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RESEARCH ARTICLE

ON EFFICIENCY OF AUTOREGRESSIVE MODELS IN BSE FINANCE SENSEX WITH FORECASTABILITY ASSESSMENT

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Abstract: The Indian stock market's finance sector is incredibly active and erratic. It's never easy to forecast the finance sector. The current study aims to develop forecasting models for the sensex of the finance sector. The value of a sector-specific model for forecasting stock prices or returns within that specific industry is then assessed. Sector-specific forecasting models also aim to be compared with other sector-wise models, and more precisely with stock price forecasting models, by comparing relevant predicting errors that each model generates. So, the main objective is to ascertain the viability of sector-wise forecasting models for stock price or return forecasting with an acceptable approximation error. Based on daily sensex data, sector-specific sensex values are predicted using the Box-Jenkins autoregressive integrated moving average (ARIMA). The data must be differenced in order to make an integrated time series stationary. Lags of the forecast errors and lags of the values of the original variable are used as regressors in the ARIMA model. Once the best model has been identified, one candidate stock from each segment and the Finance sector is chosen. The suitability of the sector and segment model for the chosen stock price projections is looked at. The forecasting error is then compared to the error value of the stock price forecasting model. The gap dictates whether the sector- and segment-wise models apply to the corresponding equities. Lastly, sector & segment models are applied to five large cap companies from the Finance sector, which are chosen in order to cross-validate the forecasting models' applicability. The validity of the sensex forecasting models unique to sectors and segments is further investigated by comparing the error numbers for each of the five equities in relation to stock price predictions. The forecasting model used in this study for the finance industry has minimal prediction errors over a variety of ARIMA parameter values. Investors might use SE models when making investments in different markets or businesses. Assets or funds can be allocated by a portfolio manager or investor according to their investment strategy to different sectors or segments. A stock that belongs to a certain industry and market segment can have its performance and price predicted utilizing linked intersecting forecasting models.

Keywords: *ARIMA, Finance, Forecasting, Random Walk, Performance, Sensex.*

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INTRODUCTION

Developing and testing models of stock market behavior has long piqued the curiosity of statisticians, economists, and finance academics. The random walk hypothesis is a significant model that this study produced.

The aforementioned hypothesis seriously challenges numerous other approaches that are widely used outside of academic circles to explain and forecast the behavior of stock prices. One may argue, for instance, that different "technical" or "graphical" methods of stock price prediction are invalid if random walk theory accurately describes reality.

In general, anyone who is only concerned in comprehending the behavior of stock prices faces challenging challenges when it comes to random walk theory. Unfortunately, non-mathematicians, who frequently find it difficult to understand, are unable to comprehend the majority of talks on Random Walk theory published in technical academic journals. The theory of random walks and how it can be used to estimate market performance based on sector or segment is briefly discussed in the current study.

Stock market investments may be impacted by market risk. The market is divided into segments and sectors. Every sector or market area has a large number of stocks, each with distinct characteristics. Understanding the sectors and segments is essential to deciding how best to allocate money among them. Marketplace hazards are associated with sectors and segments. As a result, stocks in that sector or market group are at danger.

Because of this, determining the market risk involved in an investment is crucial. The sector-specific sensex of a given industry indicates its performance. Conversely, a stock's performance is reflected in its stock price. Consequently, sector- or segment-specific sensex forecasting is crucial for making wise investment decisions in addition to stock price forecasting.

Although proponents of the efficient market hypothesis argue that sector-specific sensexes cannot be forecasted, other arguments have demonstrated that they may be reasonably predicted with appropriate definition and modeling. Using suitable functional forms or forecasting models and properly selected exogenous variables, the second school of thought focused on developing trustworthy statistical, economic, and artificial intelligence models (Ghosh & Roychowdhury, 2022). Time series analysis and decomposition are used in some theories to predict future values of the sensex.

LITERATURE REVIEW AND RESEARCH GAP

Kim, Nelson, and Startz (1991) used weekly and monthly returns to study the random walk process of stock prices in five Pacific Basin stock markets. The findings showed that the mean reversion was not a post-war phenomenon, but rather a pre-World War II phenomenon. In the variance ratio experiments, they discovered a positive serial link.

For any financial strategy that involves the future, forecasting is a necessary activity. Simultaneously, predicting the value of a financial asset such as stock or equity has shown to be very difficult. The stock market responds to different sectors in different ways. Depending on how much stock is worth, each sector is further subdivided into smaller groups.

According to Fama (1970), fundamentals determine how stock prices change. However, further empirical research has questioned this result. Shiller (1981) discovered that stock values changed more than one might expect considering the status of the economy.

Regressing the proportionate change in stock prices over time can be used to assess whether the bubble eventually begins to outweigh fundamentals, as demonstrated by Blanchard and Watson (1982). When a bubble is present, stock values fluctuate proportionately and predictably increase over time.

Research by Fama & French (1988) on the long- and short-term components of stock prices revealed that returns had significant predictable components. This discovery raised doubts regarding the stock market's effectiveness. "Bubbles" in the stock market or the fundamentals as an explanation for stock price behavior were not supported by Dwyer & Hafer's (1990) analysis of stock price behavior globally.

In 1991, Froot and Obstfeld's study on intrinsic bubbles cast doubt on the idea that fundamentals drive stock prices. A survey of the theoretical literature was conducted by Polemarchakis (1990), who also highlighted the difficulties in achieving an efficient equilibrium in the stock market with incomplete markets and proposed information control as a potential remedy. Campbell (2000) discussed the concept of dynamic equilibrium in the US stock market.

Lo and MacKinlay found a positive autocorrelation, in contrast to the negative serial correlation found by Fama and French (1988). Fama and French found that 40% of the variability in longer holding-period returns for the U.S. exchange could be predicted using past returns.

Campbell (1991) conducted an analysis of stock returns using the variance decomposition approach and came to the conclusion that the expected stock return exhibits a consistent fluctuation over time.

After accounting for the bid-ask spread and asynchronous trading, Parameswaran (2000) examined variance ratios on weekly returns extracted from the Center for Research in Security Prices (CRSP) daily returns file over a 23-year span. He made the point that large-scale enterprises do not get serial correlation from non-trading.

Predicting stock prices for Indian stock markets has been the subject of numerous research efforts. Due to the market's insufficient reaction to the disclosure of pertinent information (fundamentals), Obaidullah (1991) discovered that there exist both overvalued and undervalued stocks. Data on the BSE from 1979 to 1991 was used by Obaidullah (1991).

Barman & Madhusoodan's (1993) research indicates that stock returns develop into efficient over a longer run time, but not in the short or medium term. Jadhav et al. (2015) proposed a novel hybrid artificial neural network system that uses an ARIMA model to build a prediction model that is more accurate than artificial neural networks. In this instance, they collected information on the monthly closing stock indices of the sensex in order to develop the appropriate model, called ARIMA, which would enable us to predict the future values of the indices of the Indian stock market. This means that it can be used as a good stand-in model for the prediction task, especially when a higher degree of predictive accuracy is needed.

Banerjee (2014) collected sensex data for his study in this field. In order to predict the future values of unregulated Indian stock indices, the authors set out to develop a model. We present a grounded application of the ARIMA model in this work to estimate future stock indices that would significantly affect the performance of the Indian economy. He used the 2013 sensex data that was collected along with the validity technique to develop the model.

As'ad (2012) looked at four ARIMA models to predict the daily demand for energy produced by burning peat. The study found that the ARIMA model, which makes use of past data spanning three months, is the most accurate model for making predictions two to seven days in advance.

Devi, Sundar, and Ali (2003) conducted a time series analysis study including five stocks from the Nifty Midcap 50. They estimated stock values using the best fitted model.

The performance of the ARIMA model was assessed by Mondal, Shit, & Gosrvami (2014) in their examination of 56 Indian stocks across a range of economic sectors. After looking at how well ARlMA predictions performed across all industries, the study came to the conclusion that 50% of stocks had good predictive accuracy.

Kumar & Anand (2015) projected India's sugarcane production for the next five years using the Box-Jenkin ARIMA model. According to the report, output rose significantly in 20l3, fell precipitously in 20l4, and then increased by almost 3% yearly between 2015 and 2017.

Ariyo et al. (2014) used the New York and Nigerian stock markets to illustrate the ARIMA model's effect on stock prices. The results show how good ARIMA is for making short-term predictions.

Research Gap: A logical collection of like equities is called a sector. A sector-specific sensex indicates how that sector is performing. The majority of research to date has been solely on stock price forecasting for the Indian market. To fully comprehend the dynamics of the main stock market sectors, a thorough analysis of Finance sensex values is required.

Investors also need to evaluate forecastability and identify an effective forecasting model for sensexes that are peculiar to their industry. There has long been a perceived need for this field of study. In order to support effective and efficient investment decision making for certain industries, the current study fills this research vacuum.

This research needs to create a reliable framework so that the Indian Bombay Stock Exchange (BSE) Finance sector sensex can be forecasted on a regular basis. There is a claim that a systematic technique like this may reproduce the underlying dynamics and be adjusted to forecast real-time sensex movement across many sectors and segments.

Thus, it is imperative to conduct study on the issue of predicting the movement of the sensex values in the finance industry. Investigating the connection between stock prices and the relevant Finance sector sensex is also essential. If it is possible to forecast stock prices using the respective sector-specific sensex forecasting model, more investigation is needed.

OBJECTIVE AND METHODOLOGY

The goal is to evaluate the finance sector's forecastability. This leads to evaluating how predictable the performance of the finance sector is in the Indian stock market. A sector's performance is indicated by its sensitivity index; this study looks at the predictability of the Finance sector index. An additional objective of this research is to ascertain whether Finance sensex follows the random-walk hypothesis, which is required for improved sector efficiency.

Future values can be predicted if there is a pattern in the data collection. The pattern's prominence reveals the variable's level of forecastability (Ghosh, 2023). In order to invest money, sensex forecasting is crucial. Based on each sector's potential for profit, investment managers seek to distribute funds to various areas.

It is crucial to determine whether the sensex to be forecasted is suitable before making any forecasts. The forecastability of the pertinent index is examined in the current study as the sensitivity index of the relevant sector represents the performance of sectors and segments. For the sector-specific indexes of Indian stock markets to remain efficient, they must follow the random-walk hypothesis. To determine whether a random walk happens throughout a stock's price formation process, stock market indices are utilized.

The data was obtained from the official website of the Bombay Stock Exchange. Here, data on the daily closing values of the BSE sensex for the fiscal year 2016–2023 has been incorporated, sourced from the official website of the Bombay Stock Exchange (BSE). However, segment-specific data based on market capitalization is collected for large-cap, mid-cap, and small-cap stocks. The Finance sensex values over the last seven years are gathered, totaling 1735 records per day. Each segment's one finance business is also chosen for the purpose of cross-validating sensex-based forecasting models. The daily prices of these three stocks are gathered for the fiscal years 2016 through 2023. The data also includes the opening, closing, high, and low statistics for each day. To forecast the performance of the sensex, the exchange rate (USD to INR) has been selected as the regressor. For testing, daily exchange rate data spanning seven years (FY 2016–2023) with 1735 records is also gathered.

Testing of Random Walk by Filter Rule Test

Filter rules: Alexander (1961, 1964) used a filter rule to assess independent increment, where an asset is bought when its price rises by x% and (temporarily) sold when its price falls by x%. Alexander (1961) established a rule known as an x% filter for the following reasons: It is believed that the market's fluctuations are hiding any price trends, albeit this is a tentative assumption.

After removing any smaller motions, only the larger motions can be investigated. The overall return of this dynamic portfolio strategy serves as a barometer for the predictability of asset returns. After comparing the overall return for the Dow Jones and Standard and Poor's industrial averages to the return from a buy-and-hold strategy, Alexander concluded that "...there are trends in stock market prices."

More detailed empirical studies of filter rules by Fama (1965) and Fama and Blume (1966) revealed that they did not outperform the buy-and-hold strategy after controlling for trading expenses and dividends. Fama and Blume (1966) show that the profits from such filter rules are eliminated at merely a 0.1% roundtrip transaction cost. Very tiny filters (1% in Alexander (1964) and between 0.5% and 1.5% in Fama and Blume (1966)) do produce greater returns when transaction expenses are removed.

Testing of Random Walk by Box-Ljung Test

Ljung and Box (1978) provide the following finite-sample correction which yields a better

fit to the $X^2{}_{m}$ for small sample sizes:

$Q_m \equiv \mathrm{T(T+2)} \sum \rho^2\ \mathrm{(k)/(T-k)}$ where k=1, 2, …, m

Finding departures from zero autocorrelations in either direction and at all delays is the goal of the Ljung and Box test statistic (), which adds the squared autocorrelations. Because of this, it works well against many different types of objections to the random walk. It is important to exercise caution when selecting the number of autocorrelations, though, as using too few could mask the presence of higher-order autocorrelation, while using too many could result in negligible higher-order autocorrelations and reduce the test's power.

Forecasting models for the Finance sector sensex are the next objective of the ongoing research. The applicability of the sector-specific model for forecasting stock prices or returns within that specific sector is then assessed. Segment-specific forecasting models compare to sector-wise models, and more precisely, to stock price forecasting models, by analyzing the associated predicting errors that each model produces. Consequently, the main objective is to ascertain the viability of sector- or segment-wise forecasting models for stock price or return forecasting with a tolerable approximation error.

The Box-Jenkins autoregressive integrated moving average (ARIMA) is used to forecast sector-specific sensex values based on daily sensex data. An integrated time series needs to be differenced in order to become stationary. Lags of the original variable's values and lags of the forecast errors are used as regressors in the ARIMA model. This model is defined by three different parameters: p, d, and q. These represent the number of autoregressive terms, d the degree of differencing, and q the number of moving average terms. Box & Jenkins (1970) fitted an identified time series of data with the ARIMA model.

Since the behavior of series data might change over time, any future value projection involves a large deal of uncertainty. The problem becomes simpler, though, if the data is stationary. When the variance, autocorrelation, and mean of the series do not change over time, the data can be considered stationary time series data.

The time series is made stationary when employing forecasting techniques by differencing or any other treatment.

When assessing the stationarity of time series data, the correlogram is a helpful tool. The autocorrelation function (ACF) is plotted for various lags in order to achieve this. If ACF continuously drops over time, it is not stationary in the time series. The KPSS test, the Phillips Perron (PP) test, and the augmented Dickey Fuller (ADF) test are used to confirm the stationarity of time series.

The ADF and PP tests assume that the data is non-stationar, however the KPSS test considers stationarity to be the null hypothesis. D becomes 0 and differencing is not required if these tests indicate that the data is already steady. For every value of d, the previously specified tests are run to verify the stationarity of the differenced time series data. By contrast, differencing for non-stationarity is done under the assumption that d begins at 1 and increases to n.

The forecasting model is created by determining the minimum value of d at which the test results indicate that the time series difference is stationary. This determines the ultimate degree of differencing (d) value to apply ARIMA. An ARIMA$^{(p,d,q)}$ model equation can be stated as follows:

$$y_t = a + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} - \beta_1 \varepsilon_1 - \beta_2 \varepsilon_2 - \beta_q \varepsilon_{t-q} + \varepsilon_t$$

where α is autoregressive parameter and β is moving average parameter.

Autocorrelation function (ACF) and partial autocorrelation (PACF) plots at various lags in correlation gram analysis can be used to establish the initial values of p and q. Few potential models are found by adjusting their values within the range of the initial values. To assess the model's performance and compare possible models to find the best fit for the given time series, a variety of error measures are computed. These consist of Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

I. Once the best model has been identified, one candidate stock from each segment and the Finance sector is chosen. The suitability of the sector and segment model for the chosen stock price projections is looked at. The forecasting error is then compared to the error value of the stock price forecasting model. The gap dictates whether the sector- and segment-wise models apply to the corresponding equities.

In order to verify the validity of forecasting models, a cross-validation process is conducted on five large cap companies in the Finance sector. Sector & segment models are then applied to these stocks.

The accuracy of the sensex forecasting models specific to sectors and segments is further evaluated by comparing the error numbers for each of the five stocks.

DATA ANALYSIS: RESULTS & DISCUSSION

The 1% filter rule test result is displayed in Table 1. At 1.27, the Finance sector's 1% change ratio is higher than 1.05. As a result, the finance sector does not experience autonomous increase. This suggests that there is a pattern to the Finance sensex and that its values may be predicted.

Table 1: Random walk test for independence: 1% filter rule

1 % Filter Rule	Finance
Number of days having >=1% Increase (X)	269
Number of days having >=1% Decrease (Y)	212
1% Change Ratio R=(X/Y)	1.27
Does the sector follow independent increment? YES if 0.95<R<1.05	NO
Conclusion: Finance sector does not follow independent increment indicating forecastability of Finance sensex values.	

Table 2 displays the Box-Ljung test result. There is less than 0.05 significance for each lag. As a result, Finance sector has uncorrelated growth. This suggests that the sensex for the sector exhibit a certain pattern and that it is possible to predict its values.

Table 2: Random walk test for uncorrelatedness: Box-Ljung Test

		Finance	
Lag	Sig .<0.05?	Autocorrelation	Box-Ljung Statistic
			Value
1	Y	0.99591	1476.847
2	Y	0.99161	2941.96
3	Y	0.98743	4395.75
4	Y	0.98346	5838.827
5	Y	0.97928	7270.643
6	Y	0.97465	8689.899
7	Y	0.97022	10097.23
8	Y	0.96559	11492.11
9	Y	0.96098	12874.64
10	Y	0.95625	14244.51
11	Y	0.95158	15601.97
12	Y	0.94730	16948.15
13	Y	0.94273	18282.29
14	Y	0.93829	19604.77
15	Y	0.93404	20916.19
16	Y	0.92974	22216.44

H_0: Sensex follows uncorrelated increments

H_a: Sensex does not follow uncorrelated increments

Given that each and every Sig value is less than 0.05, Ho is rejected.

Hence, Sensex does not follow uncorrelated increments for selected sector.

Conclusion: Finance sensex does not follow independent and uncorrelated increment indicating forecastability of Finance sensex values.

The next stage is to confirm the stationarity of the Finance sensex data, as it is predictable. The results of the stationarity verification using the KPSS, PP, and ADF tests are shown in Table 3. The P-value for the ADF and PP tests is higher than 0.05, but it is lower than 0.05 for the KPSS test. Based on the provided P-value, one can conclude that Finance sensex is non-stationary. It is not stationary at this point, so the data must be subtracted to make it stationary. Consequently, forecasting models utilizing sensex data have been developed by the application of ARIMA.

Table 3: Stationarity check results

Aug. Dickey-Fuller Test		Phillips-Perron Test		KPSS Test		lnference
Test Statistic	P-value	Test Statistic	P-value	Test Statistic	P-value	
-1.6678	0.4478	-1.6370	0.4640	3.6170	0.0100	Non-stationary

There are three components to the ARIMA model. These three are auto regression (AR), constant terms, and moving average (MA). Table 4 lists the values of these ARIMA model terms for the Finance industry. These values are used in the next step of forecasting model construction.

Table 4: Forecasting by ARIMA: Model parameters for Finance sector

ARIMA Model Parameters	
Parameter	**Estimate**
Constant	2.966
AR	-0.816
Difference	1
MA	-0.847

The model parameters' significance is assessed using the t test. Because of their importance, parameters play a part in the forecasting process. Table 5 presents the Finance sector's t test findings. A parameter is ignored in the model equation construction process if its significance value is greater than 0.05. In this instance, the model equation includes the constant since the combined significance of all the components for the Finance sector is less than 0.05.

Table 5: Forecasting by ARIMA model: Significance of model parameters

t test results		
Parameter	**t**	**p value**
Constant	1.335	.182
AR	-5.496	.000
MA	-6.212	.000

The forecasting model equation for the finance industry is shown below. The forecasting error of this model is represented by the Mean Absolute Percentage Error (MAPE), which is also shown in this table. The MAPE for the finance sector is 4.67%.

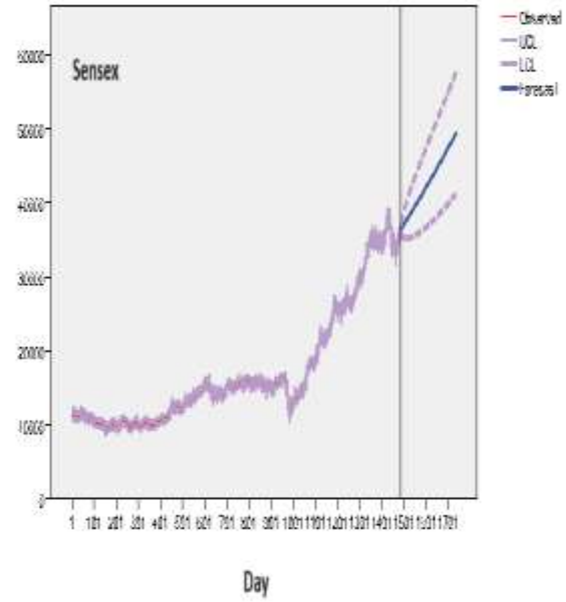
$$\hat{y}_t = -0.816\, y_{t-1} + 0.847\, e_{t-1}$$

The forecasting equation for the Finance sector when the exchange rate is included as an exogenous variable in the model. The model's predicting error is represented by the Mean Absolute Percentage Error (MAPE), which is also shown in this table. The MAPE for the finance sector is 7.27%.

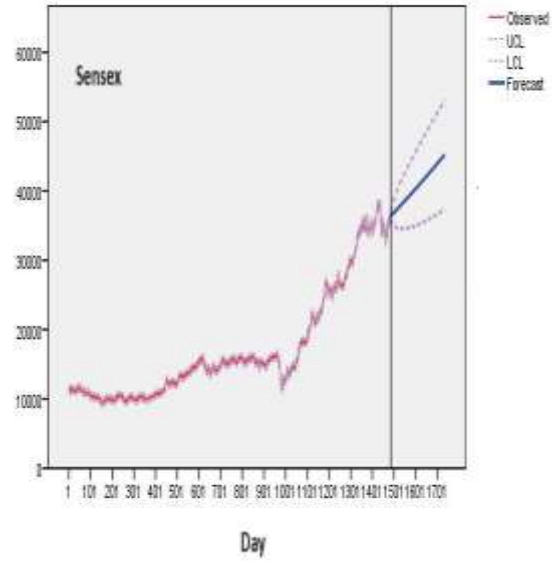
$$\hat{y}_t = -0.816\, y_{t-1} + 0.848\, e_{t-1} - 0.51\, x_{t-1}$$

Fig. 1(a) displays graphs showing the recorded and expected values of the sensex for the finance industry.

Moreover, the graph displays the upper and lower confidence ranges. Overall, the graphs exhibit an increasing tendency with a few irregular variations. Additionally, the prediction line shows a growing trend beyond the train period. If the exchange rate is included as an exogenous variable in the forecasting model, Figure 1(b) displays graphs that indicate the observed and predicted values of the Finance sector's sensex. Moreover, the graph displays the upper and lower confidence ranges. Trends in the graphs show some periodic oscillations. The prediction line shows an upward tendency after the train period.



(a) Finance sector: ARIMA



(b) Finance sector: ARIMA with Exogenous variable

Figure 1: Forecasting graphs of finance sector using ARIMA and exogenous variables

Table 6 presents the various error values for ARIMA and ARIMA with exogenous variable. These three metrics of error are Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Additionally shown are the standard deviation and mean of the IT sensex. The MAPE increased from 4.67 to 7.27 as a result of the currency rate being included as an external variable.

Table 6: Forecasting by ARIMA: finance sector

Model	ARIMA	ARIMA with Exogenous variable
MAPE (%)	4.67	7.27
RMSE	456.48	677
MAE	372.86	607
Mean of Test Period	8259.57	
Standard Deviation	573.73	

After that, five large-cap companies from the Finance sector are chosen from each sector, and sector and segment models are applied to them.

The outcome is shown in Table 7. Similar results are noted for the bulk of the stocks. The majority of the time, the forecasting error is extremely close to the error value of the stock price forecasting model, according to an analysis of the sector and segment model's validity for stock price forecasting using five selected companies.

The error difference is very modest, especially for large-cap stocks.

Table 7: Analysis of large cap stocks from finance sector

Stock	**Market Capitalization (Rs Cr)**	**MAPE measured by stock price forecasting model** (M1)	**MAPE measured by corresponding sector forecasting model** (M2)	**Difference between MAPE** |M1-M2|
HDFC Bank	899,903	5.97	7.24	1.27 (very small)
ICICI Bank	623,919	2.4	1.88	0.52 (very small)
SBI	528,827	2.86	3.93	1.07 (very small)
Kotak Mahindra	381,797	1.61	2.18	0.57 (very small)
Axis Bank	261,629	3.11	2.48	0.63 (very small)

CONCLUSION

It is evident from the test results of the current study that the Finance sensex does not fluctuate in an independent or uncorrelated manner. This suggests that there is a pattern to the Finance sensex and that its values are predictable. Thus, a forecasting model for the Finance sensex can be created. In order to achieve stronger economic stability and autonomous, uncorrelated growth, the stock market must increase market efficiency. Lowering informational barriers in the stock market will help players share information more easily and boost market efficiency.

Time series analysis is an effective way to forecast success in the stock market. The ARIMA time series approach is especially useful for predicting stock prices or the sensex. Across an interval of ARIMA parameter values, the forecasting models in the study had the lowest prediction errors. When making investments in different markets or industries, investors might make use of these models. Assets or funds can be allocated to sectors or segments based on the investment strategy of the portfolio manager or investor. Investors can learn more about the performance of the stocks in a given sector or segment by projecting the value of a sensex specific to that industry or business. When a stock is a part of a particular sector and market segment, one can use associated intersecting forecasting models to anticipate its performance and future price.

In general, large-cap stocks fluctuate less than small-cap stocks. When large-cap stocks employ their own data-driven ARIMA models for their forecasts, the forecasting inaccuracy decreases as well. Not only that, but the forecasting inaccuracy is significantly reduced when the matching sector-based ARIMA model is applied to a stock price. Therefore, we can conclude that Large Cap stocks in the Finance sector may be forecasted using a model based on the Finance sector without experiencing a major forecasting error. Although the error gap is significantly larger for Mid Cap and SmallCap stocks, sector- and segment-specific forecasting models may still be roughly used to predict the price of stocks in the Finance sector's MidCap and SmallCap sectors.

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