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COMPARISON OF ARIMA AND EXPONENTIAL SMOOTHING MODELS IN PREDICTION OF STOCK PRICES

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ABSTRACT

Stock prices tend to show trends or seasonality or have random walk movements. Time series statistical models developed over time aid prediction of stock prices to assist informed decision-making for investors. These models provide quantitative information to financial specialists at the time of placing their buy–sell orders. The paper compares the movement of two univariate time series using two forecasting models—exponential smoothing and autoregressive integrated moving average (ARIMA) (p; d; q). We predict stock prices of selected 15 companies across three sectors (banking, pharmaceuticals, and Information technology) from NIFTY 50 data for the period April 01, 2016 to March 31, 2021. All these 15 companies are representative constituents of the three sectors within the Nifty 50 index. Performances of models were assessed through forecasting error measures such as root mean square error and mean absolute percentage error. Performances of both models were identical for nine stocks. Prediction based on ARIMA was more accurate for six stocks, whereas exponential smoothing model was a better indicator of stock prices in the case of one stock. However, the differences in error measures of the both the models are marginal, and parsimony principle may drive the choice of model.

Keywords: ARIMA, exponential smoothing, mean absolute percentage error, model comparison, rolling forecast, root mean square error, stock price prediction

JEL classification: C180, C220, C580

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1 INTRODUCTION

Forecasting the stock prices is an area of interest for all stakeholders of the stock markets. Predicting stock prices is, however, a challenging task as it involves multidimensional entities right from an individual to a hedge fund, Government, regulators, and qualitative human behavior, like sentiments, herd mentality, fear, greed, and rationality or irrationality for trading and investing decisions. Predicting the prices based on historical data, analyzing current movement to anticipate the future, is what analysts, speculators, chartists, investors, and traders aim at. The underlying assumption for this area of research is that historical fundamental information is publically available and that it has some predictive associations that can be explored for future anticipated predictions. These predictions mainly aim to identify market trends and identify relevant buy time and sell time with an aim to maximize risk-return trade-offs. This will help investors and traders to develop portfolio in order to gain superior returns with proportionate risk.

The financial analysts usually base their investment decisions on time series data analysis (DeFusco, 2015). They further state that a time series is a set of observations taken at regular intervals for a variable such as daily, every week, monthly, and so on. Perceptions based on artificial intelligence (AI) and statistical perspectives can be considered as two significant domains in the research area for stock market time series analysis. While AI focuses on neural networks, statistical studies involve various time series models like autoregression (AR), moving averages (MAs), ARMA, ARIMA, VAR, SARIMA, ARCH, and GARCH among others (Hyndman and Athanasopoulos, 2018). The fundamental logic for this is to examine the existence of any link between the data collected and variations in the data. Apart from the aforementioned techniques, financial statement analysis provides a significant value add to the investor as stock prices also are influenced by them. Events such as dividends, stock splits, earning announcements by companies, mergers, acquisitions, and so on affect the stock prices.

Box and Jenkins (1960) pioneered the autoregressive integrated moving average (ARIMA), which led to a new generation of forecasting tools useful to analyze the probabilistic, or stochastic, properties of economic time series on their own (Gujarati et al., 2015). It is a key model for predicting a time series dataset. The finance domain has seen applications of ARIMA in areas of predicting time series of stock and index prices and returns and has shown proficient results in terms in terms of short-term predictions. The Holt–Winters model is essentially a method to fit appropriate curves to past data of time series (Gujarati et al., 2015). In 1957 and Holt (2004) worked on the exponential smoothing methods that showed trend and seasonality. This gained prominence after Winters (1960) tested the several exponential moving methods, which were tested with the methods of Holt empirical data and now are known as Holt–Winters forecasts.

The paper aims to do a comparative analysis of two predictive models, namely, ARIMA and exponential smoothing model in the Indian context. The performance of each model in predicting selected stock prices from NIFTY 50 index is evaluated through forecasting error measures such as root mean square errors (RMSEs) and mean absolute percentage error (MAPE).

2 LITERATURE REVIEW

Researchers have employed numerous techniques of stock price forecasting. We also find applications of econometric models for prediction of stock prices across many studies and research articles globally.

Modern literature has seen applications of ARIMA and Holt–Winters model in various time series of stock prices or indices; however, a comparative application to Indian stocks has been limited, and hence, the paper aims to bridge this gap.

Jarrett and Kyper (2011) examined the application of ARIMA time series analysis to forecast the data based on the index from the Greater China database from 1990 to 2009. From their studies, they infer that the daily stock prices are predictable and there exists an autoregressive component. They also found the usefulness of the model in providing evidence for the reduction in the Index of Shanghai A stocks. Afeef et al. (2018) undertook a study of one of the largest companies in Pakistan, that is, Oil & Gas Development Company Limited (OGDCL), based on the daily-adjusted closing prices for the period 2004–2018 consisting of 3632 observations. Their findings indicated that of the methods, ARIMA had prediction capabilities in the short run and investors would find it useful. Guei et al. (2020) undertook a study of the BRICS economies using the data post the financial crisis to test predictability performance of ARIMA and GARCH models as well as the neural network model from the riskiness perspective. On a comparative analysis, their findings indicated that ARIMA models gave a better predictive reliability as compared to GARCH except in the case of the Brazilian BOVESPA stock index. The artificial neutral network (ANN) model indicated that it could be used to predict stock market volatility, thereby enabling better risk management. Balsara et al. (2007) sampled stock market indices which were listed on the Shanghai Stock exchange. They used ARIMA and variance test ratio based on the assumptions of the random walk theory. Their findings indicated that ARIMA model gave more accurate forecasts as compared to the variance test ratio on random walk assumptions. Suresh Kumar and Joseph James (2016) examined the sensitivity of the ARMIA model across varying time horizons. These were employed in estimation of trends as well as to validate these forecasts based on the degree of precision through the use of historical stock data of stocks traded on the Indian stock exchange. They evaluated the precisions of the ARIMA forecast for both long-term and short-term estimations. Their sample consists of 262 observations across a year for State Bank of India, listed on National Stock Exchange in India.

Their findings based on dynamic and static forecasting indicated that ARIMA could be used for short-term prediction as a forecast tool. Angadi and Kulkarni (2015) proposed a forecasting model for identifying stock market trends related to technical analysis based the ARIMA model and historical data. The model aims to automate the prediction direction of stock indices and also provide an indication of the buy time and sell time of stocks. They found that ARIMA model was suitable to for short-term prediction of stock market patterns. Shuyu and Rongrong (2017) conducted a study to predict the energy demand of the Shandong state in China based on the past data from 1995 to 2015. They used GM-ARIMA (1, 1) for predicting energy demand for 10 years ending in 2015. Based on the relative average error, his findings indicated that the GM-ARIMA model was the most accurate. The energy demand of Shandong province in 2016–2020 was expected to increase at 3.9% per annum. Manoj and Madhu (2014) aimed to predict the sugarcane production in India based on the Box–Jenkins model for the period 2013–2017 based on the historical time series data of sugarcane production of past 62 years from 1950 to 2012. Using the ARIMA (2, 1, 0) model, their findings indicated that the model was able to forecast the same for the next 5 years. Based on the forecast, a 3% per annum growth is estimated for the sugarcane production. Mondal et al. (2014) examined 56 stocks from different sectors in India. They used ARIMA (with AIC) for sampled stocks. Their findings indicated that the model predicted the stock prices up to 85% across all sectors. Hiransha et al. (2018) discovered that neural network model was a better predictor than the ARIMA based on stocks selected from NYSE-USA and NSE-India with high-frequency trading across different sectors for the period 2011–2016, collated on a daily basis. Malik et al. (2017) undertook a study to forecast prices of five big banks in Pakistan (period: August 2005 to February 2013) using exponential smoothing and ARIMA. Their findings indicated that distributions across the sampled banks were non-normally distributed and ARIMA was found to be a good indicator for forecasting. Pillay (2020) examined the ARIMA model to forecast the Johannesburg stock exchange index. This was with a view to identify the optimal ARIMA model to be used for forecasting using a three-step iterative quantitative approach. The study suggests stability of ARIMA (4, 1, 4). It was a better predictor of the JSE index for ensuing 2 years. A study by Ivanovic et al. (2013) aimed to predict the Crobex and Croatian index by applying the ARIMA model on weekly close prices (period 2011–2013). They employed an iterative procedure wherein 200 models were tested. Their findings indicated that ARIMA (16, 1, 16) was found to be more suitable to predict the index values and that ARIMA outperformed the naïve model. Majid and Mir (2018) undertook a detailed study of various statistical forecasting time series models and applied them on various datasets including stock market index values, business performance, and agricultural products. Predictions were also based on diverse time periods and seasonality in datasets. Pieleanu (2016) deployed the ARIMA models due to the proven success and effectiveness on the monthly values of the BET index of Bucharest Stock exchange for a 5-year period of 2010–2014; findings indicate that ARIMA provided satisfactory results and can be relied upon to forecast the short-term and medium-term prices. Merh et al. (2011) attempted to develop, estimate, and forecast the ANN (4, 4, 1) model and ARIMA (1, 1, 1).

They predicted Sensex (BSE 30) index, India, by computing simulations using daily prices for the period April 16, 2004 to April 16, 2009. Their findings suggested that the forecasting accuracy from ARIMA was better than that of ANN for the next 30-day forecast period.

Holt–Winters have seen their models' application in diverse areas from stock markets to commodities to predicting sales. Awajan et al. (2018) undertook a comparative analysis of the performance methods for prediction based on a sample of six stock market indices from Sri Lanka, France, Australia, Netherlands, Malaysia, and US- S&P 50 (period: February 3, 2020 to June 5, 2020) and revealed that Holt–Winters (EMD-HW) presented better and more accurate estimations than the other models. Kotsialos (2005) also undertook a study by using a damped-trend of Holt–Winters's model and the feedforward multilayer neural networks (FMNNs) for the sales of two German companies for medium- to long-term (4 to 12 months) horizon. FMNN-based forecasts were found to be only marginally better the output of the Holt–Winters's method. Tratar (2014) aimed to demonstrate an improved additive method of the HW by treating the starting values for level, trend, and seasonal components and three smoothing constants as decision variables. Their study found a significant fall in the mean square error, that is, forecast error, as compared to other models of the study, when they applied the additive HW, multiplicative HW, and improved HW to predict the number of tourists in Slovenia who tool overnight stays based on the quarterly data of domestic and foreign (F) tourists for the period 2000–2009. Clear seasonal effects were found in the time series analysis including a positive significant autocorrelation coefficient of 0.878. Adeyinka and Muhajerani (2020) studied the long-term mortality rate of 0–5 year's age group in Nigeria. They did a study on the data using GMDH-type ANN and compared the predictions of ARIMA and exponential smoothing models. The outcomes were analyzed based on RMSE, RMAE, and modified Nash-Sutcliffe efficiency (NSE). Overall, it was found that the GMDH-type neural network resulted in best forecasts for under-5 mortality rates. Agustina et al. (2021) applied Holt–Winters exponential smoothing method for stock prices and model predictive control models for optimization of portfolios. Findings indicated that the Holt–Winter method is considered a better predictor as it gave a predictive error accuracy (MAPE) less than 10%, and the outcomes of the MPC suggested satisfactory results, which created wealth for the investors.

Other applications of the exponential smoothing (HW model) that were found to suggest satisfactory results in favor of the HW model are included. Suwanvijit et al. (2011) found that the HW model with additive seasonality and the nonlinear approach of Lee Carter method provided excellent estimates, 95% robust prediction, and the best fit in predicting the sparkling beverage sales for 2005–2006 in 14 provinces of Thailand for the period 2000–2004. Chawla and Jha (2009) attempted to predict natural rubber production in India for a period of 15 months ending in March 2017. They used monthly data to apply the exponential smoothing method and ARIMA. The MAPE for Winters's method was 8.01%, whereas for Holt's method, EM was 8.09%. Their findings indicated that Winters's method outperformed Holt's method. This suggests both Holt's method and Winters's method to be effective for predicting natural rubber production. Gahirwal and Vijayalakshmi (2013) aimed to predict the sales of FMCG companies based on datasets of 30 series by decomposing the series into a trend, seasonality, and an irregular component for each series. Use of ARIMA and Holt–Winters method on these intertime series indicated that the proposed decomposition-based method to forecast showed better results than the Holt–Winters method.

3 METHODOLOGY

This section describes sample data, tools, and procedures for model building, estimation, and comparison of the models used in the paper for prediction of stock prices. The objective of the research paper is to do a comparative analysis of daily stock price predictions using two models, namely, ARIMA and exponentially smoothing technique. The performance of models was assessed through forecasting error measures such as RMSE and MAPE.

3.1 SAMPLE DATA

The Nifty 50 Index is the India`s largest stock index in terms of market capitalization. It comprises companies from different sectors that largely represent Indian economy. We covered three sectors that are key constituents of NIFTY 50 index, namely, banking sector (six stocks), pharma sector (four stocks), and information technology sector (five stocks).

The published historical data of the selected stocks are collated for the trading days between April 1, 2016 and May 31, 2021 from the website www.nseindia.com. The collated data were adjusted for corporate actions.

3.2 EXPONENTIAL SMOOTHING MODEL

Brown (1959), Holt (1957), and Winters (1960) pioneered exponential smoothing, which became the foundation of widely accepted forecasting tools. The forecasts are calculated as weighted averages of historical observations. The relatively greater weights were assigned to recent observations. Thus, more recent is the observation, higher is the weight assigned. Exponential smoothing method is a collection of different methods. The choice of a method is driven by key components of time series—trend and seasonality and the way they show up in series (e.g., in an additive, damped, or multiplicative way).

3.2.1 SIMPLE EXPONENTIAL SMOOTHING

The simple exponential smoothing (SEM) is the easiest of all exponential smoothing methods. This method is widely used to forecast data which do not indicate a clear trend or a seasonal pattern. This model is represented as

$$\hat{y}_{t+1\,|t} = \alpha y_t + \alpha(1-\alpha) y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \dots,$$

where $0 \leq \alpha \leq 1$ is the smoothing parameter. One step ahead of forecast for time $t + 1$ is the weighted average of all observations up to time t. Parameter α determines the rate at which weights will decline. If α is close to 0, then fall in weights is sharp, whereas if α is close to 1, then decay in weights is gradual and slow. However, for any value of α, weights assigned to observations fall exponentially when we navigate the series backward.

3.3 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE

The foundation underpinning ARIMA is popularly known as Box–Jenkins's methodology (1976). It is used to analyze probabilistic, or stochastic, properties of economic time series. It is based on the philosophy "let the data speak for them" (Gujarati et al., 2015). ARIMA consists of two models. These are autoregressive (AR) model and moving average model (MA). These are always based on assumption stationarity of the underlying time series. Often, real-time data are nonstationary and hence subjected to differencing for achieving stationarity. Differencing converts a time series into a new time series. The values of new time series are the differences between observation time "t" and "$t - 1$" of the original time series.

3.3.1 THE AUTOREGRESSIVE MODEL

The autoregressive model of order p, AR (p), can be represented as

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + u_t = \beta_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + u_t$$

where $\beta_1, \dots, \beta_p$ are the parameters, β_0 is a constant, and u_t is a white noise error term. This model is called autoregressive of order p for it involves regressing Y at time t on its p preceding values. The value of p is established empirically with some criteria such as Akaike Information Criterion (AIC).

3.3.2 THE MOVING AVERAGE MODEL

The moving average model of order q, MR (q), can be represented as

$$Y_t = C_0 + C_1 u_t + C_2 u_{t-1} + \cdots + C_q u_{t-q} = C_0 + \sum_{i=1}^{q} C_i u_{t-i}$$

Thus, we express the value of Y at any given time t as a weighted average of the current and past white noise error terms. The order q indicates the number of past white noise error terms used in the model. The model MA (q) has q + 1 white noise terms. The value of q is also determined empirically.

3.3.3 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL

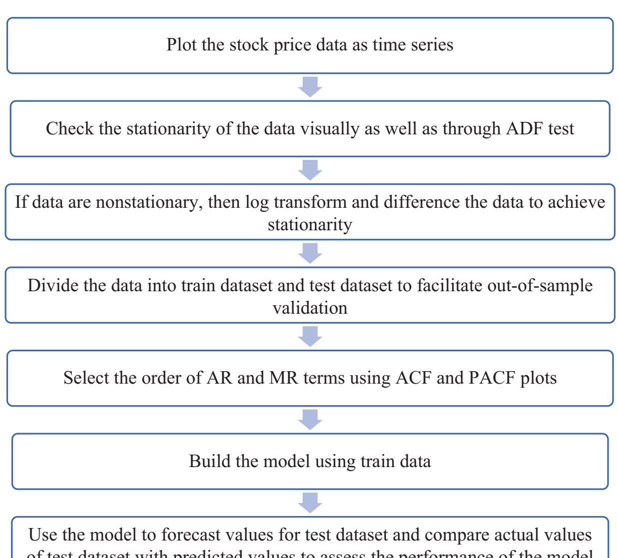
The AR (p) and MA (q) can be united with differencing to form ARIMA (p, d, q) model. ARIMA (p, d, and q) model has p AR terms and q MA terms with d degrees of first-order differencing and can be represented as

$$Y_t' = C + \beta_1 Y_{t-1}' + \beta_2 Y_{t-2}' + \cdots + \beta_p Y_{t-p}' + C_1 u_t + C_2 u_{t-1} + \cdots + C_q u_{t-q} + u_t$$

The above equation is represented using the backshift operator as

$$(1 - \beta_1 .B - \cdots - \beta_p .B^p)\ (1 - B)^d\ \ Y_t = C + (1 + C_1 .B + \cdots + C_q .B^q) u_t)$$

Graphically, the steps in ARIMA are represented below:



This research paper compares exponential smoothing model and ARIMA model using time series cross-validation through calculation of RMSE and MAPE.

3.4 ROOT MEAN SQUARE ERROR

RMSE is used to measure forecasting accuracy as well as building confidence intervals around predictions and calculated as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_t - \hat{y}_t)^2}$$

where y_t is the observation at time t, $\hat{y}_t$ is the prediction at time t, and n is the number of observations.

3.5 MEAN ABSOLUTE PERCENTAGE ERROR

MAPE is a unit-free measure of errors and expressed as percentage. It is calculated as

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \times 100$$

where y_t is the observation at time t, $\hat{y}_t$ is the prediction at time t, and n is the number of observations.

4 MODEL BUILDING, ESTIMATION, AND COMPARISON

The variance of time series was stabilized by using log transformation of stock prices. Since ARIMA model requires time series to be stationary, Augmented Dicker Fuller (ADF) test was conducted to assess the stationarity of data. Since the data were nonstationary, first-order differencing was employed to the data. The ADF tests were performed again to check for stationarity. First-order differencing resulted in the stationary data series. Table 1 displays the outcomes of ADF test before and after first-order differencing.

Data were then divided in train and test datasets for the purpose of out-of-sample validation.

1. The dataset has 1278 observations (adjusted closing prices for between 1/4/2016 and 31/5/2021 trading days) for all the selected stocks in the sample. Out of these, 1239 observations (trading days between 1/4/2016 to 31/3/2020) were used for training the models initially and one-step ahead forecast was used for predicting stock price for 1240th observation (stock

Table 1. Augmented dickey fuller test results of actual series and differenced series

Company name	Original data		Post one-order differencing	
	Pre	*p*-Value Pre	Post	*p*-Value Post
Axis Bank	−2.595	0.326	−10.668	0.010
HDFC Bank	−2.424	0.399	−11.276	0.010
State Bank of India	−2.199	0.494	−10.080	0.010
IndusInd Bank	−2.215	0.487	−9.249	0.010
ICICI Bank	−2.884	0.204	−10.987	0.010
Kotak Mahindra Bank	−2.762	0.256	−11.333	0.010
Cipla	−1.522	0.781	−10.406	0.010
Dr. Reddy	−1.626	0.737	−10.344	0.010
Sun Pharma	−1.712	0.700	−11.368	0.010
DIVISLAB	−1.956	0.597	−11.262	0.010
Infosys	−2.235	0.479	−11.511	0.010
TCS	−2.658	0.300	−11.626	0.010
Tech Mahindra	−2.103	0.535	−9.792	0.010
HCLTech	−2.607	0.322	−10.601	0.010
Wipro	−1.173	0.911	−10.384	0.010

prices for April 01, 2021). The adjusted stock prices from April 01, 2021 to May 31, 2021 (total 39 trading days) were used as a test dataset for prediction.

2. All successive observations in the test dataset (stock price from April 02, 2021 onward) were then predicted using rolling forecast method through iterative process as follows:
   (a) For predicting stock price on a particular day, the train dataset was created using all the historical observations up to the previous day.
   (b) The models were trained again using the new train data, and forecast for each day was generated using these models.
   (c) The predicted values by the models for each day and their confidence intervals at 80% and 95% were stored.
   We computed the RMSE and MAPE to assess the performance of the models using actual values and predicted values for 39 trading days from April 01, 2021 to May 31, 2021.
3. The actual values and predicted values for both the models were plotted to evaluate performance of both the models visually.

Table 2 shows the measures for forecasting accuracy (RMSE and MAPE) of both the models for all the selected stocks.

Table 2. RMSE and MAPE from ARIMA and exponential smoothing models

Sl. No.	Company name	ARIMA		Exponential smoothing	
		RMSE	MAPE	RMSE	MAPE
1	Axis Bank	0.0205	0.2483	0.0205	0.2484
2	HDFC Bank	0.0178	0.1902	0.0185	0.1982
3	State Bank of India	0.0233	0.2819	0.0233	0.2820
4	IndusInd Bank	0.0286	0.2931	0.0292	0.3196
5	ICICI Bank	0.0226	0.2796	0.0226	0.2810
6	Kotak Mahindra Bank	0.0176	0.1881	0.0177	0.1895
7	Cipla	0.0167	0.1808	0.0167	0.1808
8	Dr. Reddy	0.0172	0.1478	0.0172	0.1478
9	Sun Pharma	0.0179	0.2017	0.0178	0.2016
10	DIVISLAB	0.0130	0.1153	0.0129	0.1153
11	Infosys	0.0107	0.1170	0.0107	0.1172
12	TCS	0.0137	0.1222	0.0135	0.1210
13	Tech Mahindra	0.0136	0.1587	0.0137	0.1615
14	HCLTech	0.0140	0.1488	0.0141	0.1484
15	Wipro	0.0225	0.2649	0.0226	0.2672

As seen from the table, measures for forecasting errors (RMSE and MAPE) from both the models differ marginally, indicating better predictive performance of ARIMA for most of the stocks.

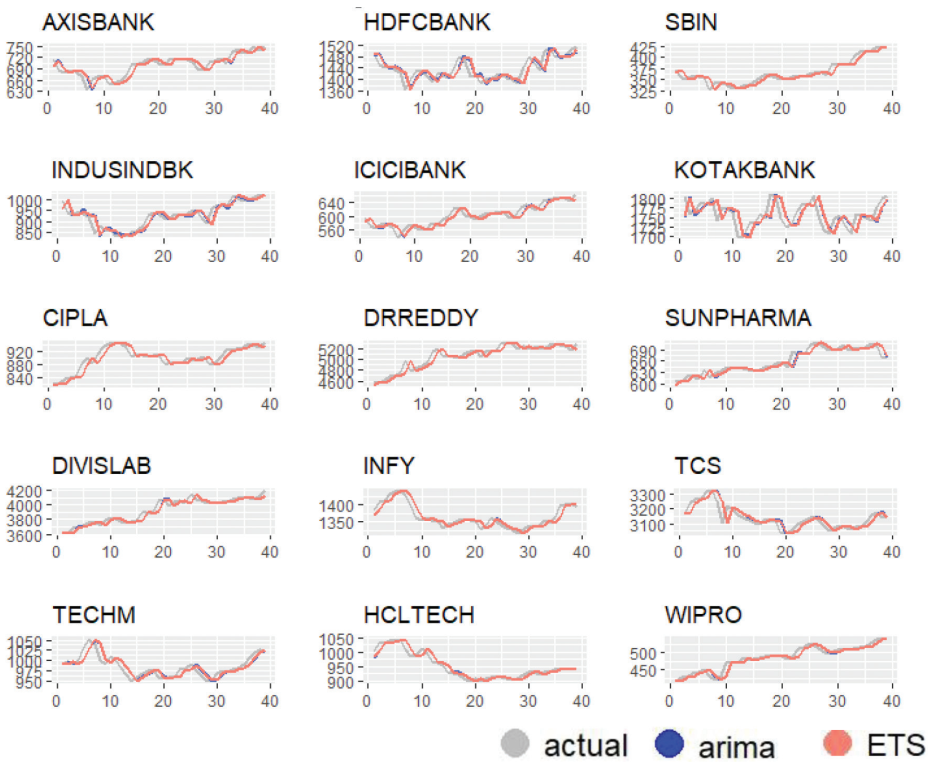
The charts below show performance of both the models for different sectors (see Exhibit 1).

As seen from the charts, performance charts of both the models follow almost the same trails, indicating a marginal difference in forecasts of stock prices from exponential smoothing model and ARIMA.

5 CONCLUSION AND DISCUSSION

In our research paper, we conducted a study on 15 stocks selected across three sectors (banking, pharmaceuticals, and information technology) from NIFTY 50 data for the period April 01, 2016 to March 31, 2021. These 15 companies are carefully selected as they are representative constituents of the three sectors within the Nifty 50 index. The trading data of 1,239 days are used to build the models initially, and stock prices are predicted using rolling forecast method subsequently for 39 trading days. The rolling window forecast allows us to incorporate the effect of the most recent price leading to greater precision in price prediction.

Exhibit 1. The charts show performances of both the models for different sectors



Source: nseindia.com

We compared the stock price movements of the selected stocks using two forecasting models – exponential smoothing and ARIMA (p; d; q). We compared the performance of the two models using two measures: RMSE and MAPE.

The findings reveal that while predicting stocks, the performances of both the models were the same for nine stocks on both the measures of forecasting errors. ARIMA performed better than exponential smoothing for prediction of five stocks (HDFC Bank, IndusInd Bank, KOTAK Bank, Tech Mahindra, and WIPRO) (Gahirwal and Vijayalakshmi, 2013), whereas exponential smoothing model was a better predictor for TCS (Awajan et al., 2018).

ARIMA model performed better in prediction of stocks from the banking sector and IT sector. The performances of both the models are the same for the pharma sector. We can conclude that ARIMA gives better overall performance in stock prediction than exponential smoothing method. An investor can arrive at decisions regarding timing of entry or exit from the market using ARIMA techniques with a fair degree of precision.

With the predicted outcomes using ARIMA, investors and traders can create portfolios which would optimize risk return trade-offs on their portfolios, which, in turn, would increase their return on investment. Further, an extended study can be carried out to test whether such portfolios consistently outperform the benchmark (SENSEX or NIFTY), thus generating alphas, that is, excess portfolio returns over the bench mark. This can be developed into a successful investment strategy.

The study can be extended by incorporating more stocks to evaluate model performance in various sectors, in particular banking, since out of the six stocks of banking, ARIMA outperformed exponential smoothing in three stocks. However, the difference in the performance was found to be marginal for the sample data across all the three sectors (Appendix 1).

We can further assess the impact of window size, that is, number of trading days used to build the models on the prediction accuracy. The study can be extended further by comparing performances of the models used in the study to other models like neural network.

6 WEBSITE

https://www.nseindia.com/get-quotes/equity?symbol=AXISBANK

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APPENDIX

BANKING SECTOR

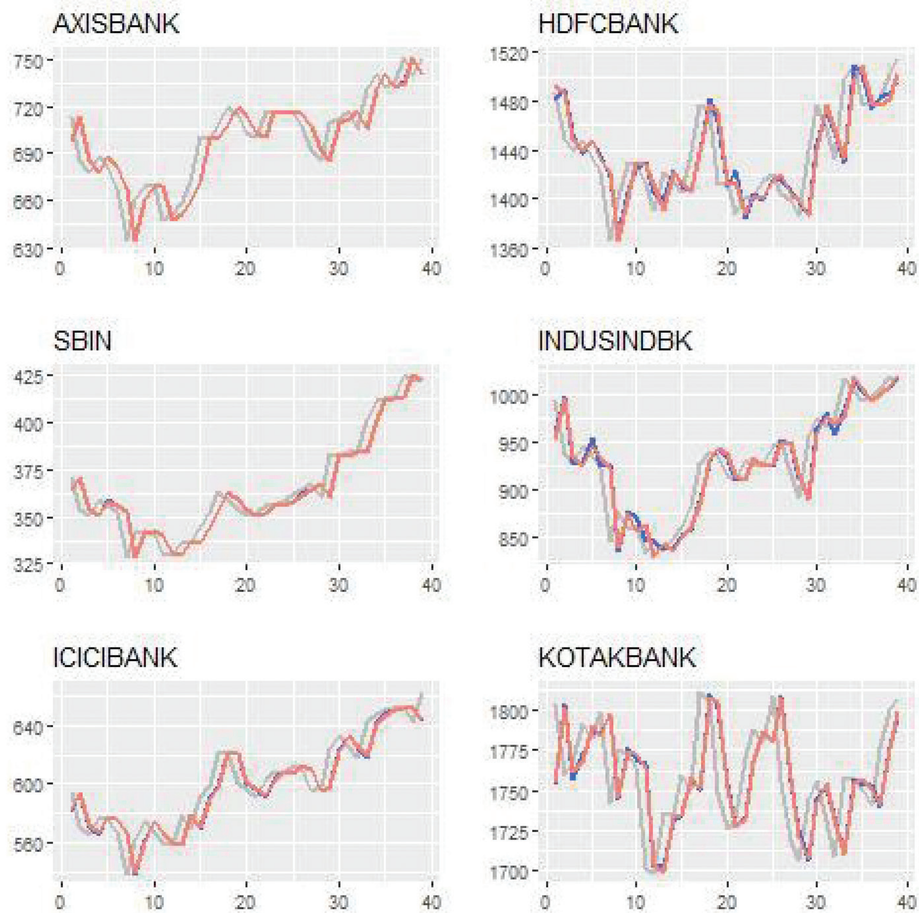

Figure 1. Sectorwise comparison of stock price predictions based on ARIMA and exponential smoothing models

PHARMACEUTICAL SECTOR

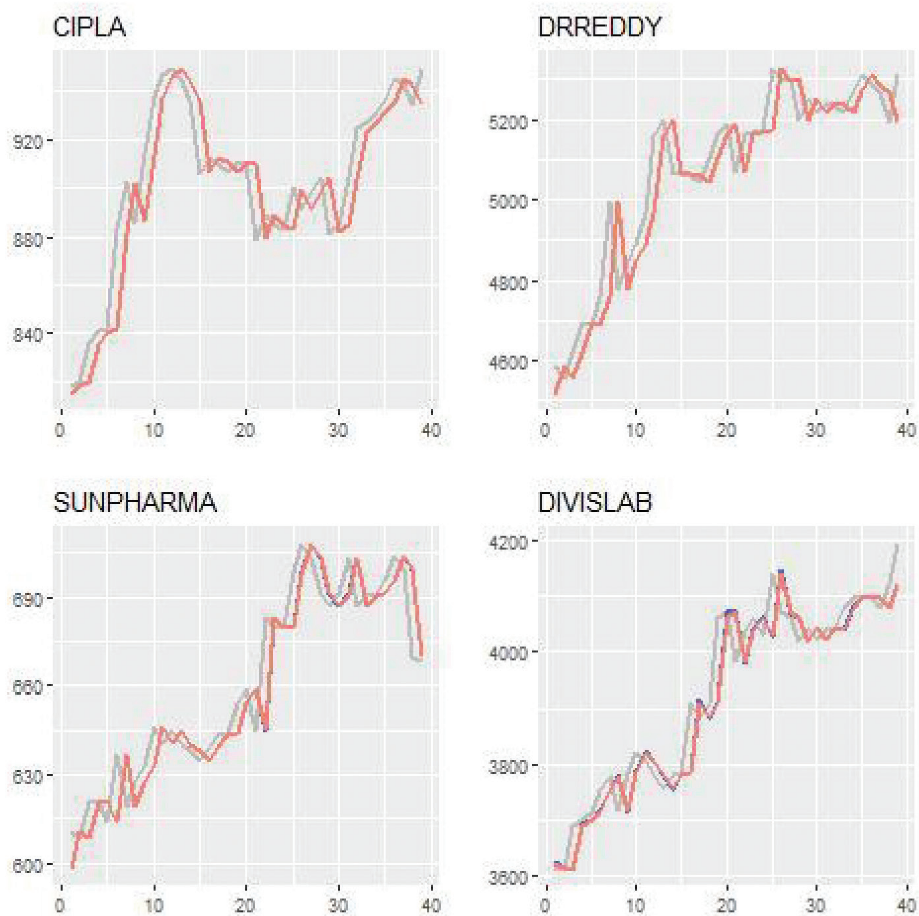

Figure 1. (*Continued*)

INFORMATION TECHNOLOGY SECTOR

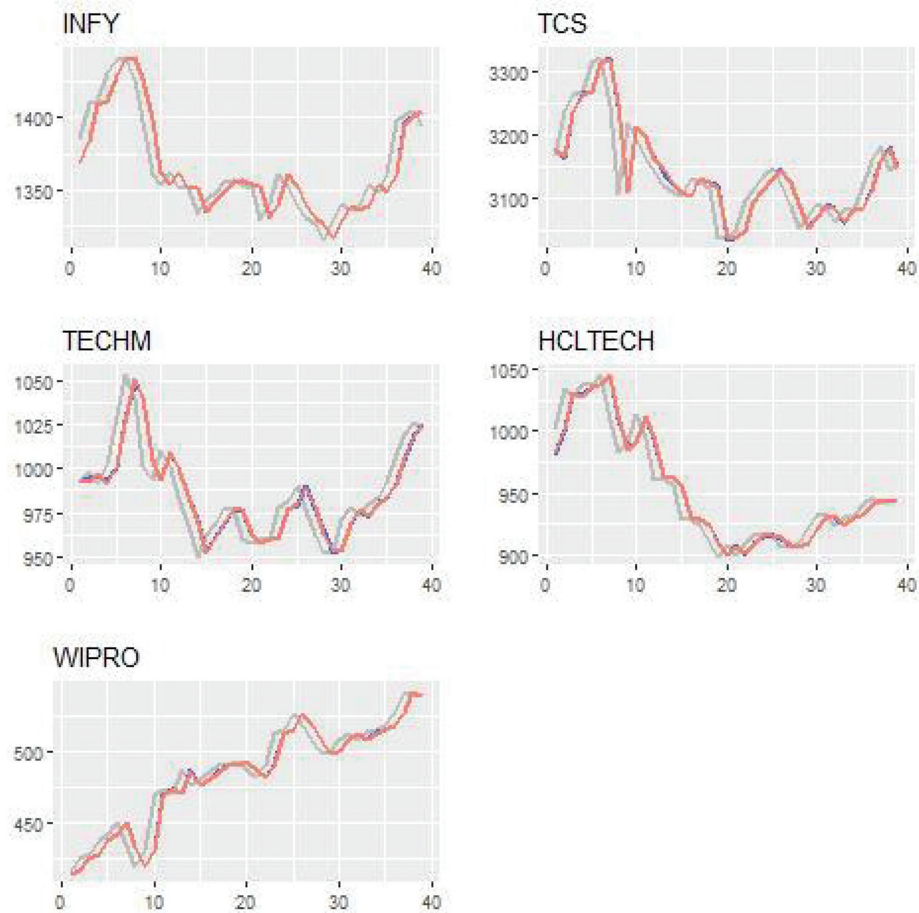

Figure 1. (*Continued*)