

# An Effective Time Series Analysis for Forecasting NIFTY Metal Price Index using ARIMA Model

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## Abstract

The paper is an endeavour to forecast NIFTY Metal Index prices using the time series forecasting model-ARIMA to enable investors to take an informed decision based on forecasting to gain better profits in the short run. To achieve this objective, the study uses descriptive statistics, tests including Dickey Fuller (DF) Test, Augmented- Dickey Fuller (ADF) Test and Phillips Perron (PP) Test and Autoregressive Integrated Moving Average (ARIMA). To further strengthen the estimated results, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Their Inequality Coefficient (TIC) tests are also conducted. The analysis reveals that data are normally distributed and non-stationary. Hence, ARIMA model is best fitted model with first order differencing. Based on the correlogram and associated ACF and PACF, the study estimated four ARIMA models and found ARIMA (3,1,4) is the best fitted model to forecast the future value of NIFTY Metal Price Index (NMPI). Based on ARIMA (3,1,4) model, Nifty Metal Index closing prices from 19/01/2022 to 30/06/2022 have been predicted.

**Keywords:** NIFTY Metal Index, ARIMA Model, Forecasting, Correlogram, Non-Stationary

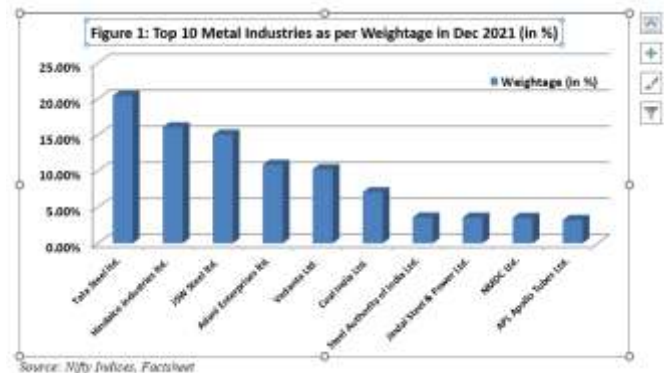
JEL Code: C22; C53; G11; G17

## Introduction

Stock markets are known for being dynamic, complex, and volatile. Investment decisions play a key part in achieving the targeted returns, through stock market forecasts. Stock or investment returns are determined by a variety of factors, the most important of which is the ability to predict stock movements. Stock returns are predicted and estimated on a certain stock exchange or exchanges, hourly. Due to the complicated nature of the stock market, price prediction is considered one of the most challenging tasks in financial forecasting P. Pai and C. Lin (2005), J.J. Wang (2012), L.Y. Wei (2013). The significance of accurately anticipating stock prices and gains, encourages researchers to

pay considerable attention on improving the model accuracy in the prediction of stock price movements and returns. Investors may create better trading strategies with the help of anticipated prices of any index, and correct forecasting undoubtedly helps in yielding greater returns. Index forecasting allows an investor to increase the quality and efficiency of his or her decision-making. Many econometric models have been employed for time series forecasting throughout the last few decades, attracting the attention of investors, speculators, governments, and researchers. (Sakowski and Turovitseva 2020), (Torre Torres et.al. 2021), (Goubuzaitė and Teresiene 2021). To forecast a time series, the most appropriate model must be developed after rigorous measurement and analysis of past observations. Understanding the constant flow and seasonal fluctuation of the Index can help both experienced and novice investors make better decisions. Forecasting models allow for the prediction of future values of time series based on historical data's behaviour. To achieve low predicting errors, a precise model fitting technique is required, therefore, advanced forecasting models are developed and tested for this purpose.

Metals are utilized as industrial raw materials and in the construction of a variety of everyday objects. These are critical components in the manufacture of batteries and the generation of nuclear energy. Because of its critical relevance, an index was created to track the behaviour and performance of the metal industry, which includes mining. In comparison to other Nifty sectoral indexes, the Nifty Metal Index has performed the better, with a return of 73.43 percent in 2020-21. Nifty IT (59%) and Nifty Realty (54%) came in second and third, respectively. The NIFTY Metal Index consists of 15 stocks that are traded on the National Stock Exchange<sup>1</sup>(NSE). Figure 1 depicts the top ten metal industry constituents in terms of their weightages. Figure 1 depicts the fact that in December 2021, Tata Steel Ltd. constitutes the largest share with 20.45 per cent weightage followed by Hindalco Industries Ltd. (16.09%), JSW Steel Ltd. (15.06%) and so on.



The free float market value is used to calculate the index for all 15 equities. The Index can be used for a variety of reasons, including benchmarking fund portfolios, ETFs, Index fund launches, structured products, and so on. Since the movement of the Index is so volatile, risk management is required to protect invested assets and maximise profits. Over the last year, the Nifty Metal index has gained by 73.43 percent, compared to a 59.56 percent growth in the benchmark Nifty 50 index. The study uses a stochastic time series ARIMA model to check stationarity in NIFTY metal Index data (which is a time series data) and forecast the direction of movement of index prices. ARIMA is a popular method for predicting univariate time series data such as GDP, inflation, exchange rates, stock prices, and commodities. The purpose of this article is to forecast NIFTY Metal Index prices for investors to make an informed decision based on forecasting to make more money in the short term.

The paper is structured as follows: Section 2 contains a thorough Literature Review, as well as an outline of the time series forecasting Model – ARIMA, research gap and research goals. The research methodology and data sources are presented in Section 3. The study's limitations are discussed in Section 4. Section 5 is dedicated to data analysis and interpretation, whereas Section 6 is dedicated to discussion and section 7 draws a conclusion and Implications.

## Literature Review

ARIMA models are recognised to be more efficient than even the most popular Artificial Neural Network Technique (ANN) techniques for forecasting, notably in the field of financial time series (L.C. Kyungjoo, et. el 2007), (N. Merh

et. el 2010). Regression technique, exponential smoothing, and Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) are examples of other statistics models. ARIMA models are capable of forecasting data from short-term financial time series (Schmitz and Watts 1970; Rangan and Titida 2006; Kyungjoo et al. 2007; Merh et al. 2010; Sterba and Hilovska 2010).

ARIMA forecasting models have been employed by several researchers to forecast stock returns. (Khasei et al. 2009; Lee and Ho 2011; Khashei et al. 2012). Nguyen Vo and Robert Slepaczuk (2021) compared ARIMA model with Hybrid models to forecast S&P 500 log returns. The result indicated that hybrid models outperform ARIMA and the benchmark (Buy and hold strategy on S&P500) over the long run. Chotani (2020) used the ARIMAX model to forecast Billet prices and determined that ARIMAX (0,2,2) (1,0,3) was the best, since it best fits the statistics. Sadhwani et al. (2019) used an ARIMA model to anticipate the MCX Comdex Index and found a range bound or steady growth in commodity prices, with a 95% confidence level. Reddy (2019) employed the ARIMA model to anticipate the NSE and BSE indices to study their stationarity. The study's findings confirmed the ARIMA model's ability to forecast future time series in the short term and would aid investors in making profitable investment selections. ARIMA (0,1,0) was found to be the best model among the others in the study. The results of ARIMA forecasting, according to the author, will guide investors in the short term. Wadhawan and Singh (2019) examined the competency and bias of various volatility estimators using several error measurement metrics. The Parkinson estimator has been recognised as a highly effective volatility estimator. It was concluded that there is a greater chance of validating ARIMA's various models by testing them over a variety of time periods. Miah (2019) attempted to forecast Bangladesh's various types of rice output and found that the equipped models are statistically well behaved in forecasting the same. Using the BOX-Jenkins approach, Ashik and Senthamarai (2017) examined NIFTY 50 stock prices and projected the index's trend. They discovered that closing prices of the NIFTY 50 based on univariate time series have a higher prediction accuracy. For the

foreseeable future, a declining tendency in the NIFTY 50 closing price and moderate decreasing fluctuation tendencies were predicted. Savadatti (2017) attempted to find the best-fit ARIMA model for forecasting food grain area, production, and productivity over a 5-year period. ARIMA (2,1,2), ARIMA (4,1,0), and ARIMA (3,1,3) models were discovered in the study for projecting the area of cultivation, production, and productivity of food grains, respectively. Guha and Bandyopadhyay (2016) investigated the use of an ARIMA model to forecast gold prices based on historical data and to advise investors on when to sell and buy gold. The authors argue that because gold has become an important investment option, it is necessary to forecast its price using a proper model. Luo, et al., (2016) used the Wavelet model for de-noising and the ARIMA model for forecasting to investigate the performance of Index prices. In developed markets, the empirical finding shown that after de-noising, better and more accurate predictions may be obtained. Saini (2016) used the ARIMA model on the daily stock process of the State Bank of India for two years to forecast future stock processes and concluded that ARIMA (0,1,1) is the best model for the study. Kwasi and Kobina (2014) described modelling and forecasting of wholesale cassava monthly prices from January 2013 to December 2013 in central region of Ghana using ARIMA model. The study demonstrates a good performance in terms of explained variability and predicting power. Adebijet al. (2014) using ARIMA model shows the potential of ARIMA models to predict stock prices on short-term basis satisfactorily.

Devi et al., (2013) use Box-Jenkins to anticipate the Nifty mid-cap (market capital) index. The prediction for the following five years was also given. This article concluded with new investment choices or advice based on the performance measurements' lowest error percentage.

Dooleya and Lenihan (2005) investigated the ability of two simple time series forecasting approaches to predict future lead and zinc prices. They claimed that ARIMA modelling outperforms lagged forward price modelling in terms of forecast accuracy. Gerra (1959) Using least squares methodology, the egg industry's stock price movements were analysed. The Jenkins ARIMA technique is more

efficient and accurate than regression and exponential smoothing, which are used in other economic models (Reid 1971; Naylor II et al. 1972; Newbold and Granger 1974). In comparison to long-term stock returns, the ARIMA model is more accurate at forecasting short-term stock returns (Sabur and Zahidul Hague 1992). ARIMA models have demonstrated their capacity to provide accurate short-term forecasts. In short-term forecasting, it consistently outperformed sophisticated structural models. This could help stock market investors make profitable investment selections.

### Research Gaps

According to the literature study, several researchers have attempted to anticipate various indices, commodities, and stock prices using the ARIMA model. It's also worth noting that ARIMA is the most applied model for forecasting univariate time-series data. So yet, very few studies applied the ARIMA model to predict the Metal Index worldwide. This study seeks to fill this void by applying the ARIMA model to forecast NSE Metal index prices.

### Research Objective

To analyze and forecast the NIFTY Metal Index closing prices using ARIMA model.

### Research Methodology and Data Source

The study has used NIFTY Metal Index data for last two years i.e. from 1st Jan 2019 to 18th Jan 2022. First, the study has analyzed the data and then we have applied ARIMA model to fit the data. The NIFTY Metal Index comprises stock opening price, closing price, lowest price and highest price. The lowest and highest prices are not suitable as it takes the extreme data while closing price is the most suitable as it maintains the balance from multi-contest that can be observed from the next trading day opening price. Moreover, a trading day closing price is also related with previous day closing price. In this study, we have used the data from NIFTY Metal Index closing price (in ₹). The time of study is from 1st Jan 2019 to 18th Jan 2022 with 513 observations after adjustments. The data has been obtained from historical data reports of NSE indices and estimation has been done by using the software Eviews 8.

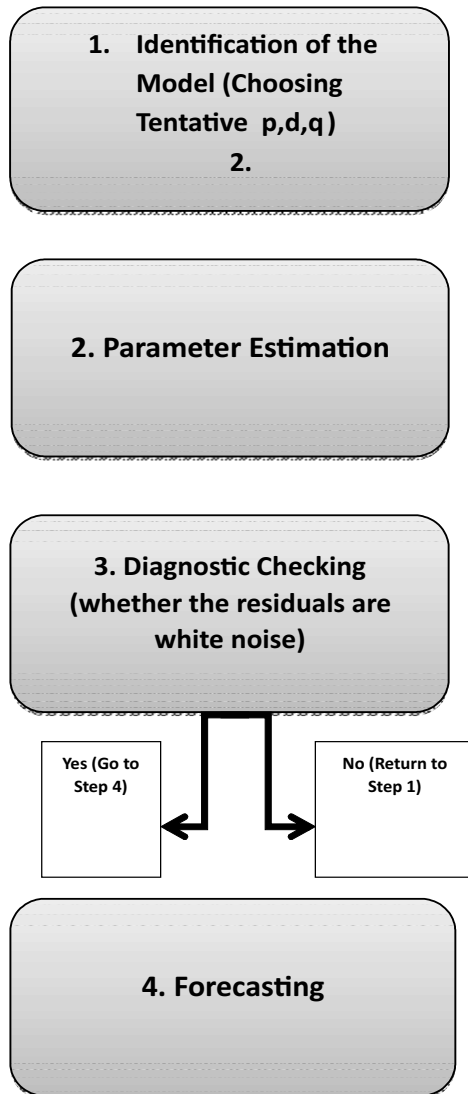
### ARIMA (Autoregressive Integrated Moving Average) Model

ARIMA is one of the most widely used statistical tool to forecast univariate time series data like GDP, inflation, exchange rate, stock prices or commodities. It was introduced by George Box and Gwilym Jenkins in 1970 and therefore, it has popularly known as Box-Jenkins method (Box, et al 1976). ARIMA model is not a single or simultaneous equation models but it is a probabilistic model i.e. group of statistical models for examining and forecasting time-series data. The model is based on the philosophy – “let the data speak for themselves”. The Box-Jenkins method allows the dependent variable ( $Y_t$ ) to be explained by the past or lagged values of  $Y$  itself along with the stochastic error terms. Hence, BJ method is sometimes called a theoretic model as it is not derived from any economic theories (Gujarati and Sangeetha, 2007). The model is one of the most protuberant methods in financial forecasting P. Pai and C. Lin (2005), N. Merh et. al (2010), N. Rangan and N. Titida (2006). ARIMA models have proven to be effective at forecasting in the short run. When it comes to short-term prediction, it consistently outperforms complicated structural models. et.al., A. Meyler (1998). The model is used either to better identify the data or forecast the future values. The ARIMA model can be expressed as:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \dots - \theta_q \epsilon_{t-q} \dots \dots \dots \text{Equ 1}$$

### Box-Jenkins Methodology

Box and Jenkins methodology consist of four steps method – identification, estimation, diagnostic and forecasting (G. Tabachnick and L.S. Fidell 2001) to opt for suitable ARIMA models to estimate and forecast univariate economic variables is shown in Figure 2

**Figure 2: Box-Jenkins Methodology**

Source: Gujarati and Sangeetha, 2007

**Stage I: Identification:** At this stage, first we have to find whether the time series data is stationary or not. If it is stationary, then we can't apply ARIMA model rather we can either use AR model or MA model or ARMA model. If the data is non-stationary then only we can apply ARIMA model (p,d,q) and determine the values of p, d and q. Here, p denotes to Autoregressive (AR) process, d denotes to integrated or differencing and q denotes to Moving Average (MA) process. Stationary means that the mean ( $\bar{X}$ ) and covariance (Cov.) of the time series do not depend on time

that is a stationary series have no trends. We can check stationary series by graph, correlograms and formal test like Dickey Fuller (DF) Test, Augmented- Dickey Fuller (ADF) Test and Phillips Perron (PP) Test. If the series is stationary, we use ARMA model else ARIMA. The main tools in identification are autocorrelation function (ACF), partial autocorrelation function (PACF) and the results of correlograms that is the plots of ACF and PACF against their lag length. ACF measures the MA process and PACF measures AR process.

**Stage II: Estimation:** This stage is a model selection criterion stage where we choose the most appropriate model by identifying the parameters of p(AR) and q(MA). There are two major approaches to fit the Box-Jenkins models that are maximum likelihood method and least square method. However, occasionally the model is complicated owing to non-linear estimation problem. In this stage we first check the significance of ARMA components then we must find the smaller value of Akaike Information criterion (AIC), Schwarz Bayesian Information criterion (SBIC) and Hannan-Quinn criteria to choose the parsimonious model that fits the data well. We also have to check the higher value of log likelihood to choose the best model.

**Stage III: Diagnostic Checking:** To test the appropriateness of the selected ARIMA model diagnostic checking is a necessitate step. In this stage we simply test the residual of the estimated model is white noise. If the residual is white noise, then we accept the particular model fit else we start over from the identification and estimation stages. Hence, the BJ method is an iterative process.

**Stage IV: Forecasting:** ARIMA model is one of the popular models for predicting the univariate economic variables based on lagged or past time series data. However, forecasting also depends on expert judgments that are based on chronological data along with experience. If the appropriate model is found satisfactory then the fitted model can be applied for forecasting.

### Data Source

The study has used NIFTY Metal Index closing prices from 1st Jan 2019 to 18th Jan 2022 to analyze and forecast the

metal prices. The data has been gathered from historical data reports of NSE indices.

### Limitations of the Study

ARIMA modelling has some limits when it comes to forecasting data. This technique is only used in a short run to detect slight data variations. It becomes difficult to capture the exact change in the data set (when the variation is big), in case of a change in government policies or economic instability (structural break), etc., and thus this model becomes ineffectual to forecast in this scenario. Asymmetric information, insider trading, and other oddities are also present and significantly affects the direction of market and may lead to inconsistency in behavior of market. Apart from this, personal bias of traders such as illusion of control, herding mentality, overconfidence, loss aversion, etc. may cause different direction in price movements. Effects of such factors are not taken into consideration while forecasting NIFTY metal price index.

- Forecasted period is only till 30th June 2022 as it is a daily data and can be forecasted only for short-term period because of volatility of the data.
- The study only forecasted the future value of Nifty Metal Index but did not identify the factors (determinants) which led to increase in Metal Price Index.

### Data Analysis and Interpretations

**Descriptive Statistics:** The descriptive statistics shown in Table 1 depicts that the minimum and maximum of NIFTY Metal Index closing prices are 6253.10 and 1496.45 respectively. The total number of original observations is 755, the average of NIFTY Metal Index closing prices is 3361.71 with a standard deviation of 1314.65. The skewness is 0.78 which is less than 1 and kurtosis is 2.16 which is less than 7 which shows that the data is normally distributed.

**Table 1: Descriptive Statistics**

<b>Mean</b>	3361.71	<b>S.D</b>	1314.65
<b>Median</b>	2874.90	<b>Skewness</b>	0.78
<b>Max</b>	6253.10	<b>Kurtosis</b>	2.16
<b>Min</b>	1496.45	<b>Total Observations</b>	755

Source: Author's Own Estimation

### Empirical Results

In this sub-section the study has shown the empirical results of the various stages of ARIMA model and further forecasting the Metal Index Closing Prices (MICP) for the period of 19th Jan 2022 to 30th Jun 2022.

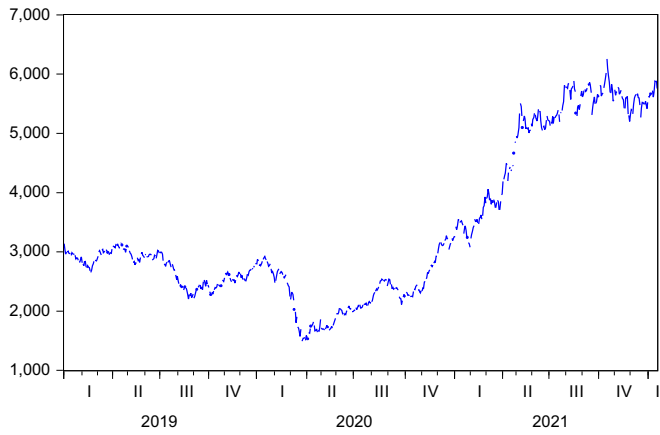
#### Stage I: Stage of Identification

In the identification stage as mentioned in sub-section 3.2, we have to first check whether the data is stationary or not. If the data is non-stationarity then only we can apply ARIMA model with differencing and further we have identify the p, d, q values as shown below:

#### (i) Stationary Check

At first, a time plot diagram has been used for NSE NIFTY Metal Index closing prices data from 1st Jan 2019 to 18th Jan 2022 shown in Figure 3. The data is a daily data and hence it shows huge volatility. Figure 3 clearly reveals that there is a decreasing trend in the third quarter of 2019 and then it starts increasing and again plummeted in the 1st and 2nd quarter of 2020 due to the noble coronavirus pandemic and worldwide lockdown. However, from the 4th quarter of 2020 onwards an uptrend in metal index prices with some fluctuations can be observed. The figure 3 clearly depicts that the time series data has shown an upward trend and hence, data is non-stationarity.

**Figure3: Time plot of NIFTY Metal Index Closing Price (MICP)**



Source: Author's Own Estimation

We further tested correlograms to check the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) shown in Figure 4. It clearly reveals that the ACF is declining continuously and PACF has dropped after the first lag which evidently shows that the time-series data is non-stationarity.

**Figure 4: Correlogram – ACF and PACF of Nifty MICP**

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	0.996	0.996	0.996	752.46	0.000
2	0.992	-0.059	0.023	1499.8	0.000
3	0.988	0.023	0.020	2242.1	0.000
4	0.985	0.020	0.017	2979.9	0.000
5	0.981	0.017	-0.009	3713.3	0.000
6	0.977	-0.009	-0.005	4442.2	0.000
7	0.974	-0.005	0.002	5166.7	0.000
8	0.970	0.002	-0.005	5888.7	0.000
9	0.966	-0.005	0.008	6602.2	0.000
10	0.963	0.008	0.019	7313.4	0.000
11	0.959	0.019	-0.014	8020.4	0.000
12	0.956	-0.014	0.004	8723.2	0.000
13	0.952	0.004	0.042	9421.9	0.000
14	0.949	0.042	-0.024	10117.0	0.000
15	0.946	-0.024	0.015	10808.0	0.000
16	0.943	0.015	-0.008	11495.0	0.000
17	0.939	-0.008	0.015	12178.0	0.000
18	0.936	0.015	-0.009	12857.0	0.000
19	0.933	-0.009	-0.018	13533.0	0.000
20	0.929	-0.018	0.010	14204.0	0.000
21	0.925	0.010	0.033	14871.0	0.000
22	0.922	0.033	-0.080	15534.0	0.000
23	0.918	-0.080	-0.043	16193.0	0.000
24	0.914	-0.043	0.040	16846.0	0.000
25	0.910	0.040	-0.014	17494.0	0.000
26	0.905	-0.014	0.017	18137.0	0.000
27	0.901	0.017	-0.022	18774.0	0.000
28	0.897	-0.022	0.008	19406.0	0.000
29	0.892	0.008	0.017	20033.0	0.000
30	0.888	0.017	-0.022	20655.0	0.000
31	0.884	-0.022	0.048	21272.0	0.000
32	0.881	0.048	-0.025	21885.0	0.000
33	0.877	-0.025	0.005	22494.0	0.000
34	0.873	0.005	0.016	23099.0	0.000
35	0.870	0.016	0.004	23699.0	0.000
36	0.867	0.004		24296.0	0.000

To further validate that the data is non-stationary we conducted Augmented Dickey Fuller (ADF) test and found that the p-value is >0.05 which denotes that we cannot reject null hypothesis of unit root and hence, the original NIFTY Metal Index closing price data is non-stationarity. Thus, ARIMA model can be best fitted in NIFTY Metal Index time-series data. To eliminate the non-stationary from the data we conduct first order differencing of the Metal Index Closing Price (MICP) data and again tested the ADF and found the p-value is <0.05 and hence, with first order differencing the data is transformed into stationarity.

**Stage II: Stage of Estimation**

The stationarity check reveals that the data is non-stationarity and hence, first order differencing has been conducted to transform the data into stationarity.

**Figure 5: ACF and PACF of first order differencing of Nifty MICP**

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	0.051	0.051	0.051	2.0025	0.157
2	-0.052	-0.054	-0.054	4.0180	0.134
3	-0.071	-0.066	-0.066	7.8420	0.049
4	0.069	0.074	0.074	11.441	0.022
5	0.061	0.047	0.047	14.230	0.014
6	-0.059	-0.064	-0.064	16.923	0.010
7	0.013	0.035	0.035	17.047	0.017
8	0.024	0.019	0.019	17.484	0.025
9	-0.047	-0.066	-0.066	19.180	0.024
10	-0.007	0.011	0.011	19.214	0.038
11	0.008	0.011	0.011	19.267	0.056
12	0.057	0.039	0.039	21.774	0.040
13	-0.045	-0.043	-0.043	23.363	0.038
14	0.000	0.020	0.020	23.363	0.055
15	-0.018	-0.026	-0.026	23.623	0.072
16	-0.006	-0.017	-0.017	23.656	0.097
17	0.011	0.017	0.017	23.743	0.127
18	0.019	0.021	0.021	24.011	0.155
19	0.045	0.036	0.036	25.548	0.143
20	0.035	0.041	0.041	26.509	0.150
21	0.002	0.008	0.008	26.513	0.188
22	0.053	0.053	0.053	28.719	0.153
23	0.047	0.044	0.044	30.457	0.137
24	0.094	0.086	0.086	37.315	0.041
25	-0.014	-0.010	-0.010	37.462	0.052
26	-0.040	-0.033	-0.033	38.740	0.052
27	0.016	0.024	0.024	38.934	0.064
28	-0.014	-0.032	-0.032	39.095	0.079
29	-0.028	-0.036	-0.036	39.725	0.089
30	-0.060	-0.045	-0.045	42.563	0.064

ARIMA model is used to analyze the past data and predict the future value in the series. The model is utilized when the data is recorded in regular intervals such as minute, daily, weekly, or monthly periods. Once the appropriate model has been identified, then it can be used to predict the future values grounded on past and present values of the time-series data. The econometric models have been able to assist the companies or investors to predict the future values of any stock and commodities which further helped them in decisions making. Based on the identification rules, the ARIMA model has been established with first order differencing. Further to determine the value of p(AR), d(1) and q(MA) we have tested correlogram on first differencing of Nifty Metal Index closing prices. The Figure 5 depicts the ACF and PACF where ACF measures the value of Moving Averages (q) and PACF measures the value of Autoregressive (AR).

**(ii) Fitted ARIMA Model**

Plotting of ACF and PACF of first order differencing on Nifty MICP shown in Figure 5 reflects the order of p and q. Based on ACF and PACF we have estimated four ARIMA models and selected the best fitted model to forecast the future metal prices. Table 2 shows the results of the estimated ARIMA models. From Table 2, we must choose the model with significant coefficient whose p-value is less than 0.05, highest Adjusted R-square which shows the model fit, maximum log likelihood and, minimum value of Akaike Information Criterion (AIC) and Schwarz Bayesian Information criterion (SBIC) which reflects the parsimony of the model. Based on the above criterion we found the best model is ARIMA(3,1,4).

**Table 2: Results of ARIMA Models of NIFTY Metal Index Closing Prices**

ARIMA Models	(2,1,2)	(3,1,4)	(4,1,4)	(30,1,30)
Log likelihood	<b>-4264.288</b>	-4258.264	-4253.888	-4110.066
Sig	0.040057	0.019808	0.044259	<b>0.000422</b>
Adj R sq	0.005907	<b>0.077850</b>	0.005657	0.018607
AIC	11.34917	<b>11.34824</b>	11.35170	11.36206
SBIC	11.36761	<b>11.36670</b>	11.37018	11.38106

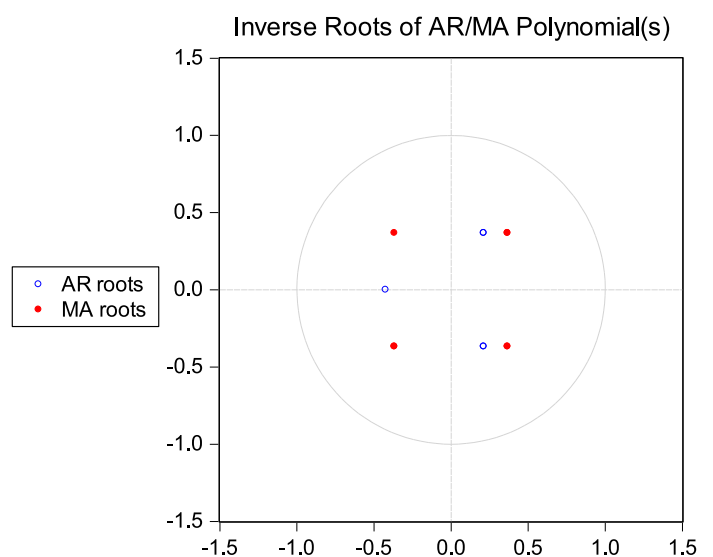
Source: Author's Own Estimation

**Stage III: Diagnostic Check: Correlogram of Residuals**

In order to validate that ARIMA (3,1,4) is the best fitted model to forecast Metal Price Index, the study conducted diagnostic check and tested correlogram of residuals. The study found that the lags of both PACF and ACF are within the level 95per cent confidence interval and therefore, the ARIMA (3,1,4) is the best fitted model and can be used for forecasting.

To further validate that the residuals of the selected model is White Noise, the study conducted Ljung-Box Q-statistic test by employing ARMA process shown in Figure 6. AR roots are used to check the stationary while MA roots are used to check invertibility. The ARMA process clearly reveals that both AR roots and MA roots of Nifty Metal Price Index lies within the circle. It denotes that the residuals are White Noise. Hence, the model is suitable to forecast the future value of NIFTY Metal Price Index.

**Figure 6: AR Roots and MA Roots of Nifty MICP**



Source: Author's Own Estimation



However, ARIMA is 'more an art than science', which means it's not a perfect model but depends on expert judgement.

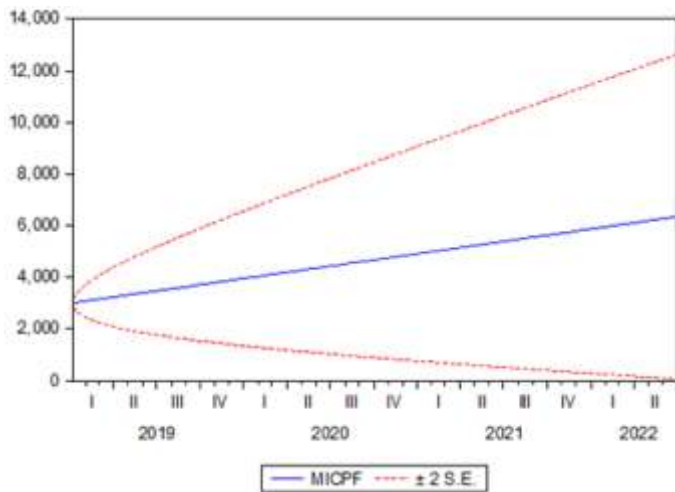
**Stage IV: Forecasting Stage**

Based on ARIMA (3,1,4) model the Nifty Metal Index closing price is predicted from 1/19/2022 to 06/30/2022 with 95 per cent confidence interval. The ARIMA (3,1,4) Model is expressed in equation 2 below:

$$Y_t = 3.667487 + 0.076450Y_{t-1} + 0.076450Y_{t-2} + \dots + 0.076450Y_{t-p} - 0.072703e_t - 0.072703e_{t-1} - 0.072703e_{t-2} - \dots - 0.072703e_{t-q} \text{ ----- Equ.2}$$

The Forecasting Graph of Nifty MICP shown in Figure 7 clearly reflects that the forecasted values of Nifty MICP (MICPF) indicated by blue line lies between ±2 Standard Errors (SE) denoted by red lines. Thus, the model accurately predicted the values of Nifty MICP. The forecasted MICP within the SE denotes that the predicted values of MICP are free from Standard Errors and hence acceptable to forecast.

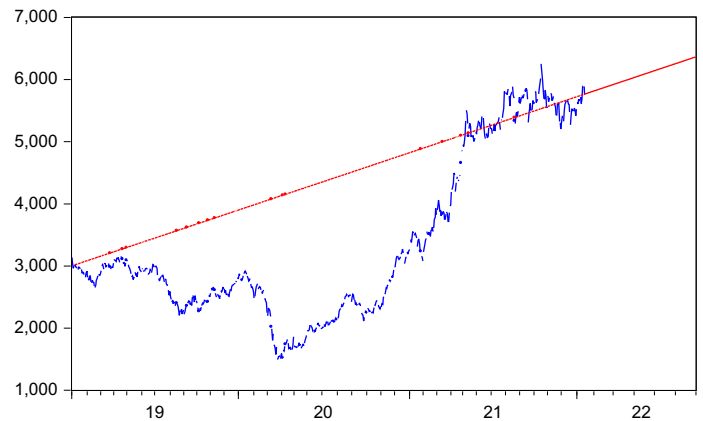
**Figure 7: Forecasting Graph of Nifty MICP**



Source: Author's Own Estimation

In Figure 8 the actual and forecasted values of Nifty MICP clearly reveals an uptrend of Metal Index Closing Prices during the forecasted period i.e. from 19th Jan 2022 to 30th June 2022. The figure clearly shows high fluctuations in the index which is owing to the daily data.

**Figure 8: Actual and Forecasted Graph of Nifty 50 closing prices**



Source: Author's own estimation

**Accuracy Check of Forecasted MICP**

To further strengthen the estimated results, we tested Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Theil Inequality Coefficient (TIC) shown in Table 3. All the above statistical tests are conducted to check the accuracy of the forecasted values. RMSE and MAE are estimated based on the errors between actual and predicted values. MAPE is used to measure the relative performance of the estimated value and lower the value of MAPE better the forecasted value while the TIC value should be less than 1 however, practically TIC value less than 0.55 are considered as good (Yorucu, 2003).

**Table 3: MAPE and TIC values of forecasted Nifty MICP**

Model Statistics	Nifty MICP
RMSE	70.19
MAE	50.22
MAPE	1.55
TIC	0.01

Source: Author's Own Estimation

The value of RMSE and MAE are 70.19 and 50.22. The MAPE value is 1.55 which is very low and TIC value is 0.01 which is much less than 0.55. The result shows that it is a good estimate and therefore, the forecasted value of Nifty MICP from 19th Jan 2022 to 30th June 2022 is realistic.

## Results and Discussion

The NIFTY Metal Index comprises 15 metal stocks listed in NSE which is constructed to identify the behaviour and performance of metal sector incorporating mining sector. Since the movement of Index is highly volatile therefore, it becomes necessary to manage risk to protect invested funds and to gain good returns. Forecasting of Index enables the investors to take appropriate decisions. The metal index is computed based on real time and hence, found high volatility. The time series data is found non-stationary and thus employed ARIMA model with first order differencing. The time plot of ACF and PACF have suggested the lag of 3 for AR(p) and 4 for MA(q). Hence, ARIMA(3,1,4) model is recommended to forecast the metal price index. The study has forecasted the value of Nifty MICP from 19th Jan 2022 to 30th June 2022.

## Conclusion and Implications

The study has analyzed the value of NSE Nifty MICP for the period of 1st Jan 2019 to 18th Jan 2022 and forecasted the value of metal price index from 19th Jan 2022 to 30th June 2022. The study has used Box-Jenkins's methodology popularly known as ARIMA model to examine and forecast univariate time series data. The original Nifty Metal index data is non-stationary and hence used first order differencing to make it stationary. In this study ARIMA(3,1,4) model has been found to be the best fitted model to analyze and forecast the Nifty MICP as the value of AIC and SBIC are the lowest. From the predicted values we further checked the accuracy of the forecasted model with MAPE and TIC values and found that the value of MAPE is low and TIC is less than 1 which reflects that the model is accurately predicting the Nifty MICP for the period between 19th Jan 2022 to 30th June 2022. The study found an increasing trend of Nifty MICP for the forecasted trading days. Hence, the study can help the investors and market regulators to take appropriate decisions based on the present analysis.

The study suggests the investors not to buy the metal stocks for the predicted trading days instead to sell the holdings of stocks and gain from rising prices.

## Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

**Funding :** The authors received no financial support for the research, authorship and/or publication of this article.

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#### End Notes:

1. National Stock Exchange of India Limited (NSE) is the leading stock exchange of India, located in Mumbai, Maharashtra, has a total market capitalization of more than US\$3.4 trillion, making it the world's 10th-largest stock exchange as of August 2021.