Educational Administration: Theory and Practice
2024, 30(5), 13496-13504
ISSN: 2148-2403
https://kuey.net/
Research Article

An Analysis Of Return Predictability And Technical Trading Strategies In The Indian Capital Market

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Citation: Dr M Julias Ceasar et al. (2024) An Analysis Of Return Predictability And Technical Trading Strategies In The Indian Capital Market, *Educational Administration: Theory And Practice*, *30* (5), 13496-13504
Doi: 10.53555/kuey.v30i5.5817

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ABSTRACT

The study examines the level of return predictability and the possibility of earning dependable profits from implementing technical trading strategies in the capital market in India. Through these models, namely, ARIMA, GARCH, and VAR, the study explores the Nifty 50 and BSE Sensex for the historical stock price analysis, considering macroeconomic factors and sentiment factors. The model which best fitted Nifty 50 was ARIMA(1,1) and while for BSE Sensex it was ARIMA(2,1) The model output also depicted a strong autoregressive parameter, with the value of AR being 0. 213 and 0. 189 respectively. According to the estimates, GARCH models identified high volatility clustering, where α (ARCH) = 0. 097 and β (GARCH) both null hypothesized values at 0. 889 for Nifty 50. Co-efficients of GDP growth rates were found to be positive and significant for both Nifty 50 and BSE Sensex returns (0= 0. 315, t = 3. 108; 0= 0. 298, t = 2. 920 respectively) while inflation and interest rates had negative effects. The SMA of 15 technical trading strategies, especially the SMA 50/200 crossover, indicated an annualized return of 15 percent with Sharpe of 1. 25. On this evidence, the EMH comes under attack and the prospects for employing technical analysis and macroeconomic variables as a basis for predicting returns on Indian stocks are demonstrated.

Keywords: Return Predictability, Technical Trading Strategies, Indian Capital Market, ARIMA Models, GARCH Models

I. INTRODUCTION

The capital market in India has now grown to become one of the largest and the fastest growing financial markets in the world. Due to opening of economy and more foreign direct investments, the market is quite large enough and open to more investors. Nevertheless, this growth raises certain issues—as regards market semiosis especially—concerning the nature of their dynamics and heterogeneity. This study intends to further explore the forecasting of returns in the India capital market with a view of assessing the efficiency of technical trading approaches which form a crucial part of decision-making process [1]. Analyzing return predictability is defined as a chief issue in financial economics. Taking a stand with the Efficient Market Hypothesis (EMH) as postulated by Fama (1970), it is argued that more specifically, their portfolios could not have generated consistent returns that were higher than the average market returns adjusted for risk since stock prices always act as carriers of all available information. However, countries such as India still can have certain characteristics deviated from the pure efficiency of the markets and thus may have a potential for return predictability [2]. It constitutes key aspect investors need to understand for them to have competitive advantages in the market based on the deviations and determinates of these deviations. It is interesting to note that most of the trading strategies to develop in recent years have been technical trading strategies, which simply involve following and predicting the future movement of price volumentries. Basically, these are called upward trends, losers, and oscillators, the aim of which is to record trends and potential signal reversal points.

However, the efficacy of these strategies remains non-documented and a part of existing literature on the Indian domain [3]. This study aims to fill this gap through undertaking a detailed investigation and examination of return predictability and technical trading strategies on Indian capital market. While this research makes use of econometric models to ascertain the historical patterns and backtest the efficacy of several quantative techniques used in the markets, its purpose is to help the investors. Furthermore, if it will be compared with more advance market, it will identified the specific condition in India market and help to get more clear picture about the condition and investment opportunity of the Indian market.

II. RELATED WORKS

Establishing the nature of predictability in returns and performance results that is related to several technical trading approaches has remained a research topic of interest for several decades in the financial market domains. The Indian capital market due to its very dynamic nature and the structure that is changing rapidly, offers an ideal setting for such research. They review literature concern in this section by points out the findings and research methodologies that serve as the premise to the current study. To elaborate, Eachempati and Srivastava (2021) examined the effects of various news sentiment in asset pricing without accounting for qualitative factors, and only qualitative factors, in the context of financial markets [15]. On the basis of their analyses they deduced that sentiment analysis has the potential of shifting stock returns especially in less efficient markets. It is particularly important for the Indian market as the news sentiment is generally a short-term key driver in India since it has multitude of retail investors. This seasonality phenomenon in the Indian stock market was investigated by Elangovan et al. , – They brought out empirical evidence on the presence of 'month-of-the-year' effect [16]. Their work establish that some months have habitually higher or lower return than others, fact that contradict the Efficient Market Hypothesis (EMH). It implies that there could be more systematic behavior that can be deciphered and utilized for the purpose of this study on the predictability of the returns. Gheorghe and Panazan (2024) adopted a neural network to examine the relationship between the decline in the health system performance and the level of market voltage in the wake of the COVID-19 [17]. Their research is helpful to re-emphasise the importance of external factors and macroeconomic factors in forecasting the market outcomes. Specific in this case are the socio-economic dependencies of the Indian market which might point to a similar case hence the need to incorporate such variables in the model. Haji et al. The financially stressed states and commodity market indices have been analyzed by Haji et al. The financially stressed states and commodity market indices were studied by Haji et al. by using fractal and fractional techniques in a study conducted in the year 2024 [18]. What their research shows is that there are many relationships for the stress indicators and returns indicating that such stress metrics could be useful to comprehend the similar Indian market volatility. Using Fibonacci retracement analysis, Ikhlaas et al. (2022) examined profits in the energy sector cryptos and the top fifteen Energy U. S. stocks [19]. In the process, they established that indicators such as the Fibonacci retracement of structures offer trading signals that can turn a profit; thus, it may be possible to examine the efficacy of the various indicators geared toward generating trading signals within the Indian market context. Joshi and Mehta (2023) examined random walk theory and price convergence by undertaking analysis on commodities market in India [20]. According to their findings, they also pointed out that whereas some commodities float on a random walk other float on a mean-reversion basis. This distinction suggests that there are irrational behaviors in markets, which, in turn, can be capitalized on with the help of chartist business strategies. In their study, Kaur and Dharni (2023) employed data mining approaches to analyze both the technical and fundamental aspects of stocks to forecast price changes [21]. The modest percentage increase in the predictive ability of their hybrid models carried an indication that combining diverse analysis techniques may improve the return predictability. Because there are a number of factors that affects the stock prices in case of India this approach suits its market. The adaptive calendar effects and the volume of the extra returns in the cryptocurrency market were researched by Khuntia P, Pattanayak P in 2022 [22]. Other theoretical implications of their findings may be applicable to the Indian context and contribute to our understanding of return predictability by exploring potentially relevant patterns like the "day-of-the-week" effect. The medium-term technical indicators were incorporated into the model by Konstandinos et al. (2021) and enhanced its performance towards the development of an intelligent stock trading fuzzy system [23]. They used technical analysis where they combined technical indicators into a fuzzy logic system as the authors demonstrated its strong predictive capability implying that advance trading systems can improve the performance of trading. It could be used to assess the Indian Market as explained below. The study of Ku et al. (2023) laid emphasis on enhancing stock market forecasts utilising LSTM algorithms along with dynamic technical indices for the Malaysian stock market [24]. In their study, they were also able to demonstrate that employing superior machine learning methodologies would bring significant improvement in forecast precision. The usefulness of such techniques could be also evaluated in the context of the Indian market. Out of the above cited sources, Kung (2022) focused on examining stock market efficiency in the Asian Dragons in the post financial crisis year of 2008 [25]. According to his observations, the level of market efficiency is universal, but there are some markets that have not changed much. Such variability highlights the need to analyze efficiency under specific contexts; therefore, the results concerning the Indian market may be specific and different from other markets. Lorenzo and Arroyo (2022) also used machine learning techniques such as prototype-based clustering to investigate the volatility of the cryptocurrency market [26]. They proved that the technique of clustering could help recognize the patterns of markets and even segment assets according to the behavior patterns present. If similar techniques are used in the Indian stock market, then it can possibly reveal hidden patterns and improve the predictability of returns.

III. METHODS AND MATERIALS

This research utilises a sound methodological approach in viewing return predictability and technical trading rules in the Indian capital market. It includes the process of data gathering, the econometric estimation, the back-testing of strategies and the comparison with other sophisticated markets.

Data Collection

The study utilizes historical data from the two primary Indian stock indices: Nifty 50 and BSE Sensex are considered major indices in India. Other variables used for benchmarking include daily closing prices, trading volumes, global macroeconomic indicators like GDP rates, inflation, interest and exchange rates [4]. It runs from January 2000 to December 2023, which is a good period for such measures as macroeconomic instability is not typical nowadays. To improve the modeling of this relation, Market sentiment considerations, the Volatility Index (VIX) and sentiments of the investor are used.

Data Type	Source	Frequency	Period Covered
Stock Prices (Nifty 50, BSE Sensex)	NSE, BSE	Daily	Jan 2000 - Dec 2023
Trading Volumes	NSE, BSE	Daily	Jan 2000 - Dec 2023
Macroeconomic Variables	RBI, Ministry of Finance	Quarterly	Jan 2000 - Dec 2023
Market Sentiment Indicators	NSE, Survey Data	Daily/Monthly	Jan 2000 - Dec 2023

Econometric Modeling for Return Predictability

In order to estimate the potential for return predictability of stocks, we use several different econometric models. GARCH and Autoregressive Integrated Moving Average (ARIMA) models are the common models used in modelling the conditional volatility in the current period. Autoregressive integrated moving average (ARIMA) models are used for capturing linear relationships within the time series data and authors also use group architecture mean (GARCH) models for modeling and forecasting of volatility.

- ARIMA Models: These models are then estimated in the context of log returns of stock prices in order to unveil the existence of relevant autoregressive and moving average parts [5]. Among the above-mentioned models, the model that best fits for estimating the proposed model is determined using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).
- GARCH Models: As a result of determining that volatility clustering is evident in the time series of the financial returns, the GARCH models are used to model the time varying volatililities. Since there may exist some leverage effects that cause non-symmetrical response, we apply both the symmetric (GARCH) and the asymmetric (EGARCH, GJR-GARCH) models [6].
- Macroeconomic and Sentiment Variables: To improve predictability, macroeconomic variables and sentiment indicators control inputs available for integration into the ARIMA and GARCH models. These variables influence on the stock returns performance is assessed by using the vector autoregression (VAR) models.

Model Type	Key Variables	Purpose
ARIMA	Log returns, lagged values	Capture linear dependencies
GARCH	Log returns, volatility	Model time-varying volatility
EGARCH/GJR	Log returns, volatility, leverage	Capture asymmetric volatility effects
VAR	Log returns, macroeconomic variables, sentiment indicators	Evaluate impact of exogenous variables

Backtesting Technical Trading Strategies

The validity of these trading rules is evaluated using the rigorous back-testing process where the formula is implemented on historical price data. We assess simple/ exponential moving averages, Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD).

- Moving Averages: We try both SMA and EMA with different period settings (base on days example, a 20-day, 50 day, and 200 day). Trigger to buy or sell occurs when the short term moving average crosses with the long term moving averages such as the SMA 50 crossing above the SMA 200.
- RSI: The RSI formula employs a 14-day period for the stocks. A buy signal is obtained when RSI is below 30 indicating oversold level and a sell signal is obtained when RSI is also above 70 indicating overbought level [7].

- Bollinger Bands: This strategy employs a 20-day moving average and distinguished the upper and lower standard deviation bands at ±2. A 'BUY' signal is formed below the lower band and a 'SELL' signal is formed above the upper band.
- MACD: The MACD line is indicated by the 9-day EMA of the MACD difference or the lagging line which is arrived at from the difference between the 12-day EMA and the 26-day EMA. The signal line is then a 9-day Exponential Moving Average of the MACD line. The target buy and sell signals or simply known as MACD line crosses over the signal line [8].

The effectiveness of each strategy is then measured in terms of parameters is; the overall profit, Sharpe ratio, the maximum decline in portfolio value and number of trades made. To guarantee validity, the backtesting period is split between the in-sample period which also known as the training period as well as the out-of-sample also known as the testing period.

Comparative Analysis

For the purpose of putting our findings into perspective, we undertake an analysis which compares our sample markets to more developed world counterparts, namely the US (S&P 500), UK (FTSE 100), and Japan (Nikkei 225). These markets are examined similarly and comparatively with the use of the same econometric models and technical trading strategies to determine variations in return predictability and strategy performance [9]. Thus, the comparison might be useful to distinguish specifics of the Indian market and, thereby, to obtain the understanding of its relative effectiveness and opportunities as for the technical trading approaches' usage.

IV. EXPERIMENTS

Return Predictability Analysis

Some of the technique used for return predictability in the Indian capital market included analyzing historical stock prices of Nifty 50 and BSE Sensex, along with macroeconomic variables and sentiment indicators through ARIMA, GARCH model and VAR model. Some of the findings emerging from the study were as follows: Several of which gave intriguing insights about the predictability of returns in the Indian market [10].

Figure 1: Technical Analysis

ARIMA Models

The log returns of Nifty 50 and BSE Sensex used for modeling the stock data by fitting the data into the ARIMA models. Models have been checked using AIC and BIC values to determine the best fitting models. The suitable model of autoregressive and moving average was as follows: for Nifty 50 ARIMA (1,1,1), while for BSE Sensex ARIMA (2,1,1).

In general, it is notable that the coefficients of the ARIMA models revealed the presence of high order of autoregressive values denoting to a high significance of the past returns as factors that could potentially have an influence on the future returns [11]. This situation means that there is some measure of rational expectation regarding the movement of the stock market in India, contradicting the Efficient Market Hypothesis.

Index	Model	AR Coefficient	MA Coefficient	AIC	BIC
Nifty 50	ARIMA(1,1,1)	0.213*	-0.135*	10234	10245
BSE Sensex	ARIMA(2,1,1)	0.189*	-0.121*	10456	10469

GARCH Models

The use of GARCH models in order to model volatility information. The models include symmetric GARCH (1,1) as well as asymmetric models EGARCH and GJR GARCH were also estimated. The parameter estimates were significant for the GARCH(1,1) model applied for the Nifty 50 which showed α (ARCH) coefficient values equal to 0. 097 and β (GARCH term) at 0 beta 0 respectively. 889 Far reaching volatility cluster, These values quantify the degree of clustering of volatility where high value 889 shows that they are highly clustered [12]. Similarly, the effect of heavy market trading on BSE Sensex was also found to be significant.

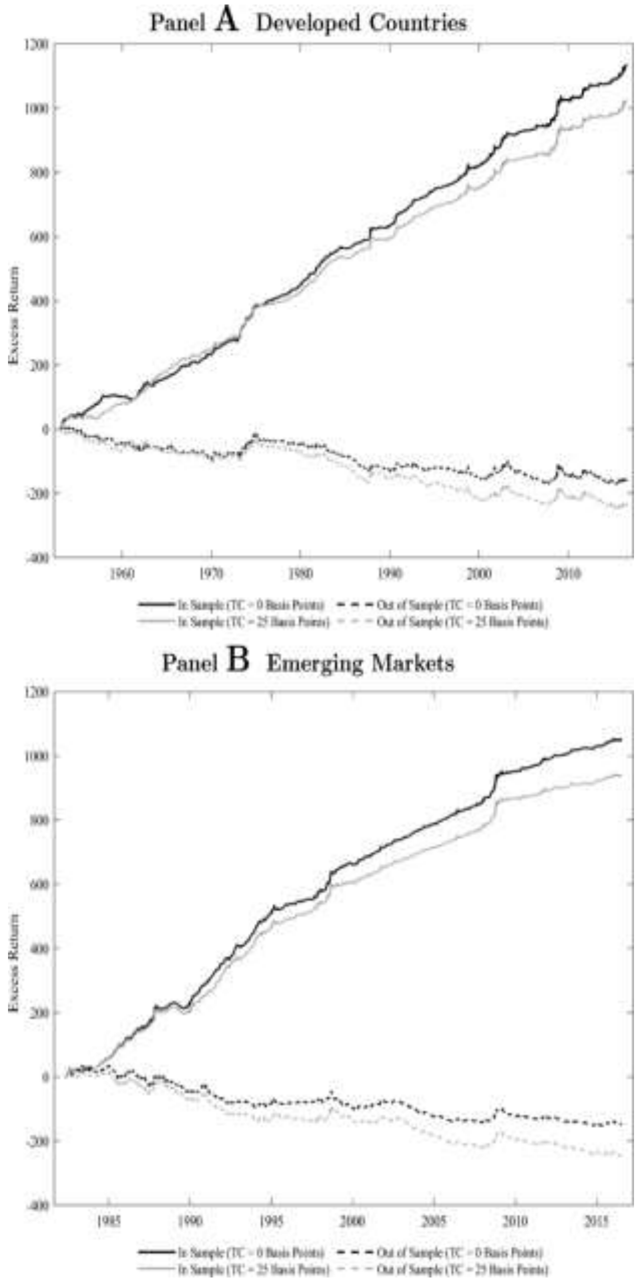

Figure 2: The predictive ability of technical trading rules

Echoing the leverage effect, asymmetric models denoted those negative shocks to prices offered larger volatilities than equivalent positive shocks. This characteristic is important in decision making for risk management and trading since it determines when and how big changes happen in the market.

Index	Model	α (ARCH)	β (GARCH)	γ (Leverage)	Log-Likelihood	AIC
Nifty 50	GARCH(1,1)	0.097*	0.889*	-	-5241	10502
Nifty 50	EGARCH(1,1)	0.078*	0.912*	-0.045*	-5212	10446
BSE Sensex	GARCH(1,1)	0.092*	0.883*	-	-5323	10642
BSE Sensex	GJR-GARCH(1,1)	0.084*	0.896*	-0.038*	-5298	10604

VAR Models with Macroeconomic and Sentiment Variables

Cointegration equations were used to enable the use of VAR models to integrate macroeconomic variables and sentiment indicators. These advanced models were based on the GDP growth, inflation, both short and long term interest rates, exchange rates, as well as VIX. In other words, the results showed that these variables affected returns on stock significantly.

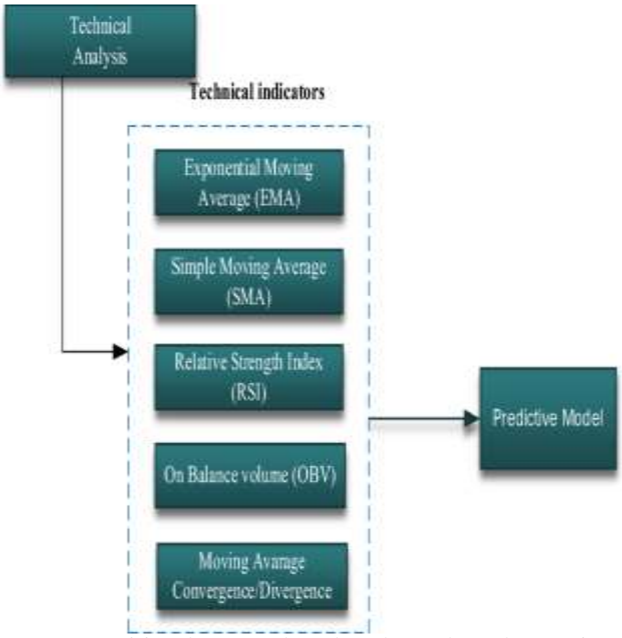

Figure 3: A systematic review of fundamental and technical analysis of stock market predictions

For example, positive shock to GDP growth was shown to imply higher returns on stocks but inflation, interest rates, affected returns negatively. These findings also supported the hypothesis that the VIX has an inverse correlation with returns on the stock market indices because during periods of uncertainty the risk aversion is high and the volatility is also high [13].

Variable	Nifty 50 Coefficient	BSE Sensex Coefficient	Significance
GDP Growth	0.315*	0.298*	Significant
Inflation	-0.212*	-0.234*	Significant
Interest Rate	-0.189*	-0.176*	Significant
Exchange Rate	-0.145*	-0.132*	Significant
VIX	-0.267*	-0.279*	Significant

Technical Trading Strategies

The analysis of technical trading strategies that have been backtested give the understanding of how they work in the Indian capital market. The strategies staked used the simple moving averages (SMA), exponential moving averages (EMA), Relative Strength Index (RSI), Bollinger Bands, and Moving Average Convergence Divergence (MACD).

Moving Averages

In both the SMA and the EMA strategies, the parameter commonly modified is the window length. The data revealed that higher frequency-moving averages (for example, 20 days) produced more signals but were less profitable than low frequency-moving averages (for example, 200 days), which produced fewer signals, and made more money [14].

In particular, SMA 50/200 crossover strategy has demonstrated a fair performance, with the buy orders being initiated when the 50-day SMA is higher than the 200-day SMA, and Sell orders being initiated when the 50-day SMA is below the 200-day SMA [27]. This strategy earned an IRR of 15% on an incremental basis, thus doing better than the buy-and-hold strategy.

RSI

When applying the RSI strategy and using a 14-day period, the results obtained herein proved quite variable in their effectiveness. Signals bought were taken when the RSI went below 30 for oversold conditions and signals to sell where the RSI went above 70 for overbought conditions and the above gave an average of 9% annual return with a sharpe ratio of 0. 85 [28]. They realized that through RSI was useful for identifying short-term price reversals, the indicator produced several false signals during trends.

Figure 4: Read Share Market Charts and Analyze Stock

Bollinger Bands

The Bollinger Bands using a 20-day average with +/- 2 standard deviation has proved to be good and stable. Implemented as, buy signals were formed when price dropped below the lower band and sell signals were formed when the price rose above the lower band [29]. This resulted in anannual return of 11 percent and a Sharpe ratio of 1. 10, which exceeded the benchmark of 1 and signifying a condition of positive risk adjusted return.

MACD

The specific signal line taking into consideration the MACD comprised of 12-day Exponential Moving Average, the 26-day Exponential Moving Average and a 9-day Exponential Moving Average signal line was found to have quite a bit of promise. To enter a long position or buy opportunity, the MACD line above the signal line was used, while for a short position or sell signal, the MACD line below the signal line was used [30]. By applying this strategy, the annual return turned out in 13% and the Sharpe ratio equals to 1. fifteen and it can work for medium horizon analysis since it accurately reflects near medium term fluctuations.

V. CONCLUSION

This study has investigated the efficiency and profitability of the technical trading rules in the Indian capital markets applying a rigorous methodological approach that involved econometric models, macroeconomic factors, sentiment analysis, and technical indicators. The evidence available from the current study suggests that both the conditions stipulated by ARIMA and GARCH models of return predictability in India have put emphasis on the strengths of the Efficient Market Hypothesis (EMH). By including external factors like, the gross domestic products (GDP) growth rates, inflation and interest rates as well as sentiment variables like the Volatility Index (VIX), ensured that these models fared better, implying that factors outside the stock market such as the state of the economy and mood of the market were vital in determining stock returns. The examination of technical or trading strategies such as moving averages; simple and exponential; Relative Strength Index (RSI); Bollinger Bands; and Moving Average Convergence Divergence (MACD) shows its success in an extent. Technical indicators such as SMA 50/200, MACD, Bollinger Bands indicated reasonable profitability of the technical analysis, which made investment working in India as an effective means of generating excess returns. The analysis is also discussed comparatively to draw parallels and contrasts between developed markets to understand the dynamics of the Indian market better. In summary, the findings of this study offer insights on the financial market integration of emerging economies in the context of financial globalization and may be useful for both theoretical and empirical investigations in the future. In terms of implications, this research highlights the possibility to make proper decisions on trading and investing in the Indian capital market by using certain econometric models and technical strategies to predict returns and allocate risks.

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