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An Empirical Examination of the Predictive Power of RSI in Indian Large-Cap Stocks (2021–2026)

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Abstract
This study investigates whether the Relative Strength Index (RSI) exhibits short-term predictive power in Indian large-cap stocks. Using daily data from January 2021 to February 2026 for seven highly liquid companies, we construct filtered RSI buy and sell signals and compute 1-day, 3day, and 5-day forward returns. To evaluate predictive ability, pooled linear regression models are employed. The empirical findings indicate that RSI signals do not generate statistically significant abnormal returns across any tested horizon. Furthermore, the regression models demonstrate negligible explanatory power, with R-squared values close to zero. The results support the weak-form Efficient Market Hypothesis in the Indian large-cap segment during the study period.

Keywords: Relative Strength Index, Technical Analysis, Market Efficiency, Indian Stock Market, Forward Returns, Empirical Finance

JEL Classification: G14, G17

Introduction
Technical analysis remains one of the most widely used approaches for forecasting short-term price movements in financial markets. Among various technical indicators, the Relative Strength Index (RSI) is particularly popular due to its simplicity and intuitive interpretation. Developed as a momentum oscillator, RSI identifies overbought and oversold conditions based on recent price changes. Traders commonly interpret RSI values below 30 as buy signals and values above 70 as sell signals.

Despite its widespread usage, empirical evidence regarding the predictive power of RSI remains inconclusive, particularly in emerging markets. While some studies suggest that technical indicators may generate abnormal returns in less efficient markets, others argue that such strategies fail to consistently outperform due to market efficiency and rapid information diffusion.

The Indian stock market, especially the large-cap segment, has experienced significant institutional participation, algorithmic trading activity, and improved liquidity in recent years. These developments raise an important question: does a simple and widely known technical indicator such as RSI retain predictive power in highly liquid and information-efficient large-cap stocks?

This study empirically evaluates whether RSI-based trading signals generate statistically significant short-term abnormal returns in Indian large-cap stocks. By employing filtered signal construction, multiple forward return horizons, and pooled regression analysis, the research provides updated evidence on the validity of technical analysis within an increasingly efficient market structure.

The contribution of this study lies in its focus on recent data, its use of filtered trading signals to remove clustering bias, and its application of multiple forward return windows to test robustness. The findings provide updated evidence on market efficiency in the Indian large-cap segment.

Literature Review

The effectiveness of technical analysis has long been debated within the framework of the Efficient Market Hypothesis (EMH). Under the weak-form EMH, current stock prices are assumed to fully incorporate historical price information, implying that trading strategies based solely on past price movements should not generate persistent abnormal returns [1]. From this perspective, widely used momentum oscillators such as the Relative Strength Index (RSI) are not expected to exhibit systematic predictive power.

Empirical findings, however, remain mixed. Brock, Lakonishok, and LeBaron (1992) document evidence suggesting that simple technical trading rules may possess forecasting ability under certain market conditions [2]. Similarly, Lo, Mamaysky, and Wang (2000) argue that technical patterns may capture nonlinear dependencies not fully explained by traditional asset pricing models [3]. At the same time, subsequent research has questioned the durability of such profitability, particularly in markets characterized by high liquidity and institutional participation.

Evidence from the Indian equity market is equally inconclusive. Jain (2019) examines RSI-based trading rules using data from the National Stock Exchange of India and reports results indicating potential short-term predictive ability [4]. In contrast, Mahajan (2015) finds that standard RSI and MACD strategies fail to outperform a buy-and-hold benchmark, suggesting limited effectiveness in relatively efficient market segments [5].

Given the structural evolution of the Indian large-cap market—marked by increased institutional ownership, algorithmic trading activity, and improved information dissemination—it is necessary to reassess the relevance of traditional technical indicators using recent data. This study contributes to the literature by evaluating RSI-based trading signals in Indian large-cap stocks over the 2021–2026 period using filtered signal construction and multiple forward return horizons.

Data and Methodology

Data

This study uses daily closing price data for seven Indian large-cap stocks over the period January 1, 2021 to February 27, 2026. The sample consists of seven large-cap stocks listed on the National Stock Exchange of India: State Bank of India, ICICI Bank, Tata Consultancy Services, Infosys, Sun Pharmaceutical Industries, Maruti Suzuki, and Asian Paints. The selected companies represent multiple sectors, including banking, information technology, pharmaceuticals, automobiles, and consumer goods, ensuring cross-sectoral representation within the large-cap segment.

Daily log returns are computed using the natural logarithm of price relatives. The Relative Strength Index (RSI) is calculated using a 14-day lookback period with Wilder's smoothing method. RSI values below 30 are classified as buy signals, while values above 70 are classified as sell signals.

To avoid signal clustering bias, consecutive RSI signals are filtered such that only the first signal in a sequence is retained. This ensures that multiple signals generated during prolonged overbought or oversold conditions are not double-counted. Observations for which forward returns could not be computed were excluded to avoid look-ahead bias. Additionally, the first few observations were omitted due to RSI initialization requirements.

The initial dataset spans January 1, 2021 to February 27, 2026. Due to the 14-day RSI lookback requirement and forward return construction, the effective sample begins on January 22, 2021.

The final five trading days are excluded to ensure availability of 5-day forward returns. The final pooled dataset consists of 8,827 stock-day observations.

Historical daily closing price data were obtained from Investing.com.

Construction of Variables

The Relative Strength Index (RSI) is computed using a 14-day lookback period following the methodology proposed by Wilder (1978) [6]. The RSI is defined as:

$$RSI_t = 100 - \frac{100}{1 + RS_t}$$

Where:

$$RS_t = \frac{\text{Average Gain over 14 periods}}{\text{Average Loss over 14 periods}}$$

Average gains and losses are calculated using Wilder's smoothing technique, which applies an exponentially weighted updating process rather than a simple moving average. RSI values below 30 are classified as buy signals, while values above 70 are classified as sell signals.

To prevent signal clustering bias, consecutive buy or sell signals are filtered such that only the first signal in a continuous sequence is retained. This ensures that multiple signals generated during prolonged overbought or oversold conditions are not double-counted.

Construction of Forward Returns

To evaluate the predictive power of RSI signals, forward returns are computed using logarithmic returns. The forward return at horizon *h* is defined as:

$$ForwardReturn_{t,h} = \ln\left(\frac{P_{t+h}}{P_t}\right)$$

where P_t represents the closing price at time t, and $h \in \{1,3,5\}$ denotes the forward return horizon in trading days.

This construction ensures that only post-signal price movements are evaluated, thereby eliminating look-ahead bias. Observations for which forward returns could not be computed were excluded from the final dataset.

Forward returns are calculated over three horizons:

- 1-day forward return
- 3-day forward return
- 5-day forward return

Empirical Model

To test whether RSI signals possess predictive power, the following pooled regression model is estimated:

$$ForwardReturn_{t,h} = \beta_0 + \beta_1 Buy_t + \beta_2 Sell_t + \epsilon_t$$

where:

- $ForwardReturnt$,*h* denotes the forward return at horizon *h*,
- Buy_t is a dummy variable equal to 1 when a filtered RSI buy signal occurs,
- $Sell_t$ is a dummy variable equal to 1 when a filtered RSI sell signal occurs,
- ϵ_t is the error term.

A statistically significant positive coefficient for β_1 or a significant negative coefficient for β_2 would indicate predictive power of RSI signals. The intercept term (β_0) represents the average forward return on days when no RSI signal is generated.

Descriptive Statistics

Table 1 presents descriptive statistics of forward returns across the three horizons. The mean 1day forward return is 0.043%, while the 3-day and 5-day forward returns average 0.13% and 0.22%, respectively. The standard deviations increase with the return horizon, reflecting typical short-term market volatility. These results indicate that while forward returns exhibit normal price fluctuations, the average drift remains modest across the sample period.

	N	Min	Max	Mean	Std. Dev
OneDayForward	8827	-0.1555	0.1172	0.000434	0.0144562
ThreeDayForward	8827	-0.1479	0.1747	0.001316	0.0253602
FiveDayForward	8827	-0.2106	0.3318	0.002245	0.0326504

Table 1: Descriptive Statistics of Forward Returns

Regression Analysis

To evaluate the predictive power of RSI signals, pooled linear regression models are estimated for 1-day, 3-day, and 5-day forward returns. The results are presented in Table 2.

Across all three horizons, the coefficients associated with both buy and sell signals are statistically insignificant at conventional significance levels. Furthermore, the R-squared values are approximately zero, indicating that RSI signals explain virtually none of the variation in forward returns.

These findings suggest that RSI-based trading signals do not generate abnormal short-term returns in Indian large-cap stocks during the sample period. The consistency of insignificant results across all three forward return horizons strengthens the robustness of the findings.

Variable	1-Day	3-Day	5-Day
Buy	0.000 (0.613)	-0.000 (0.985)	0.002 (0.419)
Sell	0.000 (0.775)	-0.000 (0.947)	0.001 (0.643)
Constant	0.000 (0.007)	0.001 (0.000)	0.002 (0.000)
R^2	0.000	0.000	0.000

Table 2: Pooled Regression Results

Note: Coefficients are reported with p-values in parentheses. All regressions are estimated using pooled OLS. Sample size = 8,827 observations.

Discussion

The empirical findings consistently indicate that RSI signals do not possess predictive power in Indian large-cap stocks during the study period. Across 1-day, 3-day, and 5-day horizons, both buy and sell signals fail to generate statistically significant abnormal returns. Furthermore, the regression models exhibit R-squared values close to zero, indicating negligible explanatory power.

These findings suggest that simple technical trading strategies based on RSI thresholds may not be effective in highly liquid and institutionally dominated market segments. The large-cap stocks examined in this study are characterized by high trading volume, substantial institutional participation, and widespread analyst coverage. Such conditions facilitate rapid information diffusion and reduce the likelihood of exploitable price patterns.

The results are consistent with the weak-form Efficient Market Hypothesis, which posits that historical price information is already incorporated into current prices. In an increasingly technology-driven and algorithmically traded market environment, widely known indicators such as RSI may lose their predictive capability. The absence of predictive power in the present study does not imply that RSI is universally ineffective. Technical indicators may exhibit stronger performance in less liquid, retail-dominated, or small-cap market segments where information diffusion is slower and behavioral biases are more pronounced. Future research may examine these segments to evaluate whether RSI effectiveness varies across market structures.

Conclusion

This study examines whether the Relative Strength Index (RSI) exhibits short-term predictive power in Indian large-cap stocks during the period 2021–2026. Using filtered RSI signals and multiple forward return horizons, the empirical analysis finds no statistically significant evidence that RSI-based buy or sell signals generate abnormal returns.

The regression results consistently demonstrate negligible explanatory power, with coefficients close to zero and R-squared values approaching zero across all tested horizons. These findings support the weak-form Efficient Market Hypothesis in the Indian large-cap segment and suggest that widely known technical indicators such as RSI may not provide reliable trading advantages in highly liquid markets.

Limitations

This study is subject to certain limitations. First, the analysis focuses on seven large-cap stocks and may not generalize to mid-cap or small-cap segments. Second, transaction costs and market frictions are not incorporated into the analysis. Third, the study evaluates only one technical indicator and does not consider combined or hybrid trading strategies. Future research may extend this framework to less liquid stocks or alternative technical indicators. Additionally, the pooled regression framework assumes homogeneity across firms and does not explicitly account for firm-specific fixed effects or sectoral heterogeneity, which may influence the effectiveness of RSI signals.

Author Biography

Piyush Prabhat is a postgraduate student at the National Institute of Securities Market, specializing in securities markets. His research interests include technical analysis, market efficiency, high frequency trading, algo trading and fundamental analysis.

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