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Bayesian Predictive Score Analysis of RSI, MACD, and Bollinger Bands

K. Balatripurasundari[1], Dr. Mini Jayan[2]

[1] Research Student, Department of Statistics and Data Science, Christ University, Bengaluru, Karnataka, India
[2] Associate Professor, Department of Statistics and Data Science, Christ University, Bengaluru, Karnataka, India

Abstract

This study applies a Bayesian framework to evaluate the predictive strength and uncertainty of three widely used technical indicators—Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands—in forecasting market direction, using daily closing price data from the past two years for five representative companies across ten primary sectors of the National Stock Exchange (NSE) of India, prior, likelihood, marginal, and posterior probabilities were computed. A novel predictive score (PS = 2 × Posterior Probability – 1) was introduced to transform posterior probabilities into a bounded metric (–1 to +1), capturing both the directionality and the strength of predictive signals while explicitly quantifying uncertainty. The results demonstrate sectoral variations in indicator performance, with MACD exhibiting higher predictive reliability for SELL signals in capital-intensive sectors, RSI showing moderate effectiveness in consumer-oriented sectors, and Bollinger Bands capturing volatility-driven movements in IT and financial sectors. The proposed PS metric provides a unified, probabilistic measure of technical indicator efficacy, enabling investors and analysts to interpret better the uncertainty embedded in trading signals. The findings contribute to the growing literature on Bayesian approaches in financial forecasting and highlight the potential for integrating probabilistic reasoning with classical technical analysis tools.

Keywords: Bayesian statistics, Stock Market forecasting, Technical Indicator Uncertainty, RSI, MACD, Bollinger Bands.

1. Introduction

The Stock Market has many participants who enter the market with the intention of making a profit. The primary classification of people buying and selling in the market is called bulls and bears. A bull is an investor, who buys a share with the conviction that the price of the stock will increase in future. If the stock really increases over time (hours/days/months), bull sells the share and books profit. A bear is an investor who sells a borrowed share from a broker with a conviction that the price of stock will fall over a short term that is allowed by the exchange. If the stock really falls in the stipulated time, bear will buy the share at a lower price and settle the transaction with the broker and books the profit as his selling price is greater than the buying price. If the stock price behaves differently from the initial conviction, bulls will make a loss if the share price falls and bears will lose money if the stock price increases. Millions of such transactions take place during the trading session of the exchange. Broadly, the players in the stock market can be grouped into four quadrants as explained in the figure.1.

Figure 1: Category of Investors

Fundamental analysis involves study of company's intrinsic value by looking at published balance sheets, company guidance during quarterly result announcements. Macroeconomic factors, such as interest rates, inflation rates and industry-specific conditions, microeconomic factors, like the company's management structure, company's product mix and strategy are considered in fundamental analysis for making long term investment decisions. Technical analysis uses historical returns and price changes, stock price chart patterns, and stock market technical indicators to arrive at trading decisions. Traders and

short-term investors depend on technical analysis method and long-term investors also use the technical analysis method as entry/exit strategy while buying or selling the stock. Quantitative analysis relies on mathematical models, statistical analysis, and algorithms to identify patterns and predict market movements.

Technical indicators such as RSI, Bollinger Bands, and MACD are widely applied for short- to mid-term forecasting in financial markets. RSI operates on the average gains and losses of closing prices over a 14-day cycle (≈3 calendar weeks), Bollinger Bands are based on the standard deviation of closing prices over a 21-day cycle (≈4 calendar weeks), and MACD is derived from weighted moving averages of closing prices over a 29-day cycle (≈6 calendar weeks). Collectively, these indicators provide a forecasting horizon of up to six weeks. Beyond this period, traders typically rely on fundamental analysis of quarterly results for mid-term trading, while long-term decisions are guided by annual results, company outlook, and macroeconomic indicators such as GDP growth. Thus, technical indicators based on closing prices serve as the initial forecasting layer, complementing fundamental and macroeconomic assessments in trading strategies. Technical indicators such as RSI, Bollinger Bands, and MACD are mathematically deterministic functions of closing prices, providing structured analytical signals that traders use as inputs for short- to mid-term forecasting. While their computation is deterministic, their role in forecasting market movements remains interpretive and is often complemented by fundamental and macroeconomic analysis. While the calculation of technical indicators is deterministic, their interpretation as forecasting tools is not. Market prices are influenced by many stochastic factors and random factors news, sentiment, macroeconomic shocks, which indicators cannot deterministically predict (Kenton, 2025).

When RSI exceeds 70, the MACD line crosses below the signal line, and the price moves above the upper Bollinger Band, the market is considered to be in an overbought condition. Analysts or system software based on pre-set threshold values determine the “topping out” or a peak point on the stock price chart to generate a sell signal. When RSI falls below 30, the MACD line crosses above the signal line, and the stock price falls below the lower Bollinger Band, the market is considered as in an oversold state. Analysts or system software based on threshold values determine the “bottoming out” or lowest price point on the stock price chart to generate a buy signal. However, market behaviour is very complex. Buy-sell decisions are not taken based on a deterministic formula of any technical indicator. Mood or sentiment of the market is influenced by market news, opinion of analysts/ influencers, investor opinions/ polls in media, guidance given by companies, and speculative social media messages, which are actively pushed across investor groups. Prices tend to remain flat or even continue to rise, notwithstanding the sell signals generated by multiple indicators. Similarly, prices tend to remain flat or decline further despite buy signals generated by multiple technical indicators. This research paper attempts to quantify the uncertainty associated with buy and sell signals generated by technical indicators using a Bayesian framework. Quantification of uncertainty of technical indicators based on historic data will give an additional validation point to interpret the buy/sell signals. The quantification will help the investors to identify likely peak and troughs of stock price movement, enabling traders to adopt a more cautious and evidence-based strategy in their decision-making.

2. Literature Review

The Relative Strength Index (RSI) was developed by J. Welles Wilder in his 1978 publication “New Concepts in Technical Trading Systems” and appeared in “Commodities” magazine in the June 1978 issue (Thomsett, 2019). This indicator is widely used by investors across the market.

Andrew Cardwell has developed several interpretations of RSI. Cardwell noticed that uptrends generally traded between RSI values of 40 and 80, while downtrends usually traded between RSI values of 20 and 60. When securities change from an uptrend to a downtrend, and vice versa, the RSI will undergo a “range shift”. Cardwell's RSI reversal strategy involves observing when the RSI is above 50 and begins to decline (Thomsett, 2019). However, Cardwell never changed the basic RSI formula.

In Agarwal’s research paper titled " Stock prediction based on technical indicators using deep learning model”, Agarwal (2022), the researcher has introduced a novel deep learning model to effectively forecast using traditional technical indicators. This research

brings in the concept of artificial intelligence into the forecasting process.

The stock market mood or sentiment is highly influenced by major events such as the union government budget. Changes in the tax structure directly alter company profitability (Ashraf and Baig, 2019), making the union budget a significant event for market participants. As a result, investors can use insights from budget announcements to analyze policy impacts on companies' balance sheets and guide their investment decisions.

The COVID period has generated keen interest and attracted young investors, "Generation Z", into the stock market. The study focuses on financial literacy and its impact on stock market investing. The results showed that financial literacy is the most significant factor positively influencing investment intentions (Nag and Shah, 2022).

RSI is typically based on 14-day average gain and loss cycles. However, it is a powerful tool for producing BUY and SELL signals even in daily and short-term trading cycles (Kotishwar, 2020).

Days of the week play a significant role in market behaviour. The first half of Mondays and the second half of Fridays do not fit into the regular trading pattern due to investor behaviour. The importance of timing the transactions to maximise profits and reduce losses based on the days of the week was highlighted by Kothari et al. (2017).

Investors tend to exhibit rash and irrational behaviour and take BUY/SELL decisions not based on technical or fundamental analysis. This type of investment can raise trading volumes, cause volatility, and lead to losses. Such trading is classified as "noise trading", (George and Suresh, 2015).

As investors extensively use stock market charts and technical indicators, there is a constant attempt by researchers to find new technical indicators. Technical magazines and periodicals are frequently used by retail investors as a source of information and investment advice (Sangondimath & Kamashetty, 2022).

The overconfidence of investors taking BUY/SELL decisions outside of technical and fundamental analysis was studied in detail in the research by Sushmita et al. (2018).

Probabilistic and statistical methods are gaining importance in financial forecasting. Application of the Bayesian Theorem to obtain prior probabilities and compute posterior probabilities based on new evidence can be very effective in forecasting. Combining regression models to establish a relationship between dependent and independent variables can lead to effective predictions (Zhao, 2021).

Ben Mrad (2025) introduced "Bayesian Networks for Multi-output Forecasting". Stock prices do not behave as stand-alone units. They are impacted by the performance of other companies and market segments across the globe. Bayesian networks is an effective tool to study multiple output forecasting. Modern stock markets have become increasingly dependent on data-intensive, evidence-based decisions.

2.1. Research Gap

The literature survey has led us to interesting papers. Research work on technical indicators highlighted their deficiencies in forecasting in different situations. There are research papers addressing the method to address the anomalies associated with one technical indicator generating a sell signal and another technical indicator generating a hold or, in extreme cases, a buy signal. In the literature, there are research papers that compare the accuracy of the prediction of different models using the same data. There are no published papers probing the uncertainty of Buy/Sell signals generated by technical indicators.

2.2. Objectives of This Research

The objective of this research is to study buy/sell signals generated by technical indicators RSI, MACD and Bollinger Bands. To thoroughly study the limitations, Buy/Sell signals, by moving the analysis into a probabilistic framework in terms of two states: market rising or market falling. This research paper aims to study and report uncertainty of buy-sell signals generated to establish whether a buy signal results in a price rise state or a sell signal results in a price fall state. Bayesian Statistics are to quantify the uncertainty of buy/sell signals.

3. Methodology

A Bayesian statistical approach was employed to compute prior, likelihood, marginal, and posterior probabilities for RSI, MACD and Bollinger-based signals. Historical daily closing prices (July 2023 to July 2025) were collected for 55 companies across 10 primary sectors listed on the India National Stock Exchange. RSI, MACD and Bollinger Bands values were calculated using

Python, and Directional Uncertainty scores were derived for each stock. Results were analysed through graphical and tabular outputs generated in Excel.

3.1. Technical Indicator Briefs

A Brief on RSI (Relative Strength Index)

The Relative Strength Index (RSI) is a momentum oscillator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions. For the typical 14-period calculation, the average gain and average loss of closing prices are first computed. Relative Strength (RS) is then obtained as the ratio of average gain to average loss, and RSI is calculated using the formula:

$$\mathbf{RSI} = \mathbf{100} - (\mathbf{100} / (\mathbf{1} + \mathbf{RS})) \quad (1)$$

Traders closely monitor RSI in conjunction with other technical indicators. An RSI value above 70 is generally interpreted as an overbought condition (potential sell signal), while a value below 30 indicates an oversold condition (potential buy signal).

A Brief on Bollinger Bands

Bollinger Bands are volatility-based envelopes placed above and below a moving average of closing prices. The middle band is typically a 20-period simple moving average (SMA), while the upper and lower bands are calculated as:

$$\mathbf{Upper\ Band} = \mathbf{SMA} + (\mathbf{k} \times \boldsymbol{\sigma}) \quad \mathbf{(2)}$$

$$\mathbf{Lower\ Band} = \mathbf{SMA} - (\mathbf{k} \times \boldsymbol{\sigma}) \quad \mathbf{(3)}$$

where σ is the standard deviation of closing prices over the chosen period, and k is usually set to 2. Prices touching or exceeding the upper band are considered overbought, while prices moving below the lower band are interpreted as oversold conditions.

A Brief on MACD (Moving Average Convergence Divergence)

The Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator derived from exponential moving averages (EMAs) of closing prices. An EMA is calculated as:

$$\mathbf{EMA} = (\mathbf{Closing\ Price} \times \mathbf{Multiplier}) + (\mathbf{Previous\ EMA} \times (\mathbf{1} - \mathbf{Multiplier})) \quad (4)$$

where the Multiplier (smoothing constant) is defined as:

$$\mathbf{Multiplier} = \mathbf{2} / (\mathbf{n} + \mathbf{1}) \quad (5)$$

with n representing the number of periods. For example, for a 10-day EMA, the multiplier is 2/(10+1) = 0.1818. The first EMA calculation uses the corresponding simple moving average (SMA) as the initial value.

The MACD line is constructed as the difference between the 12-period EMA (short-term trend) and the 26-period EMA (long-term trend). A 9-period EMA of the MACD, referred to as the signal line, is plotted to generate trading signals.

Interpretation of MACD signals:

- Bullish crossover (Buy signal): When the MACD line crosses above the signal line, it suggests potential upward momentum.
- Bearish crossover (Sell signal): When the MACD line crosses below the signal line, it indicates possible downward momentum.
- MACD above zero: Positive values reflect bullish momentum.
- MACD below zero: Negative values indicate bearish momentum.

Thus, MACD not only highlights trend direction but also provides insights into the strength and duration of momentum.

3.2. Bayesian Probabilities

Prior, Likelihood, Marginal and Posterior probabilities are the basic building blocks of Bayesian Framework. In this research paper, we are proposing a generalized Bayesian probabilities for any Sell or Buy Signal generated by any technical indicator.

- Prior: Our belief about market behavior before observing data before Buy/Sell signals
- Likelihood: How likely the observed Buy Sell data are given a hypothesis (e.g. the market will rise or fall)
- Posterior: Updated belief about market behavior after observing Buy Sell data
- Hypothesis H1: if Buy Signal the price is likely to rise.
- Hypothesis H2: if Sell Signal the price is likely to fall.
- Prior probabilities are defined as:
- P (MARKETDOWN): Probability of the price falling overall.

- P (MARKETUP): Probability of the price rising overall.
- Likelihoods are defined as:
- P (SELLSIGNAL |MARKETDOWN): probability of observing Sell Signal when price falling.

P (BUYSIGNAL |MARKETUP) probability of observing Buy Signal when the price rises

- Marginal Probabilities are defined as:
- P (SELLSIGNAL) proportion of days in the dataset when Sell Signal is generated
- P (BUYSIGNAL) proportion of days in the dataset with Buy Signal is generated

Equations of Posterior Probabilities are derived as:

P (MARKETDOWN | SELLSIGNAL) =

P (SELLSIGNAL|MARKETDOWN)* P (MARKETDOWN) /P(SELLSIGNAL) **(6)**

Where as per Figure 1,

P (SELLSIGNAL) =

P (SELLSIGNAL|MARKETDOWN)*P (MARKETDOWN)+

P (SELLSIGNAL|MARKETUP)*P (MARKETUP) **(7)**

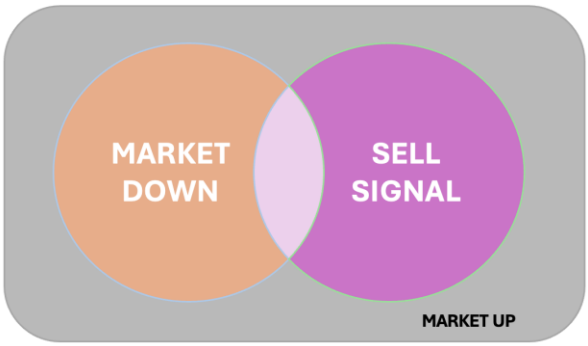

Figure 2: Venn Diagram P (MARKETDOWN| SELL SIGNAL)

Figure 3: Bayesian Approach

- Similarly

P (MARKETUP | BUYSIGNAL) =

P (BUYSIGNAL|MARKETUP)*P (MARKETUP) / P(BUYSIGNAL) **(8)**

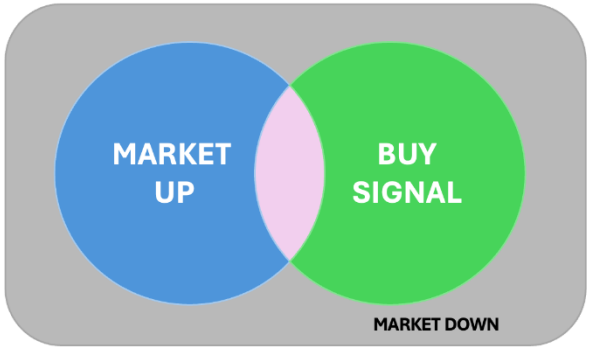

Figure 4: Venn Diagram P (MARKETUP | BUY SIGNAL)

Where as indicated in Figure 3,

P (BUYSIGNAL) =

P (BUYSIGNAL|MARKETUP)*P(MARKETUP)+

P (BUYSIGNAL|MARKETDOWN)*P (MARKETDOWN) **(9)**

Generalized Posterior Probability equations are written as:

U = MARKETUP, D = MARKETDOWN, S = SELLSIGNAL, B = BUYSIGNAL. The generalized Bayesian posterior probability equations are given as follows:

$P(D \mid S) = [\, P(S \mid D) * P(D) \,] / P(S)$ **(10)**

$P(S) = P(S \mid D) * P(D) + P(S \mid U) * P(U)$ **(11)**

$P(U \mid B) = [\, P(B \mid U) * P(U) \,] / P(B)$ **(12)**

$P(B) = P(B \mid U) * P(U) + P(B \mid D) * P(D)$ **(13)**

Here, P(D) and P(U) represent prior probabilities of market down and market up respectively. P(S|D) and P(S|U) are the likelihoods of observing a sell signal under down/up markets, while P(B|U) and P(B|D) are the likelihoods of observing a buy signal under up/down markets. P(S) and P(B) are the marginal probabilities of observing a sell or buy signal respectively.

Based on the generalized posterior probability equations, specific posterior probability equations for RSI/MACD/Bollinger Bands are derived.

P (MARKETDOWN | RSI>70) =

P (RSI>70|MARKETDOWN)* P (MARKETDOWN) /P(RSI>70) **(14)**

P (MARKETDOWN | MACDSELL) =

P (MACDSELL|MARKETDOWN)* P (MARKETDOWN) /P(MACDSELL) **(15)**

P (MARKETDOWN | BOLLINGERSELL) = P(BOLLINGERSELL|MARKETDOWN)* P(MARKETDOWN)/P(BOLLINGERSELL) **(16)**

P (MARKETUP | RSI<30) =

P (RSI<30|MARKETUP)*P (MARKETUP) / P(RSI<30) **(17)**

P (MARKETUP |MACDBUY) =

P (MACDBUY|MARKETUP)*P (MARKETUP) / P(MACDBUY) **(18)**

P (MARKETUP | BOLLINGERBUY) = P (BOLLINGERBUY|MARKETUP)*P (MARKETUP) / P(BOLLINGERBUY) **(19)**

3.4. Quantifying Buy/Sell Signal Uncertainty by using Predictive Strength Metric

In this research paper, we are proposing a metric, Predictive Strength (PS), to quantify the uncertainty of Buy/Sell signals.

PS= 2x (Posterior Probability-0.5) **(20)**

Predictive Score definition: PS = 2 × P(Posterior) – 1, bounded between –1 and +1.

PS=+1; when Buy/Sell signal is perfectly predictive **(21)**

PS=0 ; when Buy/Sell signal is random (posterior = 0.5) **(22)**

PS= -1; when Buy/Sell signal is completely misleading (posterior = 0) **(23)**

It can be interpreted that positive values of PS, Buy/Sell signals work in the expected direction. However, negative PS values indicate the Buy/Sell signals work in the wrong direction.

Transforming posterior probabilities into a center scale around zero is a standard practice in statistical learning, enabling direct interpretation of prediction strength relative to chance. In binary classification, the classification margin is often defined as m(x)=2p-1where p is the posterior probability of the predicted class (Hastie, T. et al., 2009). This formulation maps probabilities from the interval [0,1] to [-1,1] with zero corresponding to no predictive value.

Similar transformations appear in diagnostic testing through Youden's J statistic.

J=Sensitivity+ Specificity-1 **(**24**)**

J ranges from -1 to +1 and quantifies performance above chance (Fourcde, Y et al. 2018). These chance-corrected measures are widely used in medicine, and machine learning evaluation.

4. Results

The sectoral averages of Predictive Strength (PS) across RSI, MACD, and Bollinger Bands show distinct patterns as given in Tables 1,2 and 3.

RSI: Exhibits moderate predictive ability. Strongest SELL signal reliability in Utilities (0.1387) and Communication Services (0.1429). BUY signals are more consistent in Industrials (0.2308) and Consumer Discretionary (0.1776).

MACD: SELL signal reliability is relatively higher in Materials (0.2058) and IT (0.0990). BUY signals are moderately strong in Industrials (0.1230), Communication Services (0.1276), and Real Estate (0.1391).

Bollinger Bands: BUY signals are most effective in Communication Services (0.3326), Industrials (0.2799), and Financials (0.2858). SELL signals are weaker overall but slightly positive in Utilities (0.0985) and Communication Services (0.1511).

These results indicate that predictive reliability is sector-dependent, with certain indicators aligning better with sectoral dynamics. The results demonstrate sectoral variations in indicator performance, with MACD exhibiting higher predictive reliability for SELL signals in capital-intensive sectors, RSI showing moderate effectiveness in consumer-oriented sectors, and Bollinger Bands capturing volatility-driven movements in IT and financial sectors.

Table 1: Sector-wise Predictive Score Summary (Bollinger Bands)

SECTOR	PS-BOLLINGERSELL	PS-BOLLINGERBUY
COMMSERV	0.151	0.333
CONSDIS	-0.042	0.278
CONSSTAPLES	-0.018	0.104
FINANCIALS	-0.07	0.286
HEALTHCARE	0.019	0.079
INDUSTRIALS	0.028	0.28
IT	0.058	-0.153
MATERIALS	-0.081	0.062
REALEST	0.007	0.03
UTILITIES	0.098	0.151

Table 2: Sector-wise Predictive Score Summary (MACD)

SECTOR	PS -MACDBUY	PS-MACDSELL
COMMSERV	0.128	-0.002
CONSDIS	0.176	-0.074
CONSSTAPLES	-0.135	-0.007
FINANCIALS	0.086	-0.106
HEALTHCARE	-0.091	-0.01
INDUSTRIALS	0.123	-0.094
IT	-0.042	0.099
MATERIALS	0.056	0.206
REALEST	0.139	-0.091
UTILITIES	0.0	-0.063

Table 3: Sector-wise Predictive Score Summary (RSI)

SECTOR	PS-RSI SELL	PS-RSI BUY
COMMSERV	0.143	-0.038
CONSDIS	0.03	0.178
CONSSTAPLES	0.065	0.031
FINANCIALS	-0.004	0.075
HEALTHCARE	0.021	0.113
INDUSTRIALS	-0.047	0.231
IT	0.051	-0.045
MATERIALS	0.028	0.104
REALEST	-0.013	-0.034
UTILITIES	0.139	-0.1

Table 4: Sector, Company wise PS score of RSI, MACD and Bollinger Band Buy, Sell Signals

SECTOR	COMPANY	PS-RSI SELL	PS-RSI BUY	PS-MACD SELL	PS -MACD BUY	PS-BOLLINGER SELL	PS-BOLLINGER BUY
IT	LTIM	-0.076	-0.119	-0.273	-0.048	-0.103	-0.111
IT	HCL	0.01	-0.083	0.0	-0.364	-0.273	-0.5
IT	INFY	0.037	0.069	0.375	0.125	0.294	-0.167
IT	TCIS	0.143	-0.082	0.2	0.3	0.304	-0.2
IT	TECHM	0.205	-0.073	0.625	0.067	0.28	0.1
IT	WIPRO	-0.011	0.02	-0.333	-0.333	-0.152	-0.04
REALEST	PRESTIGE	0.02	-0.136	0.048	0.048	0.086	0.0
REALEST	0BEROI	-0.12	-0.045	-0.238	0.143	-0.056	-0.067
REALEST	LODHA	-0.043	0.188	0.3	0.0	-0.2	0.333
REALEST	GODREJ	0.118	-0.05	-0.1	0.048	0.259	-0.059
REALEST	DLF	0.089	0.063	0.0	0.333	0.172	0.083
REALEST	BRIGADE	-0.14	-0.222	-0.556	0.263	-0.22	-0.111
COMMSERV	TTML	0.12	-0.016	0.263	0.158	0.143	0.238
COMMSERV	MTNL	0.241	0.1	0.143	0.1	0.027	0.6
COMMSERV	IDEA	0.167	-0.259	-0.556	0.053	0.13	0.692
COMMSERV	BHARTI	0.043	0.024	0.143	0.2	0.304	-0.2
MATERIALS	ASIANPAINT	-0.041	-0.051	-0.25	0.467	0.0	-0.333
MATERIALS	GRASIM	0.012	0.097	0.143	-0.048	-0.12	0.143
MATERIALS	HINDZINC	-0.015	0.0	0.444	-0.158	-0.357	0.091
MATERIALS	JWSSTEEL	0.107	0.158	0.273	-0.182	0.043	0.067
MATERIALS	TATASTEEL	0.042	0.108	0.125	0.059	-0.053	0.263

SECTOR	COMPANY	PS-RSI SELL	PS-RSI BUY	PS-MACD SELL	PS -MACD BUY	PS-BOLLINGER SELL	PS-BOLLINGER BUY
MATERIALS	ULTRACEM	0.065	0.31	0.5	0.2	0.0	0.143
FINANCIALS	SBI	0.074	0.0	-0.048	0.182	-0.03	0.294
FINANCIALS	LICHSFIN	-0.089	0.111	-0.083	-0.04	-0.188	-0.103
FINANCIALS	ICICI	0.051	0.405	-0.1	-0.048	0.0	0.571
FINANCIALS	HDFC	-0.026	-0.04	-0.158	0.0	0.0	0.333
FINANCIALS	BAJAJFIN	-0.03	-0.099	-0.143	0.333	-0.133	0.333
CONSSTAPLES	TATACONSR	-0.169	0.08	-0.368	-0.1	0.03	0.0
CONSSTAPLES	NESTLE	0.095	0.073	0.364	-0.091	-0.111	0.0
CONSSTAPLES	ITC	0.267	0.098	0.273	-0.333	0.056	0.053
CONSSTAPLES	HINDUNLV	0.148	-0.031	-0.2	0.238	0.128	0.059
CONSSTAPLES	GODREJ	0.164	-0.077	0.0	-0.304	-0.034	0.333
CONSSTAPLES	BRITANIA	-0.114	0.043	-0.111	-0.22	-0.179	0.176
CONSDIS	TITAN	0.101	0.379	0.217	0.217	-0.188	0.571
CONSDIS	TATAMOTORS	0.22	0.055	-0.231	0.0	0.0	-0.143
CONSDIS	MNM	0.026	0.231	0.0	-0.1	0.161	0.294
CONSDIS	MARUTI	-0.042	0.103	-0.091	0.364	0.133	0.167
CONSDIS	BAJAUTO	-0.156	0.12	-0.263	0.4	-0.316	0.5
INDUSTRIALS	MAZDOCK	0.026	0.231	0.0	-0.1	0.161	0.294
INDUSTRIALS	LT	-0.042	0.103	-0.091	0.364	0.133	0.167
INDUSTRIALS	INDIGO	-0.08	0.273	-0.238	0.429	-0.149	0.231
INDUSTRIALS	HAL	-0.168	0.053	0.217	0.13	-0.111	0.333
INDUSTRIALS	BEL	-0.046	0.334	-0.143	0.3	-0.03	0.294
INDUSTRIALS	ADANIPORTS	0.026	0.391	-0.308	-0.385	0.167	0.36
UTILITIES	TATAPOWER	0.065	0.062	-0.13	0.043	0.133	0.5
UTILITIES	POWERGRID	0.246	-0.029	0.043	0.091	0.05	0.0
UTILITIES	NTPC	0.1	-0.217	-0.182	-0.091	-0.091	0.2
UTILITIES	ADANIPOWER	0.032	-0.164	-0.048	0.1	0.0	0.0
UTILITIES	ADANIGREEN	0.25	-0.151	0.0	-0.143	0.4	0.053
HEALTHCARE	TORNT	0.044	0.158	0.0	-0.375	0.029	-0.091
HEALTHCARE	SUNPHARMA	0.148	-0.031	-0.2	0.238	0.128	0.059
HEALTHCARE	MANKIND	0.087	0.222	0.0	-0.167	-0.091	0.176
HEALTHCARE	LUPIN	-0.051	0.1	0.0	-0.04	-0.081	0.667
HEALTHCARE	Dr. REDDY	-0.204	0.088	0.375	0.0	0.0	-0.053
HEALTHCARE	APOLLO	0.103	0.143	-0.238	-0.2	0.128	-0.286

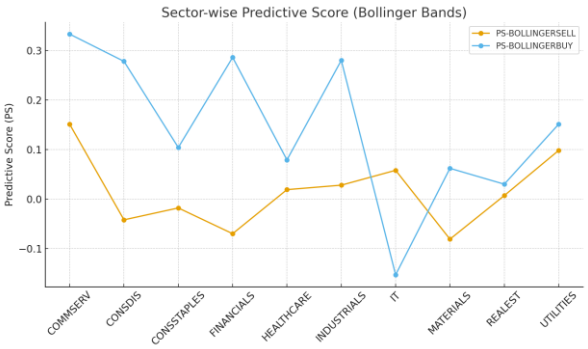

Figure 5: Sector-wise Predictive Score (Bollinger Bands)

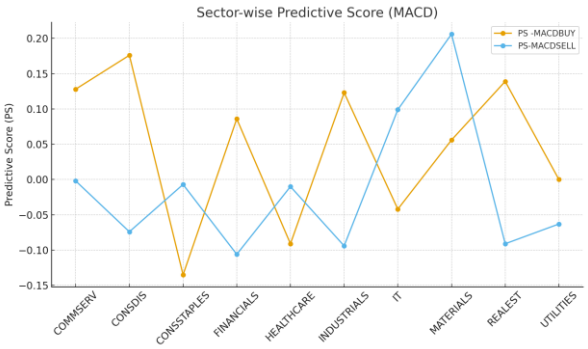

Figure 6: Sector-wise Predictive Score (MACD)

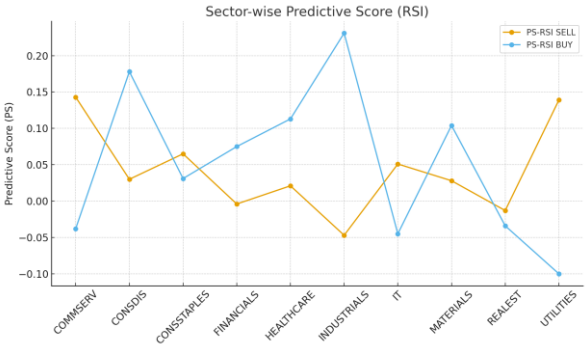

Figure 7: Sector-wise Predictive Score (RSI)

5. Discussion

The findings demonstrate that technical indicators do not perform uniformly across sectors, and Predictive Strength (PS) provides a structured way to capture this heterogeneity.

Sectoral Interpretation:

RSI appears more effective in consumer-driven and service-oriented sectors where price momentum reflects demand cycles. MACD shows reliability in capital-intensive and trend-sensitive industries such as Industrials and Materials, consistent with their slower structural adjustments. Bollinger Bands perform strongly in volatile sectors such as IT and Finance, where price fluctuations amplify deviation-based signals.

Uncertainty Mapping with PS:

PS quantifies reliability beyond deterministic thresholds (e.g., RSI >70). Signals with PS close to zero indicate weak or inconclusive predictive power, cautioning traders against over-reliance.

Comparison with Deterministic Approaches:

Traditional indicator thresholds often assume universal applicability. The Bayesian PS framework integrates uncertainty, showing that the same signal may be strong in one sector (e.g., Bollinger BUY in Communication Services, PS = 0.33) but weak in another (e.g., IT, PS = –0.15).

Practical Implications:

Traders can filter out weak signals, reducing false trades. Portfolio managers can adapt indicator strategies sector-wise, aligning with underlying structural drivers. Risk analysts gain a probabilistic mapping of false signals, improving downside protection.

6. Conclusion

This study shows that Predictive Strength (PS) provides a unified, uncertainty-based performance metric for technical indicators.

Key Insights:

Indicator effectiveness is sector-dependent rather than universal. RSI is relatively effective in consumer and services sectors, MACD in industrial and capital-intensive sectors, and Bollinger Bands in volatile sectors such as IT and Finance.

Contributions:

This research advances the literature on Bayesian forecasting and financial econometrics by integrating uncertainty into technical indicator evaluation. Demonstrates a practical framework for sector-specific trading strategies.

Future Directions:

This research can be extended as a methodology to multi-indicator fusion (joint Bayesian inference of RSI, MACD, and Bollinger) resulting in a Meta Technical indicator. Current research is limited to two years data of 55 companies on NSE. Testing across longer horizons (quarterly/annual) and intraday data for high-

frequency markets can give deeper insights. Exploring applications across emerging vs. developed markets to validate cross-market robustness will be a natural extension to this research.

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