Asian Journal of Accounting and Governance **18**: 121–134 (2022)
ISSN 2180-3838
e-ISSN2716-6060
(http://dx.doi.org/10.17576/AJAG-2022-18-09)

# Effectiveness of Geometric Brownian Motion Method in Predicting Stock Prices: Evidence from India

Krishna Prasad, Bhuvana Prabhu, Lionel Pereira, Nandan Prabhu & Pavithra S

ABSTRACT

*This research examines whether stock prices in the Indian stock markets follow a Geometric Brownian Motion (GBM). This study is keen on knowing if one can predict the simulated stock prices accurately against the actual stock prices. One-year, three-year, and five-year data of the historical stock prices of 50 stocks listed on the S&P BSE (Bombay Stock Exchange) Sensex 50 Index were employed as the base data to predict stock prices using the Monte Carlo simulation's GBM method. This study investigates whether there are statistically significant differences between the actual stock prices for three months and the simulated prices of the same period. This research has found that the GBM Monte Carlo simulation effectively predicts future stock prices for three months based on the historical data of stock prices of the past year. This study did not find significant differences between the actual and predicted stock prices when the simulation used the past one year's data. This research is original in the Indian context, as it situates the GBM method of Monte Carlo simulation in the premise of bounded rationality and efficient market hypothesis theories. There is thus the empirical evidence for bounded rationality and that the stock markets are not efficient.*

*Keywords: Monte Carlo simulation; stock prediction tools; efficient market hypothesis; bounded rationality; geometric brownian motion*

## Introduction

This study investigates whether the use of the Geometric Brownian Motion (GBM) Monte Carlo simulation method is helpful in the prediction of stock prices in the Indian stock markets (Suganthi & Jayalalitha 2019). The core issue confronting researchers who have used Monte Carlo simulation methods is whether an accurate prediction of future stock prices is possible if the base data belong to different periods (Parungrojrat & Kidsom 2019). Prior research has demonstrated that the shorter the duration of the base period, the higher the prediction accuracy in the short term (Agustini et al. 2018). For instance, researchers have found the prediction accuracy higher for one week's prediction (Hoyyi et al. 2019), as shown by lower mean absolute percentage error (MAPE). Monte Carlo simulation considers the stock prices' randomness, drift, and volatility in its predictions (Lux 2018). If all investors and analysts were completely and equally rational, the current prices would have incorporated the past information. The researchers cannot safely make this assumption, as human beings show satisficing and approximating-optimizing choices, not necessarily rational ones (Van Vliet 2017). Therefore, stock markets provide the scope for predicting stock prices. Advocates of Monte Carlo simulation argue that one can adequately capture volatility and randomness and, therefore, it is possible to predict future stock prices (Boya 2019).

This paper addresses the critical research problem of whether one can predict future stock prices in the Indian stock markets by adopting the GBM method as the predictive model. An accurate stock price prediction depends on obtaining specific answers to the research questions that address the efficacy or otherwise of the GBM method in the context of using past data from three time periods: five years, three years, and one year. Therefore, this research addresses the following questions: Do the differences between actual and simulated stock prices differ significantly if the GBM simulation method is adopted to simulate the stock prices based on five-year historical stock prices data? Do actual and simulated stock prices differ significantly if the GBM simulation method is adopted to simulate the stock prices based on three-year historical stock price data? Do actual and simulated stock prices differ significantly if the GBM simulation method is adopted to simulate the stock prices based on one year's historical stock price data?

The prior research on forecasting models of stock prices has focused on determining the efficacy of nonlinear models (Orimoloye et al. 2020), residual income models (Budagaga 2017), integrated use of fuzzy genetic systems, and artificial neural networks (Rezaee et al. 2018), and the Markov-Fourier grey model in building predictive models of stock prices (Nguyen 2019). Scholars have also used various regression methods in stock price prediction, among which the scholars have found isotonic regression to be more efficient than other regression techniques such as linear regression and least mean squares regression (Chandar 2019). Besides, the machine learning algorithms predict the prices of stocks traded in the Indian stock market with 70 percent accuracy of daily prices, whereas the monthly data of prices do not show any correlation (Rao et al. 2020). However, the critical challenge before researchers in using these methods is to account for certain and uncertain components of the movement of stock prices. The GBM method solves this vexing problem by capturing specific and uncertain components of stock price movements.

Scholars have extensively used the Monte Carlo simulation methods for stock price prediction, as they integrate variance reduction techniques and use deterministic sequences instead of random sequences (Pham et al. 2020). These methods predict different security pricing, including option pricing (Bormetti et al. 2018). The specific advantage of using the GBM method lies in the movement of stock prices with both certain and uncertain components (Parungrojrat & Kidsom 2019). Although the GBM method recognizes random walk in the movement of stock prices, it also points toward specific components, an assumption inherently present in technical and fundamental analysis theories (Liu et al. 2020). Therefore, prior research has advocated the theoretical soundness of the GBM method for predicting stock prices even as the research on providing empirical validity to the use of GBM in building stock prediction models is also growing (Agustini et al. 2018).

This research has found the significant differences between the actual and predicted stock prices based on the past three-year and five-year data using the GBM method of Monte Carlo simulation. Besides, this study did not find significant differences between the actual and predicted stock prices when the study used the past one year's data. Thus, this study shows that the GBM method helps predict stock prices if the data used for the same belonged to the previous one year. There are several contributions that this paper makes to the research discourse on building predictive models of stock prices. First, the GBM method is consistent with the assertions of the efficient market hypothesis, especially about the inability to predict stock prices in the long run (Aggarwal 2018). Second, this research has also shown that investors can use anomalies in market efficiency to make gains in stock markets in the short run. The future stock prices can be predicted for three months if the base data used for prediction belongs to the past one year. Third, the same prediction accuracy is impossible if the past data belonged to the three-year and five-year periods.

The rest of the paper is structured as follows. First, this paper explains the theoretical perspective before developing the hypotheses. After that, this study presents data analysis and the obtained results. Then, this paper discusses the theoretical, managerial, and methodological implications based on the results. Finally, the paper discusses the limitations, future directions, and the conclusion.

## Review Of Literature And Hypotheses Development

The theory of bounded rationality proposed by Simon (1982) raises some fundamental questions regarding human rationality. It mainly asks the following questions: Is it possible for individuals to be rational? What constrains the rationality of human beings? If human beings are not rational, what cognitive processes influence their sense of rationality? Is individual rationality different from organizational rationality? This section discusses these issues to build a relevant theoretical perspective for applying the Monte Carlo simulation methods for predicting stock prices.

Simon (1982) argues that humans and organizations are not entirely rational. It is impossible, practically, for them to be rational in an absolute sense because of two factors: complexity and uncertainty, which means that individuals encounter such complex situations that processing all such information is impossible. Therefore, there will always be some confounding variables that obstruct the process of complete rationality in their decision-making process. Individuals will always attempt to either satisfice or optimize their solutions. The satisficing process is searching for alternatives until one finds a reasonable alternative that possesses an acceptable threshold limit. Besides, individuals and organizations may attempt to arrive at approximate-optimum solutions to the problems they confront. Therefore, satisficing and approximate optimizations are the psychological processes that change human rationality.

This research adopts the bounded rationality's theoretical perspective as the underlying rationale of this study (Sul et al. 2017). This study assumes that markets are not always efficient because human rationality has limits. Markets do not always move toward attaining equilibrium prices. As a result, it becomes possible for informed investors to reap the benefits of information asymmetry. Thus, this gives a strong probability of using simulation techniques to predict stock prices.

The prior research has examined the probability or otherwise of the rationality of stock markets to know whether there are rational expectations during the prediction of stock price movements (Adam et al. 2017). The prior research has found no evidence to show that the rationality of expectations exists, which implies that it is possible to assume that rationality alone does not guide stock market investors (Almudhaf 2017). Therefore, the implications of the efficient market hypothesis do not hold well in an absolute sense. Thus, it might become possible for prudent investors to beat the stock market to gain higher returns than what the stock market offers, which shows the usefulness of stock prediction tools in estimating future stock prices (Masry 2017).

In order to predict future stock prices, there does not seem to be a predictable pattern in the effect of these market indicators on future stock prices, which is because the stock market is likely to identify market indicators as potential clues to understand the future movement of stock prices (Guo et al. 2017). Therefore, their effect on predicting future stock market prices will be futile when we identify them as potential market indicators. Thus, prior research has attempted to assess the impact of the mood of the entire market to predict future stock prices (Chen et al. 2019). The employment of market moods and market indicators differs from fundamental analysis, as the aim of using them is to examine their impact on the stock market index.

In contrast, the researchers do fundamental analysis to ascertain how individual securities will move in the future. However, relying on past information on stock prices to predict future stock prices is irrelevant, as current prices would have incorporated the past data, an argument that we find in the efficient market hypothesis (Ying et al. 2019). However, as markets do not possess characteristics of strong efficiency, stock market analysts have tried to take advantage of deficiencies in the price discovery process of stock markets. Therefore, the prior research has used many stock market prediction models to predict future stock prices.

The critical issue in the prediction process is: What is the efficacy of predicting stock returns over a long horizon of time compared to such a prediction over a short horizon of time? Therefore, this study builds its research hypotheses based on the historical data of stock prices for one year and multi-year historical data because the recent research states that a long horizon of time may not be suitable to predict the stock prices (Ham et al. 2019). Therefore, this research examines the relative usefulness of one year's historical stock price data against three-year and five-year data of historical stock prices to predict future stock prices. This study proposes the following hypotheses to address the abovementioned issues to predict future stock prices:

$H_1$ There is no significant difference between actual and simulated stock prices, whose prediction is based on the past five years' historical stock prices data.

$H_2$ There is no significant difference between actual and simulated stock prices if the prediction is based on three years' historical data of stock prices.

$H_3$ There is no significant difference between actual and simulated stock prices if the prediction is based on one year's historical data of stock prices.

## Method

### SAMPLE AND DATA CHARACTERISTICS

The companies in the S&P BSE Sensex 50 Index of Bombay Stock Exchange (BSE), India, were chosen as sample companies for this study. The companies in this index are financially sound, representing industries such as energy, banking, financial services, pharmaceuticals, automobile, utilities, and IT. The researchers extracted the stock prices and market capitalization data of the sample companies for the study from Bloomberg. The study collected data on the stock prices of 50 companies. Data from the following three periods were collected:

1. One-year horizon (from 1 January 2021 to 31 December 2021)
2. Three-year horizon (1 January 2019 to 31 December 2021) and
3. Five-year horizon (1 January 2017 to 31 December 2021).

This research chose data from these three periods for our analysis because this study intended to investigate the effects of short-term, medium-term, and long-term historical data of stock price movements on the efficacy or otherwise of predictive models of stock prices using the GBM Monte Carlo simulation method. Prior research has found seasonality to influence Indian stocks (Rao et al. 2020). However, seasonality shows a pattern in the movement of shares, providing a weak form of efficiency for stock markets. Therefore, this implies the possibility of predictability of stock prices, which justifies using predictive models.

### THE GBM METHOD

The stock price is predicted using GBM as given in the following equation:

$$S_{t+\Delta t} = S_t\left(\mu\Delta t + \sigma\varepsilon\sqrt{\Delta t}\right) \quad (1)$$

Where $S_t$ is the stock price, $\Delta t$ is the time interval for prediction, μ is the expected return estimated using the equation (2), t is time, $\sigma$ is the standard deviation of the returns, $\varepsilon$ is the randomly drawn number from a normal distribution.

The expected return (ER) on stocks is estimated using capital asset pricing model (CAPM) as given in equation (2):

$$\mathrm{ER_i} = R_{\mathrm{f}} + \beta\,(R_{\mathrm{m}} - R_{\mathrm{f}}) \quad (2)$$

Where $R_f$ is the risk-free rate, β is the sensitivity of the stock return to the market return, and $R_m$ is the market return. Bloomberg's dividend discount model function provided the beta value, risk-free rate, and market premium data.

The GBM method assumes that the continuously compounded periodic stock return has a certain component (drift) and an uncertain component (shock). The $\mu\Delta t$ in equation (1) is the certain component and $\sigma\varepsilon\sqrt{\Delta t}$ is the uncertain component.

Further, the prediction accuracy was measured using mean absolute percentage error (MAPE), as shown in the following equation:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (3)$$

where $A_t$ is the actual price and $F_t$ is the predicted price. The absolute value was multiplied by 100, making it a percentage error.

## Hypotheses Testing Procedure

Based on the GBM method, the researchers ran two types of tests. First, the researchers conducted 50 individual S&P BSE Sensex 50 Index stocks simulations. Second, the researchers conducted an industry-wise accuracy test to control industry bias during forecasting. Thus, the researchers controlled the three biases: volatility, expected return rates, and the industry type.

This research considered three-time horizons to compare forecast prices' accuracy with actual prices: a one-year comparison, a three-year comparison, and a five-year comparison. However, the study did the actual forecast of stock prices for three months: 1 January 2022 to 31 March 2022. Further, the study reports the results for one month only for brevity. Besides, the study compares the simulated/forecast prices with the actual prices to determine the forecast accuracy.

The study adopted the following steps to test the hypotheses:

1. This study chose 50 stocks. Using the GBM method in the Python software platform, the researchers carried out simulations of 50 S&P BSE Sensex 50 Index stocks. The study generated the simulated stock prices. The researchers compared the actual closing prices of these stocks for the testing period of one month with the simulated stock prices. The study used the data of the last (i) five years' historical stock prices, (ii) three years' historical stock prices, and (iii) one year's historical stock prices to generate the simulated stock prices.
2. Then, the study tested the correlation between the actual and simulated stock prices. This test aimed to verify whether the correlation would get corrected during the prediction period.
3. After that, the researchers calculated the mean absolute percentage error between the actual and simulated stock prices of two randomly chosen stocks.
4. Further, the study mapped the direction of prediction accuracy between actual and simulated stock prices. Based on prediction accuracy, the study tested the hypotheses on the presence or otherwise of the significant differences between the actual and simulated stock prices.
5. Finally, the study tested the null hypothesis of this relationship on the data of actual and simulated stock prices of all the 50 companies that made up the sample of this study. The researchers performed a paired sample *t*-test of actual and simulated stock prices over time horizons. In all the three cases, the past five years, three years, and one year, the study compared the actual stock prices with the simulated stock prices by using the paired sample *t*-test in order to find out the differences in the mean values of the simulated stock price and actual stock prices. The researchers log-transformed both the prices before running the *t*-test.

## Results

### Prediction Based on Five-Year Historical Data

The researchers randomly chose a company with the highest and lowest market capitalizations. ICICI and KMB were the randomly chosen companies to compare actual and simulated stock prices. Table 1 compares the actual stock prices with simulated stock prices of the two companies, i.e., ICICI and KMB.

TABLE 1. Actual and simulated prices of companies with highest and lowest market capitalization

| Date (dd/mm/yy) | ICICIBC | | KMB | |
|---|---|---|---|---|
| | Actual Closing Price (₹) | Simulated Price (₹) | Actual Closing Price (₹) | Simulated Price (₹) |
| 03/01/2022 | 764.7 | 763 | 2636.4 | 2000.12 |
| 04/01/2022 | 772.85 | 771.88 | 2675.3 | 2118.85 |
| 05/01/2022 | 788.05 | 787 | 2673.65 | 2097.2 |
| 06/01/2022 | 785.05 | 786.31 | 2620.4 | 2076.05 |
| 07/01/2022 | 793.25 | 794 | 2596.7 | 2054.1 |
| 10/01/2022 | 810.75 | 810.324 | 2659.65 | 2074.7 |
| 11/01/2022 | 810.65 | 810.652 | 2710.95 | 2097.3 |
| 12/01/2022 | 823.75 | 820.22 | 2737.5 | 2082.85 |
| 13/01/2022 | 824.7 | 822.871 | 2756 | 2053.1 |
| 14/01/2022 | 820 | 818.86 | 2712.45 | 2024.45 |
| 17/01/2022 | 819.3 | 818.22 | 2702.7 | 2024.45 |
| 18/01/2022 | 823.1 | 822.66 | 2662.5 | 1955.45 |

*continue ...*

*... continued*

| | | | | |
|---|---|---|---|---|
| 19/01/2022 | 808.6 | 809.19 | 2620.25 | 1982.9 |
| 20/01/2022 | 810.25 | 811.834 | 2569.3 | 2011.4 |
| 21/01/2022 | 804.5 | 806.22 | 2592.95 | 2035.1 |
| 24/01/2022 | 798.45 | 800.11 | 2539.8 | 1964.3 |
| 25/01/2022 | 801.65 | 802.22 | 2530.6 | 2019.6 |
| 26/01/2022 | 801.65 | 802.76 | 2530.6 | 1961.9 |
| 27/01/2022 | 794.65 | 895.821 | 2503.35 | 1953.35 |
| 28/01/2022 | 781.15 | 782.2 | 2516.5 | 1964.25 |
| 31/01/2022 | 788.8 | 788 | 2521 | 1914.2 |

The differences between the companies' actual and simulated stock prices widen as the days pass. Therefore, there was no correlation between these two values (See Table 7 for the hypothesis testing results). After that, we calculated the correlation between actual and simulated stock prices for the five years to verify the presence or otherwise of correlations in statistical terms. Then, we calculated the mean absolute percentage error between the actual and simulated stock prices generated using the five years of historical data. Further, we calculated the accuracy of stock price prediction in percentages.

Table 2 presents the relationship between the 50 companies' actual and simulated stock prices and the companies' market capitalization. Table 2 also presents the MAPE value for different periods. The prediction accuracy of the simulated/predicted stock prices, calculated based on the historical data of the past five years of actual stock prices, is also presented in the table.

TABLE 2. Summary of results for prediction based on five year's historical data

Panel A: Correlation

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Minimum | 0.45 | -0.23 | 0.73 | 0.17 |
| Maximum | -0.71 | 0.93 | 0.42 | 0.51 |
| Mean | 0.92 | 0.14 | 0.64 | 0.37 |
| Std Deviation | 0.55 | 0.55 | 0.43 | 0.73 |
| Median | 0.72 | -0.42 | 0.38 | 0.78 |

Panel B: Mean Absolute Percentage Error

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.56 | 1.78 | 1.89 | 8.22 |
| Minimum | -0.45 | -0.23 | -0.73 | -0.17 |
| Maximum | 0.26 | 0.26 | 0.26 | 0.26 |
| Mean | -0.92 | -0.14 | -0.64 | -0.37 |
| Std Deviation | 0.55 | 0.55 | 0.43 | 0.73 |
| Median | 0.72 | -0.42 | 0.38 | 0.78 |

Panel C: Direction Prediction Accuracy

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.67 | 2.23 | 1.83 | 3.78 |
| Minimum | 20% | 32% | 43% | 17% |
| Maximum | 100% | 100% | 100% | 100% |
| Mean | 92% | 31% | 67% | 17% |
| Std Deviation | 82% | 85% | 81% | 74% |
| Median | 83% | 32% | 92% | 56% |

The correlation figures are of a small value, as the standard deviation is also high across all periods. Correlation gets corrected over the periods of prediction. Therefore, correlations would imply that there might not be stock prediction accuracy if the research derives the simulated stock prices from the past five years' data. The results show that the range of MAPE increases as the horizon of the period of prediction increases. The variability of the predicted stock prices reflects this observation. Therefore, the reliability of the prediction of stock prices reduces. Thus, there is evidence to hypothesize significant differences between companies' actual and simulated stock prices when we use the Monte Carlo simulation method.

The researchers ran the *t*-test to test the hypothesis (See Table 7). On an average, simulated stock prices (M=4.04, SE= 0.13) demonstrated a significant difference from the actual stock prices (M = 3.69, SE = 0.13). Bca 95 percent, CI (-0.67, -0.27), was significant. Therefore, we reject the null hypothesis and conclude that there is a significant difference between the actual and simulated stock prices, implying that it is impossible to conclude that the predictive ability of the Monte Carlo simulation exercises its effect on the population.

## PREDICTION BASED ON THREE-YEAR HISTORICAL DATA

TABLE 3. Actual and simulated prices of companies with highest and lowest market capitalization

| Date (dd/mm/yy) | ICICIBC | | KMB | |
|---|---|---|---|---|
| | Actual Closing Price (₹) | Simulated Price (₹) | Actual Closing Price (₹) | Simulated Price (₹) |
| 03/01/2022 | 764.7 | 752.89 | 2636.4 | 2000.12 |
| 04/01/2022 | 772.85 | 712.238 | 2675.3 | 2518.85 |
| 05/01/2022 | 788.05 | 692.778 | 2673.65 | 2297.2 |
| 06/01/2022 | 785.05 | 682.223 | 2620.4 | 2476.05 |
| 07/01/2022 | 793.25 | 651.891 | 2596.7 | 2054.1 |
| 10/01/2022 | 810.75 | 662.233 | 2659.65 | 2074.7 |
| 11/01/2022 | 810.65 | 670.931 | 2710.95 | 2097.3 |
| 12/01/2022 | 823.75 | 670.233 | 2737.5 | 2082.85 |
| 13/01/2022 | 824.7 | 672.673 | 2756 | 2053.1 |
| 14/01/2022 | 820 | 691.226 | 2712.45 | 2324.45 |
| 17/01/2022 | 819.3 | 702.815 | 2702.7 | 2024.45 |
| 18/01/2022 | 823.1 | 706.135 | 2662.5 | 1955.45 |
| 19/01/2022 | 808.6 | 716.563 | 2620.25 | 1992.9 |
| 20/01/2022 | 810.25 | 718.523 | 2569.3 | 2011.4 |
| 21/01/2022 | 804.5 | 707.652 | 2592.95 | 2035.1 |
| 24/01/2022 | 798.45 | 716.221 | 2539.8 | 1964.3 |
| 25/01/2022 | 801.65 | 719.982 | 2530.6 | 219.6 |
| 26/01/2022 | 801.65 | 702.982 | 2530.6 | 1961.9 |
| 27/01/2022 | 794.65 | 701.091 | 2503.35 | 1963.35 |
| 28/01/2022 | 781.15 | 708.765 | 2516.5 | 1964.25 |
| 31/01/2022 | 788.8 | 714.22 | 2521 | 1914.2 |

*Note:* Though these results pertain to one month, a similar trend is observed in the results of prices for three months. Results' reporting was confined to one month instead of three months due to space constraints.

Table 4 presents the relationship between the 50 companies' actual and simulated stock prices and the companies' market capitalization. It also presents the MAPE value for differing periods and prediction accuracy of the simulated/predicted stock prices, calculated based on the historical data of the past three years' actual stock prices.

TABLE 4. Summary of results for prediction based on three year's historical

Panel A: Correlation

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Minimum | 0.25 | -0.78 | -0.12 | 0.23 |
| Maximum | 0.73 | 0.23 | 0.42 | 0.51 |
| Mean | 0.29 | 0.27 | 0.88 | -0.21 |
| Std Deviation | 0.4 | 0.51 | 0.49 | 0.56 |
| Median | 0.67 | -0.39 | 0.31 | 0.71 |

Panel B: Mean Absolute Percentage Error

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.78 | 1.23 | 2.24 | 8.55 |
| Minimum | -0.45 | -0.23 | -0.21 | -0.22 |
| Maximum | 0.26 | 0.26 | 0.26 | 0.26 |
| Mean | 0.34 | 0.73 | 0.78 | 0.39 |
| Std Deviation | 0.23 | 0.51 | 0.56 | 0.21 |
| Median | -0.26 | -0.31 | -0.67 | -0.88 |

Panel C: Direction Prediction Accuracy

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.67 | 2.23 | 1.83 | 3.78 |
| Minimum | 23% | 32% | 12% | 26% |
| Maximum | 100% | 100% | 100% | 100% |
| Mean | 83% | 73% | 52% | 31% |
| Std Deviation | 37% | 72% | 16% | 74% |

The correlations between actual and simulated prices were weak or negative. Similarly, the MAPE values of the predicted stock prices, when predicted based on the simulation carried out with the help of the past three years' data, suggest that they vary widely as the horizon of prediction widens, as shown by the values of the range and standard deviation. The increasing values of the median show the same. Therefore, there appears to be no association between actual stock prices and simulated stock prices if the prediction of stock prices is based on three-year historical data. Similarly, there is a wide variation in the correlation figures. Therefore, if the simulation is carried out based on the three years' historical data of actual stock prices, there is no relationship between actual and simulated stock prices.

The researchers ran the *t*-test to test the hypothesis (See Table 7). On an average, simulated stock prices (M=4.02, SE= 0.13) demonstrated a significant difference from the actual stock prices (M = 3.27, SE = 0.13). Bca 95%, CI (-0.67, -0.27) was significant. Therefore, we reject the null hypothesis and thus conclude that there is a significant difference between actual and simulated stock prices. We conclude that adopting the Monte Carlo simulation method does not affect the population's predictive ability of stock prices when such a simulation process makes the three-year historical data its basis.

### PREDICTION BASED ON ONE-YEAR HISTORICAL DATA

Table 5 presents the actual and simulated stock prices based on the one-year historical data. The table shows that the actual and simulated stock prices are almost similar. Therefore, observing the descriptive statistics and the correlations will give us a better picture of the data.

TABLE 5. Actual and simulated prices of companies with highest and lowest market capitalization

| Date (dd/mm/yy) | ICICIBC | | KMB | |
|---|---|---|---|---|
| | Actual Closing Price (₹) | Simulated Price (₹) | Actual Closing Price (₹) | Simulated Price (₹) |
| 03/01/2022 | 764.7 | 811 | 2636.4 | 1964.25 |
| 04/01/2022 | 772.85 | 814.66 | 2675.3 | 1914.2 |
| 05/01/2022 | 788.05 | 806.22 | 2673.65 | 1885.2 |
| 06/01/2022 | 785.05 | 807.345 | 2620.4 | 1937.15 |
| 07/01/2022 | 793.25 | 785.188 | 2596.7 | 1920.45 |
| 10/01/2022 | 810.75 | 791.992 | 2659.65 | 1916.35 |
| 11/01/2022 | 810.65 | 798.23 | 2710.95 | 1896.75 |
| 12/01/2022 | 823.75 | 803.33 | 2737.5 | 1873.1 |
| 13/01/2022 | 824.7 | 792.211 | 2756 | 1840.4 |
| 14/01/2022 | 820 | 751.899 | 2712.45 | 1867.4 |
| 17/01/2022 | 819.3 | 769.211 | 2702.7 | 1860.75 |
| 18/01/2022 | 823.1 | 762.344 | 2662.5 | 1793.8 |
| 19/01/2022 | 808.6 | 760.541 | 2620.25 | 1742.5 |
| 20/01/2022 | 810.25 | 742.223 | 2569.3 | 1736.55 |
| 21/01/2022 | 804.5 | 751.288 | 2592.95 | 1762.4 |
| 24/01/2022 | 798.45 | 750.788 | 2539.8 | 1775.6 |
| 25/01/2022 | 801.65 | 742.455 | 2530.6 | 1748.4 |
| 26/01/2022 | 801.65 | 705.3 | 2530.6 | 1773.45 |
| 27/01/2022 | 794.65 | 734.812 | 2503.35 | 1774.9 |
| 28/01/2022 | 781.15 | 746.22 | 2516.5 | 1764.2 |
| 31/01/2022 | 788.8 | 811 | 2521 | 1755.25 |

*Note:* Though these results pertain to one month, a similar trend is observed in the results of prices for three months. Results' reporting was confined to one month instead of three months due to space constraints.

On observation of Table 6, there appears to be a higher accuracy of the simulated stock prices if they are predicted based on the past year's data of actual stock prices. The maximum range of prediction across all time horizons is 100 percent. Further, the minimum prediction accuracy is 83 percent. Therefore, a reasonable accuracy exists to suppose that the simulated/predicted stock prices are like the actual stock prices when the stock prices are predicted based on the past data of one year's stock prices.

TABLE 6. Summary of results for prediction based on one year's historical data

Panel A: Correlation

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Minimum | -0.11 | 0.78 | -0.22 | -0.33 |
| Maximum | 0.63 | 0.71 | 0.39 | 0.62 |
| Mean | 0.59 | 0.32 | 0.78 | 0.42 |
| Std Deviation | 0.32 | 0.69 | 0.41 | 0.62 |
| Median | 0.45 | -0.29 | 0.82 | 0.31 |

*continue ...*

*... continued*

Panel B: Mean Absolute Percentage Error

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.78 | 1.23 | 2.24 | 8.55 |
| Minimum | -0.45 | -0.23 | -0.21 | -0.37 |
| Maximum | 0.19 | 0.19 | 0.19 | 0.19 |
| Mean | 0.28 | 0.51 | 0.78 | 0.39 |
| Std Deviation | 0.42 | 0.72 | 0.56 | 0.21 |
| Median | 0.21 | 0.38 | 0.28 | 0.62 |

Panel C: Direction Prediction Accuracy

| | 1 week | 1 month | 2 month | 3 month |
|---|---|---|---|---|
| Range | 1.67 | 2.23 | 1.83 | 3.78 |
| Minimum | 83% | 32% | 92% | 56% |
| Maximum | 100% | 100% | 100% | 100% |
| Mean | 83% | 13% | 32% | 29% |
| Std Deviation | 37% | 72% | 16% | 31% |

The researchers tested the hypothesis on the similarity between these two prices by carrying out the paired sample t-test. On an average, simulated stock prices (M= 3.21, SE= 0.19) did not show a significant difference from the actual stock prices (M = 3.20, SE = 0.19). Bca 95 percent, CI (–0.32, 0.09) was insignificant. Therefore, this study cannot reject the null hypothesis. There are no significant differences between the actual and simulated stock prices at a 95 percent confidence level, implying that this could have been less than a 5 percent chance because of a mere chance effect. Therefore, one is likely to find this effect on the population. Therefore, this result shows that the simulated stock prices are like the actual stock prices and thus signifies the predictive ability of the Monte Carlo Simulation method if the researchers use it to predict the stock prices based on one-year data of stock prices. Table 7 presents the results of the hypotheses testing:

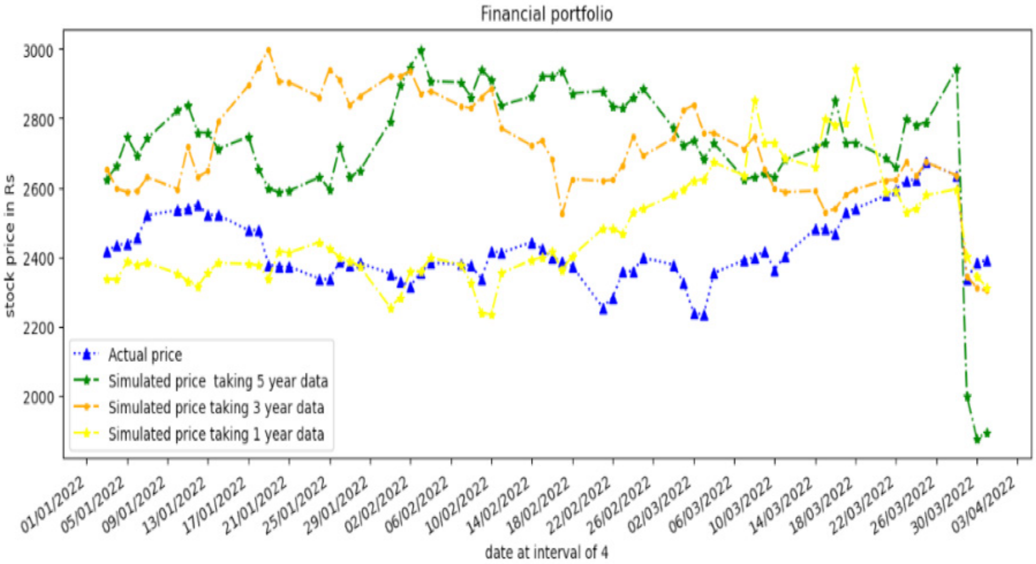
TABLE 7. Results of *t*-test for actual and simulated prices

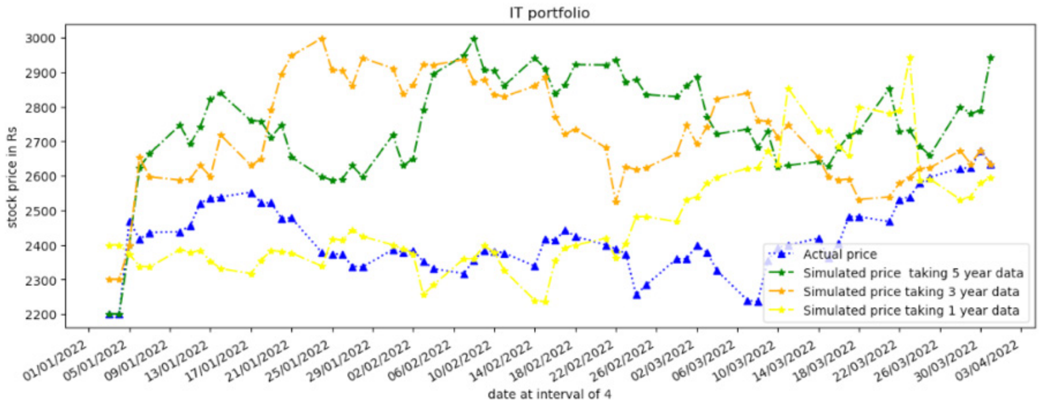
| Prediction Period | Paired differences | | | | | | 95% CI for Mean Difference | t | DF |
|---|---|---|---|---|---|---|---|---|---|
| | Simulated Price | | | Actual Price | | | | | |
| | M | SE | n | M | SE | n | | | |
| Five year | 4.04 | 0.13 | 50 | 3.69 | 0.13 | 50 | -0.67, -0.27 | -9.37*** | 49 |
| Three year | 4.02 | 0.13 | 50 | 3.27 | 0.13 | 50 | -0.67, -0.27 | -9.21*** | 49 |
| One year | 3.21 | 0.19 | 50 | 3.20 | 0.19 | 50 | -0.32, 0.09 | -1.63 | 49 |

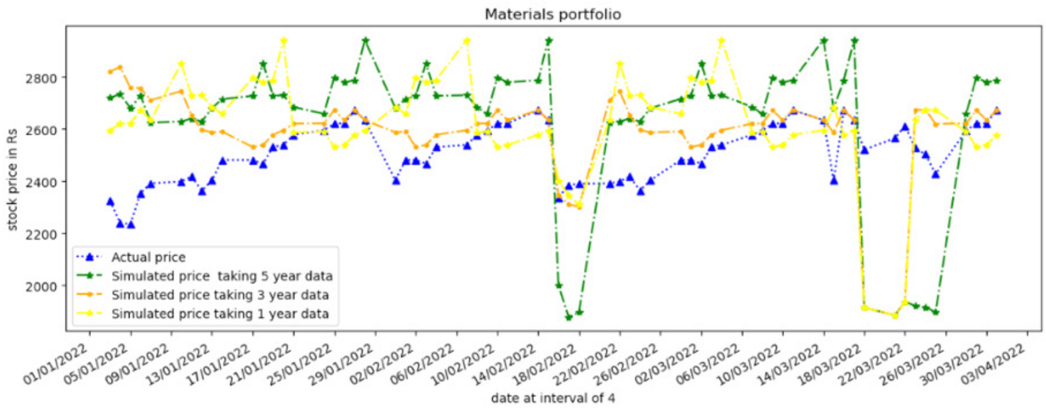
*Note:* M is the mean, SE is the standard error, n is the number of observations, CI is the confidence interval, and df is the degree of freedom. ***p<0.01

## TEST OF INDUSTRY EFFECTS

In this test, we created portfolios of stocks of companies industry-wise. This test aimed to know whether there are any industry effects on stock portfolios when using GBM for simulation. We produced charts to make comparisons between the actual and simulated stock prices. The simulation period was from 1 January 2017 to 31 December 2021.


Financial portfolio
stock price in Rs
Actual price
Simulated price taking 5 year data
Simulated price taking 3 year data
Simulated price taking 1 year data
date at interval of 4


IT portfolio
stock price in Rs
Actual price
Simulated price taking 5 year data
Simulated price taking 3 year data
Simulated price taking 1 year data
date at interval of 4


Materials portfolio
stock price in Rs
Actual price
Simulated price taking 5 year data
Simulated price taking 3 year data
Simulated price taking 1 year data
date at interval of 4

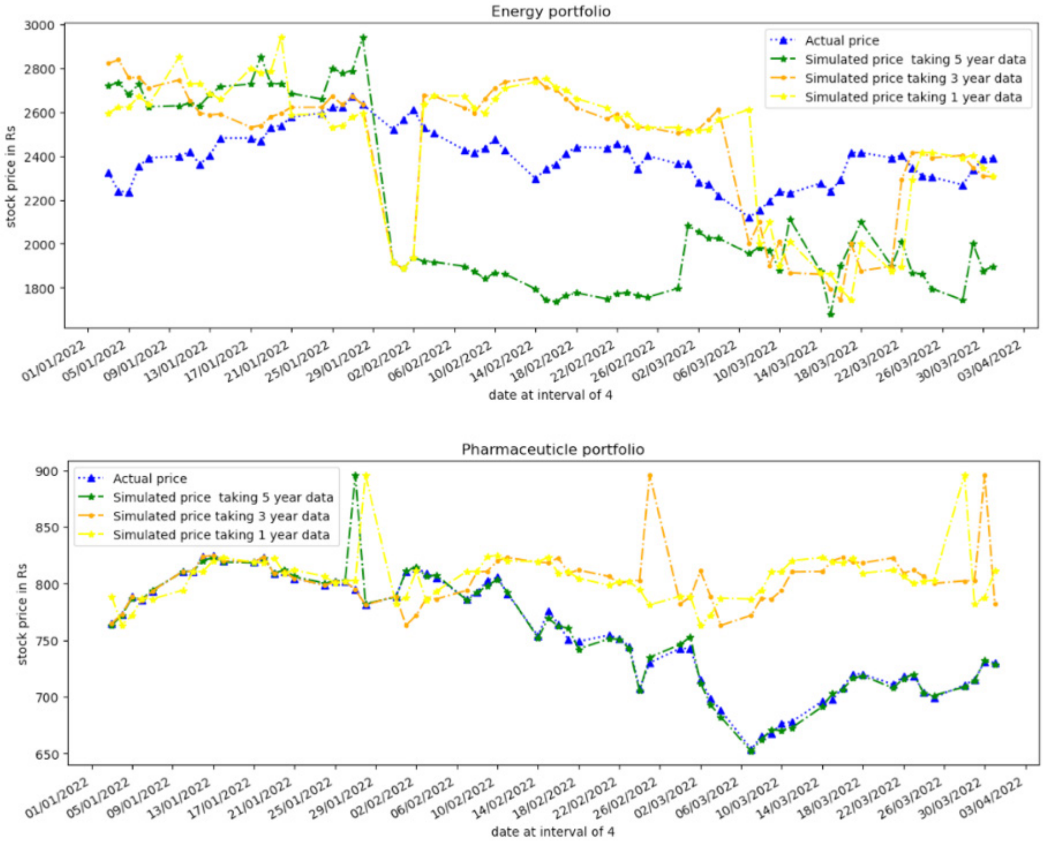



FIGURE 1. Industry-wise line charts of actual and simulated prices.

The similarity in the actual and simulated stock prices was the same across industry sectors when the researchers ran the simulation using one-year, three-year, and five-year historical stock prices. The charts presented in Figure 1 show a similar pattern across the three different periods considered in this study. There is a similarity between the results of the hypotheses testing performed for all stocks in the index and the stocks belonging to the specific industry sectors. Therefore, we conclude that there are no apparent industry effects on the predictive ability of the Monte Carlo simulation method of GBM across industry sectors.

## Discussion And Implications

This research investigated whether one can predict stock prices in the Indian stock markets accurately using the GBM method of Monte Carlo simulation. The study results have shown that this method can predict the stock prices only when the analysts use three-month historical data from the previous year to predict within the efficient market hypothesis framework. Based on the study results, this section discusses whether the predictability of stock returns is possible.

If investors are well-informed and rational, they will be in search of arbitrage opportunities (Boya 2019). However, if everybody has information about a company and the industry it belongs to, nobody will take advantage of the information they possess to make gains over others because the possibility of an increase or decrease in share prices will be sensed by those who have information (Aggarwal 2018). However, it is practically impossible to imagine investors who might possess historical information, public information, and information to which only the corporate insiders have access (Bouchaud et al. 2019). As a result, information asymmetry does not allow investors to earn similar returns (Delcey 2019). Besides, this implies that the same investors are not likely to earn similar returns on their investments in many asset classes (Ying et al. 2019). Therefore, it would become increasingly difficult for investors to beat the market, as evidenced in this study when the study attempts to predict stock prices with the past data of longer time horizons.

However, one observes sustained trends in stock markets (Bormetti et al. 2018). Therefore, it might become possible to exploit these trends in a short time horizon (Chandar 2019). This study's results show this possibility. However, this trend cannot be made based on a definitive trend in the movement of share prices in the future because whatever predictions one might make can only be described as probabilistic and speculative (Chen et al. 2018). Any sure prediction requires a standard order and an explainable pattern over a long period (Hoyyi et al. 2019). If it is impossible to do this, the resultant implication is that the movement of share prices is only random (Liu et al. 2020). The proof of this is the sudden collapse of the trend of the increasing price of a share (Nigam et al. 2018). It would defy even the best of the analysts because the moment investors realize that any movement in share price is part of a cycle. Therefore, they would dispose of those shares (Orimoloye et al. 2020). As a result, the reverse trend in the movement of share prices will begin (Rao et al. 2020). Consistent with this argument, this research has shown that it is impossible to predict stock prices over the three-year and five-year periods. Therefore, the stock price prediction models can capture future stock prices only for a limited time, as shown in this study.

Even as a positive and direct association between net income and share prices exists, there is a tendency among managers to resort to earnings management strategies. However, stock markets have shown the ability to recognize and sort out those companies that resort to these strategies (Rezaee et al. 2018). However, stock markets might not sort out such companies in the short run because of the absence of complete market efficiency (Sinha 2021). Despite their inability to 'sort out' these companies in the short run, stock markets have shown their ability to recognize such companies in the long run (Suganthi & Jayalalitha 2019). Therefore, deliberate attempts to push the stock prices upward are of little avail (Wang et al. 2022). The implications of this argument are supported by this study as well. This study has shown that stock price prediction is possible in the short run, though it is not realistic in the long run.

## Limitations And Future Research Directions

Research on building stock price prediction models has pointed out that the distribution of stock returns shows a leptokurtic pattern and, thus, displays heavy tails, which is obviously because of the high volatility in stock prices (Sinha 2021). However, researchers have argued that the GBM method cannot fully capture this phenomenon (Liu et al. 2020). Therefore, the research discourse on predicting stock prices using simulation models has suggested using alternative prediction models (Parungrojrat & Kidsom 2019). Despite such suggestions for adopting other simulation models for predicting stock prices, empirical evidence has shown no significant differences among these methods in their ability to simulate and predict stock prices (Lux 2018).

Further, prior research has also argued that the volatility of either asset prices or stock returns does not show constant return, regardless of the notion that asset prices follow a geometric Brownian motion (Suganthi & Jayalalitha 2019). The research community questioned the assumption of constant volatility, which is the underlying rationale of the GBM method because there are models that show non-constant volatility (Agustini et al. 2018). However, studies have shown that specific industries, such as established services, demonstrate geometric Brownian motion in the movement of stock prices, while other specific industries do not show those patterns (Parungrojrat & Kidsom 2019). Therefore, future research should explore more robust methods to study the predictability or otherwise of stock prices in Indian stock markets.

## Conclusion

The central purpose of this research is to find out whether the stock prices follow the Geometric Brownian Motion in the Indian stock markets and, therefore, to explore the possibility of predicting stock prices in the short run based on the historical data of one year, three, and five years. This research has shown that the GBM method effectively predicts stock prices if the base data used for prediction is from the past year. However, this method does not help predict if the researchers use the three-year or five-year base data. The GBM method captures the short-term data well for making short-term predictions. Further, these findings are consistent with the efficient market hypothesis. As stock markets are likely to gain information about companies at least, in the long run, the assertions of the efficient market hypothesis work in the long run. Therefore, predicting stock prices based on the historical data of long duration would become a distant possibility. However, the information anomalies that might exist in the historical data of stock prices of the previous year can help predict stock prices.

## References


Adam, K., Marcet, A. & Beutel, J. 2017. Stock price booms and expected capital gains. *American Economic Review* 107(8): 2352-2408.

Almudhaf, F. 2017. Speculative bubbles and irrational exuberance in African stock markets. *Journal of Behavioral and Experimental Finance* 13: 28-32.

Aggarwal, D. 2018. Random walk model and asymmetric effect in Korean composite stock price index. *Afro-Asian Journal of Finance and Accounting* 8(1): 85-104.

Agustini, W.F., Affianti, I.R. & Putri, E.R. 2018. Stock price prediction using geometric Brownian motion. *Journal of Physics: Conference Series* 974(1): 012047.

Bormetti, G., Callegaro, G., Livieri, G. & Pallavicini, A. 2018. A backward Monte Carlo approach to exotic option pricing. *European Journal of Applied Mathematics* 29(1): 146-187.

Bouchaud, J.P., Krueger, P., Landier, A. & Thesmar, D. 2019. Sticky expectations and the profitability anomaly. *The Journal of Finance* 74(2): 639-674.

Boya, C.M. 2019. From efficient markets to adaptive markets: Evidence from the French stock exchange. *Research in International Business and Finance* 49: 156-165.

Budagaga, A. 2017. Dividend payment and its impact on the value of firms listed on Istanbul stock exchange: A residual income approach. *International Journal of Economics and Financial Issues* 7(2): 370-376.

Chandar, S.K. 2019. Stock market prediction using subtractive clustering for a neuro-fuzzy hybrid approach. *Cluster Computing* 22(6): 13159-13166.

Chen, M.Y., Liao, C.H. & Hsieh, R.P. 2019. Modeling public mood and emotion: Stock market trend prediction with anticipatory computing approach. *Computers in Human Behavior* 101: 402-408.

Chen, Z., Matousek, R. & Wanke, P. 2018. Chinese bank efficiency during the global financial crisis: A combined approach using satisficing DEA and Support Vector Machines★. *The North American Journal of Economics and Finance* 43: 71-86.

Delcey, T. 2019. Samuelson vs. Fama on the efficient market hypothesis: The point of view of expertise. *Œconomia. History, Methodology, Philosophy* (9-1): 37-58.

Gigerenzer, G. 2020. What is bounded rationality? In *Routledge Handbook of Bounded Rationality*. 55-69. Routledge.

Ham, Y.G., Kim, J.H. & Luo, J.J. 2019. Deep learning for multi-year ENSO forecasts. *Nature* 573(7775): 568-572.

Hoyyi, A., Maruddani, D.A I. & Rahmawati, R. 2019. Contribution Indonesian composite index in PT Telekomunikasi Indonesia stock price model using 2-dimensional Geometric Brownian Motion. *Journal of Physics: Conference Series* 1217(1): 012091.

Guo, K., Sun, Y. & Qian, X. 2017. Can investor sentiment be used to predict the stock price? Dynamic analysis based on China stock market. *Physica A: Statistical Mechanics and its Applications* 469: 390-396.

Liu, Y., Yang, A., Zhang, J. & Yao, J. 2020. An optimal stopping problem of detecting entry points for trading modeled by geometric Brownian motion. *Computational Economics* 55(3): 827-843.

Lux, T. 2018. Estimation of agent-based models using sequential Monte Carlo methods. *Journal of Economic Dynamics and Control* 91: 391-408.

Masry, M. 2017. The impact of technical analysis on stock returns in an emerging capital markets (ECM's) country: theoretical and empirical study. *International Journal of Economics and Finance* 9(3): 91-107.

Nguyen, N.T., Phan, V.T. & Malara, Z. 2019. Nonlinear grey Bernoulli Model based on Fourier transformation and its application in forecasting the electricity consumption in Vietnam. *Journal of Intelligent & Fuzzy Systems* 37(6): 7631-7641.

Nigam, R.M., Srivastava, S. & Banwet, D.K. 2018. Behavioral mediators of financial decision making–a state-of-art literature review. *Review of Behavioral Finance* 10(1).

Orimoloye, L.O., Sung, M.C., Ma, T. & Johnson, J.E. 2020. Comparing the effectiveness of deep feedforward neural networks and shallow architectures for predicting stock price indices. *Expert Systems with Applications 139*: 112828.

Parungrojrat, N. & Kidsom, A. 2019. Stock price forecasting: Geometric Brownian Motion and Monte Carlo simulation techniques. *MUT Journal of Business Administration* 16(1): 90-103.

Pham, B.T., Nguyen-Thoi, T., Ly, H.B., Nguyen, M.D., Al-Ansari, N., Tran, V.Q. & Le, T.T. 2020. Extreme learning machine-based prediction of soil shear strength: a sensitivity analysis using Monte Carlo simulations and feature backward elimination. *Sustainability* 12(6): 2339.

Rao, P.S., Srinivas, K. & Mohan, A.K. 2020. A survey on stock market prediction using machine learning techniques. In ICDSMLA 2019. 923-931. Springer, Singapore.

Rezaee, M.J., Jozmaleki, M. & Valipour, M. 2018. Integrating dynamic fuzzy C-means, data envelopment analysis, and artificial neural network to online prediction performance of companies in the stock exchange. *Physica A: Statistical Mechanics and its Applications* 489: 78-93.

Sharma, A. 2019. The ACE trade-off model: a cost-benefit perspective to understanding the process of everyday food choice transactions. In Financial Decision-Making in The Foodservice Industry. 3-40. Apple Academic Press.

Sinha, A.K. 2021. The reliability of geometric Brownian motion forecasts of S&P500 index values. *Journal of Forecasting* 40(8): 1444-1462.

Suganthi, K. & Jayalalitha, G. 2019. Geometric Brownian Motion in stock prices. *Journal of Physics: Conference Series* 1377(1): 012016.

Sul, H.K., Dennis, A.R. & Yuan, L. 2017. Trading on Twitter: Using social media sentiment to predict stock returns. *Decision Sciences* 48(3): 454-488.

Teixeira Zavadzki de Pauli, S., Kleina, M. & Bonat, W.H. 2020. Comparing artificial neural network architectures for Brazilian stock market prediction. *Annals of Data Science* 7(4): 613-628.

Van Vliet, B. 2017. Capability satisficing in high-frequency trading. *Research in International Business and Finance* 42: 509-521.

Wang, J., Gong, B., Liu, H. & Li, S. 2022. An algorithm with a harmonious blending of distributed swarm intelligence and geometric Brownian motion for greener heterogeneous scheduling. *Applied Intelligence* 1-16.

Ying, Q., Yousaf, T., Ain, Q.U., Akhtar, Y. & Rasheed, M.S. 2019. Stock investment and excess return: a critical review in the light of the efficient market hypothesis. *Journal of risk and financial management* 12(2): 97.

Krishna Prasad*
T A Pai Management Institute
Manipal Academy of Higher Education
576 104, Karnataka, Manipal, INDIA.
E-mail: krishna.prasad@manipal.edu
Bhuvana Prabhu
Tata Consultancy Services
Bengaluru 560001, INDIA.
E-mail: kpbhuvanaprabhu@gmail.com

Lionel Pereira
The Hongkong and Shanghai Banking Corporation
Bengaluru, I56000, INDIA.
E-mail: lionelpereira52@gmail.com

Nandan Prabhu
T A Pai Management Institute
Manipal Academy of Higher Education
576 104, Karnataka, Manipal, INDIA.
E-mail: nandan.prabhu@manipal.edu

Pavithra S.
Government Polytechnic
Udupi 576104, INDIA.
E-mail: pavithra.innanje@gmail.com

* Corresponding author

ANNEXURE 1

List of Sample Companies

| Ticker | Name | Industry |
|---|---|---|
| RIL IN Equity | RELIANCE INDUSTRIES LTD | Energy |
| TCS IN Equity | TATA CONSULTANCY SVCS LTD | Technology |
| HDFCB IN Equity | HDFC BANK LIMITED | Financials |
| INFO IN Equity | INFOSYS LTD | Technology |
| HUVR IN Equity | HINDUSTAN UNILEVER LTD | Consumer Staples |
| ICICIBC IN Equity | ICICI BANK LTD | Financials |
| SBIN IN Equity | STATE BANK OF INDIA | Financials |
| BHARTI IN Equity | BHARTI AIRTEL LTD | Communications |
| HDFC IN Equity | HOUSING DEVELOPMENT FINANCE | Financials |
| KMB IN Equity | KOTAK MAHINDRA BANK LTD | Financials |
| BAF IN Equity | BAJAJ FINANCE LTD | Financials |
| ITC IN Equity | ITC LTD | Consumer Staples |
| APNT IN Equity | ASIAN PAINTS LTD | Materials |
| HCLT IN Equity | HCL TECHNOLOGIES LTD | Technology |
| WPRO IN Equity | WIPRO LTD | Technology |
| LT IN Equity | LARSEN & TOUBRO LTD | Industrials |
| MSIL IN Equity | MARUTI SUZUKI INDIA LTD | Consumer Discretionary |
| SUNP IN Equity | SUN PHARMACEUTICAL INDUS | Health Care |
| BJFIN IN Equity | BAJAJ FINSERV LTD | Financials |
| AXSB IN Equity | AXIS BANK LTD | Financials |
| ONGC IN Equity | OIL & NATURAL GAS CORP LTD | Energy |
| TTAN IN Equity | TITAN CO LTD | Consumer Discretionary |
| UTCEM IN Equity | ULTRATECH CEMENT LTD | Materials |
| PWGR IN Equity | POWER GRID CORP OF INDIA LTD | Utilities |
| NEST IN Equity | NESTLE INDIA LTD | Consumer Staples |
| ADSEZ IN Equity | ADANI PORTS AND SPECIAL ECON | Industrials |
| JSTL IN Equity | JSW STEEL LTD | Materials |
| TTMT IN Equity | TATA MOTORS LTD | Consumer Discretionary |
| NTPC IN Equity | NTPC LTD | Utilities |
| TATA IN Equity | TATA STEEL LTD | Materials |
| TECHM IN Equity | TECH MAHINDRA LTD | Technology |
| HDFCLIFE IN Equity | HDFC LIFE INSURANCE CO LTD | Financials |
| DIVI IN Equity | DIVI'S LABORATORIES LTD | Health Care |
| MM IN Equity | MAHINDRA & MAHINDRA LTD | Consumer Discretionary |
| BJAUT IN Equity | BAJAJ AUTO LTD | Consumer Discretionary |
| SBILIFE IN Equity | SBI LIFE INSURANCE CO LTD | Financials |
| COAL IN Equity | COAL INDIA LTD | Materials |
| GRASIM IN Equity | GRASIM INDUSTRIES LTD | Materials |
| DABUR IN Equity | DABUR INDIA LTD | Consumer Staples |
| HNDL IN Equity | HINDALCO INDUSTRIES LTD | Materials |
| GCPL IN Equity | GODREJ CONSUMER PRODUCTS LTD | Consumer Staples |
| BRIT IN Equity | BRITANNIA INDUSTRIES LTD | Consumer Staples |
| CIPLA IN Equity | CIPLA LTD | Health Care |
| BPCL IN Equity | BHARAT PETROLEUM CORP LTD | Energy |
| TATACONS IN Equity | TATA CONSUMER PRODUCTS LTD | Consumer Staples |
| IIB IN Equity | INDUSIND BANK LTD | Financials |
| EIM IN Equity | EICHER MOTORS LTD | Industrials |
| DRRD IN Equity | DR. REDDY'S LABORATORIES | Health Care |
| UPLL IN Equity | UPL LTD | Materials |
| HMCL IN Equity | HERO MOTOCORP LTD | Consumer Discretionary |