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FORECASTING INFLATION IN INDIA USING THE SARIMA MODEL

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Abstract:

This paper analyses and forecasts the inflationrate based on the monthly Consumer Price Index – Combined (CPI-C) and Wholesale Price Index- All-commodities (WPI-AC) of the Indian Economy. The data used for the analysis is monthly and ranges from January 2013 to May 2023 collected from the Reserve Bank of India. Analyses reveal that the CPI-C and WPI-AC Inflation Rates of India follow a seasonal Auto-Regressive Integrated Moving Average (SARIMA) Model. CPI model has SIMA properties (0,1,1)*(0,0,2)[12], while WPI model has SARI properties (1,1,0)*(2,0,1)[12]. The models are chosen to be the best model using the Bayesian Information Criterion (BIC). The robust test also proves that the forecasts obtained from it are the best representation of the original observations. Other than these the Chow test was applied to the inflation rates to see the presence of a structural break in the data and it had shown that only WPI has the presence of structural breaks while CPI is showing no structural breaks in the data.

Keywords: Inflation Rates, SARIMA Model, Chow Test, Forecasting, Structural Break.

INTRODUCTION

Prediction of time series is one of the most demanding research areas due to the nature of various time series i.e., stocks, inflation, stock indices etc. Several approaches have already been used to forecasttime series. Methods such as the Mean Method (like, Auto-Regressive Moving-Average (ARMA), ARIMA), Business Cycle Filtering (like HP Filter, BK Filter, etc.), Exponential Smoothening Method, Variance Method (like, Auto-Regressive Conditional Heteroscedasticity (ARCH), GARCH) or new methods like Machine Learning (ML) methods (neural networking, LSTM) have been suggested in the academic literature for time series forecasting.

In India, the Consumer Price Index (CPI) and Wholesale Price Index(WPI)are the two important indicators of inflation. The Government of India and the Reserve Bank of India mainly focus on these two indicators for considering inflation in India. Other than these two there are other different instruments to measure inflation that are also available such as Gross Domestic Product deflator and Private Final consumption Expenditure deflator. For this study,the inflation rate calculated from the Consumer Price Index – Combined (CPI-C) and Wholesale Price Index- All-commodities (WPI-AC) series have been used to measure inflation.

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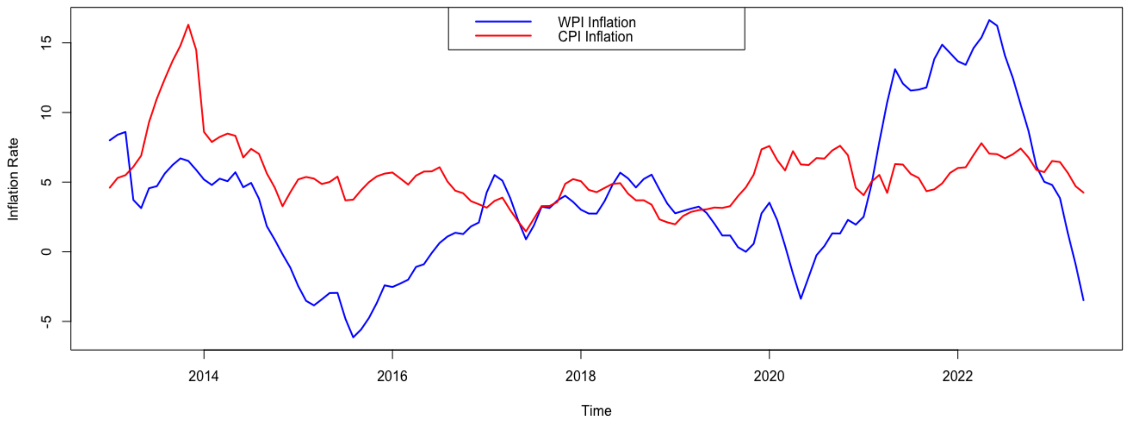
Figure (1) provides the trend of the CPI-C and WPI-AC inflation rates from January 2013 to May 2023. Figure (1) shows that WPI fluctuates more than CPI and has its lowest point near 2014-16 and highest point during 2020 to 2022 afterwards it starts declining. At the same time,CPI has a constant mean fluctuation which saw its highest peak near 2014 before the introduction of the inflation-targeting regime in India. This means due to the inflation-targeting regime it has been possible to control the fluctuation in CPI inflation. On this note, this study will analyse the future of inflation rates using the SARIMA model as it is one of the best models for forecasting inflation as suggested in the works of literature. This study will also help to know how inflation targeting will impact the future values of the respective inflation rate in India.

Figure 1 CPI and WPI trend



THEORETICAL LITERATURE REVIEW

(I) Demand-pull theories: Demand-pull theorists argue that the main cause of inflation is the persistent increase in the aggregate demand for goods against a relatively fixed supply of goods (Addison & Burton, 1980). Major demand-pull theories are the classical and modern quantity theory of money(monetarism), and the new classical and neo-Keynesian theory.

The classical quantity theory of money

The classical Theory of Inflation was developed by classical economists, including David Hume and John Stuart Mill. The quantitytheory of Money suggests a direct relationship between the money supply and the price level in an economy. Irving Fishers have provided the quantity theory of money equation. The quantity theory of money equation MV=PQ states that the money supply (M) multiplied by the velocity of money (V) equals the price level (P) multiplied by the quantity of goods and services (Q). They have analysed inflation primarily as a monetary phenomenon in which an increase in the money supply while keeping the quantity of goods and services constant leads to higher prices.This type of inflation is more international than domestic.

Monetarist Theory of Inflation

Modern Quantity Theory of Money (QTM)is given by monetaristsled by Milton Friedman. He states that "inflation is always and everywhere a monetary phenomenon". Monetarists argue that an increase in money supply leads to an increase in price level leaving the real sector of the economy completely undisturbed.

New classical macroeconomic theory

The main propounder of this group Lucas believed that changes in the money supply led to affect output and employment in the short run due to temporary expectational errors. In the long run, it will lead to inflation. these theorists emphasised more on inflationary expectations.

Neo-Keynesian theory of Inflation

Neo-Keynesian theory of Inflation is based on the view that changes in M lead to changes in Q as prices are rigid in the short run but in the long run increase in money supply will lead to an increase in prices (Mankiw and Romer,1991).

Keynesian Theory of Inflation

In the Keynesian model,an increase in Aggregate demand leads to an increase in Q and employment till full employment (FE) is reached. Post-FE, any increase in aggregate demand will lead to an inflationary gap. Money has a small direct impact on aggregate demand as it is dependent on interest rates(Samuelson, 1971). Keynesians opposed the monetarist view that the velocity of circulation of money was stable.

(II)Cost-Push theories:

Non-monetary supply-oriented variables that boost costs and thus prices are cited in cost-push inflation theories. Major cost-push theories are the First-generation cost-push (FGCP) theory andthe Conflicting claims theory.First-generation cost-push (FGCP) theory assumes that inflation is caused byan increase in factor prices usually an increase in nominal wages. Theory views that nominal wages rise which are dependent on the bargaining power of labour without an increase in labour productivity lead to inflation.Conflicting claims theory argues that inflation can be the result of a wage rise or profit rise. Conflict between the workers and the firm to raise their share of total income will result in a continuous price rise.

(III)Structural Inflation theories:

Major proponent of this group Bernanke emphasized supply-side variables as the reason for inflation.Institution bottlenecks, poor infrastructure, market imperfections and structural rigidities within a country lead to inefficiency and reduction in supply and lead to inflation.

METHODOLOGY

Theoretical Background

The Box-Jenkins(1976) ARMA model is a combination of the AR (Autoregressive) and MA(Moving Average) models as follows:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} - \alpha_1 u_{t-1} - \alpha_2 u_{t-2} - \cdots - \alpha_q u_{t-q} + u_t \quad (1)$$

The Box and Jenkins (1976)approach hasthe following stages:

- Testing stationarity of time series: The autocorrelation function (ACF), as well as the Augmented Dickey-Fuller (1984)test (ADF) and Phillips-Perron (1988) test (PP), are used for testing stationarity of time series.
- Model Identification using ARMA(p,q): We utilise the sample of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the stationary series to calculate the order of ARMA(p,q). These two charts indicate the model we should create. The partial autocorrelation coefficient determines the parameter p of the autoregressive operator and the parameter q of the moving average operator is specified by the autocorrelation coefficient. We use the limits $\pm {}^{2}/_{\sqrt{n}}$ for the non-significance of the two functions, ARMA models (a, b), where $0 \leq a \leq p, 0 \leq b \leq q$ will be identified.We use the (Akaike, 1973) (AIC) and (Schwarz, 1978)(SIC) criteria to get the best model.
- Model Estimation:The inclusion of white noise elements in an ARIMA model necessitates a nonlinear iterative procedure for parameter estimation. In general, maximum likelihood estimation is the favoured strategy.
- Diagnostic checking of the model: With diagnostic checking, an investigation is doneto know the acceptability and statistical significance of the estimated model and whether it fits well with the data or not. To know the adequacy of the estimated ARIMA model randomness of the residuals is checked to know whether the residuals are white noiseand are not serially correlated.
- Forecasting: time series models are usually made to forecast and to check the accuracy of the model forecasting error is estimated with root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the inequality coefficient of Theil (U).
  The forecast value at time t+k which is one period ahead is

$$y_{t+k} = (\beta_1 + 2)y_{t+k-1} - (1 + 2\beta_1)y_{t+k-2} + \beta_1 y_{t+k-3} + \alpha_1 u_{t+k-1} + u_t \quad (2)$$

Data Sources

The two inflation rates are used in the analysis, which is based on the Consumer Price Index-combined (CPI-C) Inflation Rate and the Wholesale Price Index- All commodities (WPI-AC) Inflation Rate. The data for the variables are collected from the Database of Indian Economy – Reserve Bank of India from the period starting from January 2013 to May 2023. The ARIMA approach is an iterative five-stage process, which includes:

1) Stationarity of the Variable;
2) Identification of the Model;
3) Estimation of the Model;
4) Diagnostic Testing of the Model;
5) Predicting Future.

RESULTS

1) STATIONARITY TESTING

To check the stationarity of variables in this analysis, we have used the Augmented Dickey-Fuller (ADF) (Said & Dickey, 1984) test,(Phillips & Parron, 1988) test,(Zivot & Andrews, 1992) test and (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) test.

Table 1: Stationarity Test using Unit Root Tests			
Variables	ADF (1984) test	PP (1988) test	KPSS (1992) test
At Level			
CPI Combined	-3.23	-2.77	0.32***
WPI	-2.24	-1.77	0.65**
At First Difference			
CPI Combined	-7.83***	-7.71***	0.04
WPI	-6.01***	-5.60***	0.14
Null Hypothesis:	Non-Stationary	Non-Stationary	Stationary

Source: Authors' Calculation on RStudio

From Table (1), it can be analyzed that CPI-C inflation and WPI-AC inflation are stationary at first difference. To verify the unit root results, we have applied Zivot and Andrews's(1992) unit root test which helps us to know the breakpoints in the variables as well. In Table (2), the result of the ZA test is given.

Table 2: Zivot and Andrews (1992) Unit Root Test			
Level		First Difference	
Variables	Statistics	Variables	Statistics
CPI-Combined	-6.2398***	CPI-Combined	-
Break Date	Nov-2011	Break Date	-
WPI	-2.3005	WPI	-7.3149***
Break Date	Jan-2021	Break Date	Dec-2020
Null Hypothesis:	Non-Stationary		

Note: Authors' Calculation on RStudio

Now before going towards the next stage of the ARIMA procedure, structural breaks are measured in the variables using the Bai and Perron (2003) test. Before applying the Bia and Perron (2003) test, we check whether the variables have structural breakpoints or not and to measure that we use the structural change (SC)Chow test (Zeileis(2006); Zeileis, Leisch, Hornik, Kleiber (2002)). The result of the Chow(1960) test is given in table (3).

Table 3: Chow (1960) Test Results		
Variables	F. Statistics	P – Value
CPI Combined	2.45	0.12
WPI	20.65	0.00***
Null Hypothesis		No Structural Break

Note: Authors' Calculation on RStudio

The findings of Chow's (1960)test show that there are insufficient pieces of evidence to reject the null hypothesis for CPI inflation, meaning that there is no structural break in the data for CPI inflation. On the contrary, the test for WPI inflation rejects the null hypothesis and shows that in WPI inflation the structural break exists. So, taking forward the result of Table (3) we'll apply the Bia and Perron (2003) test to the WPI inflation data only. The figure (2) shows the breakpoints in the WPI data.

Figure 2 Breakpoints in the WPI inflation

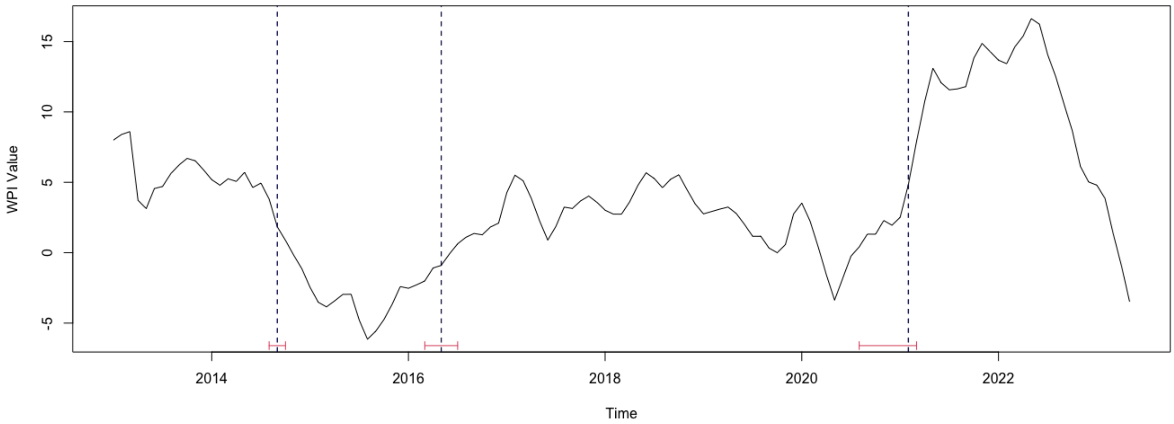


Figure (2) shows three blue dotted lines thatrepresent the breakpoint in the period while the red line represents the confidence range of the breakpoint. Analysing the figure (2), it can be seen that there are breaks in September 2014 (August to October 2014), May 2016 (March to July 2016) and February 2021 (August 2020 to March 2021).

Now moving towards the second stage of the ARIMA procedure, i.e., identification of the ARIMA model.

2) IDENTIFICATION OF THE MODEL

After determining the correct differencing order required to make the series stationary, the next step is to discover an acceptable ARMA form to model the stationary series. there are two ways to identify ARMA models. The classic method employs the Box-Jenkins strategy, which involves an iterative process of model identification, estimation, and evaluation. The Box-Jenkins process is a semi-formal approach that relies on the subjective evaluation of plots of auto correlograms and partial auto correlograms of the series for model identification.

Some authors have employed objective measurements of model adequacy, specifically the penalty function criteria, instead of the standard Box-Jenkins procedure. Gómez and Maravall(1998) provide a contemporary example of the usage of objective penalty function criteria. However, these 'objective' measures are not without flaws.

Outside of the Box-Jenkins and penalty function criterion methods, there are several alternative identification methods proposed in the literature like Corner method (Beguin, Gourieroux, & Monfort, 1980), the R and S Array method (Gray, Kelley, & Mc Intire, 1978), and canonical correlation methods (Tsay & Tiao, 1985). Since data in this study is seasonal in nature so these methods are not used.

Box-Jenkins Methodology

In the Box-Jenkins method, plots of the sample auto-correlogram, partial auto-correlogram and inverse auto-correlogram and inferring from patterns are examined. On this basis the correct form of ARMA model is selected. The Box-Jenkins methodology not only helps in the identification of the model but also for diagnostic checking.

In the case of pure AR or a pure MA process Box-Jenkins method easily identifies the model but in mixed ARMA it is difficult and subjective to identify the order of these using ACFs and PACFs. If there is random noise in the data then the identification of the model becomes more difficult.

Penalty Criterion Funcion

Due to the Subjectivity of the Box-Jenkins model**,** some other models likePenalty function statistics like the Akaike Information Criterion [AIC] or Final Prediction Error [FPE] Criterion (Akaike, 1973), Schwarz Criterion [SC] or Bayesian Information Criterion [BIC] (Schwarz, 1978), and Hannan Quinn Criterion [HQC] (Hannan, 1980)are used. For model parsimony, minimization of the sum of residual sum of squares plus a penalty term is used. This penalty term is calculated using the number of estimated parameter coefficients.

In the presence of the ARMA model, BIC is more consistent and it also imposes more penalty for any increase in parameters so it is being used here to find the model.Gómez and Maravall (1998, p. 19) also favour the BIC over the AIC.

Consumer Price Index Inflation

For the Consumer Price Index inflation, this study analyzed the models based on the BIC and found that model (0,1,1)(0,0,2)[12] is the best model among other combinations of models because of its low BIC value. Table (4) provides different SARIMA models with their BIC values.

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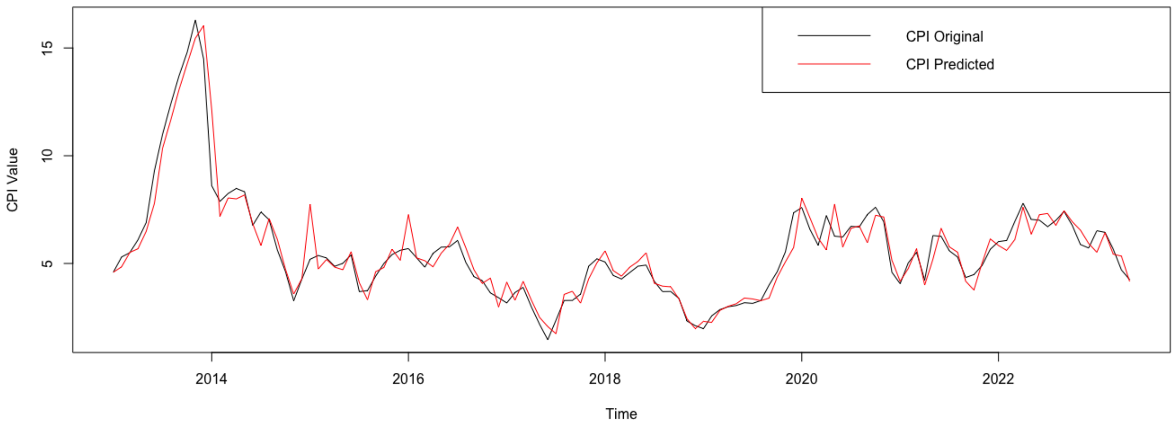
Table 4: SARIMA Model Selection for CPI

Models	BIC Statistics
ARIMA(2,1,2)(1,0,1)[12]	303.22
ARIMA(0,1,0)	345.99
ARIMA(1,1,0)(1,0,0)[12]	301.89
ARIMA(0,1,1)(0,0,1)[12]	290.39
ARIMA(0,1,1)	332.37
ARIMA(0,1,1)(1,0,1)[12]	289.24
ARIMA(0,1,1)(1,0,0)[12]	298.19
ARIMA(0,1,1)(2,0,1)[12]	293.35
ARIMA(0,1,1)(1,0,2)[12]	292.96
ARIMA(0,1,1)(0,0,2)[12]	**288.15**
ARIMA(0,1,0)(0,0,2)[12]	296.93
ARIMA(1,1,1)(0,0,2)[12]	292.97
ARIMA(0,1,2)(0,0,2)[12]	292.97
ARIMA(1,1,0)(0,0,2)[12]	289.88

Source: Authors' Calculation on RStudio

From Table (4), it can be seen that in the combination of ARIMA models, the SARIMA model (0,1,1)(0,0,2)[12] has the lowest BIC value.

Figure 3 The Trend of SARMA (0,1,1)(0,0,2)[12] Model of CPI-C inflation



Wholesale Price Index Inflation

For the Wholesale Price Index inflation, this studyanalysed models based on the BIC and found that model (1,1,0)(2,0,1)[12] is the best model among other combinations of models because of its low BIC value. Table (5) provides different SARIMA models with their BIC values.

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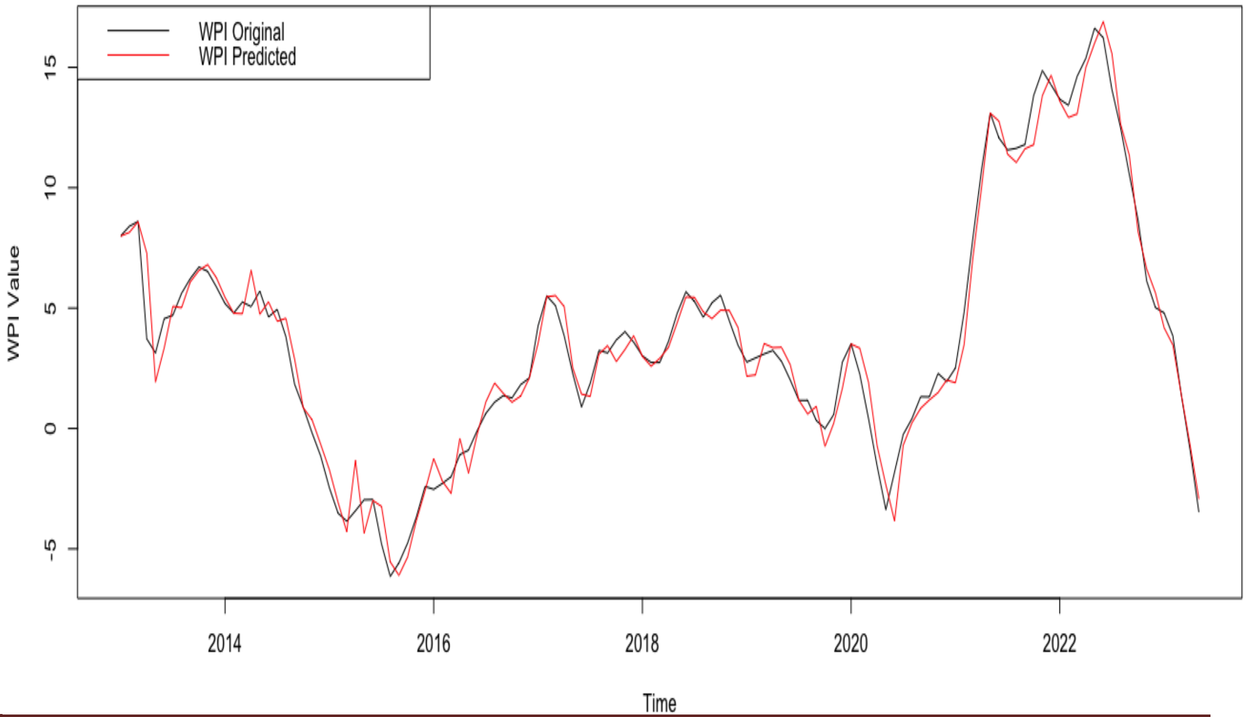
Table 5: SARIMA Model Selection for WPI	
Models	BIC Statistics
ARIMA(0,1,0)	406.55
ARIMA(1,1,0)(1,0,0)[12]	363.33
ARIMA(1,1,0)	368.32
ARIMA(1,1,0)(2,0,0)[12]	343.17
ARIMA(1,1,0)(2,0,1)[12]	**336.91**
ARIMA(1,1,0)(2,0,2)[12]	341.73
ARIMA(0,1,0)(2,0,1)[12]	361.88
ARIMA(2,1,0)(2,0,1)[12]	341.23
ARIMA(1,1,1)(2,0,1)[12]	341.27
ARIMA(0,1,1)(2,0,1)[12]	339.00
ARIMA(2,1,1)(2,0,1)[12]	345.52

Source: Authors' Calculation on RStudio

From Table (5), it can be seen that in the combination of ARIMA models, the SARMA model (1,1,0)(2,0,1)[12] has the lowest BIC value.

Figure 4 Trend of SARIMA (1,1,0)(2,0,1)[12] Model of WPI inflation



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3) ESTIMATION OF MODEL

Thereafter, the procedure carries forward to estimate the above models of CPI and WPI. The estimate of the SARIMA model of CPI-C inflation is given below:

Table 6: CPI Model Estimates	
Variables	Coefficient
MA(1)	0.3458 (0.0865)
SMA(1)	-0.9856 (0.1155)
SMA(2)	0.3630 (0.1292)

Authors' Calculation on RStudio

WPI inflation (1,1,0) (2,0,1) [12] model estimate is as follows:

Table 7: WPI Model Estimates	
Variables	Coefficient
AR(1)	0.4658 (0.0797)
SAR(1)	-0.0782 (0.1394)
SAR(2)	-0.4099 (0.1175)
SMA(1)	-0.7327 (0.1570)

Source: Authors' Calculation on RStudio

The estimated model provided in Tables (6) and (7) will now be checked through some econometric diagnostic tools. These tools help to understand that if the models estimated are robust or not.

4) DIAGNOSTIC CHECKING

The estimated model will be diagnosed to check whether it is feasible for forecasting or not and for that the residual testing will be operated on the models. For this, at first the Jarque and Bera (1980) test, and the Ljung and Box (1978) test areapplied. The Jarque and Bera (1980) test is a test that measures the goodness of fit, i.e., it tests whether the data match Skewness and Kurtosis as the normal distribution. The null hypothesis of Jarque and Bera's(1980) test is that the skewness is zero and the excess kurtosis is zero. The Ljung and Box (1978) test states whether any of the groups of autocorrelations of a time series are different from zero. The null hypothesis of the Ljung and Box (1978) test is that the data is independently distributed. In other words, it exhibits the null hypothesis of no serial correlation.

Table 8: Diagnostic Test of SARIMA models		
	Jarque-Bera Test	Ljung-Box Test
CPI-C	249.54 (0.000***)	31.029 (0.1529)
WPI	50.274 (0.000***)	25.211 (0.1935)

Source: Authors' Calculation on RStudio

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The result in Table (8) of Jarque and Bera's(1980) test for both CPI and WPI shows that there is enough evidence in the data to reject the null hypothesis of normal distribution. In other words, from the result of Jarque and Bera's (1980) test, it is clear that the residuals' Skewness and Kurtosis do not match normal distribution, i.e., the residuals do not come from normally distributed data. On the other hand, The Ljung and Box (1978) test results show that there is not enough evidence to reject the null hypothesis of no serial correlation. In other words, the Ljung and Box (1978) test states that the residuals are independently distributed.

Afterwards, figures (5) and (6) show the Residual Diagnosis of the CPI-C and WPI SARIMA models respectively.

Figure 5 Residual Diagnosis of the CPI-C SARIMA Model

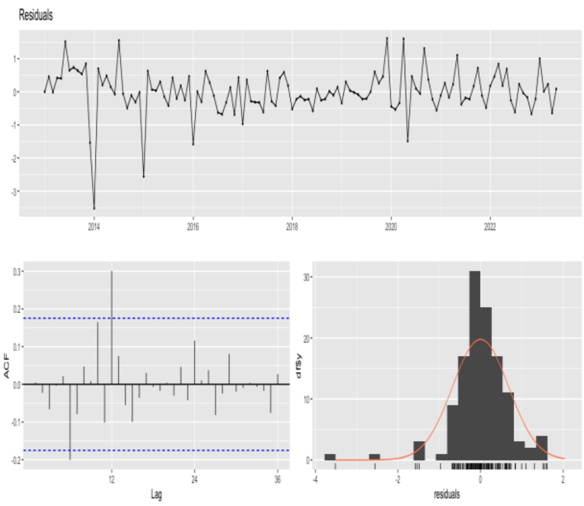
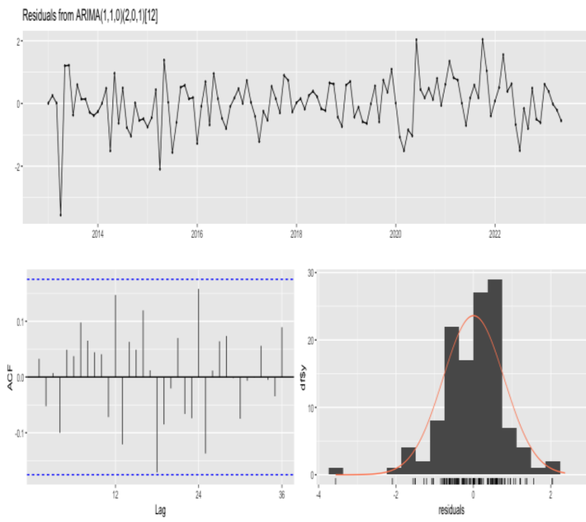


Figure 6 Residual Diagnosis of the WPI SARIMA Model



In Table (9), the robust check of the SARIMA model for CPI and WPI is provided.

Table 9: Robustness Checking of SARIMA Models

Model	CPI (0,1,1)(0,0,2)[12]	WPI (1,1,0)(2,0,1)[12]
Mean Square Error	0.46	0.62
RMSE	0.68	0.78
Mean Absolute Error	0.46	0.59
Theil's U	0.11	0.12

Source: Authors' Calculation on RStudio

Now the analysis comes towards the last stage of ARIMA analysis which is the forecasting of the ARIMA model. In the next section the forecasting of both the models are provided.

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5) FORECASTING

Forecasting of data is an important part of any time series analysis becausemuch economic researchconverges towards predicting the future. Many inflation analysts use univariate analysis tools like ARIMA modelling, exponential smoothening, Business Cycle Filters, or the new advanced tools of neural networks. These tools help in the prediction of the future for any time series data. This paper relies on the mean modelling tool, i.e., ARIMA modelling, for the prediction of future prices in the Indian Economy.

Figure (7) provides the forecast graph of the CPI model and shows that the CPI trend fluctuates with a constant mean in the future. Figure (8), which shows the forecast of the WPI model, suggests that the future trend of WPI has an upward slope with some fluctuations. This means that CPI will remain on a constant slope in future while WPI will rise in future despite the fluctuations.

Figure 7 Forecast of CPI from SARIMA (0,1,1)(0,0,2)[12]

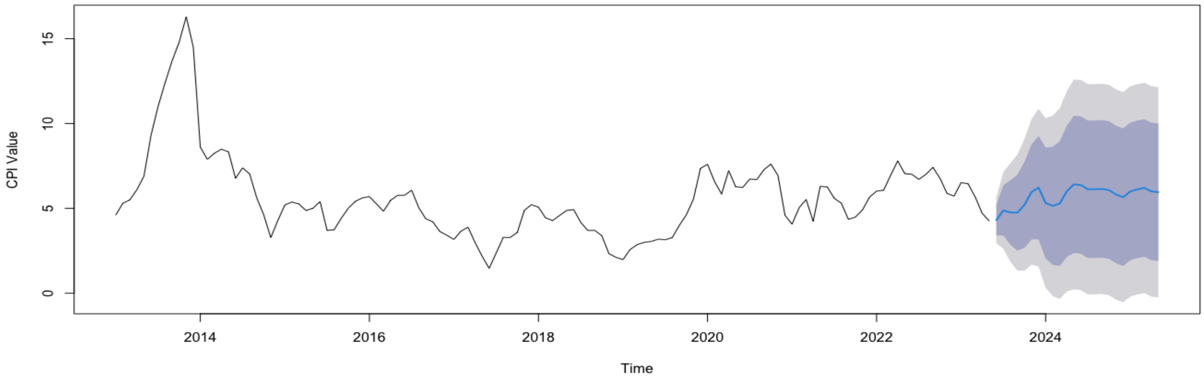

Figure 8 Forecast of WPI from SARIMA (1,1,0)(2,0,1)[12]

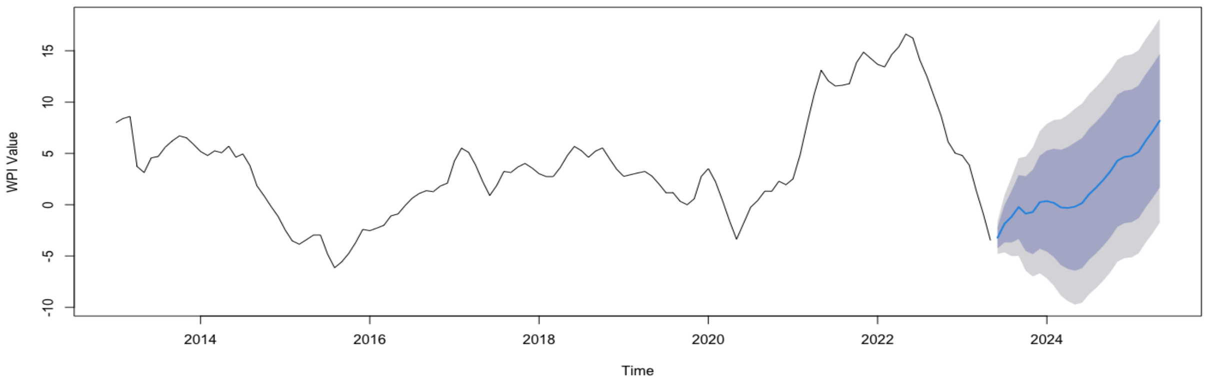

Table (10) shows the mean value or trend of the future value of both models. The value of WPI starts with a negative and consecutively increases with the passing period while the CPI value remains between the 4% to 7% range this shows the stability of the CPI value. The value of WPI remains highly volatile which can be seen in Figure (8).

Table 10: SARIMA Forecasting of CPI and WPI Inflation

Period	CPI (0,1,1)(0,0,2)[12]	WPI (1,1,0)(2,0,1)[12]
Jun 2023	4.30	-3.23
Jul 2023	4.87	-1.85
Aug 2023	4.75	-1.17
Sep 2023	4.75	-0.23
Oct 2023	5.21	-0.87
Nov 2023	5.97	-0.71
Dec 2023	6.22	0.24
Jan 2024	5.31	0.35
Feb 2024	5.15	0.18
Mar 2024	5.28	-0.27
Apr 2024	6.00	-0.32
May 2024	6.41	-0.19
Jun 2024	6.37	0.16
Jul 2024	6.12	1.03
Aug 2024	6.13	1.68
Sep 2024	6.14	2.42
Oct 2024	6.08	3.25
Nov 2024	5.81	4.28
Dec 2024	5.65	4.66
Jan 2025	5.99	4.75
Feb 2025	6.12	5.15
Mar 2025	6.20	6.21
Apr 2025	6.00	7.14
May 2025	5.95	8.18

Source: Authors' Computation

CONCLUSION

In this section, it can be concluded that SARIMA modelling is a good measure for forecasting India's inflation rates. The robust test also proved that the SARIMA model selection through BIC is the best model. This study provides evidence of the presence of a structural break in WPI while there is no break point in Consumer Price Index inflation, which can be due to the highly volatile nature of the Wholesale Price Index. The data show that WPI has three breaks in the period 2014, 2016 and 2021. The model formed for CPI is (0,1,1)(0,0,2)[12] and for WPI is (1,1,0)(2,0,1)[12]. The SARIMA forecasting has shown CPI inflation has a constant or stable trend, which means it faces a more stable growth while WPI inflation has an upward-sloping trend, which means it represents high growth. In India, the inflation-targeting concept applies only to CPI which provides a scale for fluctuation in CPI because of which the forecast of CPI has a constant trend. In the context of WPI, it can be said that because it doesn't have any interference it can fluctuate freely and because of this WPI inflation has gone negative and its forecast is showing an upward trend making it positive in future.

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