The Dynamic Relationship Between Inflation and Industrial Production in India: Evidence from Time Series Analysis

ECON F342 : Applied Econometrics

Under the Supervision of

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ABSTRACT

This study examines the dynamic relationship between inflation, measured by the Consumer Price Index (CPI) and industrial production, captured through the Index of Industrial Production (IIP), in India over the period from January 2013 to December 2023.

Utilizing monthly data, we employ multivariate time series regression techniques to investigate how variations in industrial output are associated with changes in consumer price inflation. The data for this study was taken from the RBI DATASET.

The analysis begins by checking the stationary property of the time series data which has been extracted. We then estimate a multivariate regression model to capture the contemporaneous and lagged effects between the two variables. Diagnostic tests are conducted to assess model adequacy and residual behavior.

Our findings show the strong relationship between Inflation and IIP index in India's economic environment. The results have important implications for policymakers especially in designing inflation-targeting and growth-oriented monetary policies. It also gives an idea related to inflation related policies which can smoothen the impact of seasonal business cycles.

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INTRODUCTION

A major field of study in macroeconomics has been the interaction between real economic activity and price dynamics. In recent years, the Indian economy has experienced substantial shifts in both industrial output and inflation, raising important questions about how these variables influence each other. Motivated by the evolving macroeconomic environment and the increasing importance of data-driven policy formulation, this study focuses on analyzing the dynamic relationship between industrial production and inflation in India using time series methods. Specifically, we examine how the Consumer Price Index (CPI) and the Index of Industrial Production (IIP) have co-moved over the period from 2013 to 2023. By employing multivariate time series regression analysis on monthly data, we aim to provide fresh empirical insights into a relationship that has crucial implications for monetary and industrial policy in India.

The **Index of Industrial Production (IIP)** measures the changes in the volume of production in the industrial sector over time. It acts as a short-term indicator of industrial activity and indirectly serves as a proxy for economic growth trends. The IIP is computed using a weighted arithmetic mean:

$$\mathrm{IIP} = \frac{\sum_{i=1}^{n}(W_i \times Q_i)}{\sum_{i=1}^{n} W_i}$$

where W_i is the weight assigned to item 'i' based on its importance, and Q_i is the quantity index relative to the base year.

The **Consumer Price Index (CPI)** measures the average change in prices paid by consumers for a basket of goods and services. It serves as the principal indicator of inflation and directly impacts household welfare, monetary policy, and interest rates. The CPI is calculated using the Laspeyres Price Index formula:

$$\mathrm{CPI} = \frac{\sum_{i=1}^{n}(P_i \times W_i)}{\sum_{i=1}^{n}(P_{i0} \times W_i)} \times 100$$

where P_i is the current price, P_o is the base year price, and W_i represents the weight of each good or service.

From a **theoretical standpoint**, the relationship between inflation and output growth is often described through the **Phillips Curve framework**, which basically depicts an inverse relationship between unemployment (a proxy for economic slack) and inflation. However, extensions of this theory suggest that higher industrial production can initially stimulate aggregate demand, leading to demand-pull inflation, while supply-side constraints can induce cost-push inflation.

Taking **monthly data helps us in our study.** A higher frequency leads to more data points and also captures short term dynamics. Central banks like the RBI and governments track monthly CPI and IIP to make quicker decisions on interest rates, fiscal spending and thus research based on monthly data is closer to real-world policy making needs. It also helps us capture seasonality effects and thus various unit tests of time series analysis helps us in identifying the close relationship between the two variables.

The **need for analysing this relationship** is that high inflation with stagnant production (stagflation) signals deep economic problems, while moderate inflation with rising output can indicate healthy growth. Analyzing their relationship helps assess whether the economy is moving toward stability, overheating, or recession. If rising inflation is demand-driven (linked to industrial expansion), it may call for a different policy (like tightening money supply) than if it is supply-driven (cost-push shocks).

LITERATURE REVIEW

Paper 1: The Indian inflation–growth relationship revisited: robust evidence from time–frequency analysis

Authors: Aviral Kumar Tiwari, Richard O.Olayeni, Sodik Adejonwo Olofin & Tsangyao Chang

About the paper: This paper tells us about the relationship between inflation and economic growth in India using wavelet-based methods.

Methodology: The authors utilise the Maximal Overlap Discrete Wavelet Transform to decompose the time series data into various frequency components so that we can examine relationships at different time scales. Wavelet correlation and cross correlation analyses were conducted to assess the strength and direction of the relationship between the variables across these scales. Also the scale by scale Granger causality tests were applied to determine the causal links between inflation and growth at each frequency level.

Key Findings: It finds that the inflation growth link varies by time scale. It is independent at short scales, bidirectional at medium scales, and growth-driven at longer scales. The scale by scale Granger causality reveals that economic growth often leads to inflation. We see a need for targeted inflation, monetary, and exchange rate policies.

Paper 2: Crude oil price, manufacturing index, and consumer price index: Is there any temporal link in India?

Authors: Utpal Kumar De, Girijasankar Mallik

About the paper: This study is to examine the impact of global crude oil price and fuel price on manufacturing output in India and the behaviour of consumer price index (CPI).

Methodology: Monthly data from April 1994 to August 2020 is taken. Manufacturing index (MI), a key component of the Index of Industrial Production (IIP), is used as a proxy for industrial output. ARDL model is used to examine both short-run and long-run relationships, using lag selection based on AIC.

Key Findings: There is a significant relation between CPI and manufacturing index (MI). A significant inverse relation between crude oil price with MI and CPI exists.

Paper 3: Causal Relationships between Industrial Production, Interest Rate and Exchange Rate: Evidence on India

Authors: Deepak Garg, Madhuri Agrawal, Rajesh R.K.

About the paper: This study attempts to find the causal relationships between Industrial Production, Interest Rate and Exchange Rate in India.

Methodology: Granger's Causality test and Vector Auto Regression technique are used on monthly IIP , exchange rate, and interest rate. The time period of the dataset is from April 1992 to March 2004.

Key Findings: There exists a unidirectional causality between the exchange rate and interest rate and between the exchange rate return and IIP.

Paper 4: How Indian CPI and Industrial Production Respond to Global Oil Price Shocks? Regime-Dependent Impulse Responses

Authors: Amanjot Singh, Rajdeep Singh

About the paper: This study employs a Markov-Switching Vector Autoregression model to analyse how global oil price shocks affect India's CPI and IIP.

Methodology: This study uses monthly data from 1980 to 2016. The MS-VAR model estimates parameters that switch across these regimes, allowing to analyse regime-dependent impulse response functions to oil price shocks. Regime transitions are modeled using a Markov chain, and IRFs are generated through Markov Chain Monte Carlo methods with Gibbs sampling.

Key Findings: The findings reveal that both CPI and IIP respond differently under varying oil price volatility regimes**.**

Paper 5: Does Inflation Slow Long-Run Growth in India?

Authors: Kamiar Mohaddes, Mehdi Raissi

About the paper: This study examines the long-run relationship between consumer price index industrial workers inflation and GDP growth in India.

Methodology: Data was collected from 14 Indian states over 1989–2013. Then, ARDL panel method and CSDL(cross sectionally augmented distributed lag) approach was used for estimation, to account for cross state heterogeneities, dynamics and feedback effects.

Key Findings: The authors' findings show a negative long-run relationship between inflation and economic growth in India. For states with persistently high inflation rates of above 5.5%, a significant inflation-growth threshold effect was found.

DATA AND METHODOLOGY

Description of the Dataset

Our analysis takes monthly data ranging from 2013(January) to 2023(December). We have taken the Index of Industrial Production(IIP) as our dependent variable and have tried to run a time series analysis with combined(weighted average of rural and urban) CPI percentage(as a proxy to inflation rate) as the independent variable.

The data has been taken from the RBI's Database on Indian Economy.

Model

$$\textbf{ARDL(1,1) : iip} = \beta 0 + \beta 1 \text{ L(iip,1)} + \beta 2 \text{ L(inflation,1)} + \varepsilon_t$$

$$\textbf{ARDL(2,1) : iip} = \beta 0 + \beta 1 \text{ L(iip,1)} + \beta 2 \text{ L(iip,2)} + \beta 3 \text{ L(inflation,1)} + \varepsilon_t$$

Variables and Justification of Choice

Dependent variable(Y) – Index of Industrial Production(IIP) :

- **Description :**

The Index of Industrial Production (IIP) measures the short-term changes in the volume of production across major industrial sectors such as manufacturing, mining, and electricity. It is compiled and released monthly by the Ministry of Statistics and Programme Implementation (MoSPI) in India. It is compiled using a weighted formula, with different sectors and products assigned weights based on their relative importance in the economy. IIP serves as a leading indicator of the country's economic performance, reflecting the level of industrial activity and overall economic momentum.

- **Justification :**

As the dependent variable, IIP represents the real side of the economy — capturing changes in production, investment and supply-side economic activity. Analyzing the factors that influence IIP is crucial for understanding economic growth cycles. For example, higher production levels can boost aggregate supply, potentially reducing inflationary pressures, while production bottlenecks or supply shocks can drive prices upward. By studying how inflation (captured through CPI) affects IIP, this research aims to explore whether rising consumer prices stimulate, depress, or have no significant effect on industrial output, providing valuable insights for both macroeconomic theory and policy making

Independent variable(X) – Combined Consumer Price Index(CPI) :

- **Description :**

The Consumer Price Index (CPI) measures the average change over time in the prices paid by consumers for a representative basket of goods and services. It includes expenditures on food, housing, clothing, transportation, healthcare, education, and other essentials. CPI is widely regarded as the most important indicator of inflation because it directly captures the cost of living for households. In India, CPI is computed monthly and is the main gauge used by the Reserve Bank of India (RBI) for setting monetary policy targets under the inflation targeting framework.

- **Justification :**

CPI is included as the main explanatory (independent) variable because inflation can exert important effects on industrial production. Higher inflation may increase production costs (input inflation) and suppress consumer demand (due to reduced purchasing power), leading to lower industrial output. Alternatively, moderate inflation may be associated with growing demand and higher production. Investigating CPI's impact on IIP helps to better understand how inflationary pressures interact with the real economy, particularly in an emerging market like India.

METHODOLOGY

1. Data Collection and Time Series Construction:

Data for both variables was sourced from the Reserve Bank of India (RBI)'s Database on Indian Economy. The dataset was converted into time series objects using ts() in R, with a monthly frequency (frequency = 12), and the starting point set to January 2014. Initial plots of the raw series were generated to visually inspect trends, seasonality, and fluctuations over time.

2. Testing for Stationarity

To determine the order of integration of both series, we applied two standard stationarity tests:

- Augmented Dickey-Fuller (ADF) Test
- Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test
  Results showed both IIP and Inflation series are non-stationary in levels.

After first differencing, both became stationary (I(1)).
Thus, all subsequent modeling was conducted using the first differences:

3. Lag Selection and Model Specification (ARDL)

On converting non-stationary series to stationary, the number of lags to be included in the model were identified using selection criteria.

- 27 different models for lags p and q ranging from 1 to 6 were analyzed
  Each model was evaluated based on AIC and BIC.

4. Estimation of ARDL Models and Diagnostic Testing

We estimated the ARDL(1,1) model and conducted the following diagnostic checks:

- Normality of Residuals: Shapiro-Wilk test and Q-Q plots
- Serial Correlation: Breusch-Godfrey LM test
- Model Stability: Residual analysis over time (ACF plots

Some residual autocorrelation prompted further evaluation with additional lags.

Based on improved AIC/BIC and better diagnostics, we selected ARDL(2,1):

- 2 lags for IIP
- 1 lag for Inflation

Diagnostic tests were repeated to check improvement of the model.

5. Forecasting with the Final Model

The ARDL(2,1) model was used to generate forecasts for IIP.

RESULTS AND DIAGNOSTICS

1. Summary Statistics:

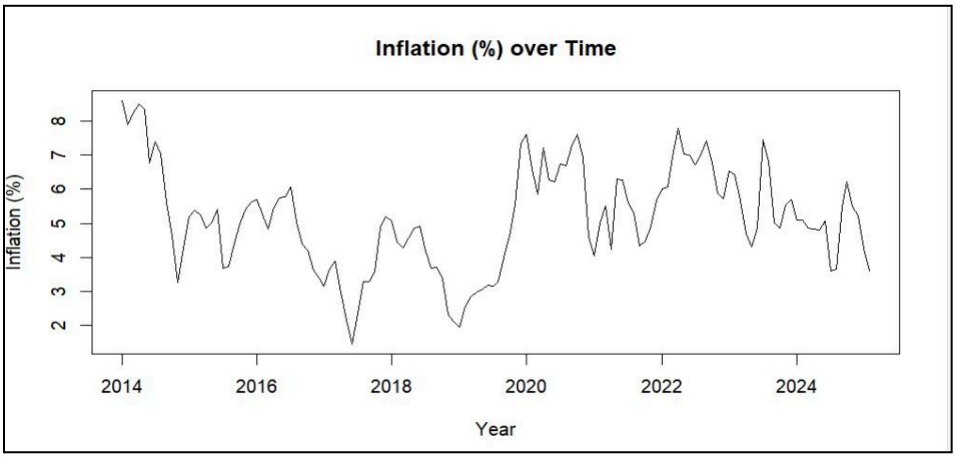
```
> summary(ae_time[, c("Inflation (%)", "IIP")])
 Inflation (%)        IIP
 Min.   :1.460   Min.   : 54.0
 1st Qu.:4.178   1st Qu.:117.9
 Median :5.075   Median :127.8
 Mean   :5.133   Mean   :128.2
 3rd Qu.:6.175   3rd Qu.:138.2
 Max.   :8.600   Max.   :161.6
```

The summary statistics provide a snapshot of the variation in monthly inflation (CPI) and industrial output (IIP) in India from 2013 to 2023. Inflation ranged from a minimum of 1.46% to a maximum of 8.6%, with a mean of 5.13%, indicating moderate inflation over the decade. The IIP values, which reflect industrial production, ranged from 54.0 to 161.6, with a mean of 128.2, suggesting a general upward trend in industrial activity.

2. Stationarity of the variables:

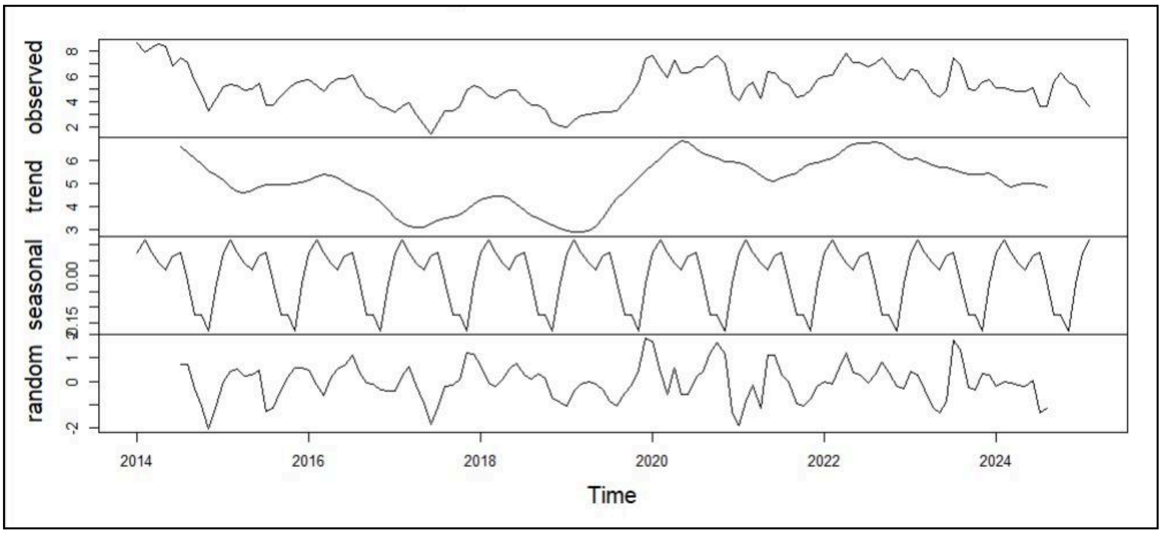
a. Inflation series

First plot : raw inflation data over time:



The plot of inflation over time shows that the average inflation rate is lower in the earlier years and higher in the later years. This shift suggests that the series may not be fully stationary, as its mean appears to change over different periods.So we go for transformation into stationary.

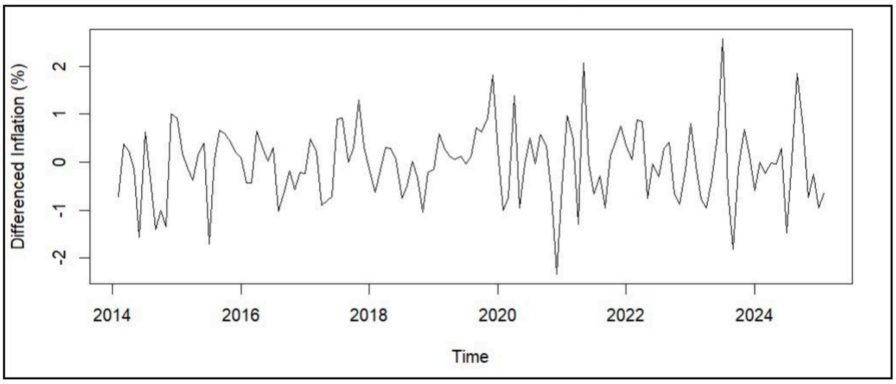
Second plot : decomposes the inflation series into trend, seasonal and random.




```
> adf.test(inflation_ts)

        Augmented Dickey-Fuller Test

data:  inflation_ts
Dickey-Fuller = -3.055, Lag order = 5, p-value = 0.1377
alternative hypothesis: stationary

> kpss.test(inflation_ts)

        KPSS Test for Level Stationarity

data:  inflation_ts
KPSS Level = 0.29202, Truncation lag parameter = 4, p-value = 0.1

Warning message:
In kpss.test(inflation_ts) : p-value greater than printed p-value
> inflation_diff <- diff(inflation_ts)
> # Check again after differencing
> adf.test(iip_diff)

        Augmented Dickey-Fuller Test

data:  iip_diff
Dickey-Fuller = -7.0528, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(iip_diff) : p-value smaller than printed p-value
> kpss.test(iip_diff)

        KPSS Test for Level Stationarity

data:  iip_diff
KPSS Level = 0.023509, Truncation lag parameter = 4, p-value = 0.1

Warning message:
In kpss.test(iip_diff) : p-value greater than printed p-value
```

The time series plot and its decomposition clearly indicate that the inflation series is non-stationary. The decomposition highlights a smooth long-term behavior, possibly a trend. It also shows a significant seasonal component. The residuals show some trend as well with varying mean and variance, pointing to potential non-stationarity. This is further confirmed by the ADF test, which fails to reject the null hypothesis of a unit root, suggesting non-stationarity in the raw series. Additionally, the KPSS test does not strongly reject the null of stationarity around a trend, providing inconclusive evidence regarding stationarity as both tests give contradictory results. However, when the series is first differenced, both the ADF and KPSS tests show significant improvements, with the ADF test rejecting the null of a unit root (p-value = 0.01) and the KPSS test supporting stationarity. These results confirm that the raw series was non-stationary, likely due to the presence of a unit root, and that differencing was an appropriate step to achieve stationarity.

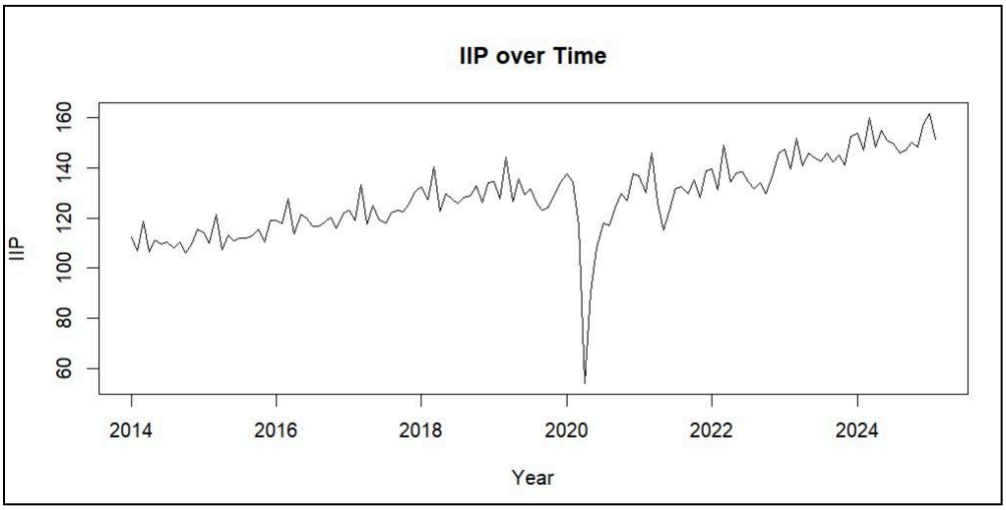
Thirdly, we have a plot of the differenced inflation series:



While the original graph displays substantial non-stationarity with inflation fluctuating between approximately 1.5% and 8% over the decade with no stable mean, the differenced graph successfully addresses these issues. The differencing transformation has created a series that consistently oscillates around zero, removed the large-scale shifts in level, and eliminated the persistence of high or low values seen in the original data. This improvement is statistically confirmed by the ADF test (now rejecting the null hypothesis with p-value = 0.01) and the KPSS test supporting stationarity.

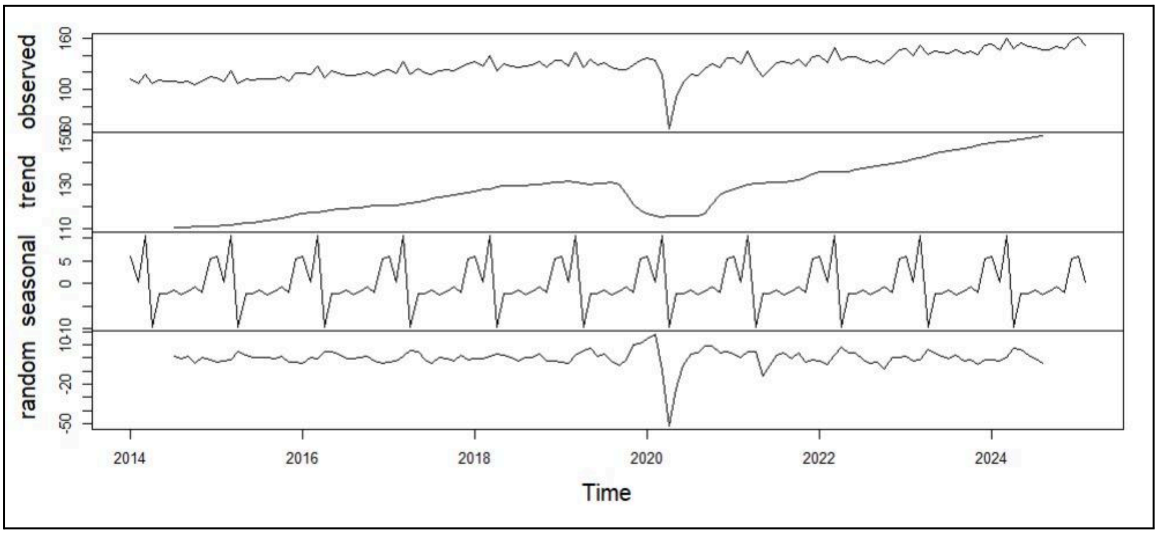
b. IIP series:

First plot : raw IIP data over time:



The IIP plot shows a clear upward trend and big swings, especially around 2020. This means the series is non-stationary, since its average level and spread change over time. To analyze it properly, we'd need to transform the data to make it more stable.

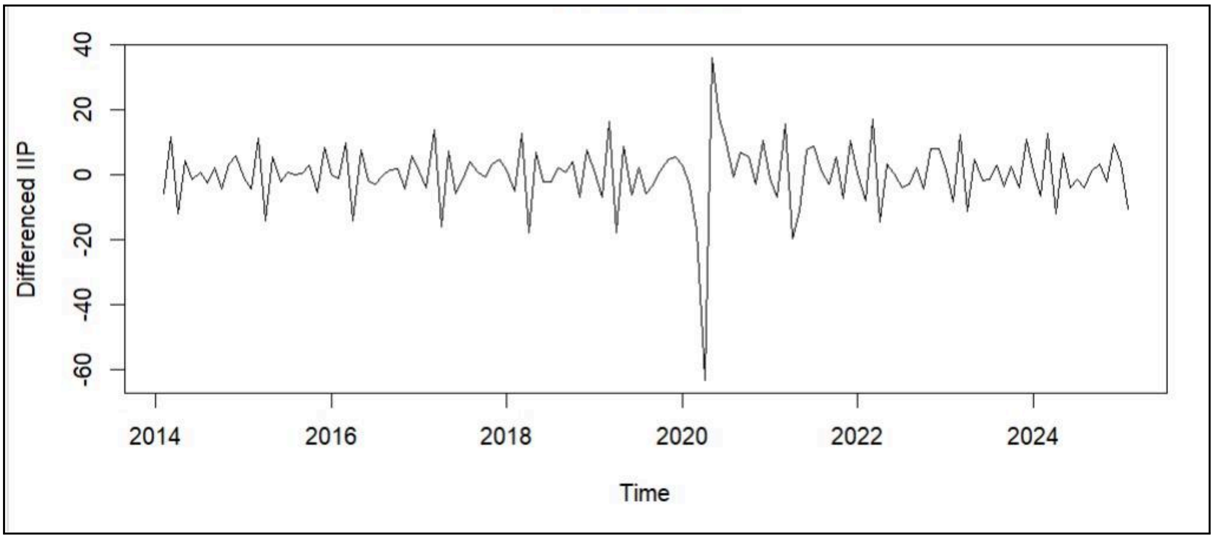
Secondly plot : decomposes the inflation series into trend, seasonal and random.




```
> # ADF Test
> adf.test(iip_ts)

        Augmented Dickey-Fuller Test

data:  iip_ts
Dickey-Fuller = -3.4389, Lag order = 5, p-value = 0.05112
alternative hypothesis: stationary

> # KPSS Test
> kpss.test(iip_ts)

        KPSS Test for Level Stationarity

data:  iip_ts
KPSS Level = 1.9713, Truncation lag parameter = 4, p-value = 0.01

Warning message:
In kpss.test(iip_ts) : p-value smaller than printed p-value
> #taking 1st difference
> iip_diff <- diff(iip_ts)
> # Check again after differencing
> adf.test(iip_diff)

        Augmented Dickey-Fuller Test

data:  iip_diff
Dickey-Fuller = -7.0528, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(iip_diff) : p-value smaller than printed p-value
> kpss.test(iip_diff)

        KPSS Test for Level Stationarity

data:  iip_diff
KPSS Level = 0.023509, Truncation lag parameter = 4, p-value = 0.1

Warning message:
In kpss.test(iip_diff) : p-value greater than printed p-value
```

The time series decomposition of the IIP data reveals important structural characteristics that align with the stationarity test results. The top panel shows the observed IIP series from 2014 to 2024, displaying a generally increasing trend with notable volatility and a significant disruption around 2020, likely due to the COVID-19 pandemic. The trend component (second panel) confirms this. The distinctive seasonal pattern shows regular cyclical fluctuations throughout the year, maintaining consistency across the entire period. The random component (bottom panel) exhibits considerable volatility, including the dramatic negative shock in 2020. These decomposition elements support the stationarity test findings: the ADF test on the original series falls just short of rejecting non-stationarity at the 5% level, while the KPSS test strongly rejects level stationarity. After first differencing, both tests align conclusively—the ADF test strongly rejects the null hypothesis of a unit root, and the KPSS test fails to reject the null of stationarity. This confirms that the IIP series is integrated of order 1, I(1), requiring first differencing to achieve stationarity, which is essential for valid time series modeling and inference.

Third plot : of the differenced inflation series:



The differenced IIP plot reveals a striking transformation of the original non-stationary series into a stationary process that exhibits key characteristics necessary for time series modeling. The differenced series oscillates consistently around a zero mean throughout the 2014-2024 period, with regular fluctuations that maintain relatively stable variance in most periods. This pattern confirms the effectiveness of first differencing in removing the upward trend observed in the original IIP data. The differenced series demonstrates mean-reverting behavior with no persistent directional movements apart from the extreme volatility during the COVID-19 pandemic in 2020, with the unprecedented negative shock followed by a sharp recovery spike, confirming the results from both stationarity tests—the ADF test strongly rejecting the null hypothesis of a unit root and the KPSS test failing to reject stationarity. This statistical evidence collectively confirms that the IIP series is indeed I(1), requiring exactly one round of differencing to achieve stationarity.

3. Fitting the model (and make necessary corrections):

a. ARDL(1,1)

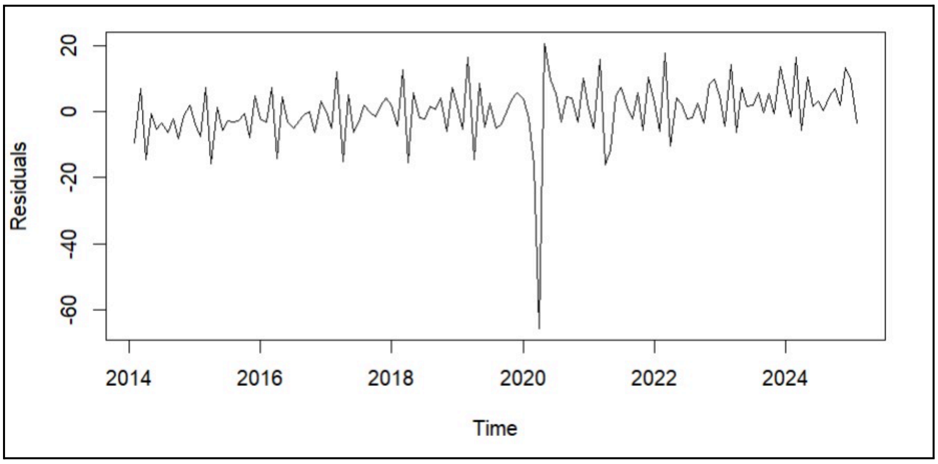
The ARDL(1,1) model reveals the following :
The coefficient for the lag of inflation is 0.08011, but it is not statistically significant, which means past inflation does not have a direct effect on current IIP growth. Meanwhile, the lag of IIP is highly significant, implying strong persistence in industrial output.

The R squared of the model suggests a good fit with 62.5% of the variation in IIP being explained by the model. The F-statistic is also significant, confirming joint significance.

```
Time series regression with "ts" data:
Start = 2014(2), End = 2025(2)

Call:
dynlm(formula = iip_ts ~ L(inflation_ts, 1) + L(iip_ts, 1))

Residuals:
    Min      1Q  Median      3Q     Max 
-65.773  -3.837  -0.055   4.821  20.560 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)        26.13288    7.75912   3.368 0.000996 ***
L(inflation_ts, 1)  0.08011    0.54254   0.148 0.882837    
L(iip_ts, 1)        0.79498    0.05419  14.671  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.403 on 130 degrees of freedom
Multiple R-squared:  0.6251,	Adjusted R-squared:  0.6193 
F-statistic: 108.4 on 2 and 130 DF,  p-value: < 2.2e-16
```

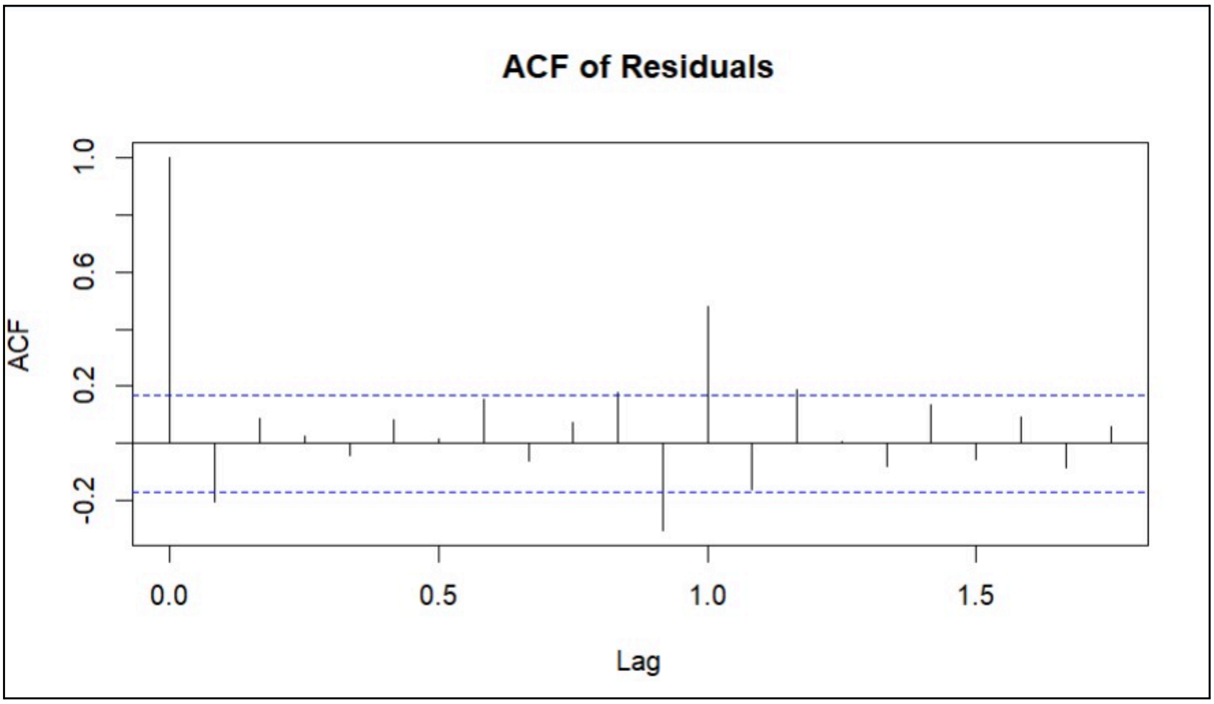
Now, diagnostic tests have been run to evaluate the robustness of the model chosen.

- <u>Residual plot over time:</u>



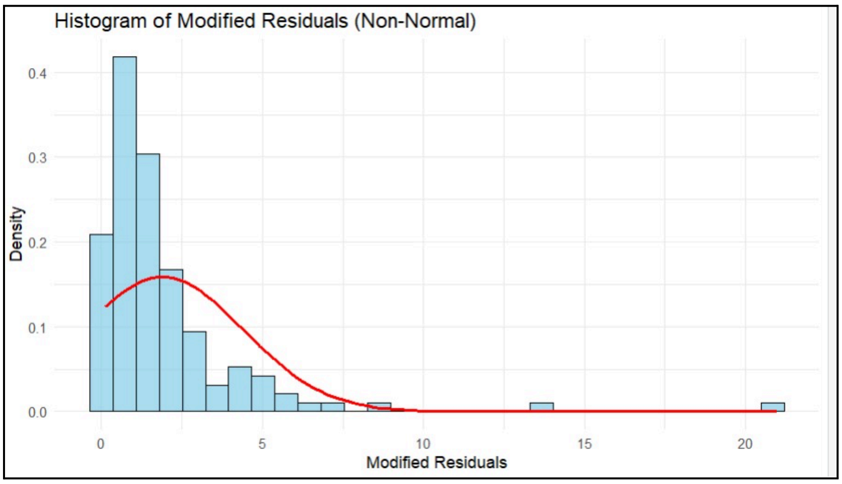
From the residual plot over time for the ARDL(1,1) model, we notice that the overall residuals appear to oscillate around zero, which is desirable and indicates that the model captures the patterns in the data fairly well. We can also say the residuals are mean reverting and approximately stationary as there is no prolonged period of large deviations of residuals.The outlier at 2020 coincides with the COVID-19 pandemic which tells us the model could not fully account for the shock, but the residuals quickly return to their normal range. This supports the robustness of the model across the rest of the sample.

- <u>ACF Plot</u>



The ACF plot indicates that the residuals are largely uncorrelated over time, which is a key requirement for a well-specified model. Autocorrelations beyond lag 0 fall within the 95% confidence bounds, suggesting no significant serial correlation. The mild spike at lag 1 remains within the confidence limits, implying that any autocorrelation at that point is not statistically significant. This supports the assumption that the residuals behave like white noise.

- <u>Residual Normality Test</u>



The histogram of residuals indicates a significant departure from normality. From the graph we see that the distribution is highly skewed to the right with a heavy concentration at zero and a long right tail. Hence the assumption of normality is violated in this model. This non-normality of residuals implies that the inference from T tests and F tests may not be fully reliable, especially for small sample sizes. The residual non-normality might be due to an incorrect functional form, and can be improved with a different lag form.

- ## Information Criteria

These criteria are used to evaluate model fit while penalising for more parameters. Lower values generally indicate a better balance between goodness-of-fit and parsimony.

To examine the dynamic relationship between CPI and IIP in India, we initially estimated an ARDL(1,1) model, where the Index of Industrial Production was regressed on its first lag and the first lag of the Consumer Price Index. While the ARDL(1,1) model provided a basic framework, further diagnostic checks revealed limitations in capturing the full dynamics of the relationship, as seen above.

	p	q	AIC	BIC
1	1	1	960.4354	972.9910
2	1	2	961.2796	975.6556
3	1	3	955.5649	972.7701
4	1	4	948.0607	968.0794
5	1	5	943.6384	966.4547
6	1	6	937.4375	963.0352
7	2	1	938.0320	963.0213
8	2	2	961.4146	978.6658
9	2	3	955.9441	976.0168
10	2	4	948.3224	971.2009
11	2	5	943.9420	969.6103
12	2	6	937.2886	965.7304
13	3	1	953.5062	970.7114
14	3	2	954.7565	974.8292
15	3	3	956.3940	979.3343
16	3	4	949.4033	975.1416
17	3	5	945.0934	973.6137
18	3	6	937.9936	969.2796
19	4	1	944.0231	964.0418
20	4	2	944.9546	967.8331
21	4	3	946.4065	972.1448
22	4	4	945.4189	974.0171
23	4	5	940.8326	972.2049
24	4	6	933.0736	967.2038
25	5	1	937.8284	960.6446
26	5	2	938.8102	964.4785
27	5	3	940.4196	968.9399

Selecting the optimal lag length is a crucial step in estimating an ARDL model, as it directly influences the model's ability to capture the relationship between CPI and IIP. First, we performed automatic lag selection with up to 15 lags using information criteria (AIC, BIC, HQ, SC, FPE) and then compared specific ARDL(p,q) model configurations to identify the best specification.

The ARDL(2,1) model was hence selected for further analysis due to slightly better economic interpretability and richer dynamics, while maintaining strong performance in terms of AIC/BIC. It also satisfied residual diagnostics better, including lower autocorrelation and improved stability in later tests.

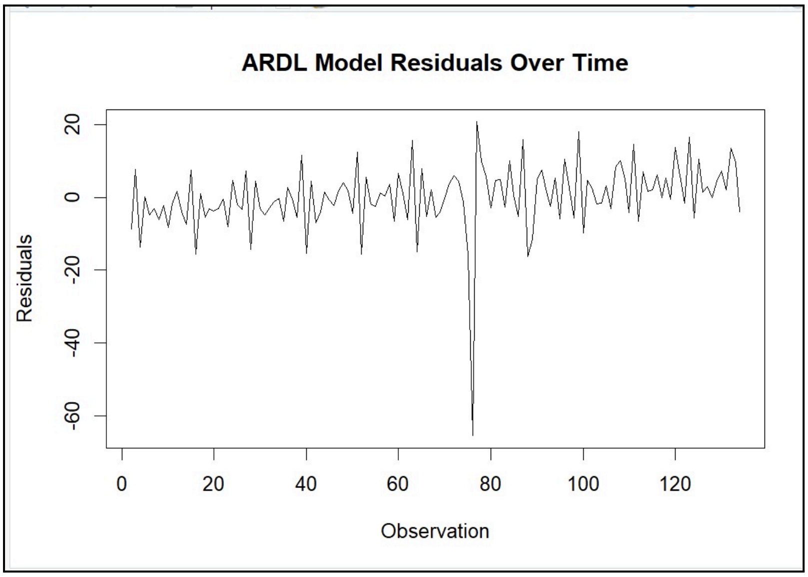
b. ARDL(2,1)

```
Residuals:
    Min      1Q  Median      3Q     Max 
-69.845  -3.775   0.395   4.211  20.638 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)        18.59105    7.94515   2.340  0.02083 *  
L(iip_ts, 1)        0.59082    0.08519   6.935 1.79e-10 ***
L(iip_ts, 2)        0.25846    0.08646   2.989  0.00335 ** 
L(inflation_ts, 1)  0.22674    0.53664   0.423  0.67336    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.125 on 128 degrees of freedom
Multiple R-squared:  0.647,	Adjusted R-squared:  0.6387 
F-statistic: 78.19 on 3 and 128 DF,  p-value: < 2.2e-16
```

The ARDL(2,1) model reveals the following
L(IIP,1) is highly significant from its p value, which means the past values of industrial production are strong predictors of current output. L(IIP,2) is also significant showing that lag 2 also contributes positively. L(Infl, 1) however, is not significant and hence doesn't significantly predict IIP.
The R squared value tells us that around 64.7% of variation of IIP is explained by the model. The F statistic of 78.19 tells us the overall model is statistically significant. While industrial production demonstrates strong internal momentum, inflation does not significantly impact IIP in the short run.

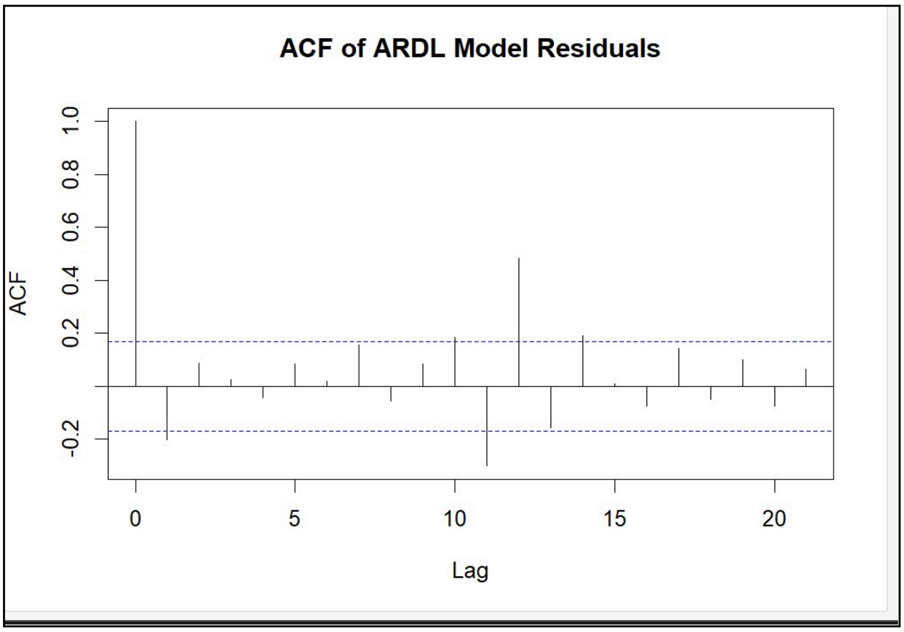
Performing the same diagnostic tests on the latter model to compare the models :

- Residual plot



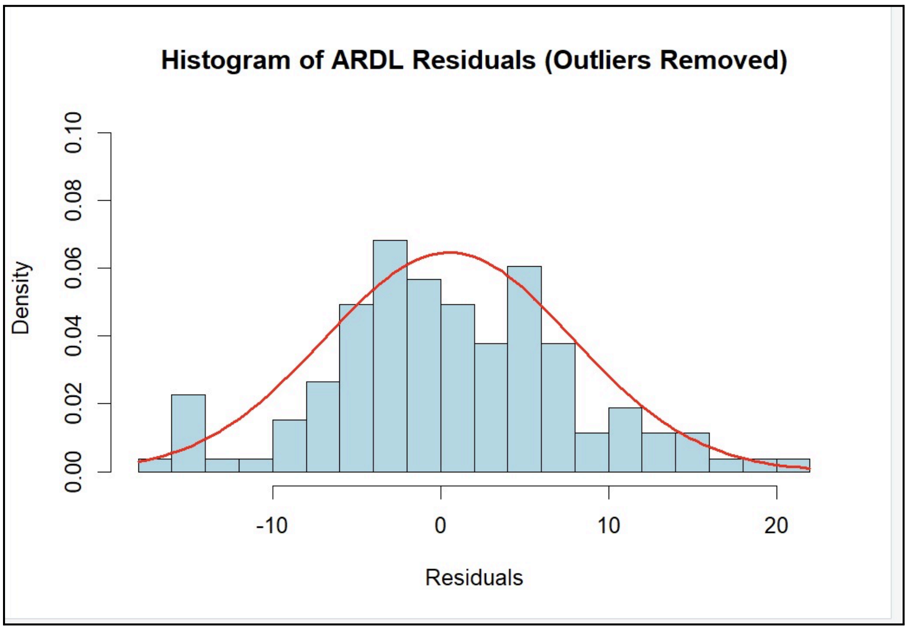
We notice that the residuals fluctuate around zero, i.e, mean reversion around zero implying the model captures the trend well. We can conclude it is homoscedastic as the variance of residuals appears consistent over time, except for one spike at around observation 75. There also seems to be no clear pattern or trend in the residuals, implying the model has no strong autocorrelation either.

- <u>ACF Plot</u>



We know that in the ACF plot, the spikes represent autocorrelation coefficients at different lags. Dashed lines are 95% confidence bounds, and any spike outside these bounds suggests statistically significant autocorrelation at that lag. But most spikes in our plot are within the bounds, indicating no significant autocorrelation at most lags.

- <u>Normality of residuals:</u>



The roughly bell-shaped histogram and the overlaid red kernel density estimate closely follows a normal distribution. This supports the assumption of normally distributed error terms, which is a key requirement for valid inference in ARDL modelling. We conclude that the residuals are reasonably symmetric as there is no strong skewness. These results reinforce the robustness of the model's estimates and support the use of standard hypothesis tests.

- Ljung Box Test

```
        Box-Ljung test

data:  residuals(model)
X-squared = 17.766, df = 10, p-value = 0.05903
```

This test is used to detect autocorrelation in the residuals. The null and alternate hypotheses are as follows

Null hypothesis (H_0): Residuals are independently distributed (no autocorrelation).

Alternative hypothesis (H_1): Residuals are autocorrelated.

Since the p-value is slightly above 0.05, we fail to reject the null hypothesis at the 5% significance level. But still we conclude no strong evidence of autocorrelation in the residuals as it was close, and the model appears to have adequately captured the relationship between CPI and IIP.From the Ljung Box and ACF plots we can see that the ARDL(2,1) model is close to white noise, with no strong evidence of autocorrelation.

- LM test results :

For ARDL(1,1):

```
> bgtest(ardl_model, order = 1)

        Breusch-Godfrey test for serial correlation of order up to 1

data:  ardl_model
LM test = 8.9279, df = 1, p-value = 0.002808
```

For ARDL(2,1) :

```
> bgtest(ardl_model, order = 2)

        Breusch-Godfrey test for serial correlation of order up to 2

data:  ardl_model
LM test = 2.2809, df = 2, p-value = 0.3197
```

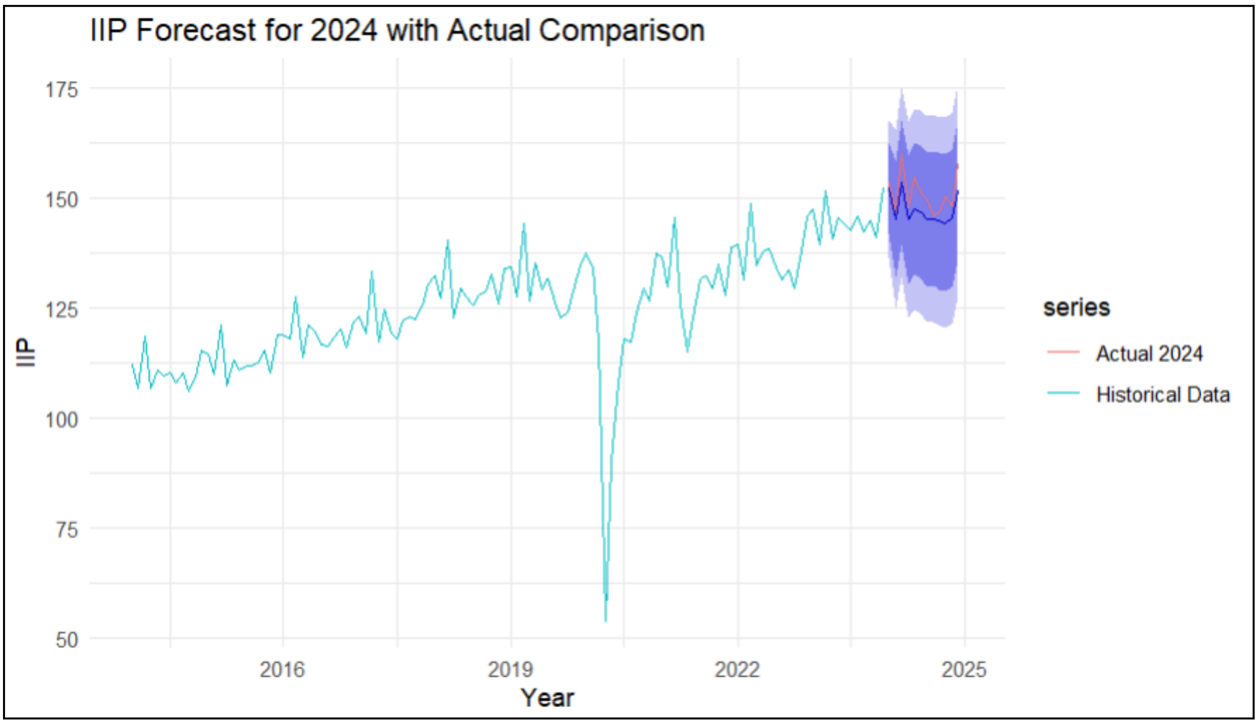
The LM test results provide important diagnostic information about the presence of serial correlation in our ARDL models examining the relationship between industrial production and inflation.

For the ARDL(1,1) model, the BG test indicates significant serial correlation with an LM statistic of 8.9279 and a p-value of 0.002808, which is below the 95% significance level.. This suggests that the residuals in our first model are not independent over time, which could lead to inefficient parameter estimates and potentially misleading inference. However, when we extended the model to ARDL(2,1), the BG test showed no significant evidence of serial correlation, with an LM statistic of 2.2809 and a p-value of 0.31972. This improvement indicates that incorporating additional lags in the autoregressive component adequately addresses the autocorrelation issue.

The ARDL(2,1) specification therefore appears more appropriate for modeling the dynamic relationship between industrial production and inflation in India, as it satisfies the crucial assumption of independent residuals necessary for valid statistical inference and reliable forecasting.

4. Out of Sample Forecast:

IIP forecast



Using holdout sample we did the following forecasting and as it can be seen it gave a satisfactory result showing the trend. It means our model was able to capture the time series effect upto a satisfactory level

	Month	Forecasted_IIP	Actual_IIP	Error
1	Jan-2024	152.13	153.6	1.47
2	Feb-2024	145.09	147.1	2.01
3	Mar-2024	153.54	160.0	6.46
4	Apr-2024	145.10	148.0	2.90
5	May-2024	147.50	154.7	7.20
6	Jun-2024	146.84	151.0	4.16
7	Jul-2024	145.17	149.8	4.63
8	Aug-2024	145.35	145.8	0.45
9	Sep-2024	144.72	146.9	2.18
10	Oct-2024	144.37	150.3	5.93
11	Nov-2024	145.36	148.1	2.74
12	Dec-2024	151.66	157.7	6.04

Using a holdout sample we did the following forecasting and as it can be seen it gave a satisfactory result showing the trend. It means our model was able to capture the time series effect upto a satisfactory level.

In this analysis, we used an ARDL(2,1) model to forecast the Index of Industrial Production (IIP) for the year 2024. Historical data from January 2014 to December 2023 was used to train the model, and the actual values for 2024 were kept as a holdout sample to evaluate the model's forecasting performance. The forecasted IIP values closely followed the general trend of the actual data, with errors mostly remaining within a reasonable range. The average deviation between forecasted and actual values was moderate, showing that the model was generally effective in capturing the seasonal behavior of industrial production.

However, some months—especially March, May, October, and December—showed larger forecast errors, indicating that the model underpredicted IIP during periods of heightened industrial activity. This suggests that while the ARDL(2,1) model can handle short-term trends and seasonality reasonably well, it may not fully capture unexpected fluctuations or structural changes in the economy. Incorporating additional economic indicators as explanatory variables in future models could potentially improve accuracy during such periods.

CONCLUSION

This study examined the relationship between inflation and industrial production in India by estimating an ARDL (2,1) model using time series data on the Consumer Price Index and the Index of Industrial Production. The lag structure was selected after evaluating several models based on information criteria and validating their statistical assumptions. The ARDL(2,1) specification was chosen for its balance between explanatory power and model parsimony, apart from minimum value of AIC, BIC.

The model output revealed that both the first and second lags of industrial production are statistically significant, implying that past values of IIP strongly influence current industrial output. This suggests that industrial production exhibits significant internal momentum and persistence over time. In contrast, the inflation variables, CPI and its lag, were not statistically significant, indicating that in the short run, inflation does not have a direct impact on industrial production in India.

The model explains approximately 64.9% of the variation in IIP, and the F-statistic confirms overall model significance. Residual diagnostics further support the robustness of the model. The residuals are approximately normally distributed, show no strong signs of autocorrelation, as confirmed by the Ljung-Box test and ACF plots, and appear homoscedastic with only one minor outlier. These diagnostics confirm that the model provides reliable estimates and valid inference.

Since past industrial output significantly predicts current performance, industrial policy should focus on sustaining momentum through consistent capital investment, infrastructure support, and easing supply-side constraints. The short-run insignificance of inflation suggests that moderate changes in CPI may not immediately affect industrial activity. Therefore, while inflation control remains important, short-term fluctuations in inflation may not require aggressive intervention if industrial growth is to be prioritised.

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