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Forecasting Nifty Using Autoregressive Integrated Moving Average Model

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JEL Classification

C2, C22, C5, C53, C87

Abstract: The study focuses on the forecasting capability of Auto Regressive Integrated Moving Average model for the nifty 50 index and how far the econometric models are dependable to prognosticate stock market indices. For this purpose, data have been collected from 15 June 2020 to 28 Jan 2022 Based on these data, forecasting is made from 18 Jan2022 to 28 Jan 2022. The series is converted into 1st difference as level data is not stationary, After making it stationary for nifty the researcher determines AR (p) lag and MA (q) lag through ACF and PACF tests. The ARIMA (1, 1, 3) model is accepted as the model that fulfills parsimony as this model having maximum significant variable, sigma square is minimum and Adjusted r^2 is maximum and AIC (Akaike info criterion) and SIC (Schwarz criterion) are minimum. The E-views 10 software package is used for ARIMA analysis. At last, it is seen that the ARIMA is not capable of forecasting data for a long period of time as time progresses it tends to forecast inaccurately. The investor cannot solely depend upon this model for their investment in securities market. Rather they must use other technical analysis tools.

1. Introduction

In a country like India a few people are investing their hard earned money in securities market but, there is always curiosity amongst the retail investors to predict the market index for a specific time period. In this approach, the econometric model plays a pivotal role in forecasting stock market indexes for a short duration. After India adopted LPG (liberalization, privatization, and globalization) in 1991 after that a lot of reforms took place and SEBI was set up in order to control securities market in a proper manner (Pandey *et al.*, 2021). While we talk about stock market in the Indian context, we basically concentrate on Nifty and Sensex.

The index of Bombay Stock Exchange is known as Sensex which comprises of top 30 (market capitalization) scripts, which are actively traded. Created in 1986, the Sensex is the oldest stock index in India and is operated by Standard & Poor's (S&P). Another popular index in India is Nifty, which is the benchmark index of national stock exchange. It comprises 50 stocks of large companies according to market capitalization. The nifty was launched on 22 April 1996. Since its inceptions, the nifty has delivered around 17 percent returns. It is surprising to note that the nifty index, which was 1000 base in November 1995 grew to 17000 in the year 2022 for the month of January. So for a layman there is always a keenness in his/her mind as to what will be the change in the forthcoming week or month so that a retail investor can buy or sale a securities at optimum price/a premium (Pandey *et al.*, 2020).

Many technical tools and econometric models are there to predict the nifty index .The Box-Jenkins model, i.e., ARIMA is quite a famous tool for prediction. Univariate time series models are so unique, where the econometricians make models and forecast financial variables by using only facts contained in their own past values and possible current as well as past values of an error term. The time series models are an attempt to capture empirically relevant features of the observed data that may have arisen from a variety of different structural models. An important class of time series model is the family of Autoregressive Integrated Moving Average (ARIMA) model which was developed by Box and Jenkins, the noble laureates in the year 1976. Time series models are widely accepted when structural models fail. When data is arranged in time wise like daily, weekly or monthly basis, the researchers use (ARIMA) autoregressive integrated moving average. It is an extension of Autoregressive Moving Average Model .The only difference between the two models is that in the case of ARMA, the data is stationary at level but in the case of ARIMA the data are stationary at 1st difference.

2. Review of Literature

Reliance, TCS, HDFC and INFOSYS from 2010 to 2020, data has been collected and applied various statistical tools like correlation, ARIMA, Monte Carlo simulation and compounded annual growth rate for detecting relationships and tried to forecast the prices of above securities using ARIMA But they conclude that the share price was not following linearity so they suggested that one should follow non-linear model (Jackson *et al.*, 2021).

Pathak and Kapadia (2021) forecasted the nifty index by using data of the preceding 5 years (September 2015 to September 2020) and they found that ARIMA model was quite capable of predicting for a short period of time and they found that ARIMA was quite capable of forecasting data for short period of time.

Kulkarni *et al.* (2020) attempted to forecast the future price of Infosys shares using ARIMA model by R programming language. In their paper, Data of Infosys share price had collected from 2007 to 201 and data (2007-2014) used for ARIMA fitted sample on the basis of above data the model trying to forecast Infosys share price from 2014 to 2015 and the authors found that ARIMA was quite capable to predict share price for a short term. Vikram *et al.* (2022) have analyzed the volatility of Indian stocks using GARCH model and identified the least volatile stocks of Indian exchange.

Agustin (2019) collected data of Indonesia stock index from jan2017 to feb2019 and applied ARIMA model after they concluded that ARIMA (1,1,1) model was best having 78% accuracy. Huang (2019) had revealed that ARIMA model was quite capable of forecasting whether American market is efficient or not. In his studies, he compared Random Walk Model and ARIMA model and MDM test. Later he found that ARIMA was quite capable of forecasting US market. He had experimented these above models on data of daily returns of S&P 500 Index starting from October 19th, 1988 to October 18th 2018.

Koulis *et al.* (2018) collected data starting from 4th Jan (2010) to 31st December (2015) and applied ordinary least square method, error correction model, ARDL model for risk management. The researcher found that varying hedge ratio was more important rather than fixed hedge ratio. Almasarweh and Wadi (2018) had taken banking data from Amman Stock Market in Jordan and tested the ability of ARIMA in forecasting banking data. In their article, the authors collected data of 2000 observations between 1993 and 2017 and applied ARIMA model. It had been seen that ARIMA(1,1,2) model having 1.4 root mean square error was the best model, further the researchers concluded that ARIMA was best for short term prediction.

The combination of ARIMA and ANN(Artificial Neural Network) will provide robust results as compared to independent use of ARIMA model (Babu & Reddy, 2014). The researchers tried to monitor accuracy of results in both ARIMA and ANN independently and jointly subsequently they found that the combination of ARIMA and ANN was more powerful rather than the single model of ARIMA or ANN.(Babu and Reddy, 2014)

Emenike (2012) had attempted to forecast index of Nigerian Stock Exchange by ARIMA model. In his research the researcher had collected data on monthly basis beginning from the year (1985) to December (2008) for fit sample whereas January 2009 to December 2009 for forecast sample .He found that ARIMA model failed to predict accurately during the period of Jan 2009 to December 2009 as it was the time period of Lehman Brother crisis. (Emenike, 2012)

Devi *et al.* (2012) the researcher had collected data of nifty50 index, Reliance, Ofss, Abb and JSW Steel from 2007 to 2011.the author used ARIMA and MAPE, PMAD and % error accuracy to discriminate between actual data and forecasted data, later they found that MAPE was more in JSW steel and PMAD is more in case of ABB further % of error accuracy in ABB followed by reliance. Balsara *et al.* (2007) found that the ARIMA model was capable to forecast accurately than the naive model. In their study the authors collected data of 2 categories of share price (class A and class B) of Shanghai Stock Exchange on daily basis from 1991 to 2005 and then applied ARIMA model to forecast the future price of the script by adopting both the naive model and ARIMA model. Later they discovered that ARIMA outperformed the naive model considerably

3. Objective and Hypothesis of the Study

3.1. Objective of the Study

The main focus of this paper is to see how far the Auto Regressive Integrated Moving Average Model is able to predict Nifty index for a short period of time.

3.2. Hypothesis of the Study

H_{01}: ARIMA model is not capable of predicting NIFTY for shorter period of time.

4. Research Methodology

The primary objective of the ARIMA model is to forecast for future on the basis of past data. ARIMA is a time series model which is widely used in finance and economics for prediction. This model used time series data to forecast future and also detect autocorrelation in the respective data. This model is a stochastic modeling approach which can be used to forecast the chances of future value lying in the overall confidence limit. The utmost necessary for ARIMA model is that the variable must be in stationary. Unlike traditional regression model, in ARIMA model Y_t the dependent variable has to be explained by the previous or lagged values of Y_t itself and the lagged value of e_t, which becomes uncorrelated random error term having arithmetic mean zero and fixed variance i.e a white noise error term.

ARIMA consists of two words AR and MA. AR means autoregressive and MA means moving average. In AR the independent variables are lagged dependent variables. There are no other independent variables.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + e_t$$

Here Y_t – It refers to the dependent variable

$Y_{t-1,}$ Y_{t-2} - These are different lags of dependent variable included as independent variable in the model

β_1 and β_{2-} these are coefficients of independent variables.

α- it is a slope or intercept or constant in the model

e_t –Error tem in the model

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_{2t-2} \ldots\ldots\ldots\ldots \beta_p Y_{t-p} + e_t$$

This is called AR order of p i.e. AR (P).

MA stands for moving average. In this we used lag error terms as independent variables.

$$Y_t = \alpha + \beta_1 e_{t-1} + \beta_2 e_{t-2} \ldots\ldots\ldots\ldots \beta_q e_{t-q} + e_t$$

In the above equation, q is the different lag error terms are used as independent variable. Independent variable $e_{t-1,\ \text{through}}$ e_{t-1} is uncorrelated error terms. Moving average models are abbreviated MA(q) as "q" has the number of lagged error terms present in the time series data. The name moving average comes from the fact the moving average of past error term with the mean of dependent variable to produce a moving average of the dependent variable. In ARIMA the word "I" stand for integrated i.e. the data must be stationary if it is not we have to make it stationary by taking the first difference, i.e., denoted by I(1).

The ARMA model equation is as follows

$$Y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_p y_{t-p} + e_t + \omega_1 e_{t-1} + \omega_2 e_{t-2} + \omega_q e_{t-q}$$

α – it is a constant

$(\beta_1 .. \beta_{p)}$- These are the coefficients of lag value of the dependent variable

$Y_{t-(1\ldots.p)}$- these are the numbers of lag of the dependent variable

E_t- error term

$E_{\ (t-(1\ldots q))}$- these are the numbers of lag for error term

$\beta(_{1..q})$ – Coefficient of error term on different lag

For determination of p and q for AR and MA, the author had conducted ACF and PACF tests. The ARIMA model has been discussed in four head

- Identification
- Estimation
- Diagnostic Test
- Forecasting

5. Data Analysis

The author has collected data for the nifty index from 15-6-2020 to 28-1-2022. The data is secondary in nature. Here the author has taken only 2 years data for forecasting as ARIMA model is only used for short term prediction. To use ARIMA model we have to see whether the variable is stationary or not as the nifty data is not stationary in level so we have to take 1st difference to became stationary. Stationary is an important condition of an ARIMA model for several reasons. One important reason is that a model whose coefficients are non-stationary will exhibit the unfortunate property that the effect of previous value of error term will have an impact on the recent value of Yt as time progresses.

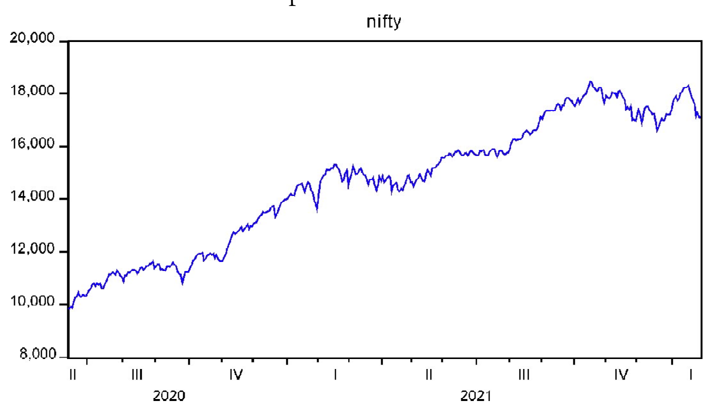


Figure 1: Nifty at Level

Source: Author's Own Compilation

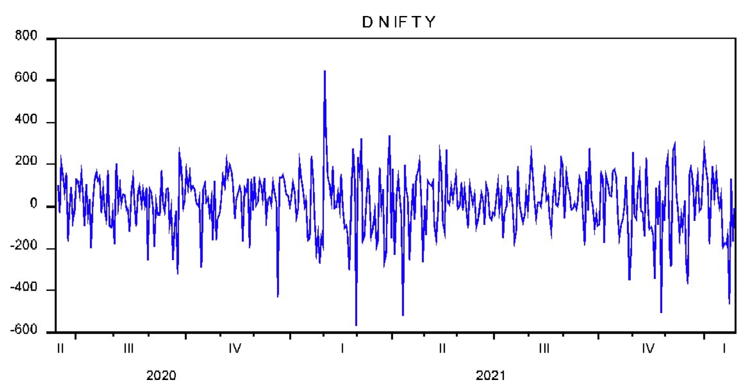


Figure 2: Nifty at 1st Difference

Source: Author's Own Compilation

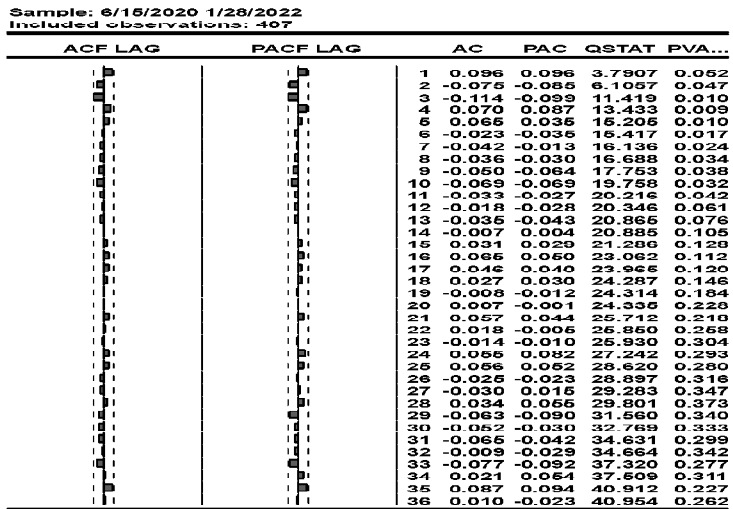
In figure 1 it is clearly visible that nifty is not stationary rather it is in trend but while we are taking 1st difference data it became stationary in figure2

Table 1: Unit Root Test for Level Data and for 1st Difference Data

Level Data	*Level of significance*	*t-Statistic*	*Prob.**
Augmented Dickey-Fuller test statistic		-1.6214	0.4707
Test critical values:	1% level	-3.4464	
	5% level	-2.8685	
	10% level	-2.5705	
1st Difference Data			
Null Hypothesis: D(NIFTY) has a unit root			
		t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic		-10.034	0
Test critical values:	1% level	-3.981	
	5% level	-3.421	
	10% level	-3.1332	

Source: Author's Own Compilation

The nifty is not stationary at level. It is confirmed form the Augmented Dickey Fuller test as the p value is .4707 which is more than .05 so we accept null hypothesis that series is not stationary so to become stationary the variable must be converted into 1st difference. From Table-1 it has been shown that the variable NIFTY is stationary at 1st difference as the probability value is 0 which is less than .05 so null hypotheses is rejected and the series has no unit root. Now we can proceed further for determination of correllagram for fixing the value of "p" and "q" for autoregressive lag and moving average lag. In order to proceed further AR and MA lag the partial auto correlation function (PACF) and auto correlation function (ACF) are used. PACF gives correlation between the dependent variable and its lag value while keeping the shorter lag constant. The first correlation value for Y_t and Y_{t-1}, second one is Y_t and Y_{t-2} then Y_t & Y_{t-3} and so forth. The correlation between Y_t and Y_{t-2} does not include the effect of Y_t&Y_{t-1}.Due to this reason it is known as partial auto correlation function. ACF is different from PACF used with autoregressive model. It gives correlation coefficient between the dependent variable and the same variable with different lag, but the effect of shorter lag is not kept constant. This means that the effect of shorter lag is included in the numbers given with autocorrelation function. The correlation among current dependent variable and its second lag include the effect of correlation between current dependent variable and its first lag. This is the opposite of PACF.

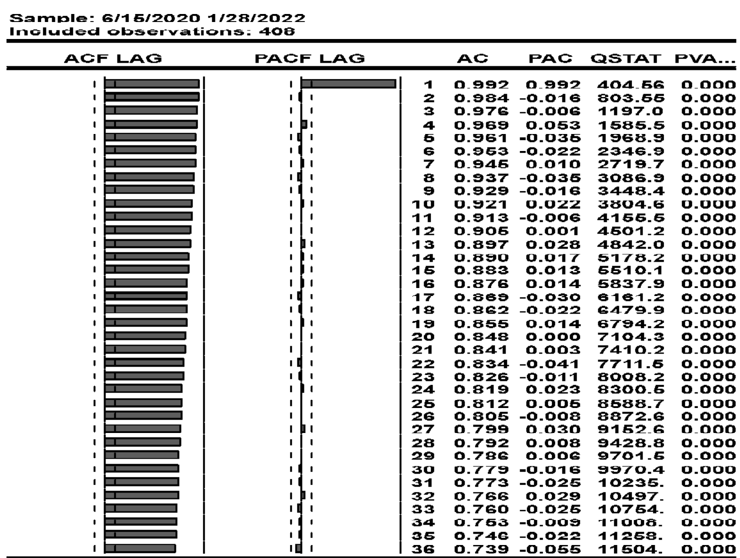


Sample: 6/15/2020 1/28/2022
Included observations: 407

ACF LAG	PACF LAG		AC	PAC	QSTAT	PVA...
		1	0.096	0.096	3.7907	0.052
		2	-0.075	-0.085	6.1057	0.047
		3	-0.114	-0.099	11.419	0.010
		4	0.070	0.087	13.433	0.009
		5	0.065	0.035	15.205	0.010
		6	-0.023	-0.035	15.417	0.017
		7	-0.042	-0.013	16.136	0.024
		8	-0.036	-0.030	16.688	0.034
		9	-0.050	-0.064	17.753	0.038
		10	-0.069	-0.069	19.758	0.032
		11	-0.033	-0.027	20.216	0.042
		12	-0.018	-0.028	20.346	0.061
		13	-0.035	-0.043	20.865	0.076
		14	-0.007	0.004	20.885	0.105
		15	0.031	0.029	21.286	0.128
		16	0.065	0.050	23.062	0.112
		17	0.046	0.040	23.965	0.120
		18	0.027	0.030	24.287	0.146
		19	-0.008	-0.012	24.314	0.184
		20	0.007	-0.001	24.335	0.228
		21	0.057	0.044	25.712	0.218
		22	0.018	-0.005	25.850	0.258
		23	-0.014	-0.010	25.930	0.304
		24	0.055	0.082	27.242	0.293
		25	0.056	0.052	28.620	0.280
		26	-0.025	-0.023	28.897	0.316
		27	-0.030	0.015	29.283	0.347
		28	0.034	0.055	29.801	0.373
		29	-0.063	-0.090	31.560	0.340
		30	-0.052	-0.030	32.769	0.333
		31	-0.065	-0.042	34.631	0.299
		32	-0.009	-0.029	34.664	0.342
		33	-0.077	-0.092	37.320	0.277
		34	0.021	0.054	37.509	0.311
		35	0.087	0.094	40.912	0.227
		36	0.010	-0.023	40.954	0.262

Figure 3: Correlogram of Nifty at Level

Source: Author's Own Compilation



Sample: 6/15/2020 1/28/2022
Included observations: 408

ACF LAG	PACF LAG		AC	PAC	QSTAT	PVA...
		1	0.992	0.992	404.56	0.000
		2	0.984	-0.016	803.55	0.000
		3	0.976	-0.006	1197.0	0.000
		4	0.969	0.053	1585.5	0.000
		5	0.961	-0.035	1968.9	0.000
		6	0.953	-0.022	2346.9	0.000
		7	0.945	0.010	2719.7	0.000
		8	0.937	-0.035	3086.9	0.000
		9	0.929	-0.016	3448.4	0.000
		10	0.921	0.022	3804.6	0.000
		11	0.913	-0.006	4155.5	0.000
		12	0.905	0.001	4501.2	0.000
		13	0.897	0.028	4842.0	0.000
		14	0.890	0.017	5178.2	0.000
		15	0.883	0.013	5510.1	0.000
		16	0.876	0.014	5837.9	0.000
		17	0.869	-0.030	6161.2	0.000
		18	0.862	-0.022	6479.9	0.000
		19	0.855	0.014	6794.2	0.000
		20	0.848	0.000	7104.3	0.000
		21	0.841	0.003	7410.2	0.000
		22	0.834	-0.041	7711.5	0.000
		23	0.826	-0.011	8008.2	0.000
		24	0.819	0.023	8300.5	0.000
		25	0.812	0.005	8588.7	0.000
		26	0.805	-0.008	8872.6	0.000
		27	0.799	0.030	9152.6	0.000
		28	0.792	0.008	9428.8	0.000
		29	0.786	0.006	9701.5	0.000
		30	0.779	-0.016	9970.4	0.000
		31	0.773	-0.025	10235.	0.000
		32	0.766	0.029	10497.	0.000
		33	0.760	-0.025	10754.	0.000
		34	0.753	-0.009	11006.	0.000
		35	0.746	-0.022	11258.	0.000
		36	0.739	-0.055	11504.	0.000

Figure 4 : Correlogram at 1st Diffrence

Source: Author's Own Compilation

In the correlogram diagram the index of nifty at level data having ACF(Auto correlation function) and PACF(Partial auto correlation function) of different lag lies outside the confidence limit in figure number 3 but while we taking 1st difference the lag structure are within the bounds limit in figure number 4. So looking at DNIFTY correlogram, the possible models for ARIMA are (1,1,1), (2,1,1), (3,1,1), (1,1,3), (2,1,3); but among 5 ARIMA structure we have to choose the best model. The model parsimony define the best having maximum significant variable, sigma square is minimum and Adjusted r^2 is maximum and AIC (Akaike info criterion) and SIC (Schwarz criterion) is minimum. Different models with regression output are as follows.

6. Result and Discussion

6.1. Model Identification

Table 2: Model (1)

Dependent Variable: D(NIFTY)
Method: ARMA

Variable	*Coefficient*	*Standard Error*	*t-Statistic value*	*Probability*
Constant	21.32067	8.061464	2.644764	0.0085
AR(1)	-0.188986	0.440552	-0.428976	0.6682
MA(1)	0.292498	0.432026	0.677037	0.4988
SIGMASQ	19453.4	976.8399	19.91463	0
		Test Results		
R^2	0.011028	AIC		12.73373
Adjusted R^2	0.003517	SIC		12.77372

Source: Author's Own Compilation

In model (1) table 2 it reveals that AR(1) and MA(1) has not significantly contributed as p value is more than .05 and also t value is less than2. In this model neither the previous value of nifty nor the

Table 3: Model (2)

Dependent Variable: D(NIFTY)
Method: ARMA

Variable	*Coefficient*	*Standard Error*	*t-Statistic value*	*Probability*
Constant	21.30751	7.366469	2.8925	0.004
AR(2)	-0.099972	0.047642	-2.098401	0.0365
MA(1)	0.082394	0.042518	1.937853	0.0534
SIGMASQ	19298.17	1014.554	19.02133	0
		Test Results		
R^2	0.018919	AIC	12.72576	
Adjusted R^2	0.011468	SIC	12.76575	

Source: Author's Own Compilation

error term previous value has significant impact for prediction. AR (1) contributing negatively as the coefficient value is -0.188986 but MA (1) contributing positively. Adjusted R^2 value is quite less so model is not acceptable.

In table 3 model 2 the AR(2) contributing negatively (-.099972) while MA(1) has positive effect but AR(2) is significant as p value is less than .05 on the other hand MA(1) have no significant effect. The adjusted r^2 value is .011 so it is more effective as compared to model1.

Table 4: Model (3)

Dependent Variable: D(NIFTY)
Method: ARMA

Variable	*Coefficient*	*Standad Error*	*t-Statistic value*	*Probability*
Constant	21.25114	7.275124	2.921069	0.0037
AR(3)	-0.134646	0.046961	-2.867197	0.0044
MA(1)	0.102389	0.042345	2.417973	0.0161
SIGMASQ	19128.65	1033.219	18.51364	0
		Test Results		
R2	0.027538	AIC	12.71703	
Adjusted R2	0.020152	SIC	12.75702	

Source: Author's Own Compilation

In table 4 model(3) it shows that all the variable are significant as the p value is less than .05 and the constant, MA(1) are contributing positive effect on nifty on the other hand AR(3) have negative effect on nifty. Adjusted R^2 is .020 so is quite effective as compared to model 1 and model 2.

Table 5: Model (4)

Dependent Variable: D(NIFTY)
Method: ARMA

Variable	*Coefficient*	*Standard Error*	*t-Statistic value*	*Probability*
Constant	21.18988	7.077473	2.993989	0.0029
AR(1)	0.083449	0.042261	1.974601	0.049
MA(3)	-0.149554	0.046649	-3.205958	0.0015
SIGMASQ	19125.62	1046.973	18.26754	0
		Test Results		
R2	0.027692	AIC		12.7169
Adjusted R2	0.020307	SIC		12.75689

Source: Author's Own Compilation

In model 4 table 5 the AR (1) and MA (3) and constant all are significant as the variables probability values are less than .05. MA (3) has negative effect on dependent variable while other are positive effect. The adjusted r^2 value is .020 it is quite high among the above model.

Table 6: Model (5)

Dependent Variable: D (NIFTY)
Method: ARMA

Variable	*Coefficient*	*Standard Error*	*t-Statistic value*	*Probability*
Constant	21.16138	6.050285	3.497584	0.0005
AR(2)	-0.090621	0.048446	-1.870557	0.0621
MA(3)	-0.137016	0.047293	-2.897195	0.004
SIGMASQ	19104.85	1063.554	17.96322	0
		Test Results		
R2	0.028748	AIC	12.71581	
Adjusted R2	0.021371	SIC	12.7558	

Source: Author's Own Compilation

In model 5 it is clear that constant have positive contribution while AR (2) and MA (3) is negative contribution towards dependent variable. AR(2) probability value is .06 which more than .05 on the other hand other variable are significant as their p value are less than 0.05.

6.2. Model Estimation

Table 7: Different Model

Arima Model	*(1,1,1)*	*(2,1,1)*	*(3,1,1)*	*(1,1,3)*	*(2,1,3)*
Significant Coefficent (max)	0	1	2	2	1
SIGMASQ (MIN)	19453.4	19298.17	19128.65	19125.62	19104.85
ADJ R2 (MAX)	0.003517	0.011468	0.020152	0.020307	0.021371
AIC(MIN)	12.73373	12.72576	12.71703	12.7169	12.71581
SIC(MIN)	12.77372	12.76575	12.75702	12.75689	12.7558

Source: Author's Own Compilation

From the figure Table 7 it is confirm that ARIMA (1,1,3) model is the best model as it follows parsimony. Besides this model has maximum significant coefficient, minimum sigma square, maximum adjusted r^2, AIC and SIC is minimum.

As per ARIMA (1, 1, 3) model the nifty equation will be as follows.

Nifty (Dy_t) = $21.18988+0.083449(y_{t-1}) +(-0.149554)_{et-3}+e_t$

6.3. Diagnostic Test

After deciding the model we have to check the error term for (1,1,3) model and it should be stationary. The stationary of error term can be checked through conventional unit root test or Q statistics.

Table 8: Unit Root Test for Error Series

H_0: Residual has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, max lag=17)

	Level of Significance	*t-Statistic*	*Prob.**
Augmented Dickey-Fuller test statistic		-19.9627	0
Test critical values:	1% level	-3.44624	
	5% level	-2.86844	
	10% level	-2.57051	

Source: Author's Own Compilation

In Table 8 as the probability value is less than .05 of unit root test for residuals so the null hypothesis is rejected error term has stationary.

6.4. Forecasting

Here the researcher tries to forecast nifty from 18-1-2022 to 28-1-2022 on the basis of sample data ranging from 15-6-2020 to 17-1-2022. The forecasted nifty versus actual nifty is as follows.

Table 9: Comparison of Actual Nifty with Forecast

Date	*Actual*	*Forecast*	*Mean % Error*
18-Jan-22	18113.05	18325.8865	-1.17505
19-Jan-22	17938.4	18350.7709	-2.29882
20-Jan-22	17757	18364.0725	-3.41878
21-Jan-22	17617.15	18384.6041	-4.35629
24-Jan-22	17149.1	18405.739	-7.32773
25-Jan-22	17277.95	18426.9243	-6.64995
27-Jan-22	17110.15	18448.1138	-7.81971
28-Jan-22	17101.95	18469.3037	-7.99531

(MEAN % ERROR) = ((ACTUAL – FORECAST)/ACTUAL*100)

Source: Author's Own Compilation

From table 9 it is confirmed that mean percentage error is increasing as time progress. The error percentage is -1.17 and -2.29 on 18th and 19th January but it became-7.81 and -7.99 on 27th and 28th January 2022.

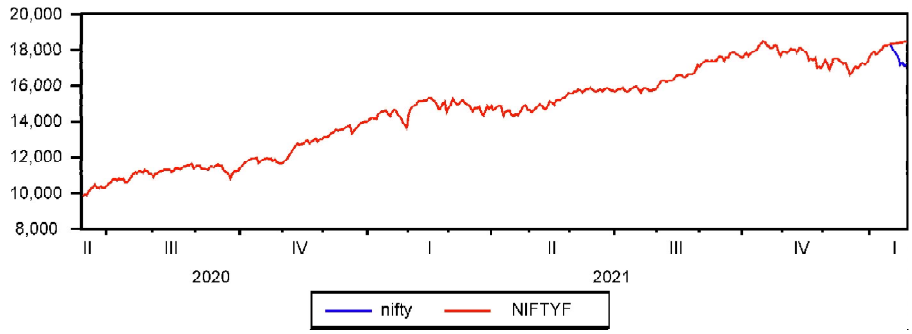


Figure 5: Nifty and Forecast Nifty Diagram

Source: Author's Own Compilation

From the figure 5 it is confirmed that ARIMA model is able to forecast nifty accurately for shorter period only. As the time progresses the chances of error increase. In this studies the error of 5% cover from 18-1-2022 to 21-1-2022 but after that margin of error significantly rises from 5% above and touch 7.99%.(24-1-2022 to 28-1-2022)

7. Conclusion

The paper concludes that the ARIMA model is not able to prognosticate nifty indicators directly (H_1) and as time progress ARIMA fails to handle the stock market volatility. The predicted result has compared with actual result later it is seen that as the time progress the error percentage is increasing. It is suggested that ARIMA model must be used in confluence with another econometric model or with artificial intelligent (ANN) so that this ARIMA model may be suitable. Further it is suggested that the investor or trader should not use this model solely for their investment. As the stock market is largely unpredictable it is better to use ARCH (Auto Regressive Conditional Hetroscedasticity) or GARCH (Generalized Autoregressive Conditional Hetroscedasticity) model for better prophecy. The biggest problem in the case of ARIMA model is that it assume future will be continue on the base of history. Thus, this model is unable to function when there is a fiscal shock or market crash. During the time of the 2008 US financial crash this model was unable as there was an unforeseen fall in the market.

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