THE INTERNATIONAL JOURNAL OF BUSINESS & MANAGEMENT

Precision in Predicting the Stock Prices – An Empirical Approach to Accuracy in Forecasting

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Abstract:
Forecasting the future prices of stock by analyzing the past and current price movements in determining the trend are always areas of interest of chartists who believe in studying the action of the market itself rather than the past and current performances of the company. Stock price prediction has ignited the interest of researchers who strive to develop better predictive models with a fair degree of accuracy. The autoregressive integrated moving average (ARIMA)model introduced by Box and Jenkins in 1970has been in the limelight in econometrics literature for time series prediction, which has been at the core of explaining many economic and finance phenomena. ARIMA models in the research domain of finance and economics, especially stock markets, have shown efficient capability to generate short-term forecasts and have hence been able to outperform complex structural models in short-term prediction.
This paper presents stock price predictive model using the ARIMA model to analyze the sensitivity of such models to different time horizons used in estimation of trends and verifies the validity of such forecasts in terms of their degree of precision. Published historical stock data, on an actively traded public sector bank's share and historical movements in the banking sector index in which the selected bank is a constituent, obtained from National Stock Exchange(NSE), India and websites of Yahoo finance are used to build and develop stock price forecasts and index movement predictive models. The experiments with dynamic as well as static forecasting methods used revealed that the ARIMA model has a strong potential for short-term prediction and can offer better precision than from long term trend estimates. As a stock price prediction or index movement forecast tool, it can be relied extensively in deciding entry and exit to and from the volatile markets, notwithstanding the fact the risk the investor faces on account of noise or shocks still can be erroneous making the entire prediction irrespective of its degree of precision irrelevant.

Keywords: *ARIMA model, forecast precision, price prediction, Short-term trend, projected index*

1. Introduction

Reading the stock market rightly in predicting future prices will be rewarding as far as an investor who holds a specific stock or a potential investor who plans to buy a particular stock are concerned. However, predicting the future prices is not an easy task. Forecasting the future prices by analyzing the past and current price movements in determining the trend are always areas of interest of chartists who believe in studying the action of the market itself rather than the past and current performances of the company. Traditionally price and volume are considered to be indicators of investor's attitude and intensity of changes in such attitude. Stock prices forecasting, still an area of continued research attempts to resolve many complex market undercurrents in arriving at reliable predictions.

Various techniques of predicting future stock prices currently used by analysts' falls broadly into the two categories of statistical perspective and artificial intelligence perspective. The artificial neural networks (ANN) belonging to the latter category is believed to be superior in terms of studying the behavior of patterns from stochastic movements of price data so as to infer the probable past movements. Despite the significance of artificial intelligence methods and other statistical models such as Regression, exponential smoothing and generalized autoregressive condition heteroskedasticity (GARCH), Autoregressive integrated moving averages (ARIMA) models, from the statistical perspective cannot be undermined or overlooked when it comes to its capability of identifying, estimating and diagnosing time series data [1].

Besides the statistical data from auditors reports, profit and loss statements, balance sheets, dividend records and policies of the company, on which the fundamentalists rely on, the demand supply equation of stock price determination is affected by other factors such as differing value opinions of security appraisers, fears, guesses and moods, both rational and irrational of hundreds of potential buyers and sellers as well as their needs and resources [4]. Stock prices are not randomly generated values rather they can be treated as

a discrete time series model and its trend can be analyzed accordingly, hence can also be forecasted. There are various motivations for stock forecasting, one of them is financial gain. A system that can identify which companies are doing well and which companies are not in the dynamic stock market will make it easy for investors or market or finance professionals make decisions [12].
The technically known ARIMA methodology, popularly known as the Box-Jenkins methodology emphasizes not on constructing a single equation or simultaneous equation models but on analyzing the probabilistic or stochastic properties of economic time series on their own under the philosophy, let the data speak for themselves. ARIMA models are sometimes called a theoretic model because they are not derived from any economic theory – and economic theories are often the basis of simultaneous equation models [5].
This paper attempts to present an extensive process of building ARIMA models for long term and short-term stock price prediction in a most actively traded scrip in Indian Stock markets, besides measuring the accuracy of the prediction capability of the model. The results obtained from real-life data relating to a banking sector company in India demonstrated the potential strength of ARIMA models to provide investors reasonably good prediction that could aid investment decision making process.
The rest of the paper is organized as follows. Section 2 discusses other related works and their findings in the form of review of literature. Section 3 sets out the objectives while section 4explains the methodology adopted in the conduct of the study. Section 5is devoted to the overview of ARIMA model and section 6 discusses the experimental results and inferences obtained, before concluding the paper insection 7.

2. Review of Literature

Various techniques of stock price forecasting have been extensively used by researchers and use of econometric models for prediction has been the topic of many studies and research articles. The available literature on economic forecasting points out fascinating findings on commodity production and prices such as sugarcane production by Kumar, M., & Anand, M. (2014))[9], Oil Palm prices by Rangan N and Titida N.,(2006) [14], currency prices by Tlegenova, D. (2015)[16],Foreign exchange rates - Babu AS, Reddy SK (2015) [2] and macroeconomic indicators such as GDP by Maity Bipasha and Chatterjee Bani (2012) [11] or unemployment levels by Nkwatoh Sevitenyi Louis (2012) [13] besides the stock prices.
Justel A et al. (2001) [8] confined their studies to identification of outliers in an auto regressive process and observes that masking and swamping effects caused by multiple outliers can be effectively handled by Gibbs Sampling followed by an adaptive procedure with block interpolation to handle patches of outliers.
Kumar Suresh KK and Elango N.M (2011) [10]examined and applied different neural classifier functions by using the Weka tool. Using correlation coefficient, they compared various prediction functions, and found that Isotonic regression function offer the ability to predict the stock price of NSE more accurately than the other functions such as Gaussian processes, least mean square, linear regression, multilayer perceptron, pace regression, simple linear regression and SMO regression.
Ly Pham (2012) in the L-Stern Group study [6] observes that ARIMA model focuses on analyzing time series linearly and it does not reflect recent changes as new information is available. Therefore, in order to update the model, users need to incorporate new data and estimate parameters again. The variance in ARIMA model is unconditional variance and remains constant. ARIMA is applied for stationary series and therefore, non-stationary series should be transformed (such as log transformation). Additionally, ARIMA is often used together with ARCH/GARCH model. ARCH/GARCH is a method to measure volatility of the series, or more specifically, to model the noise term of ARIMA model. The forecast interval for the mixed model is closer than that of ARIMA-only model. Yue Xu Selene (2012) [7] studied the significant correlation between news values and weekly price changes on Apple Stock. However, they opine that the result is dominated by a number of influential observations and is not reflective of the general trend. Devi Uma et al (2013) [3], in their study using Box Jenkins methodology applying AIC BIC Test criteria on four-year data on Nifty Index and high market values scrip from National Stock Exchange, India concludes that the best model equation that minimizes the error percentage can be arrived at. Adebiyi et.al (2014) [1] presents extensive process of building ARIMA model for stock price prediction and obtained the best ARIMA model with the potential to predict stock pricessatis factory on short-term basis which could guide investors in stock market to make profitable investment decisions.
Mondal Prapanna et al (2014) [12] studied the accuracy of predicting prices of ARIMA model selected on AIC Criterion by selecting a twenty-three-month time horizon on fifty-six scrip across seven sectors in Indian economy. They observed highest precision of ARIMA prediction in certain sectors of the economy but not in all. While all of the above studies concentrates on precision in forecasting of stock prices using various tools none of them highlights the significance of sensitiveness of forecasts to time horizon of data used in estimation of past trends and the perceived difference in precision of forecasting individual stock prices and movements in sector indices of stock exchanges.

3. Objectives

The main objectives of this paper are

i. To identify, estimate and verify a model for forecasting the univariate time series data of past prices of a most actively traded scrip in Indian Stock exchanges.
ii. To identify the extent to which precision in stock prices prediction is sensitive to the time horizon of past prices used in estimation of trend
iii. To evaluate the precision of ARIMA forecast of movement of a sector index of stock exchange both from long term and short term trend estimations

4. Methodology

This study relies upon the technique of developing ARIMA model for forecasting stock prices. The statistical analysis support was made available with the software E-Views 9 Student Version.

One of the most actively traded scrip in India in terms of volume namely State Bank of India (SBI) was purposively selected and historical daily stock prices obtained from website of Yahoo finance composing of four elements, namely: open, low, high and close price were downloaded. Since close price reflects all the activities and impact of shocks of a day, it has to be chosen as the dependent variable with time or day as the independent variable. However, the adjusted close accommodating the effect of stock splits and dividends were considered which further needed to be edited for consistency for a twenty-day period of 31 October 2014 to 19 November 2014. The historical prices spanning over five years from 1st April 2011 to 31st March 2016 were considered as long term while a short term of 52 weeks (one year) ranging from 1st April 2015 to 31st March 2016 was subjected to analysis. The forecast period was fixed as a two-month period from 1st April 2016 to 31st May 2016. Besides, in order to study the precision factor in forecasting of movement of an index, the banking sector index namely 'Bank Nifty' index representing the 12 most liquid and large capitalized stocks from the **banking** sector of National Stock exchange (NSE), India was selected.

Both in analysis of short term and long term, the price data were plotted, checked for its stationary nature using Correlogram and appropriate differencing was made to make the data series stationary which were confirmed by Unit root -Augmented Dickey Fuller-Test. The best ARIMA model was then selected using the criteria of relatively smallest BIC (Bayesian or Schwarz Information criterion). A small standard error of regression (SE of regression and high adjusted R squared were other criteria insisted for appropriate ARIMA model, which was identified through Automatic ARIMA in e-views. Manual ARIMA forecast is made for the variable with appropriate p.d and q representing Auto regressive, integrated differencing and Moving average terms before forecasts were made. The Q statistics and Correlogram of residuals were diagnosed for white noise before making the dynamic and static forecasts.

5. ARIMA Model

A time series is defined as a sequence of data observed over time. ARIMA models are a class of models that have capabilities to represent stationary as well as non-stationary time series and to produce accurate forecasts based on a description of historical data of single variable. Since it does not assume any particular pattern in the historical data of the time series that is to be forecast, this model is very different from other models used for forecasting [9].

In ARIMA model, the future value of a variable is a linear combination of past values and past errors, expressed as follows:

$\hat{y}_t = \mu + \phi_1 y_{t-1} + \phi_1 y_{t-2} + \ldots\ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$, where

$\hat{y}$is the actual value, μ is the random error at t, and ϕ and θ are the coefficients,

p and q are integers that are of ten referred to as autoregressive and moving average, respectively.

The Box-Jenkins methodology in order to build ARIMA models is based on Model Identification, Parameter Estimation and Selection, Diagnostic Checking (or Modal Validation); and Model's use. Model identification involves determining the orders (p, d, and q) of the AR and MA components of the model. Basically it seeks the answers for whether data is stationary or non-stationary? What is the order of differentiation (d), which makes the time stationary [9]?

6. Experimental Results

6.1. Long Term (5 years) Analysis of SBI Share Prices

The SBI close prices adjusted for stock splits and dividends from 1April 2011 to 31 March 2016, comprising of 1295 observations are plotted to observe whether the time series is stationary or not. Figure 1 depicts the original pattern of the series which indicates a random walk.

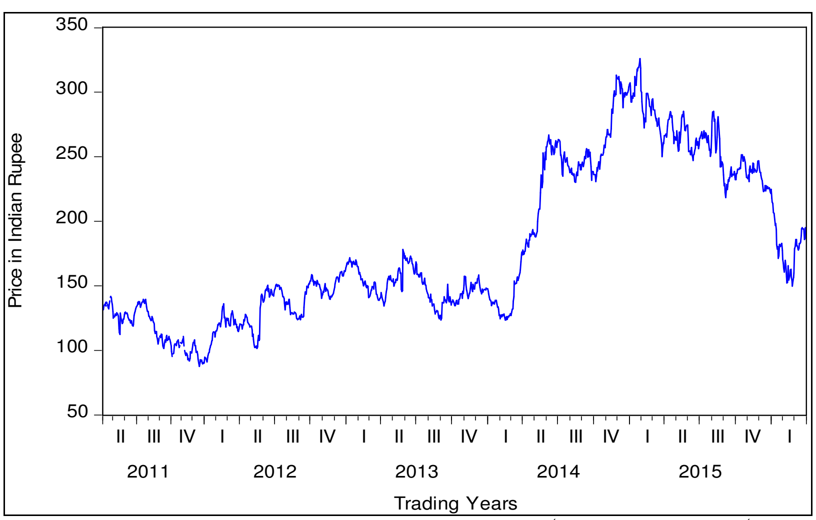

Figure 1: Graphical Representation of SBI share prices (1st April 2011 to 31st March 2016)

In order to determine whether the series is non stationary, the Correlogram, which plots the auto correlation function ACF at lag k against k for the sample raw data with default lags of 36 is analyzed for white noise or random walk of the time series under review. The results shown as figure 2 indicate that the series under analysis is non stationary since the ACF dies down very slowly.

Date: 06/15/16 Time: 08:57
Sample: 4/01/2011 3/31/2016
Included observations: 1295

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.998	0.998	1291.8	0.000
		2	0.995	-0.066	2577.8	0.000
		3	0.992	0.045	3858.2	0.000
		4	0.990	0.003	5133.4	0.000
		5	0.987	-0.025	6403.1	0.000
		6	0.985	0.012	7667.3	0.000
		7	0.983	0.050	8926.6	0.000
		8	0.981	0.023	10182.	0.000
		9	0.978	-0.047	11432.	0.000
		10	0.976	-0.080	12676.	0.000
		11	0.973	-0.009	13913.	0.000
		12	0.970	-0.003	15145.	0.000
		13	0.967	0.030	16371.	0.000
		14	0.965	0.023	17591.	0.000
		15	0.962	0.007	18806.	0.000
		16	0.960	-0.005	20016.	0.000
		17	0.957	-0.004	21221.	0.000
		18	0.955	-0.003	22420.	0.000
		19	0.952	-0.019	23614.	0.000
		20	0.950	-0.012	24802.	0.000

Figure 2: Correlogram of SBI share prices

6.1.1. First Order Differencing

The non stationary series can be transformed into a stationary series by differencing the series one or more times, de-trending or de-seasonalizing the data or by transforming data using square roots. With a view to transform the non-stationary series of SBI share price data under review to a stationary series, first difference of time series is applied and rechecked for auto correlation. The first difference of a time series is the series of changes from one period to the next.

If Y_t denotes the value of the time series Y at period t, then the first difference of Y at period t is equal to Y_t-$Y_{t-1.}$ The graphical representation of the share prices after first difference is shown in figure 3.

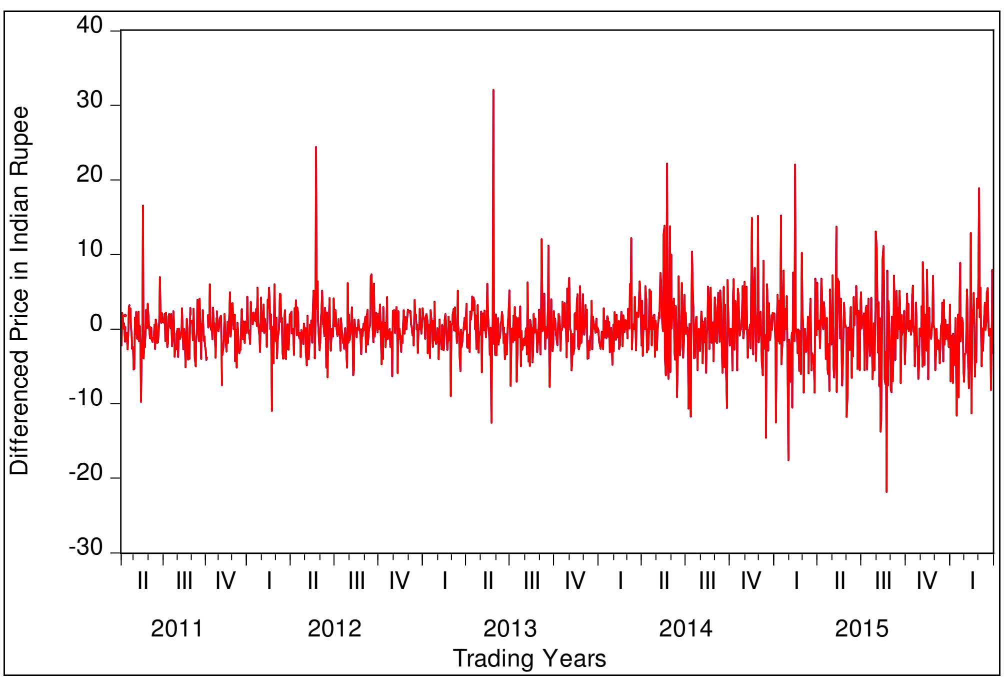

Figure 3: Graphical Representation of SBI Share prices after first differencing

The stationarity of the series after first differencing can be checked from the Auto Correlation factor (ACF) from the Correlogram of the differenced data shown in figure 4.

Date: 06/15/16 Time: 09:34
Sample: 4/01/2011 3/31/2016
Included observations: 1295

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.075	0.075	7.3950	0.007
		2	-0.039	-0.045	9.4066	0.009
		3	-0.011	-0.004	9.5610	0.023
		4	0.025	0.024	10.347	0.035
		5	-0.015	-0.019	10.628	0.059
		6	-0.060	-0.056	15.319	0.018
		7	-0.030	-0.023	16.521	0.021
		8	0.052	0.051	20.094	0.010
		9	0.094	0.085	31.696	0.000
		10	0.015	0.008	32.002	0.000
		11	0.002	0.007	32.006	0.001
		12	-0.024	-0.030	32.771	0.001
		13	-0.017	-0.019	33.137	0.002
		14	-0.013	-0.005	33.360	0.003
		15	-0.011	0.002	33.509	0.004
		16	-0.009	-0.004	33.620	0.006
		17	0.003	-0.003	33.636	0.009
		18	0.017	0.005	34.021	0.013
		19	0.009	0.002	34.136	0.018

Figure 4: The Correlogram of SBI stock prices after first differencing

It can be observed that the ACF dies down to zero and even negative in the 2^{nd} lag itself indicating that the series has become stationary after first differencing of the observed share price.

6.1.2. Augmented Dickey Fuller Unit Root Test

The stationary nature of the differenced series can further be confirmed by applying Augmented Dickey Fuller Test for unit root test, which is depicted in figure 5.The hypotheses for augmented Dickey Fuller tests are:

Null hypothesis H_0= the variable has a unit root indicating that it is non-stationary

Alternative hypothesis H_1= the variable has no unit root indicating that the series is stationary

Null Hypothesis: D(ADJ_CLOSE_ED) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-33.33122	0.0000
Test critical values:	1% level	-3.435188	
	5% level	-2.863564	
	10% level	-2.567897	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ADJ_CLOSE_ED,2)
Method: Least Squares
Date: 06/15/16 Time: 10:24
Sample: 4/01/2011 3/31/2016
Included observations: 1295

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ADJ_CLOSE_ED(-1))	-0.924066	0.027724	-33.33122	0.0000
C	0.041437	0.110597	0.374666	0.7080

R-squared	0.462140	Mean dependent var	0.000876
Adjusted R-squared	0.461724	S.D. dependent var	5.424368
S.E. of regression	3.979713	Akaike info criterion	5.601840
Sum squared resid	20478.69	Schwarz criterion	5.609819
Log likelihood	-3625.191	Hannan-Quinn criter.	5.604834
F-statistic	1110.970	Durbin-Watson stat	1.992934
Prob(F-statistic)	0.000000		

Figure 5: ADF Unit Root Test Results for first difference SBI Share prices

Since t value is lower than critical values the null hypothesis that the first difference of close price adjusted and edited [D (Adj_Close_Ed)] has a unit root is rejected, and the alternative hypothesis that the variable has no unit root is accepted. Since test statistic is much lower than all of the critical values we can reject H0 at a significance level <1%. So it can be concluded with a very low probability of making an error that the time series has no unit root. To reject the null at a significance level of 1%,(test statistic should be less than-3.435188) and p<=0.01, which in this case are so.

6.1.3. ARIMA Model Selection

The automatic ARIMA forecasting was used to determine the appropriate ARIMA model to be used and the results of summary and ARIMA criterion are shown in figure 6 and table 1 respectively.

Automatic ARIMA Forecasting Selected dependent variable: D(ADJ_CLOSE_ED) Date: 06/21/16 Time: 05:37 Sample: 4/01/2011 3/31/2016 Included observations: 1295 Forecast length: 46
Number of estimated ARMA models: 25 Number of non-converged estimations: 0 Selected ARMA model: (0,1)(0,0) SIC value: 5.64100367489

Figure 6: Summary of ARIMA Automatic forecasting

Model Selection Criteria Table
Dependent Variable: D(ADJ_CLOSE_ED)
Date: 06/20/16 Time: 22:50
Sample: 4/01/2011 3/31/2016
Included observations: 1295

Model	LogL	AIC	BIC*	HQ
(0,1)(0,0)	-3641.800481	5.629035	5.641004	5.633527
(1,0)(0,0)	-3642.135259	5.629553	5.641521	5.634044
(0,0)(0,0)	-3645.826593	5.633709	5.641688	5.636703
(2,0)(0,0)	-3640.789309	5.629018	5.644976	5.635007
(0,2)(0,0)	-3640.938971	5.629249	5.645207	5.635238
(1,1)(0,0)	-3641.264463	5.629752	5.645710	5.635741
(0,3)(0,0)	-3640.725012	5.630463	5.650410	5.637949
(3,0)(0,0)	-3640.763681	5.630523	5.650470	5.638009
(2,1)(0,0)	-3640.776526	5.630543	5.650490	5.638028
(1,2)(0,0)	-3640.834400	5.630632	5.650579	5.638118
(2,2)(0,0)	-3639.281716	5.629779	5.653715	5.638761
(3,2)(0,0)	-3636.420550	5.626904	5.654830	5.637384
(2,3)(0,0)	-3636.432150	5.626922	5.654848	5.637402
(4,0)(0,0)	-3640.374491	5.631466	5.655403	5.640449
(0,4)(0,0)	-3640.447582	5.631579	5.655516	5.640562
(3,1)(0,0)	-3640.785445	5.632101	5.656037	5.641084
(1,3)(0,0)	-3640.840104	5.632185	5.656122	5.641168
(2,4)(0,0)	-3636.343969	5.628330	5.660246	5.640307
(4,2)(0,0)	-3636.355325	5.628348	5.660263	5.640325
(3,3)(0,0)	-3636.386223	5.628396	5.660311	5.640373
(4,1)(0,0)	-3640.324380	5.632933	5.660859	5.643413
(1,4)(0,0)	-3640.432582	5.633101	5.661026	5.643580
(4,4)(0,0)	-3631.585135	5.624070	5.663964	5.639041
(3,4)(0,0)	-3636.198145	5.629650	5.665554	5.643124
(4,3)(0,0)	-3636.419965	5.629992	5.665897	5.643466

Table 1: ARIMA Criterion

The model with the lowest Akaike information criterion (AIC) and the Bayesian information criterion (BIC) or Schwarz criterion (SIC) is selected as ARIMA (p, d, q) as (0,1,1) shown above as Model (0,1) (0,0), the first part being ARMA terms p and q and the second part represents seasonal auto regressive term (SAR) and seasonal moving average term (SMA) which are not applicable in this case.

6.1.4. ARIMA Estimation

The manual ARIMA (0,1,1) was estimated as quick estimate equation d(adj_close_ed) c Ma (1) and the estimation results are shown as figure 7below.

Dependent Variable: D(ADJ_CLOSE_ED)
Method: ARMA Maximum Likelihood (BFGS)
Date: 06/22/16 Time: 11:06
Sample: 4/01/2011 3/31/2016
Included observations: 1295
Convergence achieved after 3 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.044366	0.124238	0.357109	0.7211
MA(1)	0.082218	0.022316	3.684295	0.0002
SIGMASQ	15.80650	0.296377	53.33237	0.0000

R-squared	0.006218	Mean dependent var	0.044770
Adjusted R-squared	0.004680	S.D. dependent var	3.989699
S.E. of regression	3.980352	Akaike info criterion	5.602937
Sum squared resid	20469.42	Schwarz criterion	5.614905
Log likelihood	-3624.901	Hannan-Quinn criter.	5.607428
F-statistic	4.042245	Durbin-Watson stat	2.005065
Prob(F-statistic)	0.017781		

Inverted MA Roots -.08

Figure 7: ARIMA (0,1,0) Equation output

6.1.5. Residual Diagnosis

The Correlogram of residuals (Q Statistic) is shown in figure 8.

Date: 06/22/16 Time: 11:14
Sample: 4/01/2011 3/31/2016
Included observations: 1295
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0120	
		2	-0.038	-0.038	1.9271	0.165
		3	-0.010	-0.010	2.0555	0.358
		4	0.027	0.025	2.9694	0.396
		5	-0.012	-0.013	3.1643	0.531
		6	-0.057	-0.055	7.3317	0.197
		7	-0.030	-0.031	8.4734	0.205
		8	0.047	0.042	11.403	0.122
		9	0.090	0.088	21.894	0.005
		10	0.008	0.014	21.971	0.009
		11	0.003	0.010	21.983	0.015
		12	-0.023	-0.028	22.692	0.020

Figure 8: Correlogram of Residuals

Since there are no significant spikes of ACFs and PACFs, it means that the residual of the selected ARIMA model are white noise, no other significant patterns left in the time series. Therefore, there is no need to consider any AR(p) and MA(q) further. Figure 9 depicts the actual fitted residual graph.

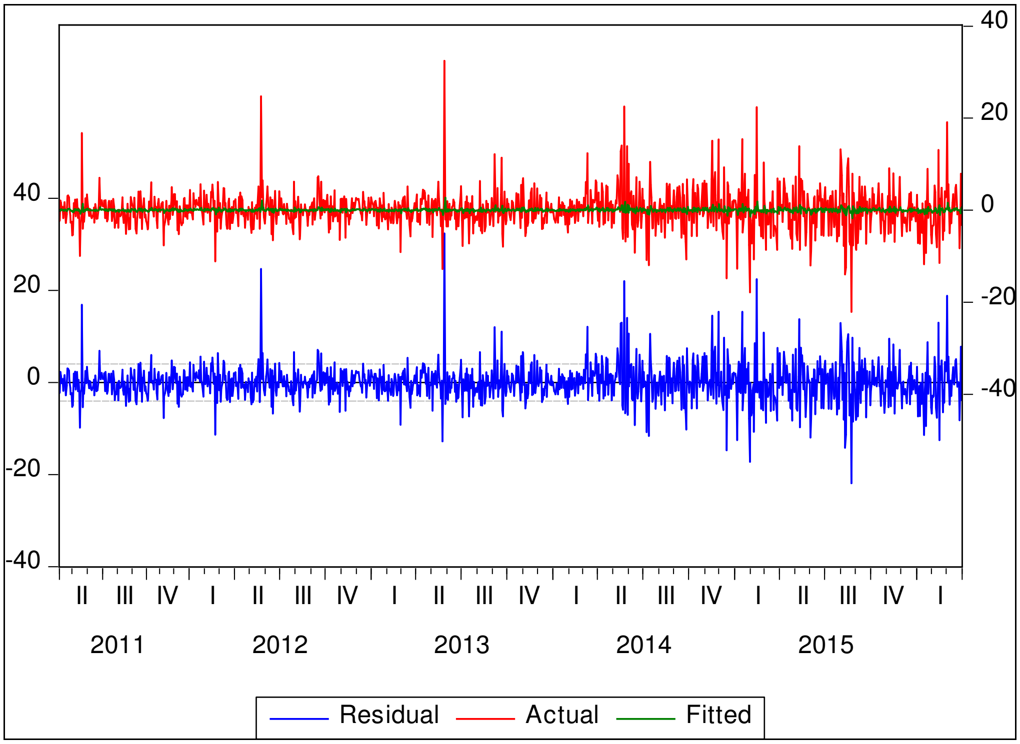

Figure 9: Actual Fitted Residual Graph

6.1.6. Histogram - Normality Test

Further, the histogram normality test (see figure 10) for residual diagnostics reveal a near less than unit skewness and kurtosis of above 3, which confirms the normality of the univariate time series under study.

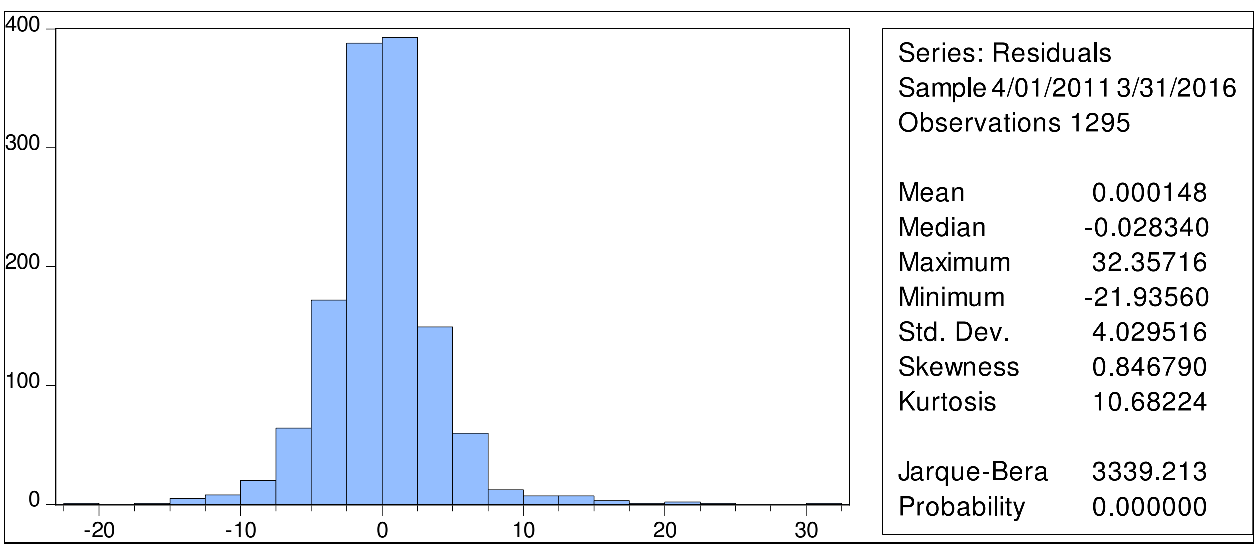

Figure 10: Histogram– Normality Test of Residuals

6.1.7. Dynamic Forecast

The ARIMA (0,1,1) model selected is then used to make a dynamic forecast for the period 1 April 2016 to 31st May 2016 and the forecast graph and forecast evaluation results obtained are depicted in figure 11.

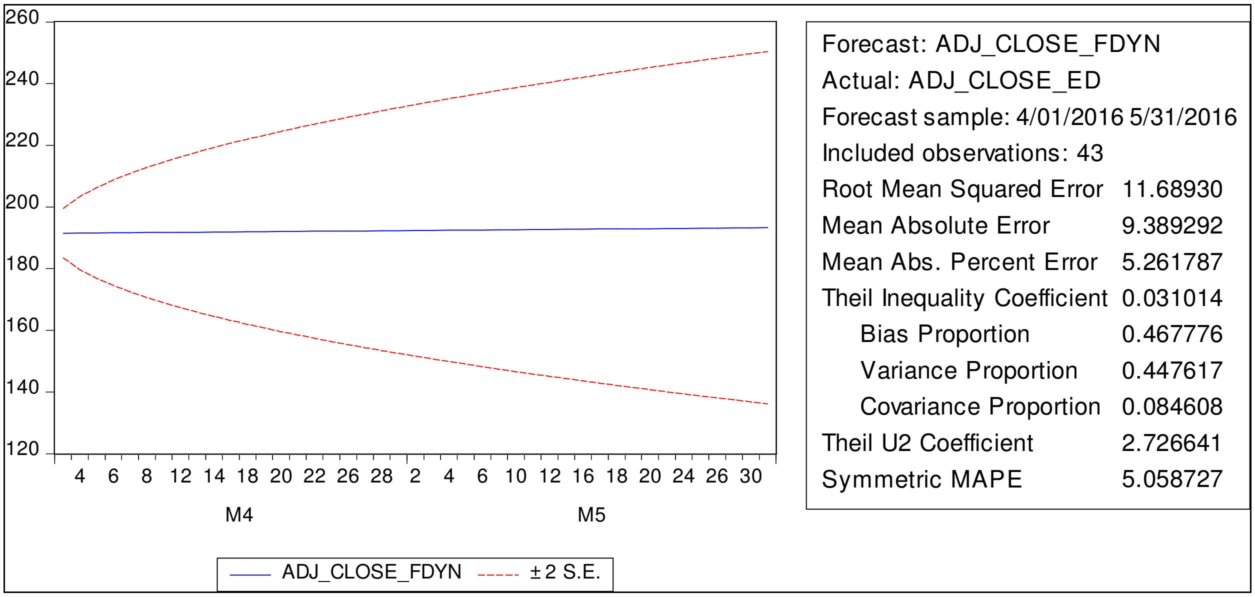

Figure 11: Dynamic forecast Graph with standard error range

6.1.7.1. Dynamic Forecast Evaluation

The dynamic forecasted values denoted as adj_close_fdyn were opened as a group with original variable adj_close_ed and the graph for the forecasted period is plotted for both of the variables as is shown in figure12.

Figure 12: Actual and dynamic forecast values of SBI share prices from 1st April 2016 to 31st May 2016

6.1.7.2. Dynamic Forecast Comparison

The comparison of actual value and dynamic forecast value of variable for the period from 1st April 2016 to 31st May 2016 in terms of absolute change (delta), percentage change (%delta) and precision % are presented in table 2.

Date (mm/dd/yyyy)	Actual ADJ_CLOSE_ED	Dynamic Forecast ADJ_CLOSE_FDYN	Change Delta	Change Delta %	Precision %
4/1/2016	193.1135	191.4514969	1.66200	0.87%	99.13189
4/4/2016	192.1758	191.4945055	0.68129	0.36%	99.64422
4/5/2016	181.96	191.5375142	-9.57751	-5.00%	94.99967
4/6/2016	181.4665	191.5805228	-10.11402	-5.28%	94.72075
4/7/2016	179.5911	191.6235315	-12.03243	-6.28%	93.7208
4/8/2016	180.7262	191.6665401	-10.94034	-5.71%	94.29199
4/11/2016	185.8095	191.7095488	-5.90005	-3.08%	96.9224
4/12/2016	185.3653	191.7525575	-6.38726	-3.33%	96.66901
4/13/2016	189.4121	191.7955661	-2.38347	-1.24%	98.75729
4/14/2016	189.4121	191.8385748	-2.42647	-1.26%	98.73515
4/15/2016	189.4121	191.8815834	-2.46948	-1.29%	98.71302
4/18/2016	184.3289	191.9245921	-7.59569	-3.96%	96.04236
4/19/2016	184.3289	191.9676007	-7.63870	-3.98%	96.02084
4/20/2016	184.8718	192.0106094	-7.13881	-3.72%	96.28208
4/21/2016	191.8304	192.053618	-0.22322	-0.12%	99.88377
4/22/2016	197.5552	192.0966267	5.45857	2.84%	97.15842
4/25/2016	194.4954	192.1396353	2.35576	1.23%	98.77393
4/26/2016	198.3448	192.182644	6.16216	3.21%	96.79359
4/27/2016	193.607	192.2256526	1.38135	0.72%	99.28139
4/28/2016	189.5602	192.2686613	-2.70846	-1.41%	98.59131
4/29/2016	186.5497	192.31167	-5.76197	-3.00%	97.00384
5/2/2016	183.5886	192.3546786	-8.76608	-4.56%	95.44275
5/3/2016	181.6639	192.3976873	-10.73379	-5.58%	94.42104
5/4/2016	177.6171	192.4406959	-14.82360	-7.70%	92.29706
5/5/2016	178.0119	192.4837046	-14.47180	-7.52%	92.48154
5/6/2016	181.96	192.5267132	-10.56671	-5.49%	94.51156
5/9/2016	186.2536	192.5697219	-6.31612	-3.28%	96.72009
5/10/2016	187.0433	192.6127305	-5.56943	-2.89%	97.10848
5/11/2016	182.6016	192.6557392	-10.05414	-5.22%	94.78129
5/12/2016	186.0562	192.6987478	-6.64255	-3.45%	96.55288
5/13/2016	182.4535	192.7417565	-10.28826	-5.34%	94.66215
5/16/2016	174.5079	192.7847651	-18.27687	-9.48%	90.51955
5/17/2016	174.5573	192.8277738	-18.27047	-9.48%	90.52498
5/18/2016	177.6171	192.8707825	-15.25368	-7.91%	92.09124
5/19/2016	170.4611	192.9137911	-22.45269	-11.64%	88.36128
5/20/2016	169.1286	192.9567998	-23.82820	-12.35%	87.65102
5/23/2016	166.2168	192.9998084	-26.78301	-13.88%	86.12278
5/24/2016	167.3025	193.0428171	-25.74032	-13.33%	86.66601
5/25/2016	172.8299	193.0858257	-20.25593	-10.49%	89.50937
5/26/2016	181.7626	193.1288344	-11.36623	-5.89%	94.11469
5/27/2016	193.3603	193.171843	0.18846	0.10%	99.90244
5/30/2016	196.272	193.2148517	3.05715	1.58%	98.41775
5/31/2016	202.2929	193.2578603	9.03504	4.68%	95.32488
				Min	86.12278
				Max	99.90244
				Mean	95.12378

Table 2: Percentage change in Actual and Dynamic Forecast Values and precision of prediction

The precision percentage representing the accuracy of forecast varied between 86.125 and 99.90% with a mean value of 95.12%, which throws light on the capability of the ARIMA method of forecasting.

6.1.8. Static Forecast

However, the static forecasting method using ARIMA with a lower root mean squared error and very low Bias proportion and Variance proportion followed by a significantly high Covariance proportion reports a very high precision percentage ranging between 94% and 99.97% with a mean of 98.1%. (see figures 13, 14 and table 3) for the same period of 1st April 2016 to 31st May 2016.

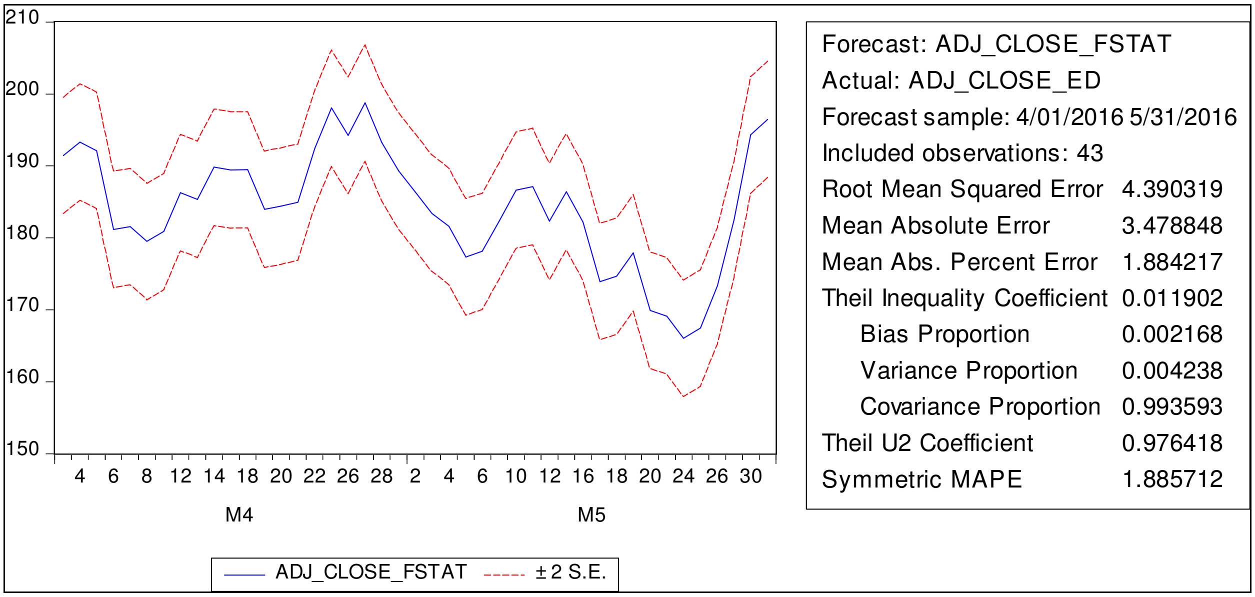

Figure 13: Static forecast Graph with Standard Error range

6.1.8.1. Static Forecast Evaluation

Figure 14: Actual and static forecast values of SBI share prices from 1st April 2016 to 31st May 2016

6.1.8.2. Static Forecast Comparison

DATE (mm/dd/yyyy)	ACTUAL ADJ_CLOSE_ED	STATIC FORECAST ADJ_CLOSE_STAT	CHANGE Delta	% CHANGE Delta %	PRECISION %
4/1/2016	193.1135	191.4515	1.662	0.90%	99.1
4/4/2016	192.1758	193.293	-1.1172	-0.60%	99.4
4/5/2016	181.9600	192.1271	10.1671	-5.30%	94.7
4/6/2016	181.4665	181.1683	0.2982	0.20%	99.8
4/7/2016	179.5911	181.534	-1.9429	-1.10%	98.9
4/8/2016	180.7262	179.4746	1.2516	0.70%	99.3
4/11/2016	185.8095	180.872	4.9375	2.70%	97.3
4/12/2016	185.3653	186.2579	-0.8926	-0.50%	99.5
4/13/2016	189.4121	185.335	4.0771	2.20%	97.8
4/14/2016	189.4121	189.7898	-0.3777	-0.20%	99.8
4/15/2016	189.4121	189.4241	-0.012	-0.000063	99.9937
4/18/2016	184.3289	189.4541	-5.1252	-2.70%	97.3
4/19/2016	184.3289	183.9511	0.3778	0.20%	99.8
4/20/2016	184.8718	184.4029	0.4689	0.30%	99.7
4/21/2016	191.8304	184.9533	6.8771	3.70%	96.3
4/22/2016	197.5552	192.438	5.1172	2.70%	97.3
4/25/2016	194.4954	198.0183	-3.5229	-1.80%	98.2
4/26/2016	198.3448	194.2492	4.0956	2.10%	97.9
4/27/2016	193.607	198.7241	-5.1171	-2.60%	97.4
4/28/2016	189.5602	193.2299	-3.6697	-1.90%	98.1
4/29/2016	186.5497	189.3019	-2.7522	-1.50%	98.5
5/2/2016	183.5886	186.3667	-2.7781	-1.50%	98.5
5/3/2016	181.6639	183.4035	-1.7396	-0.90%	99.1
5/4/2016	177.6171	181.5641	-3.947	-2.20%	97.8
5/5/2016	178.0119	177.3361	0.6758	0.40%	99.6
5/6/2016	181.96	178.1104	3.8496	2.20%	97.8
5/9/2016	186.2536	182.3191	3.9345	2.20%	97.8
5/10/2016	187.0433	186.6196	0.4237	0.20%	99.8
5/11/2016	182.6016	187.1211	-4.5195	-2.40%	97.6
5/12/2016	186.0562	182.2736	3.7826	2.10%	97.9
5/13/2016	182.4535	186.4098	-3.9563	-2.10%	97.9
5/16/2016	174.5079	182.1717	-7.6638	-4.20%	95.8
5/17/2016	174.5573	173.9217	0.6356	0.40%	99.6
5/18/2016	177.6171	174.6525	2.9646	1.70%	98.3
5/19/2016	170.4611	177.9035	-7.4424	-4.20%	95.8
5/20/2016	169.1286	169.8931	-0.7645	-0.40%	99.6
5/23/2016	166.2168	169.1088	-2.892	-1.70%	98.3
5/24/2016	167.3025	166.0224	1.2801	0.80%	99.2
5/25/2016	172.8299	167.4506	5.3793	3.20%	96.8
5/26/2016	181.7626	173.3146	8.448	4.90%	95.1
5/27/2016	193.3603	182.4992	10.8611	6.00%	94
5/30/2016	196.272	194.295	1.977	1.00%	99
5/31/2016	202.2929	196.4773	5.8156	3.00%	97
				Min	94
				Max	99.9937
				Mean	98.10218

Table 3: Percentage change in Actual and Static Forecast Values and precision of prediction

In the case of static forecast the precision percentage representing the accuracy of forecast varied between 94%and 99.9% with a mean value of 98.1%, which is highlighted by the fact that static forecasting uses actual values of the lagged variable to forecast future.

6.2. Short Term (1 year) Analysis of SBI Share Prices

With a view to analyze the sensitivity of ARIMA forecasting to different time horizons of the estimation samples, a one-year sample of 262 observations of the same SBI share prices from 1st April 2015 to 31st March 2016 are selected. By repeating all the above steps of making and testing the series stationary, identifying the appropriate p, d and q terms through modeling and forecasting using ARIMA (p, d, q) techniques the precision of forecast under dynamic forecasting and static forecasting method is arrived at.

6.2.1. Dynamic forecast Comparison

The results of comparison of actual and dynamic forecast values for the same forecast period of 1st April 2016 to 31st May 2016 are shown in table 4.

DATE (mm/dd/yyyy)	ACTUAL ADJ_CLOSE_ED	DYNAMIC FORECAST ADJ_CLOSE_FDYN	CHANGE Delta	% CHANGE Delta%	PRECISION %
4/1/2016	193.1135	191.4985483	1.61495	0.84%	99.15668
4/4/2016	192.1758	191.2656802	0.91012	0.48%	99.52416
4/5/2016	181.96	191.0330952	-9.07310	-4.75%	95.25051
4/6/2016	181.4665	190.800793	-9.33429	-4.89%	95.10783
4/7/2016	179.5911	190.5687734	-10.97767	-5.76%	94.23952
4/8/2016	180.7262	190.3370359	-9.61084	-5.05%	94.95062
4/11/2016	185.8095	190.1055801	-4.29608	-2.26%	97.74016
4/12/2016	185.3653	189.8744059	-4.50911	-2.37%	97.62522
4/13/2016	189.4121	189.6435127	-0.23141	-0.12%	99.87797
4/14/2016	189.4121	189.4129004	-0.00080	-4.23E-06	99.99958
4/15/2016	189.4121	189.1825684	0.22953	0.12%	99.87867
4/18/2016	184.3289	188.9525166	-4.62362	-2.45%	97.55303
4/19/2016	184.3289	188.7227445	-4.39384	-2.33%	97.6718
4/20/2016	184.8718	188.4932518	-3.62145	-1.92%	98.07874
4/21/2016	191.8304	188.2640382	3.56636	1.89%	98.10566
4/22/2016	197.5552	188.0351033	9.52010	5.06%	94.93706
4/25/2016	194.4954	187.8064468	6.68895	3.56%	96.43838
4/26/2016	198.3448	187.5780683	10.76673	5.74%	94.26013
4/27/2016	193.607	187.3499676	6.25703	3.34%	96.66024
4/28/2016	189.5602	187.1221443	2.43806	1.30%	98.69708
4/29/2016	186.5497	186.8945979	-0.34490	-0.18%	99.81546
5/2/2016	183.5886	186.6673283	-3.07873	-1.65%	98.35069
5/3/2016	181.6639	186.4403351	-4.77644	-2.56%	97.43809
5/4/2016	177.6171	186.2136179	-8.59652	-4.62%	95.38352
5/5/2016	178.0119	185.9871764	-7.97528	-4.29%	95.71192
5/6/2016	181.96	185.7610102	-3.80101	-2.05%	97.95382
5/9/2016	186.2536	185.5351191	0.71848	0.39%	99.61275
5/10/2016	187.0433	185.3095026	1.73380	0.94%	99.06438
5/11/2016	182.6016	185.0841606	-2.48256	-1.34%	98.65869
5/12/2016	186.0562	184.8590925	1.19711	0.65%	99.35242
5/13/2016	182.4535	184.6342981	-2.18080	-1.18%	98.81886
5/16/2016	174.5079	184.4097771	-9.90188	-5.37%	94.6305
5/17/2016	174.5573	184.1855291	-9.62823	-5.23%	94.77254
5/18/2016	177.6171	183.9615538	-6.34445	-3.45%	96.55121
5/19/2016	170.4611	183.7378509	-13.27675	-7.23%	92.77408
5/20/2016	169.1286	183.51442	-14.38582	-7.84%	92.16093
5/23/2016	166.2168	183.2912608	-17.07446	-9.32%	90.68452
5/24/2016	167.3025	183.0683729	-15.76587	-8.61%	91.38799
5/25/2016	172.8299	182.8457561	-10.01586	-5.48%	94.52224
5/26/2016	181.7626	182.6234101	-0.86081	-0.47%	99.52864
5/27/2016	193.3603	182.4013343	10.95897	6.01%	93.99184
5/30/2016	196.272	182.1795287	14.09247	7.74%	92.26451
5/31/2016	202.2929	181.9579927	20.33491	11.18%	88.82439
				Min	88.82439
				Max	99.99958
				Mean	96.46528

Table 4: Percentage change in Actual and Dynamic Forecast Values and precision of prediction

It is observed that the ARIMA (p, d, q) forecast for a short term period of one year sows a minimum 89% accuracy and maximum of 99.99 with a mean precision of 96.5% if dynamic forecasting is applied.

6.2.2. Static forecast Comparison

Table 5 presents the results of static forecasting using ARIMA for the short term period of one year, price data ranging from 1st April 2015 to 31st May 2016.

Date (mm/dd/yyyy)	Actual ADJ_CLOSE_ED	Static Forecast ADJ_CLOSE_FSTAT1	Delta	Delta%	Precision %
4/1/2016	193.1135	191.4985	1.614952	0.84%	99.15668
4/4/2016	192.1758	192.8787	-0.70287	-0.36%	99.63559
4/5/2016	181.96	191.9421	-9.98211	-5.20%	94.79942
4/6/2016	181.4665	181.7387	-0.27223	-0.15%	99.85021
4/7/2016	179.5911	181.2458	-1.65473	-0.91%	99.08702
4/8/2016	180.7262	179.3727	1.353488	0.75%	99.24543
4/11/2016	185.8095	180.5064	5.303069	2.94%	97.06212
4/12/2016	185.3653	185.5835	-0.21825	-0.12%	99.8824
4/13/2016	189.4121	185.1399	4.27221	2.31%	97.69244
4/14/2016	189.4121	189.1818	0.230331	0.12%	99.87825
4/15/2016	189.4121	189.1818	0.230331	0.0012%	99.87825
4/18/2016	184.3289	189.1818	-4.85287	-2.57%	97.43481
4/19/2016	184.3289	184.1048	0.22415	0.12%	99.87825
4/20/2016	184.8718	184.1048	0.76705	0.42%	99.58336
4/21/2016	191.8304	184.647	7.18341	3.89%	96.10965
4/22/2016	197.5552	191.5971	5.958072	3.11%	96.89031
4/25/2016	194.4954	197.315	-2.81957	-1.43%	98.57103
4/26/2016	198.3448	194.2589	4.085912	2.10%	97.89667
4/27/2016	193.607	198.1036	-4.49661	-2.27%	97.73017
4/28/2016	189.5602	193.3716	-3.81137	-1.97%	98.02899
4/29/2016	186.5497	189.3297	-2.77999	-1.47%	98.53167
5/2/2016	183.5886	186.3228	-2.73425	-1.47%	98.53252
5/3/2016	181.6639	183.3654	-1.70145	-0.93%	99.0721
5/4/2016	177.6171	181.443	-3.82589	-2.11%	97.89141
5/5/2016	178.0119	177.4011	0.610788	0.34%	99.6557
5/6/2016	181.96	177.7954	4.164568	2.34%	97.65766
5/9/2016	186.2536	181.7387	4.514869	2.48%	97.51574
5/10/2016	187.0433	186.0271	1.01619	0.55%	99.45374
5/11/2016	182.6016	186.8158	-4.21425	-2.26%	97.74417
5/12/2016	186.0562	182.3796	3.676649	2.02%	97.98407
5/13/2016	182.4535	185.8299	-3.37645	-1.82%	98.18304
5/16/2016	174.5079	182.2316	-7.72373	-4.24%	95.76159
5/17/2016	174.5573	174.2957	0.261607	0.15%	99.84991
5/18/2016	177.6171	174.345	3.272067	1.88%	98.12322
5/19/2016	170.4611	177.4011	-6.94001	-3.91%	96.08795
5/20/2016	169.1286	170.2538	-1.12521	-0.66%	99.3391
5/23/2016	166.2168	168.9229	-2.70613	-1.60%	98.39801
5/24/2016	167.3025	166.0147	1.287825	0.78%	99.22427
5/25/2016	172.8299	167.0991	5.730845	3.43%	96.57039
5/26/2016	181.7626	172.6197	9.142867	5.30%	94.70346
5/27/2016	193.3603	181.5416	11.81873	6.51%	93.48979
5/30/2016	196.272	193.1252	3.146832	1.63%	98.37057
5/31/2016	202.2929	196.0333	6.259573	3.19%	96.80688
				Min	93.48979
				Max	99.8824
				Mean	98.0753

Table 5: Percentage change in Actual and Static Forecast Values and precision of prediction

It is noteworthy that the precision of forecasts ranged been 93.5% to 99.88% with a mean of 98.07% if static forecasting method is used under ARIMA (p, d, q) technique from estimation sample of a short term period of one year.

6.3. Long Term (5 years) Analysis of Nifty Bank Index

The responsiveness of forecasting techniques to long term (5 year) and short term (1year) movements in the related index of which the particular share under study is a constituent is also subjected to analysis. The Nifty Banking Sector index of National Stock Exchange, India named Bank Nifty represents the 12 most liquid and large capitalized stocks from the banking sector which trade on the National Stock Exchange (NSE). It provides investors and market intermediaries a benchmark that captures the capital market performance of Indian banking sector. As followed in the case of SBI share prices for 5-year period the nifty bank index movement series of 5 years consisting of 1238 observations and 1 year are subjected to analysis, by making it stationary, testing for being stationary, modeling to identify the appropriate p, q and r term for ARIMA etc and forecasting dynamically and statically to compare precision ranges with that of an individual high volume traded scrip namely SBI.

6.3.1. Dynamic Forecast Comparison

Table 6 depicts the results of precision of prediction using dynamic forecast under ARIMA (0,1,1) of 1238 observation of Bank Nifty ranging long term period of 1st April 2011 to 31st May 2016.

DATE (mm/dd/yyyy)	ACTUAL CLOSE	DYNAMIC FORECAST CLOSEFDYN	CHANGE Delta	% CHANGE Delta%	PRECISION %
4/1/2016	16174.9	16140.85025	34.04975	0.21%	99.78905
4/4/2016	16190.6	16144.53987	46.06013	0.29%	99.7147
4/5/2016	15695	16148.22949	-453.22949	-2.81%	97.19332
4/6/2016	15636.95	16151.91912	-514.96912	-3.19%	96.81172
4/7/2016	15530.75	16155.60874	-624.85874	-3.87%	96.13225
4/8/2016	15568.35	16159.29837	-590.94837	-3.66%	96.34298
4/11/2016	15818.5	16162.98799	-344.48799	-2.13%	97.86866
4/12/2016	15880.2	16166.67761	-286.47761	-1.77%	98.22797
4/13/2016	16278.55	16170.36724	108.18276	0.67%	99.33098
4/18/2016	16222.7	16174.05686	48.64314	0.30%	99.69925
4/20/2016	16349.7	16177.74649	171.95351	1.06%	98.9371
4/21/2016	16637.15	16181.43611	455.71389	2.82%	97.18372
4/22/2016	16703.4	16185.12573	518.27427	3.20%	96.79784
4/25/2016	16678.65	16188.81536	489.83464	3.03%	96.97424
4/26/2016	17002.55	16192.50498	810.04502	5.00%	94.99741
4/27/2016	16872.95	16196.19461	676.75539	4.18%	95.82152
4/28/2016	16716.9	16199.88423	517.01577	3.19%	96.80852
4/29/2016	16795	16203.57385	591.42615	3.65%	96.35003
5/2/2016	16543	16207.26348	335.73652	2.07%	97.92848
5/3/2016	16388.7	16210.9531	177.74690	1.10%	98.90354
5/4/2016	16274.25	16214.64273	59.60727	0.37%	99.63239
5/5/2016	16281	16218.33235	62.66765	0.39%	99.6136
5/6/2016	16296.6	16222.02198	74.57802	0.46%	99.54027
5/9/2016	16686.1	16225.7116	460.38840	2.84%	97.1626
5/10/2016	16784.95	16229.40122	555.54878	3.42%	96.5769
5/11/2016	16754.45	16233.09085	521.35915	3.21%	96.78829
5/12/2016	16923.7	16236.78047	686.91953	4.23%	95.76936
5/13/2016	16716.9	16240.4701	476.42990	2.93%	97.0664
5/16/2016	16737.55	16244.15972	493.39028	3.04%	96.96266
5/17/2016	16762.75	16247.84934	514.90066	3.17%	96.83096
5/18/2016	16728.95	16251.53897	477.41103	2.94%	97.06236
5/19/2016	16565.25	16255.22859	310.02141	1.91%	98.09279
5/20/2016	16481.45	16258.91822	222.53178	1.37%	98.63132
5/23/2016	16407.55	16262.60784	144.94216	0.89%	99.10874
5/24/2016	16456.65	16266.29746	190.35254	1.17%	98.82977
5/25/2016	16997.45	16269.98709	727.46291	4.47%	95.5288
5/26/2016	17359.3	16273.67671	1085.62329	6.67%	93.32896
5/27/2016	17511.8	16277.36634	1234.43366	7.58%	92.41626
5/30/2016	17520.65	16281.05596	1239.59404	7.61%	92.38628
5/31/2016	17620.9	16284.74558	1336.15442	8.20%	91.79506
				Min	91.79506
				Max	99.78905
				Mean	97.12343

Table 6: Percentage change in Actual and Dynamic Forecast Values and precision of prediction (Nifty Bank Index) From 5-year estimate sample

The precision of forecasts ranged been 91.8% to 99.79% with a mean of 97.12% if static forecasting method is used under ARIMA (p, d, q) technique from estimation sample of a long term period of five years, in the case of Nifty Bank Index.

6.3.2. Static Forecast Comparison

Table 7 depicts the results of precision of prediction using static forecast under ARIMA (0,1,1) of 1238 observation of Bank Nifty ranging long term period of 1st April 2011 to 31st May 2016.

DATE (mm/dd/yyyy)	ACTUAL CLOSE	STATIC FORECAST CLOSEFSTAT	CHANGE Delta	% CHANGE Delta%	PRECISION %
4/1/2016	16174.9	16140.85025	34.04975	0.21%	99.78905
4/4/2016	16190.6	16182.08617	8.51383	0.05%	99.94739
4/5/2016	15695	16195.1639	-500.16390	-3.09%	96.91165
4/6/2016	15636.95	15647.3282	-10.37820	-0.07%	99.93367
4/7/2016	15530.75	15639.57389	-108.82389	-0.70%	99.30418
4/8/2016	15568.35	15523.26459	45.08541	0.29%	99.70956
4/11/2016	15818.5	15576.66941	241.83059	1.55%	98.44748
4/12/2016	15880.2	15847.02301	33.17699	0.21%	99.79064
4/13/2016	16278.55	15887.29654	391.25346	2.46%	97.53732
4/18/2016	16222.7	16322.41712	-99.71712	-0.61%	99.38908
4/20/2016	16349.7	16216.14976	133.55024	0.82%	99.17644
4/21/2016	16637.15	16367.10379	270.04621	1.65%	98.35007
4/22/2016	16703.4	16668.57045	34.82955	0.21%	99.79105
4/25/2016	16678.65	16710.66624	-32.01624	-0.19%	99.80841
4/26/2016	17002.55	16679.0519	323.49810	1.94%	98.06045
4/27/2016	16872.95	17039.45938	-166.50938	-0.98%	99.0228
4/28/2016	16716.9	16859.54091	-142.64091	-0.85%	99.15395
4/29/2016	16795	16705.94195	89.05805	0.53%	99.46691
5/2/2016	16543	16807.83492	-264.83492	-1.58%	98.42434
5/3/2016	16388.7	16519.49394	-130.79394	-0.79%	99.20824
5/4/2016	16274.25	16378.9585	-104.70850	-0.64%	99.36071
5/5/2016	16281	16267.18719	13.81281	0.08%	99.91509
5/6/2016	16296.6	16286.10805	10.49195	0.06%	99.93558
5/9/2016	16686.1	16301.36703	384.73297	2.36%	97.63987
5/10/2016	16784.95	16729.29754	55.65246	0.33%	99.66734
5/11/2016	16754.45	16794.35453	-39.90453	-0.24%	99.76239
5/12/2016	16923.7	16754.04186	169.65814	1.01%	98.98736
5/13/2016	16716.9	16944.81168	-227.91168	-1.35%	98.65498
5/16/2016	16737.55	16697.18556	40.36444	0.24%	99.75826
5/17/2016	16762.75	16745.38462	17.36538	0.10%	99.8963
5/18/2016	16728.95	16768.22286	-39.27286	-0.23%	99.76579
5/19/2016	16565.25	16728.60673	-163.35673	-0.98%	99.02349
5/20/2016	16481.45	16552.16466	-70.71466	-0.43%	99.57278
5/23/2016	16407.55	16477.87799	-70.32799	-0.43%	99.5732
5/24/2016	16456.65	16404.0177	52.63230	0.32%	99.67915
5/25/2016	16997.45	16465.74439	531.70561	3.23%	96.77084
5/26/2016	17359.3	17055.74004	303.55996	1.78%	98.22019
5/27/2016	17511.8	17394.16195	117.63805	0.68%	99.32369
5/30/2016	17520.65	17527.56978	-6.91978	-0.04%	99.96052
5/31/2016	17620.9	17523.62904	97.27096	0.56%	99.44492
				Min	96.77084
				Max	99.96052
				Mean	99.15338

Table 7: Percentage change in Actual and Dynamic Forecast Values and precision of prediction (Nifty Bank Index) From 5-year estimate sample

The precision of forecasts ranged been 96.8% to 99.96% with a mean of 99.2% if static forecasting method is used under ARIMA (p, d, q) technique from estimation sample of a long term period of five years, in the case of Nifty Bank Index.

6.4. Short Term (1 year) Analysis of Nifty Bank Index

All the techniques used in the above analysis of making series stationary, identification of proper ARIMA model and forecasting are used for short term analysis of Nifty Bank Index, except that the logged variable was used instead of differenced variable to arrive at the ARIMA terms which identified the p, d and q terms as 0,1,0 necessitating iteration of the variable DLOG(Close).

6.4.1. Dynamic Forecast Comparison

Table 8 depicts the results of precision of prediction using dynamic forecast under ARIMA (0,1,0) of 247 observations of Bank Nifty ranging short term period of 1st April 2015 to 31st May 2016.

DATE (mm/dd/yyyy)	ACTUAL CLOSE	DYNAMIC FORECAST CLOSEFDYN1	CHANGE Delta	% CHANGE Delta%	PRECISION %
4/1/2016	16174.9	16133.78472	41.11528	0.25%	99.74516
4/4/2016	16190.6	16125.92328	64.67672	0.40%	99.59893
4/5/2016	15695	16118.06567	-423.06567	-2.62%	97.37521
4/6/2016	15636.95	16110.21188	-473.26188	-2.94%	97.06235
4/7/2016	15530.75	16102.36192	-571.61192	-3.55%	96.45014
4/8/2016	15568.35	16094.51579	-526.16579	-3.27%	96.73078
4/11/2016	15818.5	16086.67348	-268.17348	-1.67%	98.33295
4/12/2016	15880.2	16078.83499	-198.63499	-1.24%	98.76462
4/13/2016	16278.55	16071.00032	207.54968	1.29%	98.70855
4/18/2016	16222.7	16063.16947	159.53053	0.99%	99.00686
4/20/2016	16349.7	16055.34244	294.35756	1.83%	98.16661
4/21/2016	16637.15	16047.51921	589.63079	3.67%	96.32572
4/22/2016	16703.4	16039.6998	663.70020	4.14%	95.86214
4/25/2016	16678.65	16031.8842	646.76580	4.03%	95.96575
4/26/2016	17002.55	16024.07241	978.47759	6.11%	93.8937
4/27/2016	16872.95	16016.26443	856.68557	5.35%	94.65115
4/28/2016	16716.9	16008.46025	708.43975	4.43%	95.57459
4/29/2016	16795	16000.65987	794.34013	4.96%	95.03558
5/2/2016	16543	15992.86329	550.13671	3.44%	96.56011
5/3/2016	16388.7	15985.07052	403.62948	2.53%	97.47496
5/4/2016	16274.25	15977.28153	296.96847	1.86%	98.14131
5/5/2016	16281	15969.49635	311.50365	1.95%	98.04938
5/6/2016	16296.6	15961.71496	334.88504	2.10%	97.90195
5/9/2016	16686.1	15953.93736	732.16264	4.59%	95.41077
5/10/2016	16784.95	15946.16355	838.78645	5.26%	94.73989
5/11/2016	16754.45	15938.39352	816.05648	5.12%	94.87993
5/12/2016	16923.7	15930.62729	993.07271	6.23%	93.76627
5/13/2016	16716.9	15922.86483	794.03517	4.99%	95.01324
5/16/2016	16737.55	15915.10616	822.44384	5.17%	94.83231
5/17/2016	16762.75	15907.35128	855.39872	5.38%	94.62262
5/18/2016	16728.95	15899.60016	829.34984	5.22%	94.78383
5/19/2016	16565.25	15891.85283	673.39717	4.24%	95.76263
5/20/2016	16481.45	15884.10927	597.34073	3.76%	96.23938
5/23/2016	16407.55	15876.36949	531.18051	3.35%	96.65427
5/24/2016	16456.65	15868.63347	588.01653	3.71%	96.29447
5/25/2016	16997.45	15860.90123	1136.54877	7.17%	92.83427
5/26/2016	17359.3	15853.17275	1506.12725	9.50%	90.49952
5/27/2016	17511.8	15845.44804	1666.35196	10.52%	89.48372
5/30/2016	17520.65	15837.72709	1682.92291	10.63%	89.37396
5/31/2016	17620.9	15830.00991	1790.89009	11.31%	88.68674
				Min	88.68674
				Max	99.74516
				Mean	95.73141

Table 8: Percentage change in Actual and Dynamic Forecast Values and precision of prediction (Nifty Bank Index) (From one-year estimate sample)

It is observed that the precision of forecasts ranged been 88.7% to 99.7% with a mean of 95.7% if dynamic forecasting method is used under ARIMA (p, d, q) technique from estimation sample of a short term period of one year, in the case of Nifty Bank Index.

6.4.2. Dynamic Forecast Comparison

Table 9 depicts the results of precision of prediction using static forecast under ARIMA (0,1,0) of 247 observations of Bank Nifty ranging a short term period of 1st April 2015 to 31st May 2016.

DATE (mm/dd/yyyy)	ACTUAL CLOSE	STATIC FORECAST CLOSEFSTAT1	CHANGE Delta	% CHANGE Delta%	PRECISION %
4/1/2016	16174.9	16133.78472	41.11528	0.25%	99.74516
4/4/2016	16190.6	16167.01852	23.58148	0.15%	99.85414
4/5/2016	15695	16182.71087	-487.71087	-3.01%	96.98622
4/6/2016	15636.95	15687.35236	-50.40236	-0.32%	99.67871
4/7/2016	15530.75	15629.33065	-98.58065	-0.63%	99.36926
4/8/2016	15568.35	15523.18239	45.16761	0.29%	99.70903
4/11/2016	15818.5	15560.76407	257.73593	1.66%	98.34368
4/12/2016	15880.2	15810.79218	69.40782	0.44%	99.56101
4/13/2016	16278.55	15872.46212	406.08788	2.56%	97.44156
4/18/2016	16222.7	16270.61802	-47.91802	-0.29%	99.70549
4/20/2016	16349.7	16214.79523	134.90477	0.83%	99.16801
4/21/2016	16637.15	16341.73335	295.41665	1.81%	98.19226
4/22/2016	16703.4	16629.04328	74.35672	0.45%	99.55285
4/25/2016	16678.65	16695.261	-16.61100	-0.10%	99.9005
4/26/2016	17002.55	16670.52306	332.02694	1.99%	98.0083
4/27/2016	16872.95	16994.26524	-121.31524	-0.71%	99.28614
4/28/2016	16716.9	16864.72839	-147.82839	-0.88%	99.12345
4/29/2016	16795	16708.75442	86.24558	0.52%	99.48383
5/2/2016	16543	16786.81637	-243.81637	-1.45%	98.54757
5/3/2016	16388.7	16534.93916	-146.23916	-0.88%	99.11557
5/4/2016	16274.25	16380.71434	-106.46434	-0.65%	99.35006
5/5/2016	16281	16266.32011	14.67989	0.09%	99.90975
5/6/2016	16296.6	16273.06682	23.53318	0.14%	99.85539
5/9/2016	16686.1	16288.65922	397.44078	2.44%	97.56002
5/10/2016	16784.95	16677.96943	106.98057	0.64%	99.35855
5/11/2016	16754.45	16776.77127	-22.32127	-0.13%	99.86695
5/12/2016	16923.7	16746.28613	177.41387	1.06%	98.94058
5/13/2016	16716.9	16915.45366	-198.55366	-1.17%	98.8262
5/16/2016	16737.55	16708.75442	28.79558	0.17%	99.82766
5/17/2016	16762.75	16729.39436	33.35564	0.20%	99.80062
5/18/2016	16728.95	16754.58208	-25.63208	-0.15%	99.84701
5/19/2016	16565.25	16720.79855	-155.54855	-0.93%	99.06973
5/20/2016	16481.45	16557.17832	-75.72832	-0.46%	99.54263
5/23/2016	16407.55	16473.41915	-65.86915	-0.40%	99.60015
5/24/2016	16456.65	16399.55516	57.09484	0.35%	99.65185
5/25/2016	16997.45	16448.63123	548.81877	3.34%	96.66344
5/26/2016	17359.3	16989.16772	370.13228	2.18%	97.82136
5/27/2016	17511.8	17350.8414	160.95860	0.93%	99.07233
5/30/2016	17520.65	17503.2671	17.38290	0.10%	99.90069
5/31/2016	17620.9	17512.11278	108.78722	0.62%	99.37879
				Min	96.66344
				Max	99.90975
				Mean	99.11541

Table 9: Percentage change in Actual and Dynamic Forecast Values and precision of prediction (Nifty Bank Index) (From one-year estimate sample)

It is further observed that the precision of forecasts ranged been 96.7% to 99.9% with a mean of 99.1% if dynamic forecasting method is used under ARIMA (p, d, q) technique from estimation sample of a short term period of one year, in the case of Nifty Bank Index.

6.5. Summary of Experimental Results

The results of all the experiments using ARIMA forecasting, both dynamic and static, for a two-month period of 1st April 2016 to 31st May 2016 from estimation samples of long term (5years ranging from 1st April 2011 to 31st March 2016) and short term (ranging from 1st April 2015 to 31st March 2016) in the cases of SBI stock prices and Nifty Bank index are summarized in table 10.

Sample and Criteria	Precision (%) of Forecasts		
	Min	Max	Mean
State Bank of India Long term trend – 5 Years estimate			
Dynamic Forecast	86.12	99.90	95.12
Static Forecast	94.00	99.99	98.10
Short term trend – 1-year estimate			
Dynamic Forecast	88.82	99.99	96.46
Static Forecast	93.50	99.88	98.08
Nifty Bank Index Long term trend – 5 Years estimate			
Dynamic Forecast	91.80	99.79	97.12
Static Forecast	96.77	99.96	99.15
Short term trend – 1-year estimate			
Dynamic Forecast	88.69	99.74	95.73
Static Forecast	96.66	99.90	99.12

Table 10: Summary of Results

As is obvious from table 10 the estimates from long term trend using samples of historical price data of previous 5 years tend to forecast with less precision when compared to forecast from trends using short term estimates of price data of one year. However, this is more pronounced in the case of dynamic forecasting using ARIMA especially in the case of individual share price than in the case of a sector Index.

7. Conclusion

It has been found that precision of forecasts is sensitive to time horizon of trend estimates though not significantly. However, the precision with which forecasts can be made using ARIMA technique is comment worthy. An investor who wishes to make timing of entry or exit from the market can rely on ARIMA techniques to forecast future prices with significant precision, provided the appropriate model and ARIMA terms are arrived at with the help of software, which needs certain skills to draw inferences from results of regression analysis.

It may be concluded that static forecasting appears to be more precise than dynamic forecasting irrespective of the time horizon in predicting share prices of SBI and index movements in Bank Nifty. This is because of the fact that a static forecasting uses actual rather forecasted value for the lagged variable which can only be done with actual data available and is hence is inappropriate for a future period. Investors in fact look forward to future price and cannot wait until the period is over to get actual data and predict prices. Hence dynamic forecasting can be applied to real world situations to predict future prices and if it can provide approximately above 90% precision, ARIMA can be resorted to as a tool of forecasting, provided the appropriate Auto regression (p), order of differencing (d) and moving average (q) terms can be identified through right modeling techniques.

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