Standard RSI vs. Bollinger-Filtered RSI: A Comparative Market Timing Analysis

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Abstract

Technical analysis indicators have long been employed by traders and analysts to identify potential market entry and exit points. Among these, the Relative Strength Index (RSI) stands as one of the most widely used momentum oscillators for detecting overbought and oversold market conditions. However, the standard RSI approach may generate false signals in trending or volatile markets, leading to suboptimal trading decisions. This study presents a comparative analysis of the traditional RSI indicator against a novel Bollinger-Filtered RSI approach, which combines RSI signals with Bollinger Bands to filter out potentially unreliable signals during periods of volatility. Through systematic backtesting across multiple assets, we evaluate the effectiveness of both methodologies in terms of signal accuracy and risk-adjusted returns. Our preliminary framework establishes the theoretical foundation for understanding how volatility-based filtering mechanisms can enhance traditional momentum indicators. The findings of this research aim to contribute to the ongoing discourse on technical indicator optimization and provide practitioners with empirical evidence for informed decision-making in market timing strategies.

1 Introduction

Among the vast array of technical indicators available, momentum oscillators have gained particular prominence due to their ability to quantify the speed and magnitude of price movements, thereby offering insights into potential trend reversals and continuation patterns.

The challenge of false signals in technical analysis is not unique to just one or two indicators. Market participants have increasingly sought methods to enhance the reliability of trading signals through the combination of multiple indicators or the application of filtering mechanisms.

This research explores the hypothesis that combining RSI signals with Bollinger Bands-based filtering can improve market timing performance by reducing false signals and enhancing risk-adjusted returns. The Bollinger-Filtered RSI approach utilizes Bollinger Bands as a contextual filter, only accepting RSI signals when they align with specific Bollinger Band configurations that suggest genuine momentum shifts rather than temporary price fluctuations.

The motivation for this study stems from three key observations in contemporary market analysis. First, the increasing complexity and speed of modern financial markets demand more robust signal generation mechanisms that can adapt to varying market regimes. Second, the proliferation of algorithmic trading has intensified the need for technically-based strategies that can distinguish between noise and genuine trading opportunities. Third, there exists a gap in academic literature regarding the systematic evaluation of combined technical indicators, particularly those that leverage volatility measurements to filter momentum signals.

2 Methodology

This section establishes the technical foundation for our comparative analysis by providing comprehensive descriptions of the two fundamental indicators employed in this study: the Relative Strength Index (RSI) and Bollinger Bands. Understanding the mathematical construction, interpretation principles, and inherent characteristics of these indicators is essential for appreciating the rationale behind their combination in the Bollinger-Filtered RSI approach.

2.1 Relative Strength Index (RSI)

The Relative Strength Index is a momentum oscillator that measures the velocity and magnitude of directional price movements. Developed by J. Welles Wilder Jr. and introduced in his seminal 1978 book "New Concepts in Technical Trading Systems," the RSI has become one of the most fundamental tools in technical analysis.

2.1.1 Mathematical Formulation

The RSI is calculated using the following procedure:

Step 1: Calculate Price Changes

For a given time series of closing prices P_t where t represents the time period, we first compute the price changes:

$$\Delta P_t = P_t - P_{t-1} \tag{1}$$

Step 2: Separate Gains and Losses

The price changes are then separated into gains and losses:

$$U_t = \begin{cases} \Delta P_t & \text{if } \Delta P_t > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$D_t = \begin{cases} |\Delta P_t| & \text{if } \Delta P_t < 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where U_t represents the upward price movement (gain) and D_t represents the downward price movement (loss) at time t.

Step 3: Calculate Average Gains and Losses

Wilder's original formulation employs a smoothed moving average technique. For a period of n days (traditionally 14), the initial average gain and average loss are calculated as simple averages:

$$\text{AG}_n = \frac{1}{n} \sum_{i=1}^{n} U_i \tag{4}$$

$$\text{AL}_n = \frac{1}{n} \sum_{i=1}^{n} D_i \tag{5}$$

For subsequent periods, Wilder applies an exponential smoothing method:

$$\text{AG}_t = \frac{(\text{AG}_{t-1} \times (n-1) + U_t)}{n} \tag{6}$$

$$\text{AL}_t = \frac{(\text{AL}_{t-1} \times (n-1) + D_t)}{n} \tag{7}$$

Step 4: Calculate Relative Strength (RS)

The Relative Strength is computed as the ratio of average gains to average losses:

$$\text{RS}_t = \frac{\text{AG}_t}{\text{AL}_t} \tag{8}$$

Step 5: Calculate RSI

Finally, the RSI is calculated using the normalization formula:

$$\text{RSI}_t = 100 - \frac{100}{1 + \text{RS}_t} \tag{9}$$

Alternatively, this can be expressed as:

$$\text{RSI}_t = 100 \times \frac{\text{AG}_t}{\text{AG}_t + \text{AL}_t} \tag{10}$$

The RSI oscillates between 0 and 100, with higher values indicating stronger upward momentum and lower values indicating stronger downward momentum.

The standard thresholds are 70 for overbought conditions and 30 for oversold conditions. When RSI exceeds 70, the asset is considered potentially overvalued and may be due for a price correction or reversal. Conversely, when RSI falls below 30, the asset is considered potentially undervalued and may be due for a price bounce or reversal.

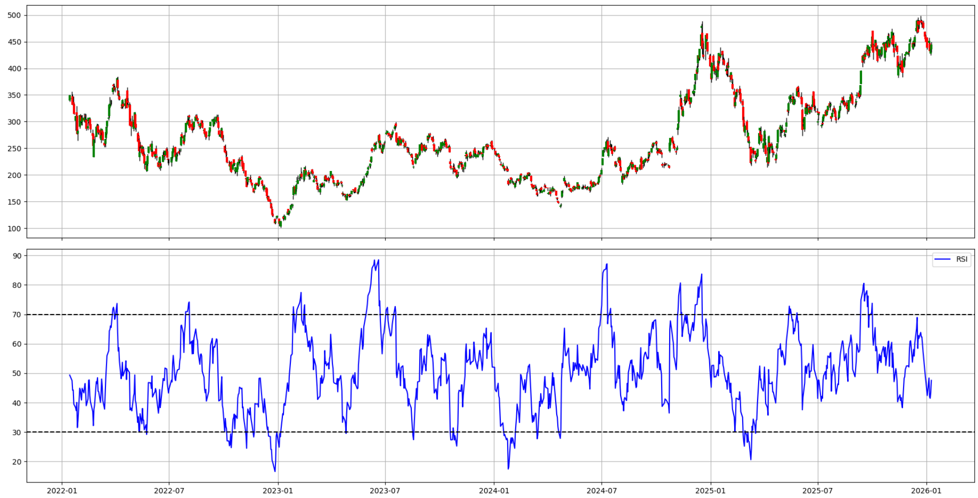

Figure 1: Tesla (TSLA) Stock Price with 14-Period Relative Strength Index (RSI). The upper panel displays the daily candlestick price, while the lower panel shows the RSI oscillator with traditional overbought (70) and oversold (30) threshold lines.

In strongly trending markets, the indicator can remain in overbought or oversold territory for extended periods, generating premature reversal signals. The standard 14-period lookback window may not be optimal for all assets or market conditions. Additionally, RSI does not account for the magnitude of price movements in absolute terms or consider market volatility context, which can lead to false signals during periods of increased volatility or whipsaw price action.

2.2 Bollinger Bands

Bollinger Bands, developed by John Bollinger in the early 1980s and introduced to the wider trading community in the 1990s, represent a volatility-based technical indicator that provides a dynamic envelope around price movements. Unlike static support and resistance levels, Bollinger Bands adapt to changing market volatility, expanding during volatile periods and contracting during calm periods.

2.2.1 Mathematical Formulation

Bollinger Bands consist of three components: a middle band (typically a simple moving average) and two outer bands representing standard deviations from the middle band.

Middle Band (MB):
The middle band is calculated as a simple moving average (SMA) of the closing prices over n periods (traditionally 20):

$$\mathrm{MB}_t = \mathrm{SMA}_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \tag{11}$$

where P_t represents the closing price at time t.
Standard Deviation:
The standard deviation of prices over the same period is calculated as:

$$\sigma_t = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(P_{t-i} - \mathrm{MB}_t)^2} \tag{12}$$

Upper Band (UB):
The upper band is calculated by adding k standard deviations to the middle band:

$$\mathrm{UB}_t = \mathrm{MB}_t + (k \times \sigma_t) \tag{13}$$

Lower Band (LB):
The lower band is calculated by subtracting k standard deviations from the middle band:

$$\mathrm{LB}_t = \mathrm{MB}_t - (k \times \sigma_t) \tag{14}$$

The parameter k is typically set to 2, which, assuming a normal distribution, encompasses approximately 95% of price action. This configuration results in:

$$\mathrm{UB}_t = \mathrm{SMA}_t(20) + 2\sigma_t \tag{15}$$

$$\mathrm{LB}_t = \mathrm{SMA}_t(20) - 2\sigma_t \tag{16}$$

2.2.2 Interpretation and Application

Bollinger Bands provide multiple layers of market information and support various trading strategies:

Volatility Assessment: The primary function of Bollinger Bands is to visualize volatility. When bands are wide, volatility is high; when bands are narrow, volatility is low. The Bollinger Squeeze, which occurs when bandwidth reaches extremely low levels, often precedes significant price movements.

Overbought/Oversold Conditions: Price touching or exceeding the upper band suggests potential overbought conditions, while touching or falling below the lower band suggests potential oversold conditions. However, unlike fixed-level indicators, Bollinger Bands acknowledge that these conditions are relative to recent volatility.

Trend Identification: In strong uptrends, prices tend to walk the upper band, repeatedly touching or exceeding it. In strong downtrends, prices walk the lower band. The middle band often acts as support in uptrends and resistance in downtrends.

2.2.3 Advantages and Limitations

Bollinger Bands offer several advantages: they adapt dynamically to market volatility, providing context-sensitive reference levels; they work across different timeframes and asset classes; they combine trend-following (middle band) and volatility (band width) information; and they provide visual clarity for identifying market regimes.

However, Bollinger Bands also have limitations. They are lagging indicators since they rely on historical price data and moving averages. Price touching a band does not automatically signal a reversal—it may indicate the beginning of a strong trend. The assumption of normally distributed returns may not hold in all market conditions, particularly during extreme events. Additionally, the standard parameters (20, 2) may require adjustment for different assets or trading styles, and bands provide reference levels but do not generate explicit buy/sell signals without additional interpretation rules.

For this study, we employ the standard Bollinger Band parameters (20, 2) to maintain consistency with widespread practice and to facilitate comparison with existing literature.

Figure 2: Tesla (TSLA) Stock Price with Bollinger Bands (20, 2). The chart displays the daily candlestick price with Bollinger bands enveloping it.

2.3 Trading Strategies

This study compares two distinct approaches to market timing using the RSI indicator: the traditional threshold-based RSI strategy and a novel Bollinger-Filtered RSI strategy. Each approach generates discrete trading signals that are evaluated across multiple holding periods to assess their effectiveness under different time horizons.

2.3.1 Standard RSI Strategy

The Standard RSI Strategy employs the classical interpretation of RSI overbought and oversold levels as primary trading signals. This approach has been widely documented in technical analysis literature and serves as our baseline methodology.

Signal Generation Rules:

Let $\mathrm{RSI}_t(14)$ denote the 14-period RSI at time t. The strategy generates signals according to the following rules:

Long Signal: A long (buy) signal is generated when:

$$\mathrm{RSI}_t(14) \leq 30 \tag{17}$$

This condition indicates that the asset has entered oversold territory, suggesting potential upward price reversal or bounce.

Short Signal: A short (sell) signal is generated when:

$$\mathrm{RSI}_t(14) \geq 70 \tag{18}$$

This condition indicates that the asset has entered overbought territory, suggesting potential downward price reversal or correction.

Position Management:

Upon signal generation at time t, a position is established and held for a predetermined number of periods. We define the holding period as $h \in \{5, 8, 14\}$ periods, where each value represents a different time horizon for mean reversion to occur.

For a long position initiated at time t, the return is calculated as:

$$R_t^{\text{long}}(h) = \frac{P_{t+h} - P_t}{P_t} \tag{19}$$

For a short position initiated at time t, the return is calculated as:

$$R_t^{\text{short}}(h) = \frac{P_t - P_{t+h}}{P_t} \tag{20}$$

where P_t represents the closing price at time t, and h is the holding period in number of bars (periods).

Signal Formalization:

We define the signal indicator function S_t^{RSI} as:

$$S_t^{\text{RSI}} = \begin{cases} +1 & \text{if } \text{RSI}_t(14) \leq 30 \text{ (Long)} \\ -1 & \text{if } \text{RSI}_t(14) \geq 70 \text{ (Short)} \\ 0 & \text{otherwise (No signal)} \end{cases} \tag{21}$$

The strategy does not initiate a new position if one is currently active. Overlapping signals are ignored until the current position expires after h periods.

2.3.2 Bollinger-Filtered RSI Strategy

The Bollinger-Filtered RSI Strategy represents an enhancement to traditional RSI analysis by applying Bollinger Bands directly to the RSI values rather than to price. This approach leverages volatility-adjusted thresholds that adapt to the RSI's own behavior, potentially filtering out false signals that occur during periods when RSI exhibits abnormal volatility patterns.

Bollinger Bands on RSI Construction:

First, we calculate Bollinger Bands using the RSI values themselves as the input series. Let $\text{RSI}_t(14)$ be the 14-period RSI at time t. The Bollinger Bands on RSI are computed as follows:

Middle Band:

$$\text{MB}_t^{\text{RSI}} = \frac{1}{n} \sum_{i=0}^{n-1} \text{RSI}_{t-i}(14) \tag{22}$$

where $n = 20$ periods (standard Bollinger Band period).

Standard Deviation of RSI:

$$\sigma_t^{\text{RSI}} = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} \left(\text{RSI}_{t-i}(14) - \text{MB}_t^{\text{RSI}}\right)^2} \tag{23}$$

Upper Band on RSI:

$$\text{UB}_t^{\text{RSI}} = \text{MB}_t^{\text{RSI}} + 2\sigma_t^{\text{RSI}} \tag{24}$$

Lower Band on RSI:

$$\text{LB}_t^{\text{RSI}} = \text{MB}_t^{\text{RSI}} - 2\sigma_t^{\text{RSI}} \tag{25}$$

Signal Generation Rules:

The Bollinger-Filtered RSI strategy generates signals based on the RSI breaking through the dynamically adjusted bands:

Long Signal: A long (buy) signal is generated when the RSI breaks below the lower

Bollinger Band:

$$\text{RSI}_t(14) < \text{LB}_t^{\text{RSI}} \text{ and } \text{RSI}_{t-1}(14) \geq \text{LB}_{t-1}^{\text{RSI}} \tag{26}$$

This condition captures moments when the RSI experiences extreme downward deviation relative to its recent behavior, suggesting an oversold extreme that exceeds typical volatility patterns.

Short Signal: A short (sell) signal is generated when the RSI breaks above the upper Bollinger Band:

$$\text{RSI}_t(14) > \text{UB}_t^{\text{RSI}} \text{ and } \text{RSI}_{t-1}(14) \leq \text{UB}_{t-1}^{\text{RSI}} \tag{27}$$

This condition captures moments when the RSI experiences extreme upward deviation relative to its recent behavior, suggesting an overbought extreme.

Signal Formalization:

We define the Bollinger-filtered signal indicator function $S_t^{\text{BB-RSI}}$ as:

$$S_t^{\text{BB-RSI}} = \begin{cases} +1 & \text{if } \text{RSI}_t(14) < \text{LB}_t^{\text{RSI}} \text{ and } \text{RSI}_{t-1}(14) \geq \text{LB}_{t-1}^{\text{RSI}} \\ -1 & \text{if } \text{RSI}_t(14) > \text{UB}_t^{\text{RSI}} \text{ and } \text{RSI}_{t-1}(14) \leq \text{UB}_{t-1}^{\text{RSI}} \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

Similar to the standard RSI strategy, positions are held for $h \in \{5, 8, 14\}$ periods, and overlapping signals are not executed during active positions.

Conceptual Rationale:

The key distinction between the two approaches lies in their threshold mechanisms. The Standard RSI Strategy employs fixed thresholds (30/70) that remain constant regardless of market regime or RSI behavior patterns. In contrast, the Bollinger-Filtered RSI Strategy employs adaptive thresholds that expand during periods when RSI exhibits high volatility and contract when RSI exhibits low volatility. This adaptive nature theoretically filters out signals that occur within the RSI's normal range of fluctuation, focusing instead on statistically significant deviations.

For example, in a strongly trending market where RSI consistently hovers between 40 and 60, the Bollinger Bands might be narrow (low σ_t^{RSI}), making it difficult to generate signals. Conversely, during ranging or choppy markets where RSI swings widely, the bands expand, potentially capturing more extreme mean reversion opportunities while filtering out minor fluctuations.

2.3.3 Holding Period Analysis

Both strategies are evaluated across three distinct holding periods:

- **Short-term ($h = 5$ periods):** Tests the hypothesis that mean reversion occurs quickly after extreme RSI readings, suitable for active trading strategies.

- **Medium-term ($h = 8$ periods):** Provides a balanced timeframe that allows for more complete mean reversion while limiting exposure duration.

- **Long-term ($h = 14$ periods):** Matches the RSI lookback period, testing whether mean reversion requires a full cycle equivalent to the indicator's calculation window.

The comparative analysis across these holding periods enables assessment of optimal position duration for each strategy and reveals whether one approach demonstrates consistent superiority or if effectiveness varies with time horizon.

2.4 Performance Evaluation Metrics

To comprehensively assess and compare the effectiveness of the Standard RSI and Bollinger-Filtered RSI strategies, we employ a suite of performance metrics that capture different dimensions of trading system quality. These metrics evaluate profitability, consistency, risk-adjusted returns, statistical significance, and efficiency.

2.4.1 Profit Factor

The Profit Factor (PF) measures the ratio of gross profits to gross losses, providing insight into the strategy's overall profitability per unit of risk taken.

Definition:

Let $\mathcal{W}$ denote the set of winning trades (trades with positive returns) and $\mathcal{L}$ denote the set of losing trades (trades with negative returns). The Profit Factor is calculated as:

$$\text{PF} = \frac{\sum_{i \in \mathcal{W}} |R_i|}{\sum_{j \in \mathcal{L}} |R_j|} \tag{29}$$

where R_i and R_j represent individual trade returns.

Interpretation:

- $\text{PF} > 1$: Strategy is profitable (gross profits exceed gross losses)

- $\text{PF} = 1$: Break-even strategy

- $\text{PF} < 1$: Losing strategy

A higher profit factor indicates a more robust strategy. Professional trading systems typically aim for profit factors above 1.5, with values above 2.0 considered excellent. The profit factor is advantageous because it considers both the magnitude and frequency of wins and losses, providing a holistic view of profitability.

2.4.2 Hit Ratio

The Hit Ratio (HR), also known as win rate or accuracy, measures the proportion of profitable trades relative to the total number of trades executed.

Definition:

$$\text{HR} = \frac{N_{\text{win}}}{N_{\text{total}}} = \frac{|\mathcal{W}|}{|\mathcal{W}| + |\mathcal{L}|} \tag{30}$$

where N_{win} is the number of winning trades, N_{total} is the total number of trades, and $|\cdot|$ denotes set cardinality.

Interpretation:

The hit ratio ranges from 0 to 1 (or 0% to 100%), with higher values indicating greater consistency in generating profitable trades. However, the hit ratio alone does not account for the magnitude of wins and losses. A strategy with a 40% hit ratio can still be highly profitable if average wins significantly exceed average losses.

Relationship to Profit Factor:

The hit ratio and profit factor are related through the win/loss ratio:

$$\text{PF} = \text{HR} \times \frac{\bar{R}_{\text{win}}}{(1 - \text{HR}) \times \bar{R}_{\text{loss}}} \tag{31}$$

where $\bar{R}_{\text{win}}$ is the average winning trade return and $\bar{R}_{\text{loss}}$ is the average losing trade return (in absolute terms).

2.4.3 Sharpe Ratio

The Sharpe Ratio measures risk-adjusted returns by comparing the strategy's excess returns to its volatility. It is one of the most widely used metrics in quantitative finance for evaluating investment performance.

Definition:

For a series of trade returns $\{R_1, R_2, \ldots, R_N\}$, the Sharpe Ratio is calculated as:

$$\text{SR} = \frac{\bar{R} - R_f}{\sigma_R} \tag{32}$$

where:

- $\bar{R} = \frac{1}{N} \sum_{i=1}^{N} R_i$ is the mean return per trade
- R_f is the risk-free rate (assumed to be zero for this analysis)
- $\sigma_R = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (R_i - \bar{R})^2}$ is the standard deviation of returns

With $R_f = 0$, the formula simplifies to:

$$\text{SR} = \frac{\bar{R}}{\sigma_R} \tag{33}$$

Interpretation:
The Sharpe Ratio quantifies how much excess return is received for the extra volatility endured by holding the risky asset. Higher Sharpe Ratios indicate better risk-adjusted performance:

- SR < 1: Sub-optimal risk-adjusted returns
- $1 \leq$ SR < 2: Good risk-adjusted returns
- SR ≥ 2: Very good risk-adjusted returns
- SR ≥ 3: Excellent risk-adjusted returns

The Sharpe Ratio penalizes strategies with high volatility, making it particularly useful for comparing strategies with different risk profiles.

2.4.4 T-Statistic

The t-statistic evaluates the statistical significance of the strategy's mean return, testing whether the observed returns are significantly different from zero (i.e., whether the strategy generates returns beyond random chance).
Definition:
The t-statistic for the mean return is calculated as:

$$t = \frac{\bar{R}}{\text{SE}(\bar{R})} = \frac{\bar{R}}{\sigma_R/\sqrt{N}} \tag{34}$$

where:

- $\bar{R}$ is the mean return per trade
- σ_R is the standard deviation of returns
- N is the number of trades
- $\text{SE}(\bar{R}) = \sigma_R/\sqrt{N}$ is the standard error of the mean

This can be rewritten in terms of the Sharpe Ratio:

$$t = \text{SR} \times \sqrt{N} \tag{35}$$

Hypothesis Testing:
The t-statistic is used to test the null hypothesis:

$$H_0 : \bar{R} = 0 \quad \text{(Strategy has no edge)} \tag{36}$$

against the alternative hypothesis:

$$H_1 : \bar{R} \neq 0 \quad \text{(Strategy has an edge)} \tag{37}$$

Under the assumption that returns are approximately normally distributed, the t-statistic follows a Student's t-distribution with $N - 1$ degrees of freedom.

Interpretation:

Critical values for statistical significance (two-tailed test):

- $|t| > 1.96$: Significant at the 5% level ($p < 0.05$)
- $|t| > 2.58$: Significant at the 1% level ($p < 0.01$)
- $|t| > 3.29$: Significant at the 0.1% level ($p < 0.001$)

A higher absolute t-statistic provides stronger evidence that the strategy's performance is not due to random chance. The t-statistic is particularly valuable because it accounts for both the consistency of returns (through $\bar{R}$), their variability (through σ_R), and the sample size (through $\sqrt{N}$).

2.4.5 Comparative Framework

The four metrics employed in this study provide complementary perspectives on strategy performance:

- **Profit Factor and Hit Ratio** assess raw profitability and consistency
- **Sharpe Ratio** evaluates risk-adjusted returns
- **T-Statistic** establishes statistical significance

A strategy that excels across all metrics demonstrates robustness and practical applicability, while one that performs well on some metrics but poorly on others reveals specific strengths and weaknesses that inform optimal deployment contexts.

3 Results

This section presents the empirical findings from our comparative analysis of the Standard RSI and Bollinger-Filtered RSI strategies. We evaluate both approaches across five prominent US equities: Tesla (TSLA), Microsoft (MSFT), Apple (AAPL), Goldman

Sachs (GS), and Disney (DIS). These stocks represent diverse sectors—technology, financial services, and entertainment—providing insight into how the strategies perform across different market dynamics and volatility regimes.

The results are organized by holding period, with separate tables presenting performance metrics for 5-period, 8-period, and 14-period holding horizons. Each table reports four key metrics: Hit Ratio (HR), Profit Factor (PF), Sharpe Ratio (SR), and t-statistic (t-stat). These metrics collectively provide a comprehensive view of profitability, consistency, risk-adjusted performance, and statistical significance.

For each asset and holding period combination, we present results for both the Standard RSI Strategy (using fixed 30/70 thresholds) and the Bollinger-Filtered RSI Strategy (using dynamic Bollinger Band thresholds on RSI). This side-by-side comparison enables direct evaluation of whether the adaptive filtering mechanism provides meaningful performance improvements over the traditional approach.

3.1 5-Period Holding Period Results

Table 1 presents the performance metrics for both strategies with a 5-period holding horizon. This short-term timeframe tests the hypothesis that mean reversion occurs rapidly following extreme RSI readings.

Table 1: Performance Metrics for 5-Period Holding Period

Asset	**Strategy**	**HR**	**PF**	**SR**	**t-stat**
TSLA	Standard RSI	45.24%	1.48	1.02	1.319
	Bollinger RSI	40.00%	0.589	-1.425	-2.33
MSFT	Standard RSI	38.89%	0.808	-0.576	-0.769
	Bollinger RSI	45.45%	1.448	0.949	1.535
AAPL	Standard RSI	41.75%	0.666	-1.094	-1.564
	Bollinger RSI	46.03%	0.967	-0.092	-0.145
GS	Standard RSI	50.00%	0.836	-0.406	-0.555
	Bollinger RSI	49.24%	1.193	0.455	0.736
DIS	Standard RSI	48.42%	0.605	-1.227	-1.685
	Bollinger RSI	47.62%	0.696	-0.945	-1.614

3.2 8-Period Holding Period Results

Table 2 presents the performance metrics for both strategies with an 8-period holding horizon. This medium-term timeframe provides a balanced approach between active trading and allowing sufficient time for mean reversion dynamics to unfold.

Table 2: Performance Metrics for 8-Period Holding Period

Asset	Strategy	HR	PF	SR	t-stat
TSLA	Standard RSI	52.38%	1.222	0.421	0.688
	Bollinger RSI	45.19%	0.631	-0.988	-2.046
MSFT	Standard RSI	42.22%	0.656	-0.967	-1.635
	Bollinger RSI	54.55%	1.304	0.573	1.173
AAPL	Standard RSI	39.81%	0.621	-1.023	-1.85
	Bollinger RSI	48.41%	0.931	-0.154	-0.308
GS	Standard RSI	48.94%	0.616	-0.868	-1.5
	Bollinger RSI	54.96%	1.156	0.281	0.572
DIS	Standard RSI	48.42%	0.57	-1.084	-1.883
	Bollinger RSI	44.90%	0.712	-0.66	-1.426

3.3 14-Period Holding Period Results

Table 3 presents the performance metrics for both strategies with a 14-period holding horizon. This longer-term timeframe matches the RSI calculation window, testing whether optimal mean reversion requires a full indicator cycle.

Table 3: Performance Metrics for 14-Period Holding Period

Asset	Strategy	HR	PF	SR	t-stat
TSLA	Standard RSI	53.57%	1.565	0.701	1.515
	Bollinger RSI	50.37%	0.731	-0.489	-1.34
MSFT	Standard RSI	44.44%	0.68	-0.622	-1.392
	Bollinger RSI	59.85%	1.571	0.738	1.99
AAPL	Standard RSI	45.63%	0.64	-0.765	-1.831
	Bollinger RSI	50.00%	0.867	-0.237	-0.628
GS	Standard RSI	55.91%	0.878	-0.199	-0.452
	Bollinger RSI	57.25%	1.373	0.471	1.271
DIS	Standard RSI	49.47%	0.75	-0.463	-1.063
	Bollinger RSI	38.78%	0.699	-0.53	-1.514

3.4 Comprehensive Cross-Period Analysis and Key Findings

The empirical results across all three holding periods reveal a clear dichotomy in strategy effectiveness based on asset volatility characteristics. High-volatility assets strongly favor the Standard RSI approach with fixed 30/70 thresholds, exemplified by Tesla achieving consistent profitability across all horizons (PF: 1.48 $\rightarrow$ 1.222 $\rightarrow$ 1.565) with the 14-period delivering optimal performance (SR = 0.701, t-stat = 1.515). Conversely, lower-volatility institutionally-traded equities demonstrate substantial preference for the Bollinger-Filtered RSI strategy, with Microsoft achieving the study's strongest results (14-period: PF = 1.571, SR = 0.738, hit ratio = 59.85%, t-stat = 1.99—approaching statistical significance at the 5% level) and Goldman Sachs showing consistent profitability across all horizons (PF range: 1.156-1.373). The Bollinger-Filtered approach achieves superior hit ratios when effective (often 54-60% vs. 42-50% for Standard RSI), suggesting that adaptive thresholds successfully filter noise in stable volatility environments while becoming overly restrictive in high-volatility regimes where the bands expand excessively.

Holding period analysis demonstrates that the 14-period horizon generally delivers optimal performance for successful strategy-asset combinations, providing sufficient time for complete RSI cycle mean reversion to materialize, though the 5-period shows competitive results for rapid reversions in high-volatility contexts. Critically, not all assets exhibit exploitable RSI-based mean reversion—both Apple and Disney generate consistent losses across all strategies and holding periods, emphasizing that proper asset selection is as important as strategy choice. The modest statistical significance observed even for the best combinations (only Microsoft's Bollinger-Filtered RSI at 14-period approaches $t = 1.96$) suggests limited sample sizes inherent to infrequent RSI extreme signals and counsels conservative position sizing in practical deployment.

The study's central contribution is demonstrating that adaptive volatility filtering via Bollinger Bands enhances traditional RSI strategies selectively rather than universally, with effectiveness determined primarily by the underlying asset's volatility regime and mean reversion characteristics.