-seasonal time series data is given by:

$$\Phi(B)\Delta^d Y_t = \mu + \theta(B) e_t \qquad (4)$$

Where: $\Phi(B)=1- \Phi_1 B^1- \Phi_2 B^2- \Phi_3 B^3-\ldots- \Phi_p B^p$ and $\theta(B) =1- \theta_1 B^1- \theta_2 B^2-\theta_3 B^3- \ldots - \theta_q B^q$

B is the backward shift operator and $\Delta= 1 - B$, Φ(B) and θ(β) is the non-seasonal AR and MA operator, d is the order of integration and e_t is Gaussian white noise, Y_t is the variable of interest CPI and μ is a constant. The Box and Jenkins ARIMA model has three main stages, i.e., identification, estimation and diagnostic checks.

ARIMA model assumes the time series data is stationary. The main weakness of ARIMA model is that it needs long time series data, have week forecast performance for long term and sensitive to outliers. When we see the strength of ARIMA model it only depends on the existing past time series data and have good forecast performance for short term and stable data.

3.3.3. Error Correction Model (ECM) Technique

ECM is useful to analysis both the short and long run effect between dependent and independent variables. Basically, ECM can be written as:

$$\Delta Y_t = \alpha + \beta_1 \Delta X_{1t} + \beta_2 \Delta X_{2t} + \beta_3 \Delta X_{3t} + \ldots + \beta_k \Delta X_{kt} - \gamma(Y_{t-1} - \delta_1 X_{1t-1} - \delta_2 X_{2t-1} \delta_3 X_{3t-1} - \ldots - \delta_k X_{kt-1}) + \varepsilon_t \qquad (5)$$

Where, Y and X are dependent and independent variables respectively, α is constant, $\delta_1, \delta_2, \delta_3 \ldots, \delta_k$ And $\beta_1 \ldots, \beta_k$ are parameter estimates for long run and short run effect of an increase in X's on Y. γ Estimates the speed of adjustment to equilibrium after a deviation and ε_t is an error term. Based on the above ECM estimation techniques, the model with variables are specified as follows:

$$\Delta CPI_t = \alpha + \beta_1 \Delta \log(M2_{1t}) + \beta_2 \Delta\log(NEERI_{2t)} + \beta_3 \Delta\log \mathrm{RGDPGAP}_{7000_{3t}}$$
$$+ \beta_4 \Delta\log RFEA_{4t} + \beta_5 \Delta\log WTPP_{5t} - \gamma(CPI_{t-1} - \delta_1 \log(M2_{1t-1}) - \delta_2 \log(NEERI_{2t-1})$$
$$- \delta_3 \log(\mathrm{RGDPGAP}_{7000_{3t-1}}) - \delta_4 \log(RFEA_{4t}) - \delta_5 \log(WTPP_{5t-1}) - \delta_6) + \varepsilon_t$$

ECM model assumes there is co-integration between the variables of interest. The weakness of the ECM is exogenouity issue and its strength is it considers both short run and long run effects which give best forecast performance i.e. less affected by outliers than ARIMA model.

3.3.4. VARs

Since variables like inflation can be affected by many factors considering multivariate models is also important to forecast it and VAR model is one among those multivariate models. VAR model is a set of dynamic statistical equations involving a set of variables where every variable is used to determine every other variable in the model and it became important for the last four decades for forecasting and evaluation of macroeconomic policy (Henry and Pesaran, 1993).

The standard linear reduced-form VAR model takes the form

$$Yt = A_{0+} \sum_{i=1}^{p} A_i Y_{t-i} + u_t \qquad (6)$$

Where, $\mathbf{Yt} = (\mathrm{CPI_t},\ \mathrm{M2_t},\ \mathrm{NEER_t}, \mathrm{RGDPA_t}, \mathrm{FEA_t})$ is the vector of variables in the model and P is lag order selected using information criteria.

The forecasts from the VAR model are computed recursively

Where $Y_{t+h-i} = E\left(Y_{(t+h-i)/t}\right)$ *if t+h-i>t and* Y_{t+h-i} otherwise.

VAR model is used only when the variables are stationary at level or if there is no long run relationship between the variables and if the variables are stationary after differencing. But if the variables are not stationary and have co-integration instead of VAR model VECM is used.

The VECM provides a systematic way to treat non-stationary variables in a simultaneous equation system. The VECM captures both long run and short run relationship and it is written as follows:

$$\Delta Y_t = \alpha_0 + \beta Y_{t-1} + \sum_{i=1}^{p-1} \emptyset_{i+1} \Delta Y_{t-p+1} + e_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots . (7)$$

Where, $\boldsymbol{\beta}$ contains co-integrating relations, or long run parameters. $\mathbf{e_t}$ is the corresponding error term; and Y_t is vector containing time series variables.

$$\text{i. e. } \mathbf{Y_t} = (\text{CPI}_t, \text{M2}_t, \ \text{NEERI}_t \text{RGDPA}, \text{RFEA}_t)$$

The maximum likelihood estimation method which maximizes the log likelihood to obtain the parameter estimates. The main assumptions of VECM are that each variable should have the same number of lags and should satisfy stability condition. The strength of VECM model it allows us to obtain jointly long term and short term relationship between variables. The main weakness is that including more lags on VECM model has implications on degree of freedom.

3.3.5. Bayesian VARs (BVAR)

In using VAR there is an over parameterization problem which affects the accuracy of forecasting performance by consuming the models degree of freedom (Kapetanios, 2007). BVAR model was proposed by litterman in 1979 as an alternative model to standard VAR by solving the over-parameterization problem. Starting from defining the standard linear reduced-form VAR takes the form as specified above equation 6

$$Y_t = A_{0+} \sum_{i=1}^{p} A_i Y_{t-i} + X_t + u_t$$

Where $\mathbf{Y_t} = (\text{CPI}_t, \ \text{M2}_t\ \text{EX}_t, \text{RGDPA}_t, \text{RFEA}_t)$ is the vector of variables in the model with lag order p which is selected by using information criteria, X_t is exogenous variable(WTPP_t) , A_0 is a data vector of n random variables (5 x 1) vector (c_1, c_2, c_3, c_4, c_5) is a vector of constants, $A_1, A_2, A_3, \ldots$, A5 are 5 x 5 matrices of VAR coefficients, $\mathbf{u_t} \sim \mathbf{N(0, \Sigma)}$

In BVAR model VAR is estimated by using the Bayesian shrinkage combining modeler's prior beliefs with data. Let say the parameter of interest is given by $\theta = (\beta, \boldsymbol{\Sigma}_\varepsilon)$ and data by y then the prior distribution is given by $\pi(\theta)$, likelihood $L(y/\theta)$ and the posterior distribution ($\pi(\theta/y)$) is given by

$$\pi(\theta/y) = \frac{\pi(\theta)L(y/\theta)}{\int \pi(\theta)L(y/\theta)d\theta}$$

Where the denominator $\int \pi(\theta)L(y/\theta)d\theta$ is a normalizing constant which has no randomness and the posterior is proportional to the product of the likelihood and the prior.

$$\pi(\theta/y) \ \propto \pi(\theta)L(y/\theta)$$

To overcome the VAR over-parameterization problem of VAR model, BVAR allows shrinking parameters and in this paper Litterman/Minnesota prior was considered to shrinkage the parameters to be estimated. The overall degree of shrinkage for Litterman prior is controlled by hyper-parameter λ. As $\lambda \to 0$, shrinkage increases and prior dominates making data less influential (with a $\lambda = 0$ prior equals posterior), whereas $\lambda \to \infty$, data dominates the prior (with $\lambda = \infty$ gives OLS estimates). In Minnesota prior four scalar parameters to be specified which are $\mu 1, \lambda 1, \lambda 2, and\ \lambda 3$. The value assigned to the hyper parameter λ for the BVAR model under this study was determined by using machine learning algorism based Graeme (2016).

3.3.6. Phillips Curve

According to the Gordon's triangle model (1988) inflation is a function of three components: inertia, demand pull which is represented by the employment gap and cost push inflation (energy and food commodities prices shocks) that affect aggregate supply. So the Gordon's triangle model of inflation is specified as

$$\pi_t = \mu + \alpha\pi_{t-1} - \beta(u_t - \hat{u}) + \gamma z_t + \varepsilon_t \ldots \ldots \ldots \ldots \ldots \ldots (8)$$

Where, π_{t-1} is built in inflation/expectation, $(u_t - \hat{u})$ unemployment gap and z_t supply factor. The unemployment gap is proxy by the output gap or capacity utilization gap. In this paper the researcher considers consumer price index as inflation rate, demand pull factor output gap which is a proxy of unemployment rate gap based on Okun's law relationship between the output gap and unemployment rate gap i.e. $(u_t - \hat{u}) = -\theta(y_t - \hat{y}$, M2 and cost-push factors (energy price,). Therefore, the triangle model for Ethiopian inflation forecast is specified as:

$$\pi_t = \mu + \alpha\pi_{t-1} + \delta(y_t - \hat{y}) + \gamma z_t + \varepsilon_t \ldots \ldots \ldots \ldots (9)$$

Where, z_t is a vector of cost push factors which includes energy price (Average Petroleum Spot Price) obtained from an equally weighted average of three crude oil spot prices (i.e. West Texas Intermediate, Dated Brent, and Dubai Fateh) and Official Exchange Rate. The modified triangle model to forecast Ethiopia's inflation rate with all listed variables is as follows:

$$CPI\_SA_t = \mu + \alpha CPI\_SA_{t-1} + \delta(RGDPA_t - RGDPP) + M2_t + EX_t + EP_t + \varepsilon_t \dots\dots\dots (10)$$

3.4. Forecast Evaluation

Selecting the best forecasting techniques from alternative models is an important issue in time series forecasting. Dieng (2008) uses RMSE to select best models from exponential smoothing, naïve, ARIMA and Spectral model and found that ARIMA model was the best model to forecast vegetable prices in Senegal. Ajayi(2019) compares different inflation forecasting models in the case of OPEC and BRICS countries. Using MAPE, RMSE and Theil's U-statistic and found that ARIMA models outperform than other modes for countries that have stable inflation and VAR outperform than Univariate modes for high inflation countries. Akdogan et al. (2012) use RMSE to compare forecast performance and found models which incorporate more economic information outperform than single equation model. Zardi C. (2017) using RMSE found that multivariate modes forecasts outperform than benchmark models.

To sum up the quality of inflation forecast is evaluated by using MAPE and RMSE. RMSE is relatively best to compare forecast performance of different models. In this study RMSE is used to select the best model and forecast combination which is calculated as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \dots\dots\dots\dots\dots\dots\dots\dots (11)$$

Where, n is number of observation, $\hat{y}$ is the predicted value and y_i is the actual observed value of consumer price index. RMSE is calculated based on in-sample forecast and pseudo out of sample forecast. A model that have low RMSE as compared to other model indicates the model have good forecast performance than those models that have high RMSE.

3.5. Forecast Combination

In forecasting some models may adapt quickly structural changes while others may be slowly responding. To solve this single model forecast problem forecast combination is important. By combining forecasts from models with different degrees of adaptability we may produce better performing forecasts compared to a single model. In addition to structural breaks using combining forecasts helps to reduces individual forecasting models misspecification biases by averaging out the biases and can yield unbiased forecasts even if the individual forecasts are biased (Granger and Ramanathan, 1984, Bates and Granger 1969). Stock and Watson (2004) on seven OECD countries, Lack (2006) and Kapetanios et al(2006) on UK inflation and Kapetnaios et al(2007) on UK GDP growth found that forecast combination outperforms than single and bench mark models. Akdogan et al. (2012) combine their forecasts and the results reveals that forecast combination leads to a reduction in forecast error compared to most models, although some of the individual models perform alike in certain horizons. Zardi (2017) combine forecast values by means leads to a reduction in forecast error compared to individual models.

There are different methods of forecast combination among those methods simple average, median, trimmed mean, Winsorized mean and ordinary least squares (OLS) regressions are the most common ones that are applied in this research paper.

3.5.1. Simple Average/ Equal Weight

According to Stock and Watson (2004) simple average forecast combination is found to be best combination methodology which outperforms more sophisticated forecast combinations. Simple average forecast combination for N models is given as follows:

$$F^c = \frac{1}{N}\sum_{i=1}^{N} Fi \dots\dots\dots\dots\dots\dots\dots\dots (12)$$

3.5.2. Median Forecast Combination

Median forecast combination is insensitive to outliers (Palm and Zellner, 1992). It is rank based forecast combination methodology proposed by Armstrong (1989), Hendry and Clements (2004), Stock and Watson (2004) and Trimmermann (2006). To do median forecast combination the variable of interest (CPI), there are N not perfectly collinear predictors, $f_t = (f_{1t,} f_{2t,} \dots\dots\dots\dots . f_{Nt,})$For each point in time, the median method gives a weight of 1 to the median forecast and a weight of 0 to all other forecasts the combined forecast is obtained by $\widehat{f_t} = median(f_t)$ i.e.

For odd number of models $\widehat{f_t} = f(\frac{N}{2} + 0.5)$,

For even number of models $\widehat{f_t} = \frac{1}{2}(f_{N/2}) + (f_{N/2+1})$

3.5.3. Trimmed Mean

Trimmed mean method of forecast combination is an interpolation between simple average and median and it is less sensitive to outliers than simple average approach which was proposed by Armstrong (2001), stock and Watson (2004) and Jose and Winkler (2008). Let Y_t is the variable of interest (CPI) and there are N predictors

$f_t = (f_{1t,}f_{2t,} \dots\dots\dots\dots f_{Nt,})$ for each point in time. The order of forecast is computed as $f_t^{ord} = (f_{(1)t,}f_{(2)t,} \dots\dots\dots\dots f_{(N)t,})$. Using trim factor λ(i.e.the $\frac{\text{top}}{\text{bottom}}$ $100 * \lambda\%$), let $\lambda = 20\%$ are trimmed and the combined forecast is

$$\hat{y_t} = \frac{1}{N(1-2\lambda)} \sum_{i=\lambda N+1}^{(1-\lambda)N} f(i) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (13)$$

3.5.4. Winsorized Mean

It gives weight in handling outliers instead of removing all together as of trimmed mean approach do by limiting outliers at certain level rather than removing them, allowing at least some degree of influence. Let say Y_t is the variable of interest and there are N not perfectly collinear predictors $f_t = (f_{1t,}f_{2t,} \dots\dots\dots\dots f_{Nt,})$ for each point in time the order forecasts are

$f_t^{ord} = (f_{(1)t,}f_{(2)t,} \dots\dots\dots\dots f_{(N)t,})$. Using a trim factor λ (i.e.the $\frac{\text{top}}{\text{bottom}} \lambda\%$ *are winsorized*) and setting $K = N\lambda$ the combined forecast is calculated as (Jose and Winkler, 2008). let $\lambda = 20\%$

$$\hat{y_t} = \frac{1}{N}\left[K f_{(k+1)t} + \sum_{i=\lambda N+1}^{(1-\lambda)N} f_{(i)t} + K f_{(N-K)t}\right] \dots\dots\dots\dots\dots\dots\dots\dots\dots (14)$$

3.5.5. Ordinary Least Squares (OLS) Regression

This method of forecast combination used OLS estimate coefficients as a weight for forecast combination. For N individual predictors given the variable of interest Y_t against forecasts

$$Y_t = \alpha + \sum_{i=1}^{N} w_i f_i + \varepsilon_t$$

Which helps to find the estimated value of $\hat{w}_i$ from the OLS and used as a weight for forecast combination and the forecast combination will be found as

$$\hat{Y_t} = \hat{\alpha} + \sum_{i=1}^{N} \hat{w}_i f_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (15)$$

3.5.6. Bats/Granger Method

Bates and Granger use the estimated RMSE to compute combination weights.

$$f^c = \sum_{i=1}^{N} fi * \frac{\hat{\delta}^{-2}(i)}{\sum_{j=1}^{N} \hat{\delta}^{-2}(j)} \dots\dots\dots\dots\dots\dots\dots\dots\dots (16)$$

Where $\hat{\delta}^{-2}(i)$ is the estimated mean squared prediction error of model i.

3.6. Method of Data Analysis

The collected data based on the specification model was analyzed using eviews. To accomplish the study inferential analysis was used and to maintain the validity and robustness of the model different diagnostics tests was conducted depending on the nature of the model.

4. Result and Analysis

In this section unit root test, model estimation, selection and forecast combination analysis was done and best forecast models and combination techniques were selected based on RMSE.

4.1. ADF Unit Root Test

Table 1: ADF Unit Root Test

Variables	With Intercept		Intercept and Trend	
	t-Statistic	Prob.*	t-Statistic	Prob.*
LCPI_SA	1.174	0.998	-2.487	0.334
LRGDPA	-0.319	0.917	-2.688	0.244
LM2_SA	3.107	1.000	-3.057	0.123
LRFEA_SA	-1.929	0.318	-2.112	0.532
LRGDPGAP_7000	-3.112	0.029	-2.965	0.148
LNEER	-1.300	0.6266	0.387	0.999
LEX	2.536	1.0000	-0.8903	0.9519
LEP	-2.256	0.189	-2.240	0.462
LWTPP	1.7632	0.9997	0.0654	0.9965
DLCPI_SA	-4.666	0.000	-4.995	0.001

Variables	With Intercept		Intercept and Trend	
	t-Statistic	**Prob.***	**t-Statistic**	**Prob.***
DLNEERI	-8.545	0.000	-8.487	0.000
DLRGDPA	-9.138	0.000	-9.089	0.000
DLM2_SA	-6.132	0.000	-7.399	0.000
DLEX	-3.722	0.005	-6.940	0.000
DLRFEA_SA	-15.449	0.000	-15.482	0.000
DLRGDPGAP_7000	-5.488	0.000	-5.469	0.000
DLEP	-8.218	0.000	-8.185	0.000
DLWTPP	-4.930	0.001	-5.2031	0.002

Source: Author's Computation

To smooth the data logarithmic transformation and seasonal adjustment was applied. CPI, M2, RFEA have seasonality and seasonally adjusted data were used for model analysis. The unit root test analysis of ADF unit root test shows that all variables are not stationary at log level rather all variables are stationary at first difference as presented in table 1.

4.2. Co integration Test

Since the variables Log(CPI_SA), Log(M2_SA), log(NEERI), Log(RGDPA), Log(RFEA_SA) are stationary at first difference for VAR model specification, checking the existence of co integration is important. To check the existence of co integration Johansson co-integration test was used and the test result shows there exists co integration between the specified variables. Due to the existence of co-integration instead of VAR, VECM which considers long run and short run effect was used to forecast Ethiopian inflation.

4.3. BVAR Prior of Hyper Parameter Determination

In using BVAR model before estimating the posterior setting the priors is a precondition using likelihood and prior information model. Based on Graeme (2016) priors of hyper-parameters for the litterman/Minnesota priors were set using a machine learning algorism from the available observation. To select the priors for Univariate AR estimate with theil's inequality coefficient was considered. In determining priors based on Graeme (2016) $\mu 1, \lambda 1$ *and* $\lambda 2$ was set between 0.1 and one and using a machine learning algorism one, 0.95 and 0.95 was selected as a prior respectively. For $\lambda 3$ the prior was set between 0.1 and 3.5 and 0.1 was selected as a prior. Based on the determined hyper parameter priors and using litterman/Minnesota the BVAR model was estimated.

4.4. Testing the Existence of RW for CPI Data

Testing the existence of RW in the given data is an important diagnostics test before using RW model. Therefore, before using a RW model for inflation forecasting whether the time series data follows a random walk or not was tested. To check this there are two tests time series plot and statistical analysis and in this study a more formal test, statistical analysis was used. There is a hypothesis test outlined in 1979 by Dicker and Fuller, and it is called the augmented Dickey-Fuller test. The null hypothesis states slope or the coefficient of the lagged values is equal zero (RW) vs not equal to zero (not RW).

$$dlog(CPI\_SA) = c + \beta log\left(CPI\_SA_{(-1)}\right) + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots.(17)$$

Table 2: Augmented Dickey-Fuller Test Random Walk test
Dependent Variable: DLOG(CPI_SA)
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.020245	0.020127	-1.005901	0.3172
LOG(CPI_SA)	0.013151	0.005042	2.608224	0.0107
F-statistic	6.802833	Durbin-Watson stat		1.546995
Prob(F-statistic)	0.010692			

Source: Author's Computation

The result of augmented Dickey-Fuller test shows the probability value of coefficient of lag value log(CPI) is 0.01 which is less than 5%. The null hypothesis of the CPI data follows a RW process is rejected therefore; RW model is not used to forecast Ethiopian inflation.

4.5. Forecast Evaluation

To compare the model forecast performance both in-sample and Pseudo Out-of-Sample forecast evaluation techniques were considered. For in-sample forecast evaluation total data which ranges from 1999/2000q1 to 2021/22q3 was used for estimation and forecast performance of models was evaluated using RMSE as follows:

Table 3: In-Sample Forecast Evaluation of different models

Accuracy Measure	Model				
	ARIMA(2,1,2)	ECM	VECM	BVAR	Phillips
RMSE	9.62	9.93	13.76	10.30	12.70

Source: Author's Computation

Using in-sample forecast the 1st, 2nd and 3rd best models for Ethiopian inflation forecast are ARIMA (2,1,2), ECM and BVAR as compared to VECM and Phillips.

A pseudo out-of-sample model forecast performance evaluation was also done by dividing the total data in to training and testing time period. The first estimation for all models is done with data ranging from 1999/2000Q1 to 2018/19Q4 and forecasts was done up to 2019/20q4 which helps to compute RMSE. The estimation is then extended by incorporated one quarter forecast ranges from 1999/2000q1 to 2019/20Q1 and the four quarters ahead forecast is obtained from 2019/20Q2 to 2020/21Q1 and the RMSE is again computed. This process continues recursively until the estimation sample reaches to 2020/21q4 and forecast is done up to 2021/22q3. Given the above recursive window procedures the RMSE is presented in table 4 for all five models.

Table 4: Pseudo Out-of-Sample Forecast Evaluation using RMSE

Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
ARIMA(2,1,2)	1.393	3.537	3.472	4.142	5.183	10.613	15.679	20.676
ECM	6.688	7.932	8.347	8.725	9.379	17.771	27.396	34.447
VECM	8.439	12.314	15.730	19.416	22.539	28.575	34.917	41.559
BVAR	6.081	8.049	8.015	7.363	10.252	18.598	24.725	29.566
Phillips	5.917	9.208	12.064	14.731	16.261	19.668	22.703	25.591

Source: Author's Computation

A pseudo out-of-sample forecast evaluation was done for eight quarters ahead forecasts to compare the different models. For pseudo out-of-sample forecast different ARIMA models was compared and ARIMA (2,1,2) was selected as a best model using training data sets. As shown in table four, the best performing individual model of each horizon differs except ARIMA model which performs best up to eight quarters ahead forecast consistently. So far, the performance of the BVAR, ECM and Phillips has close forecast superiority on average for the specified quarters.

In both pseudo out of sample and in-sample forecast evaluation ARIMA model outperforms all models. Following ARIMA, BVAR, ECM and Philips performs best than VECM respectively. While VECM performs least as compared to ARIMA, ECM, BVAR and Philips models.

4.6. Forecast Combination

To combine forecast values from different models simple average/equal weight, Median, Trimmed mean, Winsorized mean, Ordinary Least Squares regression and Bats/Granger forecast combination methods were considered. The comparisons for the forecast combination accuracy were done using RMSE for both in-sample and outsample forecast models which are presented as follows:

Table 5: In-Sample Forecast Evaluation for Different Forecast Combinations

Accuracy Measure	Equal Weight	Median	Trimmed Mean	Winsorized Mean	OLS	Bats/Granger
RMSE	6.1927	5.8305	5.8199	5.8274	5.924	5.9399

Source: Author's Computation

Based on the in-sample model forecast accuracy measure of RMSE the 1st, 2nd and 3rd best forecast combination methods for Ethiopian inflation are trimmed mean, winsorized mean and median as compared to the equal weight, OLS and Bats/granger method of forecast combination. Based on the pseudo out-of-sample model forecast the 1st, 2nd and 3rd best forecast combination methods for Ethiopian inflation are Winsorized Mean, Median and trimmed mean as compared to the equal weight, OLS and Bats/granger method using RMSE as a forecast accuracy measure.

Evaluation of forecast combination performance for the specified six forecast combination techniques which includes equal weight, median, winsorized mean, OLS and Bats/granger is presented in table 6.

Table 6: Pseudo Out-of-Sample Forecast Evaluation for Different Forecast Combinations

Combination Method	h ahead forecast							
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8
Equal Weight	7.99	11.49	13.29	15.23	17.87	26.58	35.19	42.79
Median	9.21	11.91	12.67	13.24	15.21	26.30	34.88	41.60
Trimmed Mean	8.67	11.72	13.17	14.34	16.76	26.08	34.97	42.06
Winsorized Mean	7.51	10.77	12.35	13.91	16.07	24.58	33.57	40.97
Bats/Granger Method	9.34	13.04	15.37	17.69	20.65	29.63	38.62	46.52
OLS	24.86	20.07	17.17	21.37	26.34	31.92	37.05	44.09

Source: Author's Computation

To sum up the forecast combination performance of Winsorized mean, median and Trimmed mean outperforms best than other forecast combination techniques which includes OLS, Equal weight, Bats/Granger Method.

4.7. Discussion

To finalize this study theoretical and time series models which includes ARIMA, RW, ECM, VECM, BVAR and Phillips curve model were used. Before using a RW model for inflation forecasting checking whether the time series CPI data follows a RW or not was checked using augmented Dickey-Fuller test. The null hypothesis slope or the coefficient of the lagged values equal zero (RW) was rejected and RW model cannot be used for forecasting Ethiopian inflation. Therefore, the remaining models which are ARIMA(2,1,2), ECM, VECM, Phillips curve and BVAR were used for comparison of forecast performance of Ethiopian inflation.

Table 7 shows that ARIMA(2,1,2) model has best forecast performance as compared to ECM, VECM, Phillips curve and BVAR both for in-sample and pseudo out sample forecasting which is supported by (Kinene, 2016). The empirical result in this study shows that univariate model ARIMA(2,1,2) model have best forecast performance than multivariate time series model is not in-line with the finding of Akdogan et al. (2012) and Ajayi (2019) who found multivariate models peform better than univariate models.

Table 7: Forecast Evaluation of Different Models and Combination Techniques

Model	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	Average Forecast performance	Rank
ARIMA(2,1,2)	1.4	3.5	3.5	4.1	5.2	10.6	15.7	20.7	8.09	1
BVAR	6.1	8.0	8.0	7.4	10.3	18.6	24.7	29.6	14.09	2
ECM	6.7	7.9	8.3	8.7	9.4	17.8	27.4	34.4	15.08	3
Phillips	5.9	9.2	12.1	14.7	16.3	19.7	22.7	25.6	15.78	4
Winsorized-Mean	7.5	10.8	12.4	13.9	16.1	24.6	33.6	41.0	19.99	5
Median	9.2	11.9	12.7	13.2	15.2	26.3	34.9	41.6	20.63	6
Trimmed Mean	8.7	11.7	13.2	14.3	16.8	26.1	35.0	42.1	20.99	7
Equal Weight	8.0	11.5	13.3	15.2	17.9	26.6	35.2	42.8	21.31	8
VECM	8.4	12.3	15.7	19.4	22.5	28.6	34.9	41.6	22.93	9
Bats/Granger Method	9.3	13.0	15.4	17.7	20.6	29.6	38.6	46.5	23.84	10
OLS	24.9	20.1	17.2	21.4	26.3	31.9	37.0	44.1	27.86	11

Source: Author's Computation

As of Akdogan et al. (2012), Zardi (2017) and Timmermann (2004) forecast combination peforms better than each specific model forecasting but in the case of ethiopian acording to this research paper investigation ARIMA, ECM and BVAR model have best forecast performance than different forecast combinaiton techiniques applied in this study. BVAR model best performance next to ARIMA model is supported by Papavangjeli (2019) who found that BVAR models peform better than VAR model in the case of Albanian.

5. Conclusion and Recommendations

5.1. Conclusion

The main objective of this paper is to select the best forecasting models and forecast combination techniques for producing Ethiopian inflation forecast. The study considers six models; RW, ARIMA, ECM, VECM, BVAR and Phillips curve models. Before using RW model whether the Ethiopian CPI time series data follows a RW or not was tested but for the specified data coverage it doesn't follow a RW process. So ARIMA, ECM, VECM, BVAR and Phillips curve were considered for forecasting Ethiopian inflation and their forecast performance was evaluated using RMSE for in-sample and pseudo out of sample forecast. ARIMA model fits best compared to ECM, VECM, BVAR and Phillips curve models using RMSE for both in-sample and pseudo out of sample forecasting. BVAR and ECM perform best following ARIMA model as compared to VECM and Phillips curve models while, VECM model have least forecast performance than Phillips, ECM, BVAR, ARIMA for both in-sample and pseudo out of sample forecasting.

In addition to forecast performance of different econometrics models forecast combination analysis was done in this study. Using forecast combination is important because a single model may be affected by structural changes and model specification bias which will be captured by forecast combination of more than one model. Forecast combination techniques considered in this study were Winsorized Mean, Trimmed Mean, Median, Bats/Granger Method, Equal Weight and OLS. The forecast combination result evaluation using RMSE shows that Winsorized Mean, Median and Trimmed Mean performs best for both in-sample and pseudo out of sample forecast.

5.2. Recommendation

- Since forecast performance of ARIMA model is best as compared to ECM, VECM, BVAR and Phillips curve NBE better to continue using ARIMA model to forecast inflation especially for short period of time.
- In addition to ARIMA model, NBE better to adapt BVAR, ECM and Phillips curve models which capture structural changes or policy changes and have good forecast performance respectively next to ARIMA (bench mark model).
- Since forecast combination techniques reduce bias like structural changes and model specification bias as compared to single model so NBE better to use Winsorized Mean, Median and Trimmed Mean method of forecast combination techniques which have good forecast performance as compared to Bats/Granger Method, Equal Weight and OLS.

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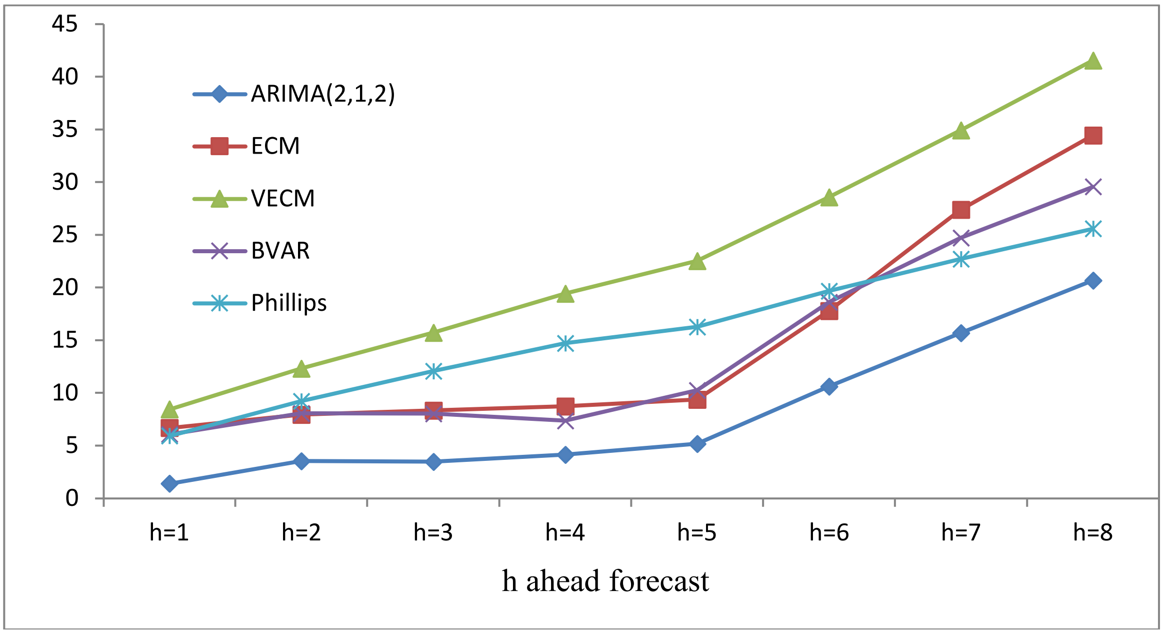
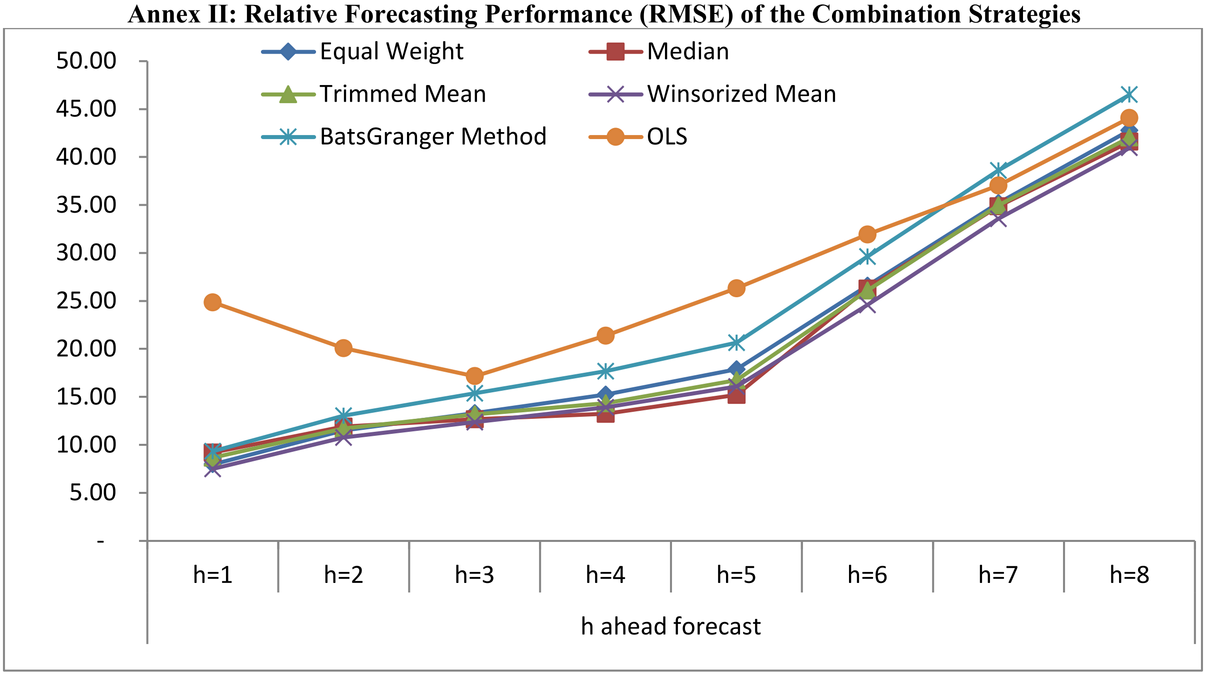
Annex I: Individual Models RMSEs for Each Horizon

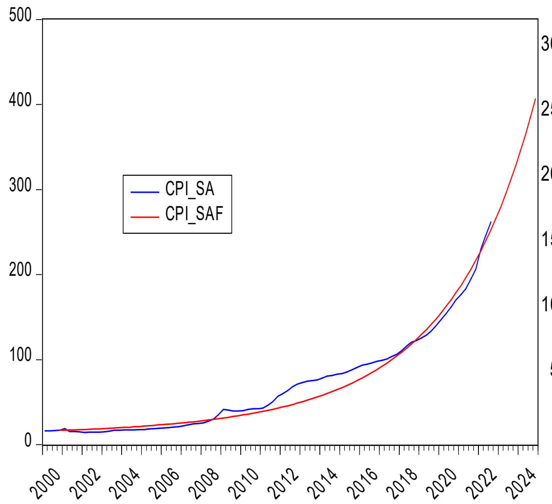


Annex II: Relative Forecasting Performance (RMSE) of the Combination Strategies

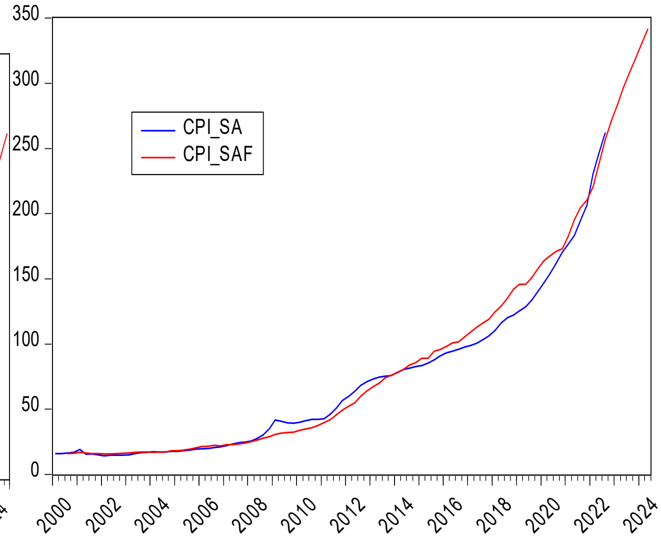


Annex III: Comparison between Actual and Model Forecast of CPI_SA

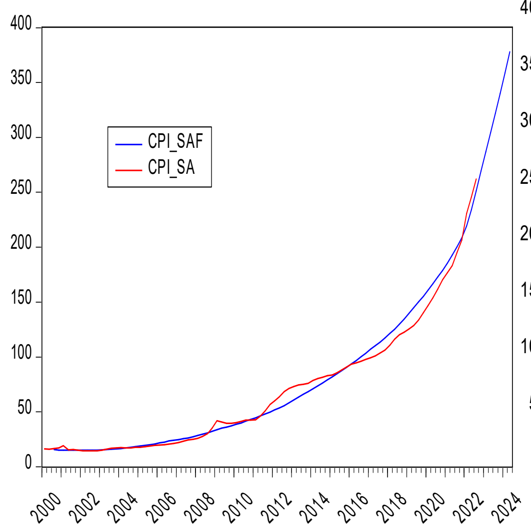
ARIMA(2,1,2) Model Forecast



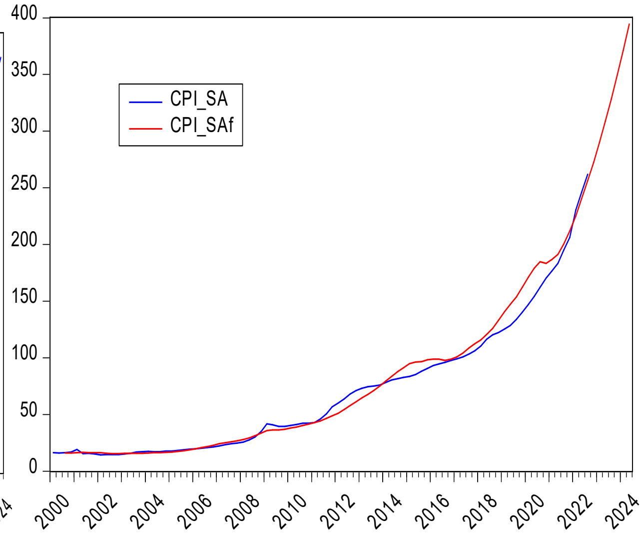
ECM Model Forecast



BVAR Model Forecast



VECM model Forecast



Phillips Model Forecast