Modeling Inflation in India : A Univariate Approach

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Abstract

To attain a high level of economic growth with a moderate level of inflation is one of the prime objectives of a developing country. However, a high rate of inflation has become a matter of great concern for many developing countries since the last decade. In India, a high inflation rate has always been an issue of serious concern for the government, policy makers, and academic researchers. In this context, the paper aimed to reach an appropriate diagnosis to understand the nature, structure, and factors responsible for the rise of inflation. The paper focused on the analysis and examination of the monthly inflation spiral of the Indian economy. We used the "Box – Jenkins Methodology" for empirical investigation and the modeling of inflation in India for the monthly WPI data from January 2000 – March 2020. The results of the research indicated that in India, monthly WPI series is non-normal and integrated of order one. Furthermore, research conclusions indicated that the data is integrated of order one, and the estimated ARIMA (1,12–1–0) model fit well with the data and provided essential information for forecasting inflation patterns in India. The model developed as a result of the study can be used as a tool for framing macroeconomic policies as well as can be used in the business decision-making process.

Keywords : inflation, WPI, Box–Jenkins

JEL Classification : C530, E310, E370

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Attaining high level of economic growth along with a moderate level of inflation is always desired by a developing country. However, during the last decade, the major concern for these countries was the high rate of inflation. Inflation has always been a great concern for the government, policy makers, and academic researchers in India. It is also a fact that the impact of inflation on the poor and vulnerable segment of the society is harder and more direct. Furthermore, the issue of inflation becomes a matter of greater concern when the economy does not possess effective inflation hedges. Thus, it will be appropriate if we consider inflation as one of the prominent enemies of the poor, and consequently, maintaining low inflation is seen as a necessary part of an effective anti-poverty strategy.[1]

Following the above, it is clear that the central banks should have a method of forecasting inflation accurately. This is because the formulation and implementation of monetary policy weighs heavily on how inflation pans out into the future.[2] For a developing economy like India, a proper diagnosis and understanding of inflation are all the

[1] See Callen & Chang (1999).

[2] This has been well articulated by Liew (2012).

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more important and relevant to develop appropriate poverty eradication policies. Inflation also causes relative price variability in the economy as the prices of all the commodities do not adjust equally to the changes in the rate of inflation. As a result, there may be a loss of efficiency and it becomes hindrance for a sustainable economic growth and development. Further, it is pertinent to note that the uncertainty regarding future prices discourages investment in the economy. Thus, a proper inflation forecast is useful not only for central banks, but also for many economic decisions, whether made by policy makers, firms, investors, or consumers.

In the context discussed so far, the prime objective of the present study is to analyze and examine the monthly inflation spiral in the Indian economy and develop a univariate time series model using monthly WPI data from January 2000 – March 2020. It is expected that this will be useful for developing appropriate macroeconomic policies and also for making business decisions. Apart from developing the model, the study also aims to carry out appropriate model diagnostics to validate the estimated model. Further, the in-sample forecast has been carried out using the estimated model along with the forecast diagnostics.

Review of Literature

Over the years, various models have been developed to study the nature, causes, and effects of inflation for both developed as well as developing economies. These studies have been conducted to understand the nature and structure of inflation for inflation forecasting based on different approaches. In a pioneering study, Meyler, Kenny, and Quinn (1998) used the ARIMA technique for forecasting inflation for the Irish economy and compared this model with the Penalty function statistics.[3] They showed that the ARIMA approach provided a better forecast than the other models.

Lack (2006) carried out a study for forecasting Swiss inflation using a multivariate analysis approach. He applied VAR models for empirical analysis. He observed that the VAR models provided essential information for the future movement of inflation. The study showed that bank loans and monetary aggregate M3 were the most critical variables for inflation forecasting. He also concluded that the central banks should, therefore, not be lulled into a false sense of security by low inflation expectations, but be open and self-critical when analyzing inflationary risks.

Buelens (2012) analyzed how euro area inflation forecasts were affected by the financial and economic crisis. He evaluated the accuracy of three inflation forecasting models (rules of thumb and benchmark models, autoregressive moving average models, autoregressive distributed lag models) under a direct and an indirect approach, respectively. The paper found that the direct forecasting models selected, which are based on a penalty function, generally dominate simple benchmark models. The analysis further suggested that when an appropriate specification for the component-specific models is found, indirect forecasts outperform the corresponding direct forecasts.

Doguwa and Alade (2013) applied SARIMA and SARIMAX approach for the inflation forecasting for Nigeria and found that the SARIMA inflation forecast consistently outperformed the SARIMAX model, therefore, the SARIMA model should be used for forecasting core inflation. Similarly, Hanif and Malik (2015) compared various methods for inflation forecasts like the Random walk model, ARIMA model, VAR, and ARDL models for the Pakistan economy. They showed that the ARDL approach for inflation forecasting performed better over the other techniques of inflation forecasting.

Few studies of forecasting of inflation have been undertaken for the Indian economy also. In one of the earliest studies, Callen and Chang (1999) carried out an extensive exercise to model inflation and to forecast inflation for the Indian economy for the period from 1983 – 1999. They used a structural approach to model inflation and

[3] Penalty Function Statistics include: Akaike information criterion (AIC), Final prediction error (FPE), Schwarz information criterion (SIC), Bayesian information criterion (BIC), and Hannan —Quinn criterion (HQC).

found that the monetary aggregate M1 and M2 appeared to contain better information for the prediction of future headline inflation. However, for the prices in the manufacturing sector, the import prices, exchange rate, stock prices, and prices of primary products also provided useful information about future price development in India. Further, Kundan (2009) examined the role of money in inflation modeling and forecasting for India. He used the P-star approach for inflation modeling and observed that the real money gap was a significant predictor of future inflation for the full sample period. Liew (2012), on the other hand, carried out an exercise to forecast inflation for Asian economies, including India. He used univariate, autoregressive, and bivariate Philips curve models to forecast the inflation. He concluded that the autoregressive model did improve on the single equation model as the forecast horizon increased.

Mahasuar's (2012) study examined the relationship between inflation and growth and also the relationship between inflation and business cycles in India. Further, the author also analyzed the impact of government policies on inflation. From his study, the author concluded that growth was a function of numerous factors and, therefore, caution needed to be exercised while attributing inflation as a determinant of growth. Accordingly, the study showed that government intervention for the growth of an economy was required.

The study by Saxena and Bhadauriya (2013) attempted to estimate a more specific relationship between inflation in India during April 2001 – March 2011 and its determinants using Johansen co-integration and vector error correction model (VECM). The Johansen co-integration test, applied on selected data, indicated four long-run equilibrium relationships for inflation with its determinants. The results of VECM indicated a positive relationship between GDP and the CPI, and a high degree of interdependence between money supply, crude oil prices, and inflation in India.

It is evident from the literature review that most of the studies either followed a monetarist approach or a structuralist approach and that too mostly by using annual data or quarterly series information about prices. Further, some studies examined the relationship between growth and inflation as well as its determinants. However, for the study of the short-term behavior of the general price level, it is essential to analyze monthly inflation.[4] It is in this context that the present study attempts to develop a univariate model for monthly WPI data by considering the principle of parsimony.

Methodology

For inflation modeling and forecasting, various structural and time series econometric techniques such as univariate time series methods, VAR models, ARDL models have been developed and used from time to time in the macroeconomic literature. Of this, the Box – Jenkins (autoregressive integrated moving average - ARIMA) methodology is one of the conventional methods for the univariate time series analysis.[5] This study uses the same method for inflation modeling and forecasting for India.

The Box – Jenkins (ARIMA) Methodology

George E. P. Box and Gwilym M. Jenkins developed the method in 1972. Since then, it has become one of the popular techniques for univariate time series analysis. The technique involves the ARIMA (autoregressive integrated moving average) approach for the time series analysis. ARIMA methods for forecasting time series are mostly agnostic as it does not assume knowledge of any underlying economic model or structural

[4] It is essential to undertake the short term analysis of the inflation as it can be helpful for making business decisions, developing business policies to deal with short term fluctuation in the general prices, developing short term economic policies, and can also provide a framework for long term monetary policy.

[5] A fundamental idea behind the analysis and estimation of Box – Jenkins methodology is the principle of parsimony. Box – Jenkins argued that the parsimonious models provide better results than over-parameterized models (Enders, 2014).

relationships. It assumes that past values of the series plus previous error terms contain information for forecasting (Meyler et al., 1998).

For a stationary time series,[6] the general form of ARMA (*p,q*) (autoregressive moving average) is presented as follows :

$$Y_t = \theta + \beta_1 Y_{t-1} + \ldots + \beta_p Y_{t-p} + e_t + \alpha_1 e_{t-1} + \ldots + \alpha_q e_{t-q} \qquad (1)$$

In the present study, Y stands for wholesale price index (WPI) based inflation, p and q represent the order of autoregressive process and moving average process, respectively, and e_t is the white noise error term in the period t.

If the series is found to be non-stationary, ARIMA (*p-d-q*) model can be applied, in which *I* represents the order of integration that is applied to make the series stationary.

The ARIMA (1-1-1) can be presented as :

$$\Delta Y_t = \theta + \beta_1 \Delta Y_{t-1} + e_t + \alpha_1 e_{t-1} \qquad (2)$$

where, $\Delta Y_t = Y_t - Y_{t-1}$

Stationarity Test

According to Gujarati, Porter, and Gunasekar (2017), when time-series data are used for the analysis, it is essential in the econometric process to check for the order of integration of the time series. If a time series is stationary, its mean, variance, and autocovariance (at various lags) remain the same no matter at what point the measurement is done. In other words, the probability distribution of a stationary time series does not change over a while. If a series does not follow the said characteristics, the time series is understood to be a non-stationary process. Thus, for ARIMA analysis, the order of integration of a series is an essential aspect. Therefore, the first step is to check for the stationarity properties in the time series of WPI inflation. For which, augmented Dickey – Fuller (ADF) and Phillips – Perron (PP) tests are applied.

(1) Augmented Dickey – Fuller Test (ADF) : The ADF test for the unit root tests the null hypothesis H0 : $\mu = 0$ against the one-sided alternative H1: $\mu < 0$ in the regression, which is described as follows :

$$\Delta Y_t = \beta_0 + \mu Y_{t-1} + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \ldots + \delta_p Y_{t-p} + u_t \qquad (3)$$

Under the null hypothesis, the series Y_t has a unit root, which means that the series is not stationary, and under the alternative hypothesis, the series is said to be stationary. If the series is stationary around a deterministic linear trend, then the trend t must be added, and the following equation is estimated :

$$\Delta y_t = \beta_0 + \alpha t + \mu Y_{t-1} + \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \ldots + \delta_p Y_{t-p} + u_t \qquad (4)$$

The ADF tests whether $\mu = 0$, meaning that the time series under consideration is non-stationary. The lag length p can be selected based on Akaike's information criteria (AIC).[7]

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[6] A time series is said to be stationary if its means, variance, and auto covariance (at various lags) remains the same no matter at which point they are measured (Enders, 2014).

[7] The lag that is selected is that value of Akaike's information criteria (AIC) which is minimum (Gujarati et al., 2017).

(2) Phillips – Perron (PP) Test : The PP test has an advantage over the ADF test as it gives robust estimates when the series has serial correlation and time-dependent heteroscedasticity, and there is a structural break (Gujarati et al., 2017). The PP test can be carried out by estimating the following equation :

$$\Delta Y_t = \alpha + \pi Y_{t-1} + \theta_{t-t/2} + \sum_{i=1}^{m} \theta_i \Delta Y_{t-1} + e_t \qquad (5)$$

The null hypothesis that the series is a non-stationary time series is rejected if π is less than zero and is statistically significant.

(3) ARIMA Forecasting : The most important use of ARMA analysis is to forecast the variable under analysis. First-order forecast for the AR(1) process can be obtained as :

$$Y_{t+1} = \theta + \beta_1 \Delta Y_t + e_{t+1} \qquad (6)$$

which can be written as $E_t Y_{t+1} = \theta + \beta_1 \Delta y_t$.
where, $E_t Y_{t+1}$ is the conditional expectation of Y_{t+1}, given the information at t.

In the same way, the one-step-ahead forecast of an ARMA (p-q) can be represented in equation seven, where h is the forecast origin, and F_h is the available information.

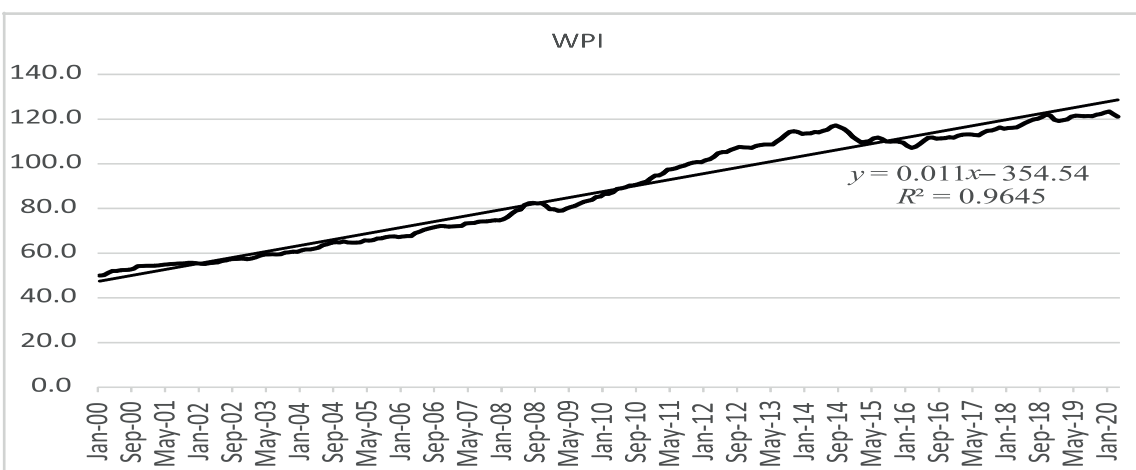
$$\hat{y}_h(1) = E(y_{h+1}|F_h) = \varnothing_O + \sum_{i=1}^{p} \varnothing_i \, y_{h+1-i} - \sum_{i=1}^{d} \partial_i e_{h+1-i} \qquad (7)$$

The empirical analysis has been carried out by using the Month-on-Month time series data of wholesale price index (WPI) for the period between January 2000 and March 2020. In India, the WPI measure of inflation has been considered as a better indicator of measuring inflation as compared to other measures of inflation, that is, consumer price index (CPI) and gross domestic product (GDP) deflator (Pattnaik & Samantarasya, 2006 ; Reddy, 1999). The data for the WPI for the Indian economy were sourced from the Office of Economic Advisor and *Handbook of Statistics*, Reserve Bank of India.

Analysis and Results

Figure 1 shows the movements of the monthly behavior of the wholesale price index (all commodities) along with

Figure 1. ***Wholesale Price Index (WPI) from Jan. 2000 to Mar. 2020***

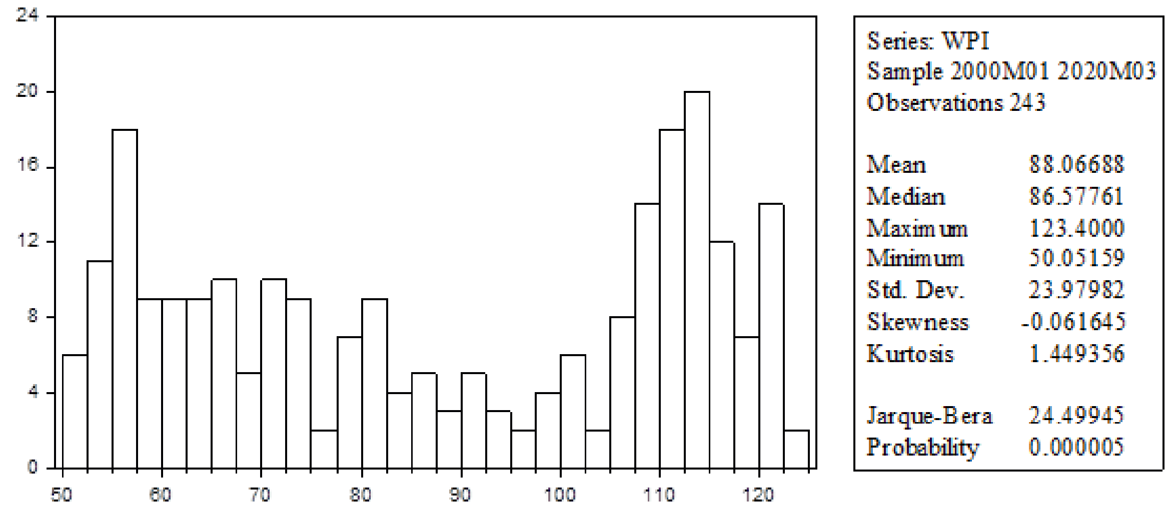


Source : *Handbook of Statistics,* Reserve Bank of India and Authors' computation.

the linear trend line. As expected of prices, that was an upward movement of the series over the period. However, there were short-run ups and downs in WPI movements. The linear trend line also indicates a positive trend. It is pertinent to note that the WPI continuously decreased from September 2014 – September 2019.

Table 1 represents the descriptive statistics along with the frequency distribution of the WPI series. As indicated by the skewness, kurtosis, and Jarque – Bera statistics, the WPI series is not normally distributed. The mean of the series is 88.06.

Table 1. ***Frequency Distribution and Descriptive Statistics of WPI***



As discussed, it is essential to check for the stationarity property of the process under analysis before the application of the Box – Jenkins (ARIMA) methodology. Mainly two tests, the Augmented Dickey – Fuller (ADF) test and Phillips – Perron (PP) test, have been applied for the stationarity test. The results of stationarity tests have been shown in Table 2. Both the tests indicate that the series under study is non-stationary at level form as the *t*-statistics (with the trend and with trend & intercept) is significant at more than 50% level of significance. Thus, the null hypothesis that the series is non-stationary is accepted. Further, to understand and check for the stationarity, the tests are conducted by taking the first difference. Both the tests (ADF and PP) indicate that the *t*-statistics are significant at 1%, indicating the rejection of the null hypothesis that the series is non-stationary and the alternative hypothesis that the series is stationary is accepted.

Table 2. ***Stationarity Test***

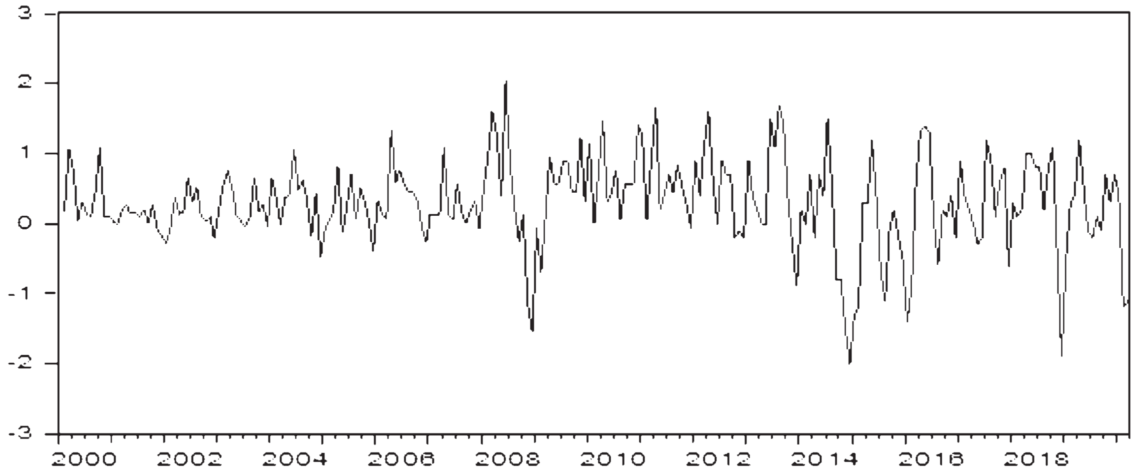
Variable	Test	Level (*t*-statistic)		1st Difference (*t*-statistic)	
		Intercept	Trend and Intercept	Intercept	Trend and Intercept
WPI	**ADF**	–0.924****	–1.363****	–8.967*	–8.948*
	PP	–0.826****	–1.124****	–8.537*	–8.545*

Note. ADF = Augmented Dickey – Fuller Test, PP = Phillips – Perron (PP) Test.

* represents the level of significance at 1% and **** represents the level of significance at more than 50%.

Based on the first difference of WPI (DWPI), the behavior of the DWPI is shown in Figure 2. It indicates that the series is stationary in its definition. Thus, the DWPI series can be used for the Box – Jenkins (ARIMA) analysis.

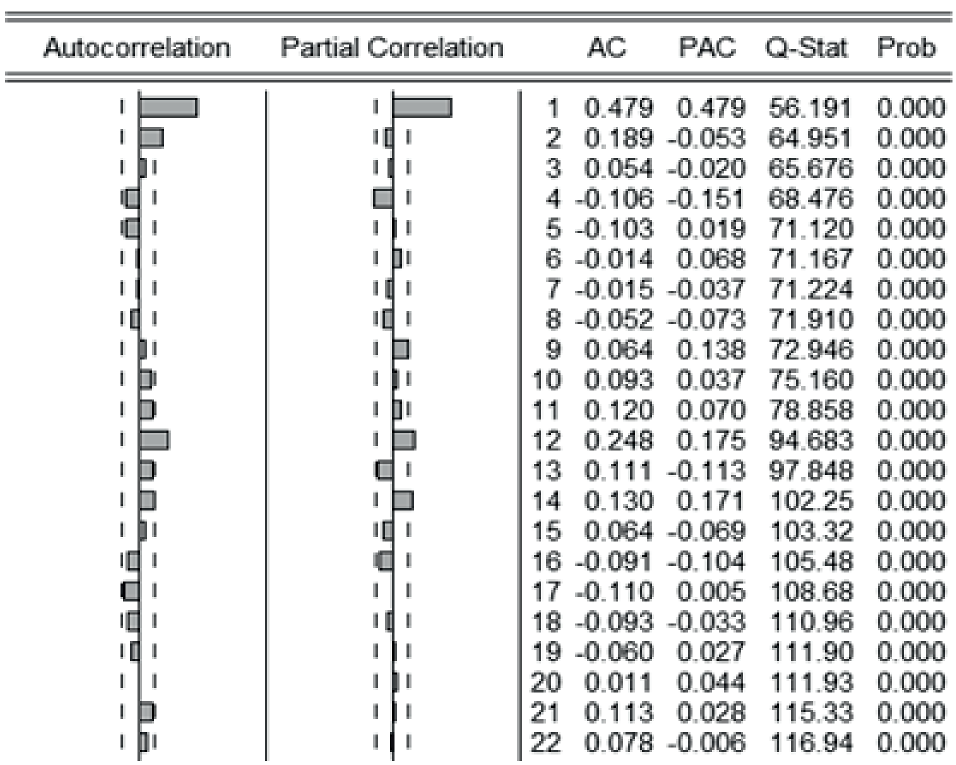
Figure 2. ***First Difference of WPI (DWPI)***



Based on the order of integration of the series, so decided, the next step is to decide the order of autoregressive (AR) and moving average (MA) terms. For this, the correlogram is useful, which is presented in Figure 3. As per the representation of the correlogram, the various models of AR and MA orders are estimated, but the model AR (1,12) fits well as per the Akaike and Schwarz information criterions.

The results of the ARIMA analysis are shown in Table 3. The coefficients of AR(1) and AR(12) are positive

Figure 3. ***Correlogram of DWPI***



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.479	0.479	56.191	0.000
		2	0.189	-0.053	64.951	0.000
		3	0.054	-0.020	65.676	0.000
		4	-0.106	-0.151	68.476	0.000
		5	-0.103	0.019	71.120	0.000
		6	-0.014	0.068	71.167	0.000
		7	-0.015	-0.037	71.224	0.000
		8	-0.052	-0.073	71.910	0.000
		9	0.064	0.138	72.946	0.000
		10	0.093	0.037	75.160	0.000
		11	0.120	0.070	78.858	0.000
		12	0.248	0.175	94.683	0.000
		13	0.111	-0.113	97.848	0.000
		14	0.130	0.171	102.25	0.000
		15	0.064	-0.069	103.32	0.000
		16	-0.091	-0.104	105.48	0.000
		17	-0.110	0.005	108.68	0.000
		18	-0.093	-0.033	110.96	0.000
		19	-0.060	0.027	111.90	0.000
		20	0.011	0.044	111.93	0.000
		21	0.113	0.028	115.33	0.000
		22	0.078	-0.006	116.94	0.000

and highly significant, as indicated by the t-statistics. It means that the immediate past and the 12th past period have positively and significantly affected the monthly DWPI. The R-squared is 29%, and the DWD stat is 1.9. It indicates that there is no autocorrelation in the estimated model. The actual DWPI, fitted (estimated) DWPI, and the residual are plotted in Figure 4, which also indicates that the estimated model captures the movement of DWPI very well.

Table 3. ***Estimation of ARIMA***

Dependent Variable : *D(WPI)*

Method : ARMA Generalized Least Squares (Gauss—Newton)

Sample : 2000M02 2020M03

Included observations: 242

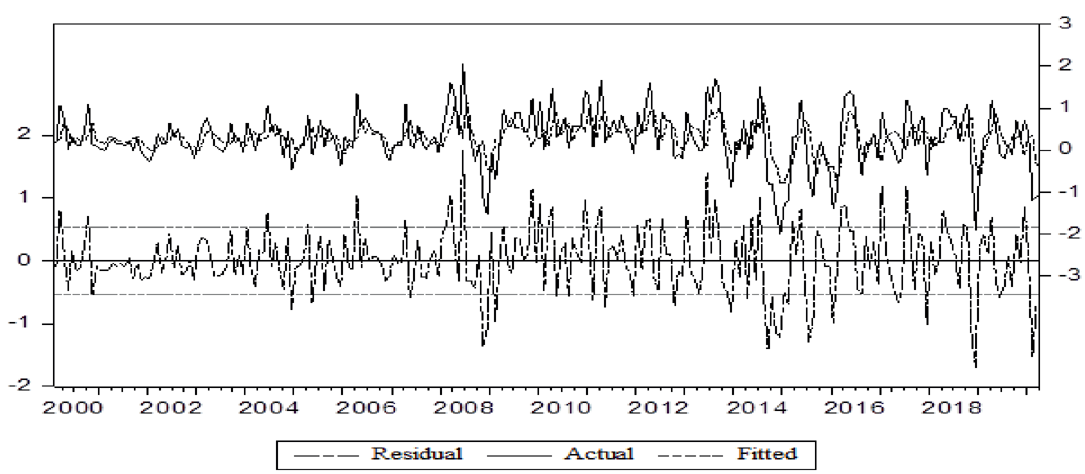
Convergence achieved after 5 iterations

Coefficient covariance computed using the outer product of gradients

d.f. adjustment for standard errors & covariance

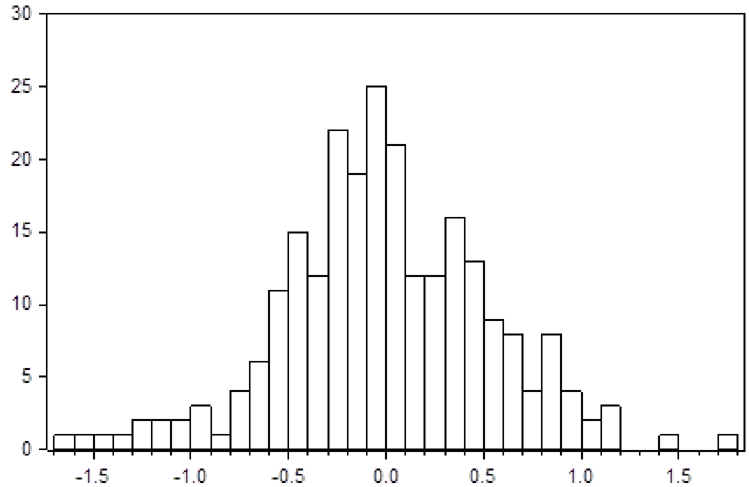
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.282066	0.100095	2.817990	0.0052
AR(1)	0.461313	0.056317	8.191305	0.0000
AR(12)	0.203322	0.057589	3.530551	0.0005
R-squared	0.271404	Mean dependent var		0.293588
Adjusted R-squared	0.265307	S.D. dependent var		0.630042
S.E. of regression	0.540036	Akaike info criterion		1.621728
Sum squared resid	69.70175	Schwarz criterion		1.664980
Log-likelihood	–193.2291	Hannan—Quinn criterion		1.639151
F-statistic	44.51398	Durbin—Watson stat (DWD)		1.882345
Prob (F-statistic)	0.000000			

Figure 4. ***Actual, Fitted, and Residual***



Further, it is also essential to check the stability of the estimated model to use it for more analysis and forecasting. One of the fundamental properties of the ARIMA analysis is that the residual of the estimated model is normally distributed. The descriptive statistics with the frequency distribution of the residual of the estimated model have been shown in Table 4. As per the Jarque – Bera statistics, the residuals are normally distributed.

Table 4. ***Descriptive Statistics of Residual***

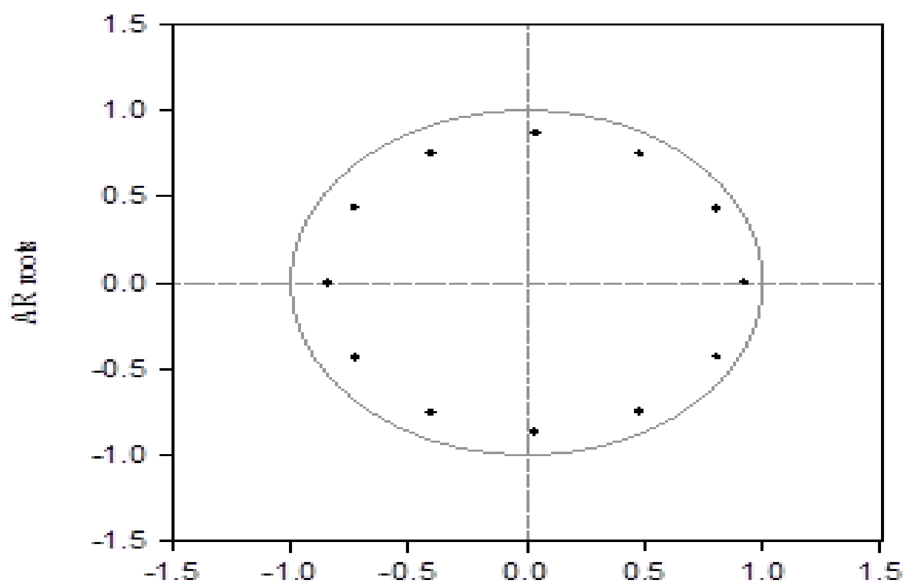


Series: Residuals
Sample 2000M02 2020M03
Observations 242

Mean	-0.000647
Median	-0.037613
Maximum	1.764313
Minimum	-1.688077
Std. Dev.	0.537790
Skewness	-0.073696
Kurtosis	3.642049
Jarque-Bera	4.375678
Probability	0.112159

The Roots diagnostics to check the stability of the ARIMA structure (Figure 5) also indicates that the estimated model is stable as all the root values lie within a critical limit. The Roots diagnostics to check the stability of the ARIMA structure (Figure 5) also indicates that the estimated model is stable as all the root values lie within a critical limit.

Figure 5. ***Inverse Roots of ARIMA Polynomial(s)***



The estimated model and the model diagnostics indicate that the fitted model is stable and can be used for forecasting the monthly inflation for the Indian economy. With the help of the Equation-6, both static (one period ahead) and dynamic in-sample ARIMA forecast has been carried out for the period from April 2019 – March 20. The result is depicted in Table 5.

Table 5. ***In-Sample Forecast of WPI***

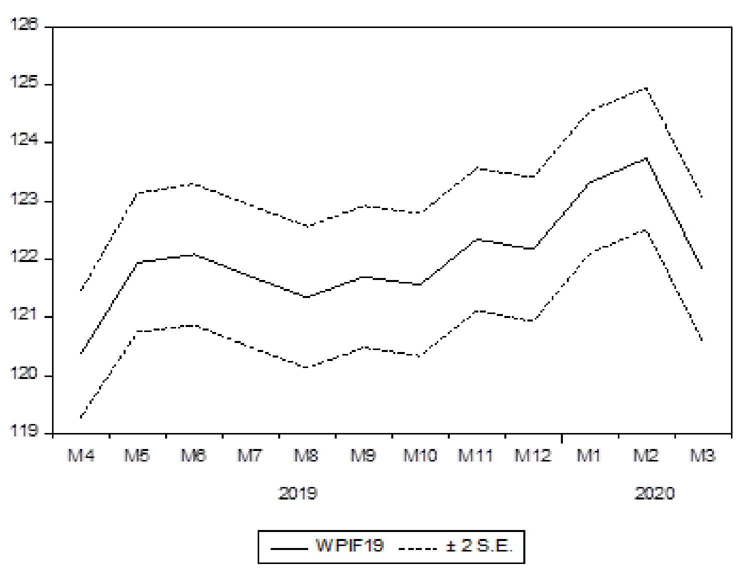
Month	Actual WPI	Forecasted WPI (Static)	Forecasted WPI (Dynamic)
Apr-19	120.10	120.37	120.38
May-19	121.60	121.94	120.90
Jun-19	121.50	122.08	121.40
Jul-19	121.30	121.71	121.89
Aug-19	121.40	121.34	122.25
Sep-19	121.30	121.70	122.67
Oct-19	122.00	121.56	123.18
Nov-19	122.30	122.34	123.43
Dec-19	123.00	122.17	123.26
Jan-20	123.40	123.32	123.17
Feb-20	122.20	123.74	123.28
Mar-20	121.1*	121.82	123.51

Source : *Handbook of Statistics,* RBI and Authors' computation.

Note. * Represents a provisional estimate.

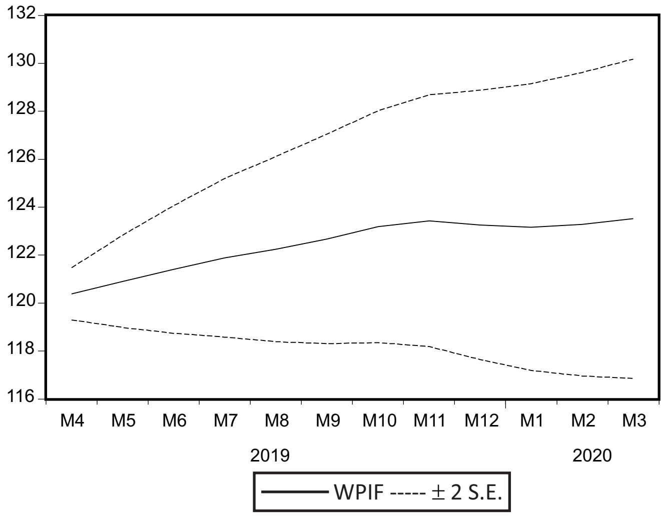
It is also essential to check for the stability of the forecast carried out based on the estimated ARIMA model. The forecast diagnostics have been presented in Table 6 and Table 7 for static and dynamic forecasts, respectively. The forecast statistics indicate that the value of Theil inequality coefficient (TIC) for the static forecast is 0.002, while for the dynamic forecast, the value is 0.004. The mean absolute percentage error (MAPE) for the static

Table 6. ***Static Forecast Diagnostics***



Forecast: WPIF19	
Actual: WPI	
Forecast sample: 2019M04 2020M03	
Included observations: 12	
Root Mean Squared Error	0.651392
Mean Absolute Error	0.513279
Mean Abs. Percent Error	0.421332
Theil Inequality Coefficient	0.002671
Bias Proportion	0.059946
Variance Proportion	0.033111
Covariance Proportion	0.906942
Theil U2 Coefficient	1.040901
Symmetric MAPE	0.420702

Table 7. ***Dynamic Forecast Diagnostics***



Forecast WPIF	
Actual : WPI	
Forecast Sample : 2019M04 2020M03	
Included Observations : 12	
Root Mean Squared Error	1.070395
Mean Absolute Error	0.884973
Mean Abs. Percent Error	0.727586
Theil Inequality Coefficient	0.004381
Bias Proportion	0.308010
Variance Proportion	0.083604
Covariance Proportion	0.608386
Theil U2 Coefficient	1.782215
Symmetric MAPE	0.724331

forecast is 0.42% and for the dynamic forecast, it is 0.73%. It is also important to note that the confidence interval of the dynamic forecast increases during the forecast period, indicating that the efficiency of the forecast reduces. Though the TIC and MAPE are low for both static and dynamic forecasts, the static (short-run) forecast seems to be better. This indicates that the ARIMA model fitted for the monthly WPI is suitable for short-run forecast and does not perform well for the long-run forecast.

The results so obtained are in line with the study results obtained by Liew (2012) to forecast inflation for Asian economies, including India, by using univariate time series analysis. However, the results are in contradiction with the findings of Hanif and Malik (2015), who had shown that the ARDL approach for forecasting inflation is a better technique as compared to other techniques.

Policy Implications

Inflation forecasting is of paramount importance for the conduct of monetary policy. Since monetary policy transmission is associated with significant lags, central banks aiming to achieve price stability need to be forward-looking in their decisions as well – which underscores the importance of inflation forecasting. Hence, the formation of expectations is central to the question of what drives (and helps predict) inflation but also to policymaking (Duncan & Garcia, 2018). The fitted model of the present study would help policy makers to understand the inflation dynamics in the context of the Indian economy. Moreover, thus, it will be useful to formulate appropriate economic policies for controlling inflation to achieve macro-economic targets.

Concluding Remarks

Inflation is one of the critical issues of macroeconomic analysis. Unlike the other macroeconomic variables, the effects of inflation are observed more quickly in the market by the society. Thus, inflation has always been a matter of discussion and investigation for researchers and policy makers. A good inflation forecast is useful not only for central banks, but also for many economic decisions, whether made by policy makers, firms, or investors. The present study has attempted to forecast inflation using the ARIMA model for the Indian economy.

Based on the results, it is clear that the Month-on-Month WPI in India is integrated of order one, which means that the series becomes stationary after the first difference. The fitted ARIMA model AR (1, 12) describes the WPI well. The forecasting carried out based on the estimated model is also suitable as per the forecast diagnostics. Thus, the fitted model can also be used for out of sample forecasting.

Limitations of the Study and Scope for Further Research

The study has been conducted for the period from January 2000 – March 2020 by considering monthly data of WPI only and did not include the Consumer Price Index (CPI) data. However, it is pertinent to note that inflation is also a structural and monetary phenomenon, and many other macroeconomic variables affect the behavior of inflation in an economy. The present study is limited by the fact that it is based on the univariate time series analysis, and other important variables that may affect the inflation in an economy have not been taken into account. The method of ARIMA forecasting is suitable for the short-run period and not for the long-run.[8]

The study can further be extended to understand the inflation dynamics by taking into account other macroeconomic variables, and multivariate time series analysis can be carried out by considering yearly and quarterly data (Hanif & Malik, 2015). The study has considered only one measurement of inflation – WPI. Other measurements of inflation, such as CPI, GDP deflator, and headline inflation, can be part of further research works.

Authors' Contribution

Dr. Dinkar Nayak conceived the idea and overall theme of the research study. He also extracted research papers of high repute and conducted their review to highlight the research gap. Mr. Ketan Kathodia performed the computations and the analytic calculations using EViews-10. Both of the authors discussed the results and contributed to the final manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter, or materials discussed in this manuscript.

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