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Inflation Forecasting Using Automatic ARIMA Model in Sri Lanka

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Abstract: Elevated inflation again has been a key macroeconomic problem that impacts negatively on economic activities in recent times. Inflation is widely used as a short run monetary policy tool that has impact on redistribution of resources through price transmission mechanism in economies. Forecasting is also a challenging task with high volatilities of the price index that use to measure inflation. However, inflation forecasts are essential in setting monetary policy targets and the decision-making process in the short run. In Sri Lanka inflation recorded at its highest level ever in the year 2022 reversing its single digit inflation maintained in a decade. The aim of this paper is to estimate an inflation forecasting model using Automatic ARIMA technique in Sri Lanka employing data from 2014M01 to 2023M01 towards forecasting end point to end 2024, using secondary sourced monthly data. Accordingly, Colombo Consumer Price Index shows a further upward trend forecasting range given in CCPIC index point from 224 to 260 during the period for inflation measured using year on year base is in declining trend, below 10 per cent, but not par equal to the mid-single level as per the data, CCPI 2013=100. Given the demand full inflation factors, policies to encourage supply and production are recommended in the medium term.

Keywords: Inflation, Forecasting, Automatic ARIMA, Sri Lanka

1. Introduction

Inflation has turned to an interesting macroeconomic variable at its detrimental level and pervasive effects to the economies in recently. Inflation has again risen in many countries at the contraction of economic activities that severed with the Covid 19 Pandemic. Policy makers change their policy targets from lower inflation towards flexible inflation targeting deviating from other medium- and long-term targets. In this situation, inflation forecasting, estimation has been an important target and tool in implementing monetary policy decisions. inflation targeting has been an anchor of the monetary policy time to time while others are monetary targeting, exchange rate targeting and interest rate targeting. Inflation forecasting also a challenging task in a volatile period of economies. Anyway, requirement of an inflation forecasting is higher to the decision makers in an inflated economy than any other variable that stabilize the economy in short run. Inflation can be identified as a continuous increase of a general price level of a country as measures by price indices. Inflation forecasting techniques has been improved in line with the theoretical relationships, empirical evidence and with sophisticated analytical tools in making policy recommendations. This paper aims to forecast inflation in Sri Lanka using automatic ARIMA forecasting model, one step ahead model to popularized ARIMA techniques.

2. Literature Review

This section aims to brief theorical background and to review empirical literature that capture the effect of inflation on economic growth, productivity. Further literature on gradually developed inflation forecasting models are also discussed in selecting a methodology for the study.

The problem of inflation is as old as the market system, that goes before the usage of money. In general inflation is the rate that inflate the economy. Inflation is defined as a considerable and persistent rise in the general price level over a period of time. There is no universally accepted definition for inflation. There are enough number of theories and literature reviews on inflation and inflation foresting. In the theoretical literature, inflation is identified as a demand side factor or aggregate demand side factor as given in classical, neoclassical, Keynesian and in monetarism. As per the monetarism “inflation is always and everywhere a monetary phenomenon”. In modern theories, inflation is identified as caused by both demand and supply side factors. Demand full factors cause to shift the Aggregate demand curve. Such demand full factors are monetary factors/money supply and non-monetary factors which refers to increase in government expenditure, tax, investment, saving, import and export. Supply side factors that cause to cost push inflation in modern theory are wages, profit and supply shocks created in a monopolistic market condition. Wage related factors are not always necessarily cause of inflation due to a wage rise in productivity increase, inflation, existing a small proportion of unionized labour, and when the wages are determined by market forces. Theories of inflation is mostly relevant to the developed countries due to the assumptions made based on the characteristics of that countries. Some of the assumptions are, a balanced and integrated structure of the economy, smooth intersectional flows of resources in response to market signals, quick adjustments among consumption, production and investments. Smooth and free play of market forces. Therefore, structuralist' view on inflation is explained the causes of inflation for developing countries. Some of the reasons are food scarcity, resource imbalances, foreign exchange bottlenecks, infrastructure bottlenecks, social and political constraint. However, again these reasons can be identified as demand and supply side factors that cause inflation. Against the theoretical literature, empirical literature emphasis the cause and effect of inflation based on the data given for a particular period of a country. Anyway, economist argue that there must be a certain level of inflation to encourage economic activities.

The desirable level of the inflation of an economy is depended on the capacity of an economy or country which include the economic and social needs. Evident in empirical literature on desired level of inflation has directed in “The minimum inflation rate for Euroland [1]”. The study demonstrates to keep a minimum aggregate inflation as 0.94 percent in Euro countries and extended to 1.5 per cent for Eastern Europe countries to ensure price stability in conducting a common monetary policy. However, it seems that this number also should be under consideration for the desired level of inflation in the higher inflation context during downturn of economic activities. A broad-based study on “Inflation and economic growth: a multi-country empirical analysis [2]” is conducted covering 70 countries of major industrialized, newly industrialized and developing countries using annual data spanning from 1960 to 1989. Several country wise findings are made in this study. Accordingly, there is a causal relationship between inflation and economic growth in industrial countries. Accordingly, in a low inflation regime, inflation will redistribute growth opportunities and benefits towards industrialized countries and away from developing countries. As theoretically explained, inflation is beneficial for resource redistribution in developed countries. Further, number of studies find a negative inflation-growth correlation in linear model while few studies show it as a nonlinear relationship. A study on “When does inflation hurt to economic growth [3]” examined the different nonlinearities for different economies. It concludes that effect of inflation on growth is nonlinear. Therefore, there is indeed of a threshold level at which inflation starts to have a negative impact on growth. This threshold level, critical inflation rates that hurt growth is quite different for developed and developing countries. It concludes that the negative impact of inflation is effected for and above 8 per cent growth in industrial countries and 3 per cent or less growth for developing countries. Further, harmful inflation led to decline the growth significantly by 50 per cent for developing countries. Therefore, Inflation may be harmfully impacted, in the current context of less economic growth in developing countries.

Empirical literature covering the Asian region support that inflation is negatively impacted in the short run. However, positive relationship also noted among inflation and growth in Asian countries against with the theory. A study covering Pakistan economy on “Inflation and economic growth: Evidence from Pakistan [4]” examines that inflation and economic growth is positively related while unidirectional causality is existing from inflation to growth. Threshold level up to 9 per cent of inflation is growth benefited while above 9 per cent inflation starts to lower economic growth in Pakistan. Therefore, single digit inflation is required Pakistan to enrich economic growth. Study conducted for Sri Lanka on “Inflation and economic growth in Sri Lanka: An ARDL bound testing approach [5]” confirmed that both inflation and economic growth shows a long run nexus with appearing negative signs for the period from 1970 -2014 using annual data. Another study on “Impact of inflation on economic growth in Sri Lanka [6]” concluded that there is a long run negative and significant relationship between inflation and economic growth in Sri Lanka for the period 1988-2015. Study covering Sri Lanka for the period from 2006 - 2020 examines the impact of inflation on labour productivity [7], discussing on a broader variable refers to competitiveness. It concludes that inflation and labour productivity is inversely related in the short run. Therefore, a single digit lower-level inflation might result a higher labour productivity. As given in the empirical evidence, inflation is a macroeconomic variable that has been negatively impact on economic activities in the short run. Its effectiveness in the short in achieving long run objectives of an economy is vital. Therefore, forecasting inflation accurately to an inflation targeting, flexible inflation targeting monetary policy is utmost important in making policy level decisions.

In discussing the inflation forecasting models, the study on “Real-time inflation forecasting in a changing world” has developed an inflation forecasting model using reduced form Phillips curve forecast model [8]. It proposes a Phillips curve forecast to estimate inflation. Further, study on “Are Phillips curves useful for forecasting inflation?” concludes that modern Phillips curve-based models are useful tools for forecasting inflation [9]. Model is based on non-accelerating inflation rate of unemployment and further it argues that these forecasts are not much different from the naïve forecast. A study on forecasting inflation [10] by Stock and Watson, examine inflation forecast for 12-month horizon period using the Phillips curve and other macroeconomic variables. According to the findings, inflation forecast using Phillips curve is more accurate than the forecast using the other macroeconomic variables including interest rates, money, and commodity prices. Accordingly, Phillips's curve relationship is still effective to estimate inflation accurately. A study on "Short-term inflation forecasting models for Turkey and a forecast combination analysis [11]" examines short-term inflation forecasting models for Turkey. They use number of econometric models and combination strategies to improve forecast. findings suggest that the models which incorporate more economic information outperform the benchmark random walk. Further, the relative performance of forecasts are on average 30 per cent better for the first two quarters ahead.

ARIMA model has been a widely used techniques in forecasting inflation after the popular study by Box and Jenkins in 1970s [12]. Accordingly time series variables can be forecasted using the its past values due to time varient features. Therefore, forecasting techniques are evolving with more shopisticated analytical tools and high frequency data to better capture and reflect the dynamic of the movements of data. Jesmy [13] estimates the future inflation in Sri Lanka Using ARIMA model, for the period from 1959 to 2009 covering a longer period. In this study, the best model is estimated using model selection criterions for several ARIMA models. ARIMA (1,1,2) has selected as the best model to forecast inflation during the period. Inflation in Pakistan is examined in "Forecasting inflation through econometric models: An empirical study on Pakistani data [14]" using two models VAR and ARIMA. The results concludes that VAR is not a better performed model than ARIMA in forecasting inflation. It further points out the general implications for small scale macro-economic models. Doguwa and Alade [15] conducts a short-term inflation forecasting models for Nigeria using SARIMA and SARIMAX model that includes the seasonality to the ARIMA model. Best forecasting outcome is given through SARIMAX model for headline inflation and SARIMA model for core inflation. In this study two models are estimated for headline and core inflation. In addition, Nyoni and Nathaniel [16] investigate modeling rates of inflation in Nigeria using ARMA, ARIMA and GARCH models. Comparing the three-model criterion, it suggests ARMA as the best model to forecast inflation in Nigeria for the data from 1960 -2016, forecast period ending 2021. Another study [17] is employed three models VAR, ECM and ARIMA to measure the predictive power of inflation. It concludes that ARIMA can be used as a benchmark model, VAR for short run and ECM for long run inflation forecasting model. However, a study by Meyler, Kenny and Quinn [18] in forecasting Irish inflation using ARIMA models considerers two alternative approaches, in sample and out of sample forecasts. Further, practical issues of ARIMA model are also pointed out.

In concern to the empirical literature, it is clear that inflation forecasting model has been initiated with the theoretical Phillips curve relationship between inflation and unemployment. It has gradually improved by adding other macro-economic variables and again emphasized that forecasting in line with the conventional relationship is much better. In some empirical evidences, several time series models are employed to select the best model and ARIMA model is selected as the most appropriate model to forecast inflation. Further, inflation forecasting models using ARMA, ARIMA also rapidly developed recently, and the best model can be selected using forecast evaluation criterion and through combining forecast and forecast averaging etc. As pointed out in some empirical studies, there are some issues in ARIMA forecasting also. Anyway, inflation forecasting is performed using more sophisticated data analyzing tool to estimate and capture the uncertainty, dynamics in decision making in short run subject to a given probability level. There may be inflation forecasting on monthly basis to support the decision-making process with relevant authorities. However, empirical literature is hardly found on inflation forecasting in Sri Lanka. With these concerns and gaps on empirical literature, this study aims to estimate inflation forecasting model employing the data from 2014 to 2023M01 towards 24 months ahead forecast using Automatic ARIMA forecasting model that gives in EViews as the best solution for ARMA type forecasting models.

3. Methodology

Types of forecasts are basically two-fold as non-econometric forecasts and econometric forecasts. We refer here for econometric forecast. Single variable models and vector type/multi variable models are used for econometric forecasts. These models include MA (p,d) AR (d,q), ARIMA(p,d,q,), VAR and VECM. Auto Regressive Integrated Moving Average (ARIMA) model was introduced in 1970 by Box and Jenkins [12] is widely used as a macroeconomic forecasting model using the lag of its own variables. There are enough number of studies in empirical literature that uses ARIMA forecasting tool to forecast inflation. In ARIMA model, Autoregressive, and Moving Average terms should be determined using Auto Correlation (ACF) and Partial Auto Correlation Functions (PACF) respectively. Further diagnostic test also should be done to check the goodness of the fit. Model is estimated using past values of the series and past values of the error term, can be given as follows:

$$Y = \beta_1 Y_{(t-1)} + \beta_2 Y_{(t-2)} + \ldots\ldots + e_t - \alpha_1 e_{(t-1)} - \alpha_2 e_{(t-2)} \quad (1)$$

Y: Targeted variable

β_1, β_2: Coefficient, the rate which indicate the impact on Y by a change in $Y_{(t-1)}$, $Y_{(t-2)}$

$Y_{(t-1)}$, $Y_{(t-2)}$: Previous year/ month values of the variable

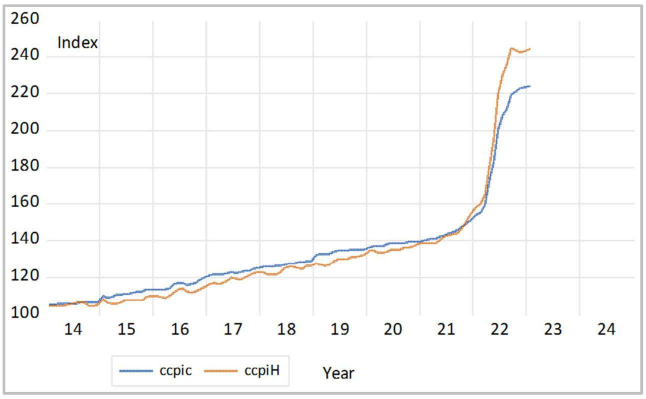
e_t: Error term

Automatic ARIMA forecasting model is an analyzing tool that automatically selects all criteria out of higher number of estimations in EViews. In ARIMA forecasting, the best model is selected after comparing the model selection criterion for the estimated 5-10 models based on the ACF and PACF for selecting AR and MA terms respectively. Sometimes, in those types of forecasting the best model might have been missing since all possible models are not estimated. In the automatic ARIMA forecasting techniques, the best model is selected considering and comparing with all possible models using the given criterion. Therefore, automatic ARIMA estimates could be more representative, comparable, benchmark forecasting model compared to the ARIMA forecasting. Considering this, in this study Automatic ARIMA forecasting models are estimated for core and headline inflation employing secondary sourced monthly data from 2014 to 2023M01 for the forecasting horizon of 24 months. Secondary sources data is obtained from the Department of Census and Statistics (DCS) for CCPI core and headline inflation. The difference of the log values of CCPIC and CCPIH variables is considered in line with the unit root test result for non-stationary variables. Forecasting is presented using pre and post-test to be considered for time series data. Forecasting performance and the accuracy of the model is discussed compared to the selected benchmark model.

4. Inflation in Sri Lanka

Inflation can be simply defined as a continuous increase in general price level of a country as measured using a prices index for a given time period. It is one of key economic and statistical indicators to measure the changes in general price level. Generally, Colombo Consumer Price Index, named as the official price index, cost of living index and is used to measure the movements of the prices of goods and services, compiled by the DCS. CCPI has been revised in several years compared to the other indicators. Thus, incorporating the findings of the surveys on the consumption and expenditure patterns of the consumers, the base year of the CCPI and the weights of the basket of goods and services has changed in many years from 1952 to 2013=100 over time, under 13 subcategories of goods and services. Therefore, CCPI 2013 =100 is considered as the variable in this study to measure and forecast inflation using an ARIMA model for the period from 2014 to 2023M01.

Figure 1 exhibits the movements of inflation as given in CCPI for headline inflation (CCPIH) and core inflation (CCPIC). Core inflation refers to the inflation based on the CCPI covering the inflation of all goods and services except volatile food and fuel prices. CCPI guides in forecasting long term inflation trends. Headline inflation refers to the inflation based on the CCPI covering the inflation of food and energy categories, that capture the volatile prices of the food basket, is a measure of short-term inflation in developing country.



Source: Department of Census and Statistics

Figure 1. *Movement of CCPI in Sri Lanka.*

As given in the figure 1, both headline and core inflation has increased over the period showing a rapid increase in the index after April 2022. Continuation of this sharp increase in prices towards the period is an evident of a disaster with many adverse impacts on the economic activities although it shows slight declines in the index recently. Index value is still higher although it is increasing at declining rate. Forecasting inflation is a challenging task when such volatilities are in the index. Anyway, it guides towards a direction for decision making subject to a given confidence level and probability.

5. Results and Findings

Two models are estimated for core inflation (CCPIC) and headline inflation (CCPIH) for the period from 2014M01 to 2023M01, for 108 observations towards the forecasting horizon of 2 years using the Automatic ARIMA forecasting in EViews. Details are in Appendix 1 and 2 for Automatic ARIMA Forecasting Models using CCPIC, CCPIH respectively. Appendix 3 provides the detail result of the same forecasting using ARIMA model in manual estimation.

Table 1. *Summary of the Forecasting.*

CCPI 2013 = 100	Selected Dependent Variable	Model maximums (AR, MA) Max Diff (SAR, SMA)	ARMA models estimated	Selected ARMA model	AIC value
1. Core inflation, (CCPIC)	Dlog(CCPIC)	(4,4,)2(0,0)	25	(1,2) (0,0)	-6.2248
2. Headline Inflation (CCPIH)	Dlog(CCPIH)	(4,4,)2(0,0)	25	(3,2) (0,0)	-5.7290

As per the summery given, automatic ARIMA forecasting model estimations, core inflation forecasting model is estimated using log difference of CCPIC as the variable is stationary at level one. Twenty five number of ARMA model has been estimated to give the best forecasting model of selected AR (1) MA(2), lowest AIC was -6.224 for given model. Variable for headline inflation (CCPIH) is log difference of CCPIH. AR (3) MA (2) has been selected out of 25 models estimated. The results of the forecast comparison graph, equation output, ARMA criterion and graph for diagnostic test and residual test to check the goodness of the fit is in appendix.

Accordingly, the best model is selected as per the lowest AIC out of selected models. Forecast comparison graphs that help to evaluate and select the best forecast out of selected 25 forecasts are also in annex I.

Inflation forecasting model for CCPIC as per the AR (1) MA (2) has been selected as the best solution for the given data through automatic ARIMA forecasting in EViews out of 25 estimated models. Forecasts using the selected solutions is given below.

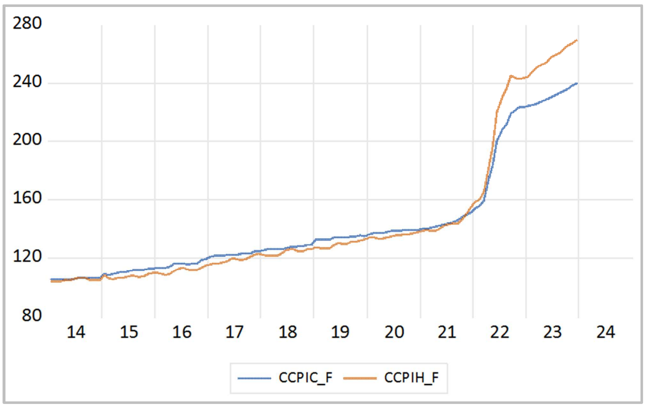


Figure 2. *Colombo Consumer Price Index, (core and headline) - forecast.*

As per Figure 2, it shows an upward trend in the CCPI core index across next 23rd months period, according to the model estimated using the data from 2014M01 to 2023M01 through automatic ARIMA forecasting solution in EViews. CCPIC index value is increasing from 239.68 in 2023M02 to 260 in 2024M12 subject to 95 percent confidence interval limit. Headline inflation, the price increases in food and energy category, the index number will further increase from 247.65 in 2023M02 to 296.25 in 2024M12 reflecting an upward trend of the index value over the period according to the forecast results for the data given during the period. Further, CCPI for headline inflation that reflect the price changes in food and energy category is considerably higher compared to the prices of all other commodities in the food basket considered. CCPI headline is surpasses the CCPI core from 2022 Q1, at the initial point, where reflecting many problems in the economy signaling through price increases in the short run. The gap between CCPI Headline and the core is widening towards the period.

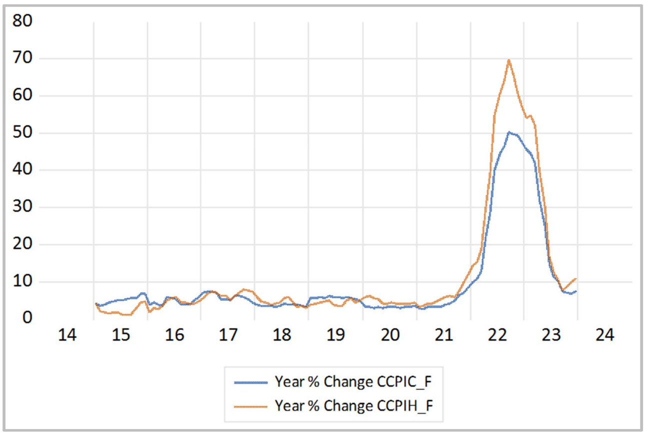


Figure 3. *Forecasting core and headline inflation.*

Inflation, as measured by price indices, is the percentage change in the price index compared to the previous period. Accordingly, inflation forecast from 2023M02 to 2025M01 is exhibited below, extending actual inflation to the same figure from 2023M01.

As per as the inflation is considered in figure 3, it is in disinflation path from 2023 onwards given the estimated results, based on the sample data during period subject to 95 percent confidence level. The above figure can be divided in to two as before 2022 that depicts on average a single digit inflation and after 2022 that shows an elevated inflation which is more than 5 to 7 times higher the inflation was in 2021. The sudden increase of inflation is really a shock to a country where inflation was below 10 per cent in last decade, although inflation is in disinflation path. As per the forecasted data, inflation is declining path but there is no evidence to restore towards a single digit inflation given the macroeconomic factors that are not much favorable in medium term. Accordingly, if we compare inflation, based on year-on-year change, both core and headline inflation are in the declining trend to reverse the elevated trend in 2022. Aggregate demand may further contract several times due to these types of demand shock policies that impacted negatively to encourage economic activities, production, and growth. This forecast result may change due to a change in data, sample, number of observations or any of the reasons. Details of the forecasting are in appendix as per order given in EViews.

5.1. Forecast Comparison

In this section forecast comparison is attended in two-fold. First, forecasts are compared separately for CCPIC and CCPIH with all models as given in the forecast comparison graph in EViews. Secondly, results of the forecast are compared with respect to Automatic ARIMA Forecasting and ARIMA forecasting to ensure the confidence of the same results received from both ways of forecasting.

Forecasting comparison support to compare the benchmark forecast, selected forecast with all other estimated forecasting models. This further ensures the representativeness and suitability of the selected model in comparison to other models. Forecast comparison graph for CCPIC and CCPIH is given below.

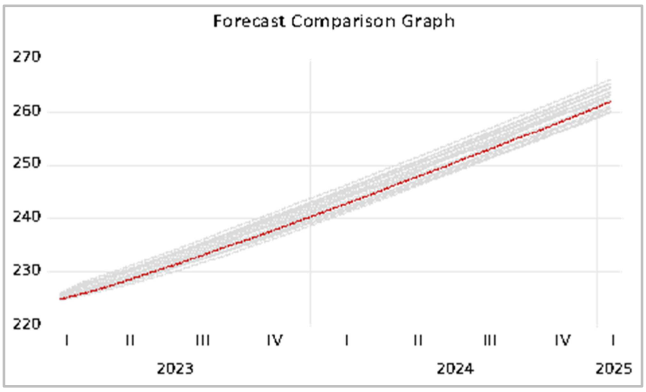


Figure 4. *Forecast comparison graph for CCPIG.*

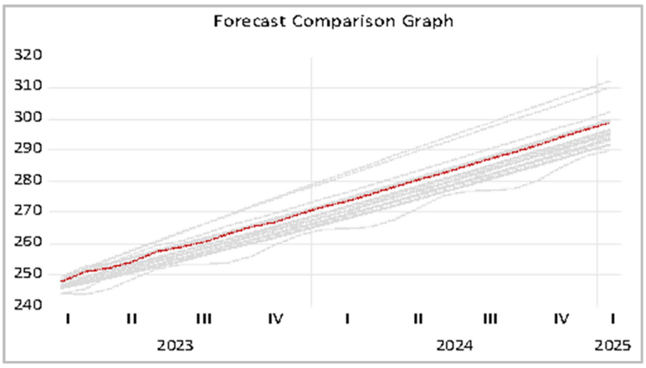


Figure 5. *Forecast comparison graph for CCPIH.*

Accordingly, the selected models in automatic ARIMA estimation are highlighted, ARIMA (1,2) (0,0) for CCPI for core inflation indicates the as the best model out of 25 models estimated where can be trace among other 25 forecast clearly. Further, relating to headline inflation CCPIH, ARIMA (3,2) (0,0) is selected as the best model and highlighted in figure 4. In comparison to the two models estimated, CCPIC is less volatile compared to the CCPIH reflecting the higher volatility in the CCPI for headline inflation. As per the forecast, CCPI indexes, CCPIH is higher than the CCPIC considering the higher index points in CCPIH compared to CCPIC that noted after 2019. Accordingly, CCPIC index forecast increases to index points 260 and CCPIH reaches to index point 300 as per the data CCPI 2013 = 100 considered in the sample.

In model selection criteria, AIC is considered. AIC for each top 20 forecasting models using CCPIC and CCPIH is given figure A3 and figure A6 respectively in the appendix.

Forecasting with the lowest AIC is selected as the best model. Accordingly the selected two models ARIMA (1,2) (0,0) and ARIMA (3,2) (0,0) indicate the lowest AIC -6.2248 for CCPIH and -5.7290 for CCPIH in the figures respectively in appendix.

5.2. Comparison of the Automatic ARIMA Forecasting Model with ARIMA

This comparison is attended to compare the results of automatic ARIMA forecasting model with the ARIMA model that involves number of manual steps in estimating such as checking stationarity, ACF, ADCF, diagnostics test, post-test estimations, forecast comparison and forecast averaging to select the best model. Accordingly, the forecasting model using automatic ARIMA forecasting can be estimated in manual ARIMA forecasting also. This is evident that researchers can more easily engage forecasting models using automatic ARIMA tool in EViews.

Comparison summary is 100 percent the same for both models. This comparison summary is involved based on two steps. The first step, estimating the forecasting model using automatic ARIMA in EViews, the best, benchmark model. Then the manual ARIMA is estimated using the estimation criterion that used in model one. However, the reverse may not be valid, or it does not mean that ARIMA estimation using manual process always gives the best model due to limited number of models involved compared to all possible types of models run in automatic ARIMA process. Details of forecasting using automatic ARIMA and ARIMA models are given in section Appendix 3.

6. Conclusion

The objective of this paper is to estimate a model for forecasting inflation in Sri Lanka using monthly, secondary sourced data from 2014 to 2023 for 2-year forecasting horizon period. Accordingly, two models were estimated for CCPI core and CCPI Headline Inflation using automatic ARIMA forecasting tool available in EViews. Accordingly, ARIMA (1 1 2) and ARIMA(2 1 3) were selected as the most appropriate models to forecast core and headline inflation respectively. As per inflation forecasting models, both core inflation and headline inflation is in declining path towards 2024. Although inflation is in declining path, it is still 5 times higher than the inflation was in 2021. Inflation has been identified as a macroeconomic variable to signal the market and encourage economic activities in the short run. Therefore, the declining path of inflation is a good signal to the market. Other factors such as interest rates, GDP growth, productivity, debt sustainability, gross official reserves should be in a favorable position towards the continuation of disinflation path. As per the empirical evidence, a single digit inflation is recommended to encourage economic activities in the short run towards achieving a higher production in medium term objective. Further policies related to improvement of supply-side conditions should be focused on towards the medium run.

Appendix

Appendix 1. Inflation Forecasting Using Automatic ARIMA Model for CCPIC (Core Inflation)

Table A1. *Forecasting Summary for CCPIC.*

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(CCPIC)
Sample: 2014M01 2023M01
Included observations: 108
Forecast length: 23
Model maximums: (4,4) 2 (0,0)
Regressors: C
Number of estimated ARMA models: 25

Number of non-converged estimations: 0 Selected ARMA model: (1,2) (0,0) AIC value: -6.22484570915

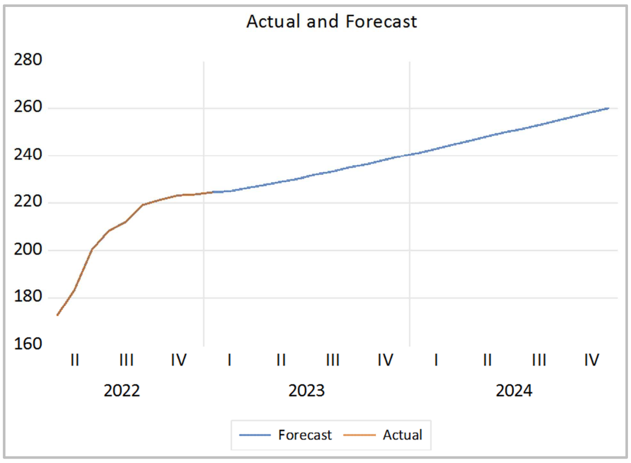


Figure A1. *Forecast Graph for CCPIH.*

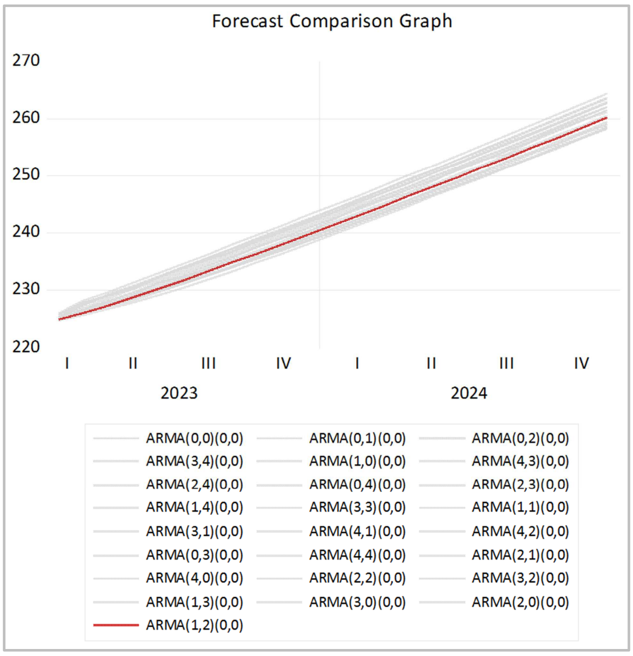


Figure A2. *Forecast Comparison Graph.*

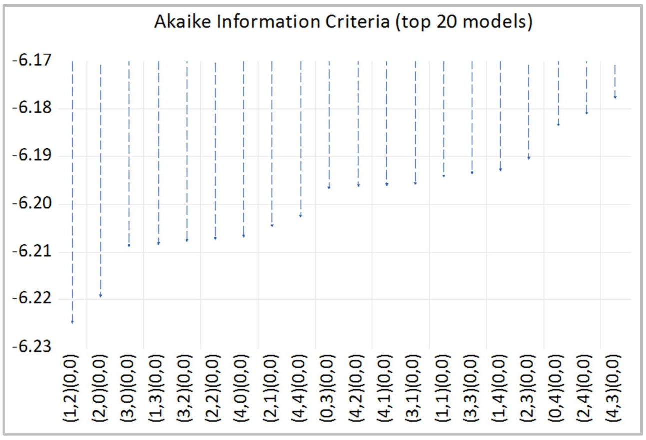


Figure A3. *ARMA criteria Graph.*

Table A2. *Equation output.*

Dependent Variable: DLOG(CCPIC)				
Method: ARMA Maximum Likelihood (BFGS)				
Sample: 2014M02 2023M01				
Included observations: 108				
Convergence achieved after 9 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.01	0.01	1.36	0.18
AR(1)	0.62	0.09	7.33	0.00
MA(1)	(0.14)	0.09	(1.54)	0.13
MA(2)	0.30	0.07	4.31	0.00
SIGMASQ	0.00	0.00	14.84	0.00
R-squared	0.46	Mean dependent var		0.01
Adjusted R-squared	0.44	S.D. dependent var		0.01
S.E. of regression	0.01	Akaike info criterion		(6.22)
Sum squared resid	0.01	Schwarz criterion		(6.10)
Log likelihood	341.14	Hannan-Quinn criter.		(6.17)
F-statistic	22.34	Durbin-Watson stat		2.00
Prob(F-statistic)	0.00			
Inverted AR Roots	0.62			
Inverted MA Roots	.07+.54i	.07-.54i		

Table A3. *ARMA Criteria Table.*

Model Selection Criteria Table				
Dependent Variable: DLOG(CCPIC)				
Sample: 2014M01 2023M01				
Included observations: 108				
Model	**LogL**	**AIC***	**BIC**	**HQ**
(1,2) (0,0)	341.14	(6.22)	(6.10)	(6.17)
(2,0) (0,0)	339.84	(6.22)	(6.12)	(6.18)
(3,0) (0,0)	340.27	(6.21)	(6.08)	(6.16)
(1,3) (0,0)	341.24	(6.21)	(6.06)	(6.15)
(3,2) (0,0)	342.22	(6.21)	(6.03)	(6.14)
(2,2) (0,0)	341.19	(6.21)	(6.06)	(6.15)
(4,0) (0,0)	341.17	(6.21)	(6.06)	(6.15)
(2,1) (0,0)	340.05	(6.20)	(6.08)	(6.15)
(4,4) (0,0)	344.94	(6.20)	(5.95)	(6.10)
(0,3) (0,0)	339.62	(6.20)	(6.07)	(6.15)
(4,2) (0,0)	342.59	(6.20)	(6.00)	(6.12)
(4,1) (0,0)	341.58	(6.20)	(6.02)	(6.13)
(3,1) (0,0)	340.57	(6.20)	(6.05)	(6.14)
(1,1) (0,0)	338.48	(6.19)	(6.09)	(6.15)
(3,3) (0,0)	342.45	(6.19)	(5.99)	(6.11)
(1,4) (0,0)	341.41	(6.19)	(6.02)	(6.12)
(2,3) (0,0)	341.29	(6.19)	(6.02)	(6.12)
(0,4) (0,0)	339.90	(6.18)	(6.03)	(6.12)
(2,4) (0,0)	341.77	(6.18)	(5.98)	(6.10)
(4,3) (0,0)	342.59	(6.18)	(5.95)	(6.09)
(1,0) (0,0)	335.58	(6.16)	(6.08)	(6.13)
(3,4) (0,0)	341.41	(6.16)	(5.93)	(6.07)
(0,2) (0,0)	335.61	(6.14)	(6.04)	(6.10)
(0,1) (0,0)	323.08	(5.93)	(5.85)	(5.90)
(0,0) (0,0)	307.78	(5.66)	(5.61)	(5.64)

Appendix 2. Inflation Forecasting Using Automatic ARIMA Model for CCPIH (Headline Inflation)

Table A4. *Forecasting Summary for CCPIH.*

Automatic ARIMA Forecasting
Selected dependent variable: DLOG(CCPIH)
Sample: 2014M01 2023M01
Included observations: 108
Forecast length: 23
Model maximums: (4,4) 2 (0,0)
Regressors: C

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (3,2) (0,0)
AIC value: -5.72909499999

Table A5. *Equation output.*

Dependent Variable: DLOG(CCPIH)				
Method: ARMA Maximum Likelihood (BFGS)				
Sample: 2014M02 2023M01				
Included observations: 108				
Convergence achieved after 113 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.01	0.01	1.42	0.16
AR(1)	0.12	0.14	0.86	0.39
AR(2)	(0.44)	0.13	(3.25)	0.00
AR(3)	0.50	0.12	4.21	0.00
MA(1)	0.56	34.90	0.02	0.99
MA(2)	1.00	125.51	0.01	0.99
SIGMASQ	0.00	0.01	0.02	0.99
R-squared	0.52	Mean dependent var		0.01
Adjusted R-squared	0.49	S.D. dependent var		0.02
S.E. of regression	0.01	Akaike info criterion		(5.73)
Sum squared resid	0.02	Schwarz criterion		(5.56)
Log likelihood	316.37	Hannan-Quinn criter.		(5.66)
F-statistic	18.07	Durbin-Watson stat		1.97
Prob(F-statistic)	0.00			
Inverted AR Roots	0.65	-.26-.84i	-.26+.84i	
Inverted MA Roots	-.28+.96i	-.28-.96i		

Table A6. *ARMA criteria table.*

Model Selection Criteria Table				
Dependent Variable: DLOG(CCPIH)				
Sample: 2014M01 2023M01				
Included observations: 108				
Model	**LogL**	**AIC***	**BIC**	**HQ**
(3,2) (0,0)	316.37	(5.73)	(5.56)	(5.66)
(1,0) (0,0)	312.20	(5.73)	(5.65)	(5.70)
(0,3) (0,0)	314.19	(5.73)	(5.60)	(5.68)
(1,2) (0,0)	313.43	(5.71)	(5.59)	(5.66)
(3,3) (0,0)	316.40	(5.71)	(5.51)	(5.63)
(4,2) (0,0)	316.40	(5.71)	(5.51)	(5.63)
(1,3) (0,0)	314.38	(5.71)	(5.56)	(5.65)
(0,4) (0,0)	314.27	(5.71)	(5.56)	(5.65)
(2,0) (0,0)	312.24	(5.71)	(5.61)	(5.67)
(1,1) (0,0)	312.23	(5.71)	(5.61)	(5.67)
(4,4) (0,0)	318.16	(5.71)	(5.46)	(5.61)
(3,0) (0,0)	312.72	(5.70)	(5.57)	(5.65)
(1,4) (0,0)	314.64	(5.70)	(5.52)	(5.63)
(2,2) (0,0)	313.49	(5.69)	(5.55)	(5.63)
(2,3) (0,0)	314.45	(5.69)	(5.52)	(5.62)
(2,1) (0,0)	312.34	(5.69)	(5.57)	(5.64)
(2,4) (0,0)	315.24	(5.69)	(5.49)	(5.61)
(3,4) (0,0)	316.06	(5.69)	(5.46)	(5.60)
(4,0) (0,0)	312.77	(5.68)	(5.53)	(5.62)
(3,1) (0,0)	312.73	(5.68)	(5.53)	(5.62)
(4,3) (0,0)	315.51	(5.68)	(5.45)	(5.59)
(0,2) (0,0)	310.23	(5.67)	(5.57)	(5.63)
(4,1) (0,0)	313.16	(5.67)	(5.50)	(5.60)
(0,1) (0,0)	300.96	(5.52)	(5.44)	(5.49)
(0,0) (0,0)	279.40	(5.14)	(5.09)	(5.12)

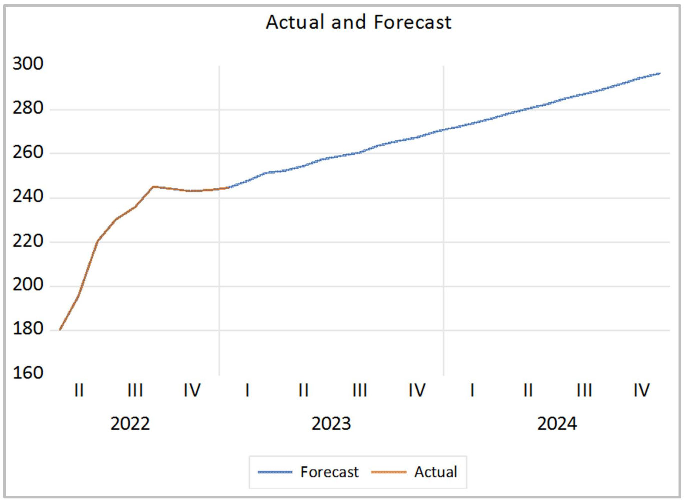


Figure A4. *Forecast graph.*

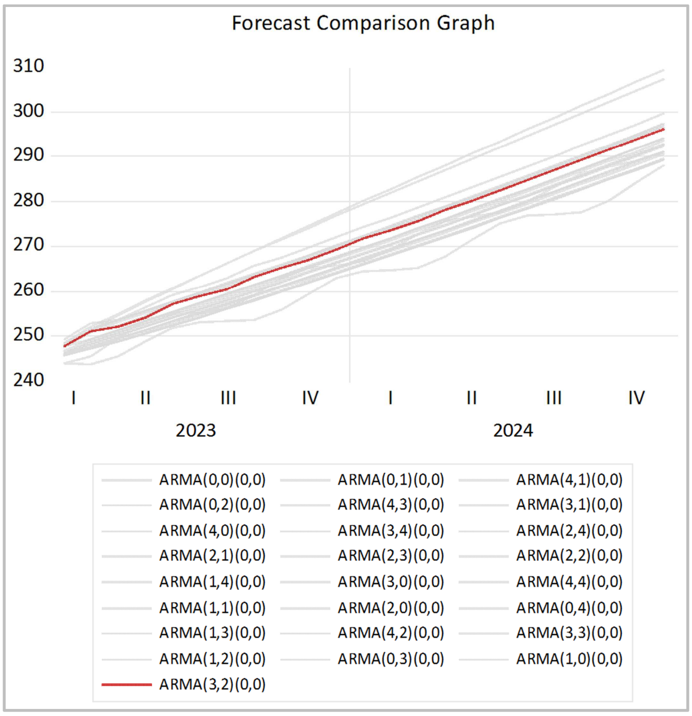


Figure A5. *Forecast Comparison graph.*

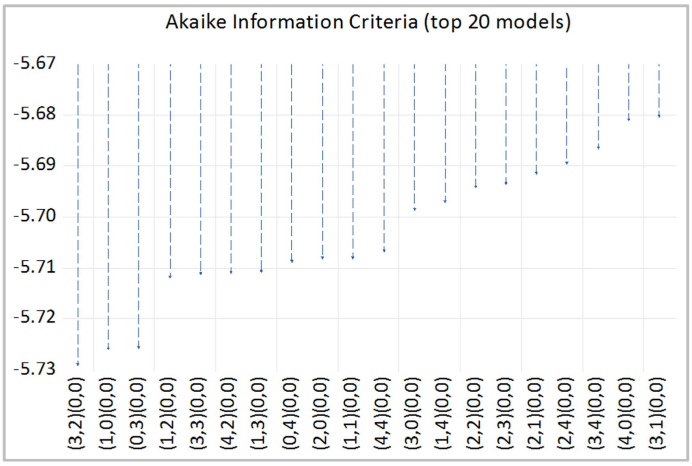


Figure A6. *ARMA criteria Graph.*

Appendix 3. ARIMA Forecasting

Table A7. *ARIMA Forecasting for CCPIC.*

Dependent Variable: DLOG(CCPIC)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Sample: 2014M02 2023M01				
Included observations: 108				
Convergence achieved after 66 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.01	0.01	1.36	0.18
AR(1)	0.62	0.09	7.33	0.00
MA(1)	(0.14)	0.09	(1.54)	0.13
MA(2)	0.30	0.07	4.31	0.00
SIGMASQ	0.00	0.00	14.84	0.00
R-squared	0.46	Mean dependent var		0.01
Adjusted R-squared	0.44	S.D. dependent var		0.01
S.E. of regression	0.01	Akaike info criterion		(6.22)
Sum squared resid	0.01	Schwarz criterion		(6.10)
Log likelihood	341.14	Hannan-Quinn criter.		(6.17)
F-statistic	22.34	Durbin-Watson stat		2.00
Prob(F-statistic)	0.00			
Inverted AR Roots	0.62			
Inverted MA Roots	.07+.54i	.07-.54i		

Table A8. *ARIMA Forecasting for CCPIH.*

Dependent Variable: DLOG(CCPIH)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Sample: 2014M02 2023M01				
Included observations: 108				
Convergence not achieved after 500 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.01	0.01	1.42	0.16
AR(1)	0.12	0.14	0.86	0.39
AR(2)	(0.43)	0.13	(3.25)	0.00
AR(3)	0.50	0.12	4.20	0.00
MA(1)	0.55	0.21	2.68	0.01
MA(2)	1.00	0.71	1.41	0.16
SIGMASQ	0.00	0.00	1.63	0.11
R-squared	0.52	Mean dependent var		0.01
Adjusted R-squared	0.49	S.D. dependent var		0.02
S.E. of regression	0.01	Akaike info criterion		(5.73)
Sum squared resid	0.02	Schwarz criterion		(5.56)
Log likelihood	316.37	Hannan-Quinn criter.		(5.66)
F-statistic	17.94	Durbin-Watson stat		1.97
Prob(F-statistic)	0.00			
Inverted AR Roots	0.65	-.26-.84i	-.26+.84i	
Inverted MA Roots	-.28+.96i	-.28-.96i		

References

[1] Sinn, Hans-Werner, and Michael Reutter. *The Minimum Inflation Rate for Euroland*: National Bureau of Economic Research, 2001. Print.

[2] Paul, Satya, Colm Kearney, and Kabir Chowdhury. "Inflation And Economic Growth: A Multi-Country Empirical Analysis." *Applied Economics* 29.10 (1997): 1387-401. Print.

[3] *When Does Inflation Hurt Economic Growth?* Different Nonlinearities for Different Economies. Available As A Claremont Working Paper At< Http://Spe. Cgu. Edu/Institutes/Conference/Mainindex. Html. 2000. Print.

[4] Hussain, Shahzad, and Shahnawaz Malik. "Inflation and Economic Growth: Evidence From Pakistan." *International Journal of Economics and Finance* 3.5 (2011): 262-76. Print.

[5] Aslam, AL, and SM Lebbe. "Inflation and Economic Growth In Sri Lanka: An Ardl Bound Testing Approach." (2017). Print.

[6] Madurapperuma, Wasanthi. "Impact of Inflation on Economic Growth in Sri Lanka." *Journal of World Economic Research* 5.1 (2016): 1-7. Print.

[7] Liyanage, Rohini Dunuwita. "Impact of Inflation on Labour Productivity In Sri Lanka." *Organization* 9.3 (2021): 57-70. Print.

[8] Groen, Jan JJ, Richard Paap, And Francesco Ravazzolo. "Real-Time Inflation Forecasting in a Changing World." *Journal of Business & Economic Statistics* 31.1 (2013): 29-44. Print.

[9] Atkeson, Andrew, and Lee E Ohanian. "Are Phillips Curves Useful For Forecasting Inflation?" *Federal Reserve Bank Of Minneapolis Quarterly Review* 25.1 (2001): 2-11. Print.

[10] Stock, James H, and Mark W Watson. "Forecasting Inflation." *Journal of Monetary Economics* 44.2 (1999): 293-335. Print.

[11] ÖğÜNç, Fethi, et al. "Short-Term Inflation Forecasting Models for Turkey and A Forecast Combination Analysis." *Economic Modelling* 33 (2013): 312-25. Print.

[12] Box, George EP. "GM Jenkins Time Series Analysis: Forecasting and Control." San Francisco, Holdan-Day (1970).

[13] Jesmy, ARS. "Estimation of Future Inflation in Sri Lanka Using Arima Model." (2012). Print.

[14] BOKHARI, SM Husnain, and Mete Feridun. "Forecasting inflation through econometric models: An empirical study on Pakistani data." Doğuş Üniversitesi Dergisi 7.1 (2006): 39-47.

[15] Doguwa, Sani I, and Sarah O Alade. "Short-Term Inflation Forecasting Models for Nigeria." *CBN Journal Of Applied Statistics* 4.3 (2013): 1-29. Print.

[16] Nyoni, Thabani, and Solomon Prince Nathaniel. "Modeling Rates of Inflation in Nigeria: An Application of Arma, Arima And Garch Models." (2018). Print.

[17] Uko, AHAM KELVIN, and Emeka Nkoro. "Inflation forecasts with ARIMA, vector autoregressive and error correction models in Nigeria." European Journal of Economics, Finance & Administrative Science 50 (2012): 71-87.

[18] Meyler, Aidan, Geoff Kenny, And Terry Quinn. "Forecasting Irish Inflation Using Arima Models." (1998). Print.