



DO THE FORECASTING ABILITY OF TECHNICAL ANALYSIS VARY ACROSS MARKET REGIMES: EMPIRICAL ANALYSIS OF BSE IT STOCKS

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Abstract: *Purpose:* Financial markets are erratic exhibiting periods of varying volatility. The study aims to analyse whether the forecasting accuracy of technical analysis varies during different market regimes. *Methodology:* The study used trend, volatility and momentum-based technical indicators. Markov Regime Switching model was used to identify high and low-volatility regimes. Machine-learning and deep-learning prediction models were employed to forecast the returns. *Findings:* The study ascertained that adding regime-based analysis to technical trading signals improves their predictive ability with superior performance in high-volatility markets. Short-term moving averages, RSI, MACD, STOCH and MFI were effective predictors during low-volatility while W%R and BB were better predictors during high-volatility. SVM outperforms other prediction models with directional accuracy of 59.24%. *Originality:* To the best of the author's knowledge, this study is a novel approach that integrates a regime-based framework with technical indicators for forecasting stock returns. *Implications:* The study holds practical implications for portfolio managers and traders for implementing technical analysis-based investing strategies and offers policy implications for financial market regulators to improve market transparency.

Keywords: Technical analysis, Regime-switching, Stock market prediction, Machine learning, Deep learning

JEL classification codes: G11, G17, C53

I. Introduction

Forecasting the stock market is a challenging endeavor in the financial market due to its complicated, erratic, unpredictable and volatile nature (Li & Bastos, 2020).

Volatility is an inherent part of the stock market. It exhibits periods of varying volatility and structural changes which are referred to as market regimes. It can be used to categorise the market into two regimes. A high-volatility regime where there are opportunities to earn higher returns and a low-volatility (stable) regime which is characterised by lower returns.

Technical analysis is a method for predicting future stock market movements using trend, momentum, and volatility-based technical indicators. Although technical indicators are widely used in prediction studies but their forecasting accuracy is still a debated topic, especially during volatile market conditions. Previous studies have attempted to forecast markets as a whole using technical indicators and Artificial Intelligence (AI) models. There is a dearth of studies that integrated regime-switching frameworks with technical indicators in the context of the Indian stock market. To overcome this gap, the present study aims to examine the accuracy of technical indicators in predicting stock market returns across different market regimes using multiple prediction models. By combining regime-switching techniques with machine learning prediction models, the study underscores the conditions under which technical indicators are most effective.

The predictability of technical indicators varies across different regimes due to the presence of uncertainty and noise in financial markets. It is important to assess the predictive accuracy of technical indicators across different regimes to make optimal portfolio investment decisions by employing regime-based trading strategies. Previous studies have attempted to forecast markets as a whole using technical indicators without accounting for regime switching (Jafar et al., 2023; Sedighi & Roodposhti, 2022). This study divides the market into stable and volatile regimes using the Markov Regime Switching model given by Hamilton (1989). Technical indicators that work well during trending markets may fail during sideways or low-volatility periods (Wang et al., 2025). There is improvement in financial forecasting accuracy when the regime-switching model is used as indicated by the number of violations and tail-loss tests (Salhi et al., 2016). Separate prediction models will be developed for each regime to determine which regime yields the more accurate prediction. Moreover, the study also identifies important technical indicators in each regime that provide higher prediction accuracy. A comparative analysis of econometrics, machine-learning and deep-learning prediction models provides an in-depth understanding of the forecasting accuracy of technical analysis.

The present study attempts to answer the following research question:

Q1: What is the accuracy of technical indicators in predicting stock market returns across different market regimes using multiple prediction models?

Q2: What are the most effective technical indicators in predicting returns across different market regimes?

The paper has been divided into the following subsections. The first section provides a background of the study along with the gaps addressed in the present study. The second section is a review of the literature. The third section details research methodology. The fourth section presents findings and results of the study. The fifth section discusses the implications of the study. The last section concludes the major findings and suggests future research areas.

II. Literature Review

1. Theoretical Evidence

Technical analysis attempts to forecast movements in stock prices using technical indicators based on historical price and volume data (Chandrika & Srinivasan, 2021; Jafar et al., 2023). The efficient market hypothesis given by Eugene F. Fama (1970) is the cornerstone of stock market prediction studies. It states that the current stock price reveals all public, private and historical information that makes it impossible to beat the market. However, the applicability of EMH is still a disputed topic. Subsequent studies challenged the assumptions of EMH and found that markets are not always efficient due to the presence of market anomalies. During market inefficiency, certain trading strategies can be employed that possess forecasting power to accurately predict and beat the market (Chong et al., 2010; Phuoc et al., 2024). Fama (1970) categorised the market efficiency into weak, semi-strong and strong forms. The weak form of market efficiency states that the prevailing current price represents all historical price information which makes it difficult to predict returns. Since technical trading strategies are based on historical prices and trading volumes, the weak form of efficiency confronts the predictive ability of technical analysis. Previous research on technical analysis supports the adaptive market hypothesis which states that during market inefficiency, technical indicators can predict the market (Wang et al., 2025).

2. Empirical Evidence

Technical indicators transform price and volume data into signals that capture momentum, trend, volatility and market sentiment. Popular indicators include

moving averages, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), stochastic oscillators and Bollinger Bands (BB). Several studies have used combinations of these indicators to forecast stock returns and market direction. Research suggests that combining multiple indicators may improve predictive performance because each indicator captures different market dynamics (Chong et al., 2010; Phuoc et al., 2024; Singh et al., 2021; Srivastava et al., 2021).

Early empirical work by Brock et al. (1992) tested simple moving average and trading range breakout rules in the US stock market and found that technical trading strategies generated returns significantly different from a random walk. The results suggest that historical price patterns may contain useful predictive information. Chen et al. (2018) developed a technical analysis-based stock forecasting model utilising indicators such as SMA, RSI, and stochastic oscillator, achieving up to 76.74% accuracy in predicting trading signals. The model employs an adaptive indicator selection and SVM optimised with PSO to enhance forecasting precision. Lee et al. (2021) predicted the short-term price movements of the Taiwan stock exchange ETF using technical indicators under the setup of deep neural networks and found that the model attained the prediction accuracy of 83.6 % in the rise, fall and flat categories.

Dua & Tuteja (2021) utilised Markov regression to understand the regime-switching behaviour in equity and international currency markets and found two market regimes. On one hand, a turbulent regime exists, which was featured by high volatility and low returns. On the other hand, a tranquil regime with high returns and low volatility. A study by Wang et al. (2025) shows that integrating the Time-Varying Transition Probability (TVTP) Markov regime-switching model with technical indicators significantly improves the prediction of future energy returns as proxied by the CSI 500 index by capturing market regime dynamics and nonlinear behaviour.

After reviewing the literature, limited studies integrated regime-switching frameworks with technical indicators in the context of the Indian stock market. The objective of the present study is to address this gap.

III. Research Methodology

1. Sample Size

The study aims to examine the prediction accuracy of technical analysis in stock return prediction across different market regimes. The study used Information

Technology (IT) stocks of the Bombay Stock Exchange (BSE) as part of the sample. The IT sector is considered the backbone of the Indian economy. Any volatility in this sector can significantly impact the overall market. It is important to develop a standalone prediction model for the IT sector to capture market anomalies and assist trading decisions. The final sample consists of 43 IT sector stocks. The open, high, low, close and volume data were obtained from the BSE website and Prowess database for 5 years initiating from 1 April 2020 till 31 March 2025.

2. Technical indicators

The following technical indicators were computed on MS Excel using price and volume data:

- **Trend-based:** Simple Moving Average (SMA), Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD) and Directional Movement Index (DMI)
- **Volatility-based:** Relative Strength Index (RSI), William % R (W%R), Money Flow index (MFI) and Stochastic Oscillator (STOCH)
- **Momentum-based:** Bollinger Bands (BB) and Keltner Channel (KC)

3. Regime Identification: Markov Regime Switching Model

The returns and technical indicators are calculated and the data is pre-processed to handle missing values. The dataset is divided into 2 regimes using the Markov regime switching model given by Hamilton (1989). It is predominantly used in finance research to find structural breaks in asset returns and volatility. Previous research suggests that the behaviour of stock returns differs across regimes.

4. Prediction Models

The study employs a combination of econometric, machine learning, and deep learning models to examine the performance of technical indicators in predicting stock returns. Logistic regression (logit) is used as a benchmark econometric model, while Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), and Extreme Gradient Boosting (XGB) represent machine learning approaches. A neural network (NN) deep learning model is further implemented to capture complex nonlinear relationships in the data. All the analysis has been done on Google Colab.

IV. Findings and Results

1. Descriptive Statistics

Table 1 represents the descriptive statistics. The dataset comprises 53,363 observations, featuring 12 technical indicator variables and a stock return as the target variable. Stock returns exhibit significant non-normality characterised by extreme negative skewness and very high kurtosis, indicating the presence of large market shocks that are consistent with financial time series behaviour. Momentum indicators such as RSI, Stochastic Oscillator and Williams %R exhibit relatively stable distributions with limited extreme values and smooth oscillatory behaviour. MACD exhibits extreme non-normality indicating the presence of large and infrequent shocks. High kurtosis in several variables indicates frequent extreme values which supports the presence of market shocks and volatility clustering.

The descriptive statistics indicate that stock returns and several technical indicators exhibit significant non-normality, characterised by skewness and excess kurtosis. In particular, the extreme kurtosis observed in stock returns and MACD suggests the presence of fat tails and large market shocks. These findings justify the use of regime-switching and machine learning approaches because traditional linear models may fail to capture such nonlinear and extreme behaviour. The study employs logistic regression, machine and deep-learning models as these techniques do not require normality assumptions and therefore do not affect the predictive analysis.

Table 1: Descriptive statistics

<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>Min</i>	<i>Max</i>	<i>Skewness</i>	<i>Kurtosis</i>
Stock Return	0.0013	0.0314	-1.5607	0.252	-7.9106	385.6525
RSI	0.0498	0.2634	-0.8633	0.9945	0.0828	-0.0987
SMA (10 days)	0.0067	0.0542	-0.7691	0.5171	-0.1379	17.9366
SMA (50 days)	0.0328	0.1443	-0.7848	1.5702	1.0392	8.6216
EMA (10 days)	0.0055	0.0461	-0.7502	0.4168	-0.7097	23.147
EMA (50 days)	0.0275	0.1224	-0.7834	1.0956	0.5522	6.6492
MACD	0.0033	0.0704	-2.1753	0.2552	-10.932	249.9809
W%R	-0.4981	0.2866	-1	0	-0.0406	-1.2143
BB	0.5463	0.3356	-0.5775	1.577	-0.0224	-0.6981
DMI	0.2684	0.1158	0.069	0.9174	1.0786	1.1357
KC	0.5648	0.5072	-6.5187	8.0523	-0.1509	17.7654
STOCH	0.4938	0.2601	0	1	-0.0168	-1.1941
MFI	0.1074	0.4164	-1	1	-0.2318	-0.6254

Source: Author's own compilation

2. Regime Identification Results

The results of the Markov Regime Switching model divide the data into two distinct regimes of the market based on stock return volatility. Regime 0 is featured by a low return and low volatility. In contrast, Regime 1 is characterised by higher returns and higher volatility. The market tends to be quite persistent in Regime 0 while transitions from Regime 1 to Regime 0 are less likely. Regime-switching resulted in a 30% of high volatility regime and 70% of low volatility. The descriptive statistics of both regimes are given in Table 2. The regime visualisation is given in Figure 1 where red segments represent a high-volatility regime and blue segments represent a low-volatility regime.

Table 2: Regime identification results

Parameter	Regime 0 (Low Return, Low Volatility)	Regime 1 (High Return, Higher Volatility)
Mean volatility	-0.0086	0.0252
Variance	6.197e-05	0.0004
Transition probability	p[0→0]: 0.9299 p[0→1]: 0.0701	p[1→1]: 0.8606 p[1→0]: 0.1394

Source: Author's own compilation

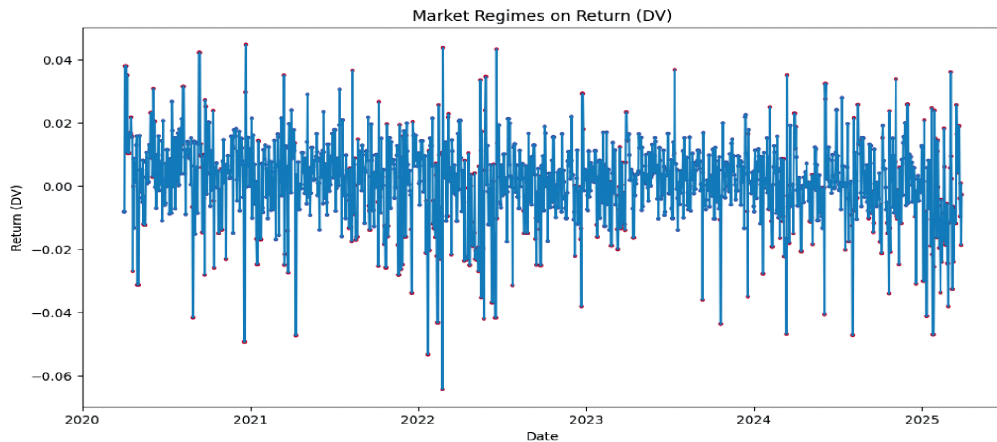


Figure 1: Regime Visualisation

Source: Visualised using Google Colab

3. Results of Multiple Prediction Models In Terms of Directional Accuracy

The study strongly supports the effectiveness of a regime-switching approach as the stock return predictability is highly dependent on the prevailing regime. The

directional accuracy of prediction models is higher during high-volatility periods, ranging between 56-59% than during stable market periods where the directional accuracy ranges between 50-53%. The SVM model gave the highest prediction accuracy of 59.24% followed by logistic regression with 59.14% accuracy in the high-volatility regime. The results were similar to the study by Chen et al. (2018) where SVM achieved the highest accuracy. The gradient boosting model outperformed other models in the low-volatility regime with a prediction accuracy of 53.32%. The classification models achieved accuracies that were statistically significant and better than random guessing in predicting the direction of returns in both regimes. This confirms that the models are capturing genuine patterns in the data rather than just noise. The study also discovered that prediction accuracy is better when the market is divided into different regimes than when the overall market is taken as a single regime. The comparative results of econometrics, machine learning and deep learning models in predicting stock market returns across different regimes is presented in Table 3.

Table 3: Results of multiple prediction models in terms of Directional Accuracy

<i>Model</i>	<i>Low Volatility</i>	<i>High Volatility</i>	<i>Overall</i>
Logit	52.00% (p-value= 0.00052)	59.14% p-value=2.37e-24	53.12%
RF	52.20%	56.14%	53.31%
SVM	52.09%	59.24%	53.17%
GB	53.32%	57.85%	53.11%
XGB	52.44%	57.11%	52.17%
NN	50.51%	57.11%	51.17%

Source: Author's own compilation

4. Effective Technical Indicators Across Regimes

4.1. Trend-based Indicators

A rising short-term SMA (10 days) strongly predicts returns in Regime 0 but has no significant effect in Regime 1. Long-term SMA (50 days) does not appear to be a significant predictor in either regime. A rising short-term EMA (10 days) strongly predicts higher returns in Regime 0 but has no significant prediction in Regime 1. Long-term EMA (50 days) is not a significant predictor in either regime. MACD is a significant negative predictor in Regime 0 but its forecasting is not significant in Regime 1. DMI has no effect in Regime 0 but a strong positive effect in Regime 1.

4.2. Volatility-based indicators

In both regimes, higher RSI tends to be associated with slightly lower returns. The prediction is stronger and more statistically robust in Regime 0. W%R has no significant effect in Regime 0 but is a significant positive predictor in Regime 1. STOCH is a robust negative predictor in Regime 0 but its forecasting is not significant in Regime 1. MFI is a robust negative predictor in Regime 0 and marginally significant in Regime 1.

4.3. Momentum-based indicators

BB has no effect in Regime 0 but is a negative and statistically significant predictor in Regime 1. KC is a positive predictor in both regimes with a slightly stronger forecasting in Regime 1.

Table 4 demonstrates that the relationships between technical indicators and returns are highly regime-dependent. What is statistically significant in one regime may not be in another regime. Short-term moving averages (SMA 10, EMA 10) and oscillators (RSI, MACD, STOCH, MFI) tend to show more significant negative association with future returns in Regime 0. In contrast, indicators like W%R, BB and DMI show significant prediction only in Regime 1.

Table 4: Effective Technical Indicators Across Regimes

<i>Variable</i>	<i>Regime 0 Coefficient</i>	<i>P-Value</i>	<i>Regime 1 Coefficient</i>	<i>P-Value</i>
RSI	-0.0047	0.023	-0.0087	0.054
SMA (10 days)	-0.0925	0.000	0.0371	0.414
SMA (50 days)	0.0008	0.869	0.0148	0.180
EMA (10 days)	0.1263	0.000	-0.0414	0.471
EMA (50 days)	0.0096	0.114	-0.0210	0.138
MACD	-0.0151	0.002	-0.0112	0.142
W%R	0.0014	0.364	0.0183	0.000
BB	0.0000	0.999	-0.0082	0.003
DMI	0.0000	0.988	0.0146	0.000
KC	0.0018	0.033	0.0039	0.012
STOCH	-0.0034	0.017	-0.0050	0.124
MFI	-0.0010	0.038	-0.0021	0.054

Source: Author's own compilation

V. Discussion and Implications

The noisy, uncertain and volatile nature of the financial markets affects the effectiveness of technical trading signals across different regimes. The predictive performance of technical indicators varies significantly across market regimes. The Markov Regime-switching resulted in 30% of high-volatility regime and 70% of low-volatility regime. The directional accuracy of prediction models is higher during high-volatility periods than during stable market periods. Due to complex market dynamics, the key technical indicators differed across the two regimes rather than being dominated by a few. The SVM model gave the highest prediction accuracy of 59.24% in the high-volatility regime which was similar to the study by Chen et al. (2018) where SVM also achieved the best accuracy. The study provides evidence that incorporating regime-based analysis enhances the predictive power of technical trading signals. The study contributes to the literature on financial market predictability by underscoring the importance of regime-dependent modelling.

The findings of this study carry important theoretical, methodological, and practical implications. From a theoretical perspective, the empirical findings support the Adaptive Market Hypothesis. It suggests that market efficiency is not constant but varies across different market conditions. The evidence of higher directional accuracy during high-volatility regimes indicates that market inefficiencies are more pronounced during turbulent periods. It thereby challenges the strict assumptions of the Efficient Market Hypothesis. The conventional single-regime models may fail to capture the dynamic nature of financial markets. Therefore, this study highlights the prominence of incorporating regime-switching frameworks such as the Markov Regime Switching Model in financial market forecasting.

The results of the study have practical implications for investors and traders who should adopt regime-dependent strategies as different technical indicators appear to perform better during varying periods of volatility. This implies that active trading strategies may be more effective during a turbulent market regime while passive approaches may be more suitable during stable periods. The present study also has policy-based implications for financial market regulators for improving market transparency and closely monitoring periods of erratic volatility.

VI. Conclusion and Future Research Avenues

Financial markets exhibit periods of varying volatility and structural changes referred to as market regimes. These regime shifts may influence the effectiveness of technical trading strategies. The study examined the prediction accuracy of technical

indicators for future stock returns of BSE IT stocks in low and high-volatility market regimes. A Markov regime switching model was used to identify the regimes along with a comparative analysis of econometrics, machine learning and deep-learning models in predicting returns in the stock market.

The study strongly supports the effectiveness of a regime-switching approach as the stock return predictability is highly dependent on the prevailing regime. The directional accuracy of prediction models is higher during high-volatility periods ranging between 56-59% than during stable market periods where the directional accuracy ranges between 50-53%. The SVM model gave the highest prediction accuracy of 59.24%, followed by logistic regression with 59.14% accuracy in the high-volatility regime. The gradient boosting model outperformed other models in the low-volatility regime with a prediction accuracy of 53.32%. The classification models achieved accuracies that were statistically significant and better than random guessing in predicting the direction of returns in both regimes. This confirms that the models are capturing genuine patterns in the data rather than just noise.

The analysis also showed that the most effective technical indicators differed across the two regimes. Short-term moving averages (SMA 10, EMA 10) and oscillators (RSI, MACD, STOCH, MFI) tend to show significance in Regime 0. In contrast indicators like W%R, BB, and DMI show significant prediction only in Regime 1. The results emphasised that incorporating regime-based analysis enhances the predictive power of technical trading signals. The results support the adaptive market hypothesis and criticise the efficient market hypothesis.

The study also opens several avenues for future research. First, advanced deep learning models including LSTM and hybrid CNN-LSTM architectures can be explored to better capture nonlinear and temporal dependencies in financial data. Second, this study can be applied to other sectors and commodity markets. Third, the inclusion of macroeconomic variables such as interest rates, inflation, and exchange rates can enhance the explanatory power of the models. Fourth, future studies can extend the analysis to high-frequency or intraday data to capture short-term market dynamics and improve prediction accuracy. The study holds immense relevance to traders, investors and financial market regulators.

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