INVESTIGATING THE EFFICACY OF RSI DIVERGENCE IN NIFTY & NON-NIFTY STOCKS

by

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Dedication

This work is dedicated to my beloved wife, Smt. Nidhi Vishnoi, whose unwavering love, understanding, and patience have been my greatest source of strength. To my parents, whose blessings have always guided me, and to all those who believed in me when I needed it the most. Your faith and support have made this journey possible.

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ABSTRACT

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OCTOBER, 2024

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This dissertation examines the efficacy Relative Strength Index (RSI) divergences by comparing two distinct types of stock categories: “a highly liquid large-cap stock (RELIANCE)” and “a smaller, more volatile non-NIFTY 50 stock (LIBERTSHOE).”

The key findings indicate that divergence formation durations differ between NIFTY 50 and non-NIFTY 50 stocks, with RELIANCE exhibiting longer formation periods, especially for bearish divergences, while LIBERTSHOE demonstrates quicker resolution due to higher volatility. Both stocks show similar overall success rates for divergences, though bullish signals are more reliable. Furthermore, the study confirms that RSI divergence-based trading strategies are profitable in both stock categories, with RELIANCE providing higher returns due to greater liquidity.

This research underscores the importance of tailoring technical analysis strategies to specific stock characteristics and highlights the potential of RSI divergences as a tool for optimizing trading strategies in diverse market environments.

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CHAPTER 1: INTRODUCTION

The chapter provides a comprehensive overview of the Relative Strength Index (RSI) and its application in stock market trading through technical analysis. It begins by contextualizing the RSI within the broader financial analysis framework, drawing distinctions between fundamental and technical methodologies. It introduces the Relative Strength Index, a pivotal momentum oscillator in technical analysis developed by J. Welles Wilder Jr. in 1978, elucidating its computation and interpretation.

The discussion then delves into RSI divergence, a critical facet of this study, where inconsistencies between the RSI and stock prices can serve as potent indicators of trend reversals. This concept of divergence is instrumental in identifying shifts in market sentiment before they materialize in price patterns, furnishing traders with a strategic edge. The chapter outlines the research problem, objectives, and significance, laying the groundwork for the empirical assessment of RSI divergence and its dependability across stocks within and outside NIFTY50.

1.1 Introduction

In financial analysis, understanding the movement of assets is crucial for informed decision-making. Financial analysis can be broadly categorized into two main approaches: fundamental and technical analysis. Fundamental analysis involves evaluating the intrinsic value of a security by examining economic, financial, and qualitative factors, such as revenue, earnings, and management effectiveness. It is often employed to assess the long-term potential of a company or investment.

Technical analysis, on the other hand, focuses on historical price and volume data to predict future price movements. Traders use chart patterns, trends, and technical indicators to make informed decisions. Charting is a key element of technical analysis, visually representing price movements over time and helping analysts recognize patterns and trends that could signal buying or selling opportunities.

Within the realm of charting, indicators play a pivotal role in offering insights that are not immediately apparent from the price alone. These indicators, such as moving averages, MACD, and the Relative Strength Index (RSI), provide statistical analysis of the price action to help traders make more informed decisions.

The Relative Strength Index (RSI), developed by J. Welles Wilder Jr., is a pivotal momentum oscillator that quantifies the speed and change of price movements (Wilder 1978). In his seminal work "New Concepts in Technical Trading Systems," Wilder introduced the RSI along with detailed methods of calculation and various applications.

1.1.1 Calculation of RSI

RSI calculation involves a two-step process. The first RSI value is computed using the formula: RSI = 100 – [100 / (1-RS)] where Relative Strength (RS) is defined as: RS = Average Gain over 14 periods / Average Loss over 14 periods. Wilder (1978) emphasized that the averages are simple means of the gains and losses over the past 14 periods. This initial calculation requires summing all positive and negative price changes separately and dividing each by 14.

For subsequent periods, Wilder introduced an exponential moving average (EMA) to smooth the RSI values. The formulas for the average gain and average loss become:

- Average Gain = (Previous Average Gain × 13 + Current Gain) / 14
- Average Loss = (Previous Average Loss × 13 + Current Loss) / 14

This smoothing technique ensures that the RSI remains responsive to recent price changes while filtering out short-term volatility (Bansal 2023).

1.1.2 Tops and Bottoms

The Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. It oscillates between zero and 100, providing insights into overbought and oversold conditions in the market. When the RSI value rises above 70, it typically indicates that an asset is overbought. This suggests that the asset has been purchased extensively in a short period, and a price correction or pullback might be imminent. Traders may view this as an opportunity to sell or short the asset.

Figure 1.1a: Tops & Bottoms On S&P 500, Source: Screenshot By Author

Conversely, when the RSI falls below 30, it signals oversold conditions. This means the asset has been sold off aggressively, potentially making it undervalued. Traders might see this as a buying opportunity, anticipating a price rebound. However, it's important to note that during strong trends, the RSI can remain in overbought or oversold territories for extended periods. Therefore, while RSI tops and bottoms are useful, they should be used in conjunction with other technical indicators to confirm potential reversals.

1.1.3 Chart Formations

Chart patterns are visual representations of price movements that can signal future market behavior. Interestingly, these patterns can also appear on the RSI chart itself. Recognizable formations like head and shoulders, triangles, double tops and bottoms, and trendlines can manifest within the RSI oscillator. For example:

Head and Shoulders: This pattern on the RSI may indicate a reversal from an uptrend to a downtrend. If the RSI forms a peak (shoulder), followed by a higher peak (head), and then another lower peak (shoulder), it could signal that buying momentum is decreasing.

Triangles: Ascending, descending, or symmetrical triangles on the RSI can suggest continuation or reversal signals, depending on the breakout direction.

Figure 1.1b: Double Bottom Pattern On NIFTY 50, Source: Screenshot By Author

By identifying these patterns on the RSI, traders can gain early insights into potential market movements before they are evident on the price chart. This can provide a strategic advantage in timing entry and exit points.

1.1.4 Failure Swings

Failure swings, also known as support or resistance failures, occur independently within the RSI and do not consider price action. They are strong indicators of potential market reversals and are categorized into bullish and bearish failure swings.

Bullish Failure Swing: The RSI drops below 30, It then rises above 30, The RSI dips again but stays above the previous low. It then moves upwards, breaking above the previous high. This pattern suggests that selling pressure is weakening, and a bullish reversal may occur. Traders might interpret this as a signal to enter long positions.

Bearish Failure Swing: The RSI rises above 70, It then falls below 70. The RSI rises again but remains below the previous high. It then drops below the previous low. This indicates diminishing buying pressure, signaling a potential bearish reversal. Traders may consider this a cue to enter short positions or exit long ones.

Figure 1.1c: Bearish Failure Swing On STI, Source: Screenshot By Author

Failure swings focus on the momentum indicated by the RSI rather than price movements, offering a purer view of market sentiment.

1.1.5 Support and Resistance Levels

The RSI can develop its own support and resistance levels, which may not align with those on the price chart. These levels are identified by observing historical peaks and troughs in the RSI values.

RSI Support Level: A level where the RSI frequently stops declining and reverses upward. If the RSI approaches this level, it may rebound, indicating a potential rise in price.

RSI Resistance Level: A point where the RSI often stops rising and turns downward. Approaching this level could signal a forthcoming price decline.

By monitoring these levels, traders can anticipate potential changes in price direction. For example, if the RSI breaks through a long-held resistance level, it may suggest strong bullish momentum, prompting traders to consider buying. Conversely, a drop below a significant support level could indicate growing bearish sentiment.

Figure 1.1d: Support & Resistance On NIFTY 50, Source: Screenshot By Author

Incorporating RSI support and resistance analysis helps traders make more nuanced decisions, especially when these levels coincide with critical price support and resistance zones.

1.1.6 Divergence

An advanced application of the RSI is the study of RSI Divergence, which occurs when the price of an asset and the RSI move in opposite directions. RSI divergence is often seen as an early warning signal for potential price reversals, offering traders insight into potential shifts in market sentiment. It is a powerful tool in identifying discrepancies between price action and momentum, and this study aims to delve into its significance, particularly in relation to trade opportunities in financial markets. Divergence can be divided into two major categorized based on trade type:

Bullish Divergence occurs when the price reaches lower lows, but the RSI forms higher lows. This suggests weakening downward momentum and the likelihood of an upward reversal.

Figure 1.1e: Bullish Divergence On S&P 500, Source: Screenshot By Author

Divergence is particularly valuable because it can provide early warnings of trend changes before they become evident through other indicators or price patterns. However, it's essential to confirm divergence signals with additional analysis, such as volume trends, candlestick patterns, or other momentum indicators, to reduce the risk of false signals.

1.2 Research Problem and Significance

Understanding RSI divergence's role in predicting market trends is vital. While its effectiveness is well-documented on NIFTY 50 (Bansal 2023; Khatavkar 2024), its robustness across broader stock categories remains under-investigated. Such an investigation is critical for traders seeking reliable indicators beyond well-established indices.

This study aims to fill a notable gap by evaluating the reliability of RSI divergence not only within the NIFTY 50 but also across non-NIFTY 50 stocks.

Understanding the diverse applicability of RSI divergence is paramount for both academic research and practical trading strategies. It could significantly enhance the predictive power of RSI as an indicator, offering valuable insights across the full spectrum of market capitalization.

1.3 Research Question

The research is centered around a single research question:

- Is RSI divergence a reliable indicator for stocks outside NIFTY50?

To address this question, the following sub questions can be formed:

- How do the timeframes for divergence formation and extension compare between NIFTY 50 and non-NIFTY 50 stocks?

- How does the accuracy of RSI divergences compare between NIFTY 50 and non-NIFTY 50 stocks?
- Does RSI divergence, while accounting for all transactional costs, lead to profitable outcomes in both NIFTY 50 and non-NIFTY stocks?

1.4 Research Objectives

The primary objective of this research is to evaluate the efficacy of RSI divergence as a trend reversal indicator across different stock categories and to draw comparisons between NIFTY 50 and non-NIFTY 50 stocks. This involves:

- Retesting the results of Khatavkar (2024) validation phase using RELIANCE as a NIFTY50 stock but on a broader period (2000-2024).
- Extending Bansal (2023) and Khatavkar (2024) studies by comparing the results of RELIANCE with LIBERTSHOE as a non NIFTY50 stock.

1.5 Research Hypotheses

To guide this empirical analysis, the following hypotheses have been formulated:

- H1.1: RSI divergence reliably predicts stock trend reversals in both NIFTY 50 and non-NIFTY 50 stocks.
- H1.2: RSI divergences typically form and signal trend reversals within similar timeframes in both NIFTY 50 and non-NIFTY 50 stocks.
- H1.3: Certain types of RSI divergences demonstrate higher predictive reliability, in both NIFTY 50 and non-NIFTY 50 stocks.
- H1.4: Trading strategies based on reliable RSI divergences remain profitable after accounting for all transactional costs, in both NIFTY 50 and non-NIFTY 50 stocks.

1.6 Scope, Limitations, and Contributions

This study encompasses a comprehensive analysis of a NIFTY 50 and a non-NIFTY 50 stock and follow the same procedures as defined by Khatavkar (2024) to ensure comparability.

While this study aims to provide thorough insights, it uses manual data collection through observation method as no automated tool that can replace a human level accuracy exists at the time of this study. However human level accuracy is prone to error whether being ignorance or subjective bias.

This research holds the potential to significantly advance both academic understanding and practical application of RSI divergence. It will enhance knowledge of RSI divergence's effectiveness across different stock categories, extending beyond NIFTY50 Index.

1.7 Chapter Summary

This chapter has laid the groundwork for comprehending the Relative Strength Index (RSI) and its significance in technical analysis, with a specific focus on RSI divergence. The provided background encompasses fundamental aspects of RSI calculation, interpretation of peaks and troughs, chart patterns, and failure swings, in addition to support and resistance levels. Emphasis is placed on the significance of RSI divergence, particularly its potential to serve as an early indicator of potential shifts in trends, a crucial aspect for traders and analysts.

Moreover, the chapter has introduced the research problem to investigate the resilience of RSI divergence across stocks beyond the NIFTY 50, aiming to bridge gaps in current research. This problem sets the stage for the subsequent empirical analysis. The research objectives, inquiry, and hypotheses have been developed to direct the analysis. The scope, limitations, and contributions of the study have been delineated, with specific attention to the challenges and potential advancements that this research may offer to academic literature and practical trading strategies.

Subsequent chapters will expand upon this foundational framework, commencing with a literature review to contextualize the research within the wider domain of technical analysis. Furthermore, the empirical findings will delve into the reliability and applicability of RSI divergence across diverse stock categories, drawing comparative insights from both NIFTY 50 and non-NIFTY 50 stocks.

CHAPTER 2: LITERATURE REVIEW

This **chapter** delves into the literature on technical analysis, encompassing fundamental concepts such as trend analysis, chart patterns, indicators**.** Furthermore, the **chapter** critically evaluates the Relative Strength Index (RSI), a widely employed indicator, examining its performance and constraints across diverse markets and time frames.

2.1 Theories, Tools & Techniques in Technical Analysis

Technical analysis has long been a cornerstone of financial market analysis, offering traders and investors tools to forecast future price movements based on historical data (Murphy 1999). Rooted in the belief that price reflects all relevant information, technical analysis bypasses fundamental considerations to focus on patterns, trends, and statistical indicators derived from market activity (Pring 2002). Over the decades, numerous theories have emerged, each contributing unique insights into market behavior. This literature review section synthesizes key theories within technical analysis, examining their origins, principles, applications, and critiques, to provide a cohesive understanding of the field's evolution.

The genesis of technical analysis is often attributed to Charles H. Dow, whose writings in the late 19th and early 20th centuries laid the groundwork for modern trend analysis (Dow 1900). Dow Theory posits that markets move in identifiable trends—primary, secondary, and minor—and that these trends persist until definitive signals indicate reversal (Hamilton 1922). The theory emphasizes that the market discounts all news, with price movements reflecting collective investor sentiment (Brown 1999).

Building upon the concept of trends, later analysts introduced tools to quantify and visualize these movements. Moving averages, both simple (SMA) and exponential (EMA), were developed to smooth out price data, making it easier to identify underlying trends (Pring 2002). The use of trendlines and channels further enhanced traders' ability to detect and follow market directions, forming the basis of trend analysis techniques widely used today (Kirkpatrick & Dahlquist 2010).

Pattern recognition has been a fundamental aspect of technical analysis, with practitioners seeking recurring formations in price charts to predict future movements (Bulkowski 2005). Classic chart patterns like Head and Shoulders, Double Tops and Bottoms, Triangles, Flags, and Pennants are believed to signal potential reversals or continuations in market trends (Murphy 1999). The identification of these patterns relies on the assumption that human psychology and behavior in the markets are consistent over time, leading to repeatable price formations (Edwards & Magee 2007).

Candlestick charting techniques, originating from Japanese rice traders in the 18th century, offer another dimension to pattern analysis (Nison 1991). Candlestick patterns such as Doji, Hammer, and Engulfing provide visual cues about market sentiment and potential turning points (Colby 2003). The integration of candlestick patterns into Western technical analysis has enriched the toolkit available to traders, emphasizing the universality of price behavior patterns across cultures and markets (Nison 1994).

The application of mathematical concepts to technical analysis has led to the development of several theories aimed at enhancing predictive accuracy. Fibonacci Retracement and Extension levels, derived from the Fibonacci sequence, are used to identify potential support and resistance levels based on key ratios like 38.2%, 50%, and 61.8% (Pesavento & Jouflas 2009). Traders employ these levels to anticipate areas where price corrections may occur within a trend (Boroden 2008).

Elliott Wave Theory, introduced by Ralph Nelson Elliott in the 1930s, proposes that market prices unfold in specific patterns or "waves" influenced by collective investor psychology (Elliott 1938). The theory suggests that markets move in a fractal pattern consisting of impulsive and corrective waves, with Fibonacci ratios playing a crucial role in predicting wave lengths (Frost & Prechter 1978). Despite criticisms regarding its subjective interpretation, Elliott Wave Theory remains a popular tool among technical analysts (Park & Irwin 2007).

Gann Theory, developed by W.D. Gann, incorporates geometric angles and time cycles to forecast price movements (Gann 1927). The theory emphasizes the relationship between price, time, and geometry, introducing tools like Gann angles and the Square of Nine (Jenkins 1978). While some practitioners report success with Gann's methods, the complexity and esoteric nature of the theory have limited its widespread adoption (Katz & McCormick 2000).

Behavioral finance theories have significantly influenced technical analysis by incorporating psychological factors that affect investor behavior and market outcomes (Kahneman & Tversky 1979). Concepts such as herding behavior, overreaction, and loss aversion explain why markets may deviate from purely rational models (Thaler 2005). Understanding these cognitive biases helps technical analysts anticipate market movements that are driven by emotional responses rather than fundamental data (Barberis & Thaler 2003).

The Wyckoff Method, formulated by Richard D. Wyckoff, focuses on supply and demand dynamics through price and volume analysis, emphasizing the role of the "Composite Man"—a metaphor for the market's collective actions (Wyckoff 1910). By analyzing accumulation and distribution phases, traders aim to align their strategies with the activities of smart money or institutional investors (O'Neil 2009).

Sentiment analysis extends the psychological approach by assessing the overall mood of investors to predict market trends (Baker & Wurgler 2007). Tools like the Fear and Greed Index, put/call ratios, and the Volatility Index (VIX) provide quantitative measures of market sentiment, aiding in contrarian strategies that exploit extreme bullishness or bearishness (Tetlock 2007).

Volume analysis theories posit that trading volume is a critical component in confirming trends and identifying potential reversals (Granville 1963). Indicators such as On-Balance Volume (OBV) and the Accumulation/Distribution Line integrate volume data with price movements to provide insights into the strength of a trend (Murphy 1999). Volume Spread Analysis (VSA) further delves into the relationship between price movement, spread, and volume to detect supply and demand imbalances (Tom Williams 1993).

Intermarket analysis examines correlations between different financial markets—stocks, bonds, commodities, and currencies—to forecast price movements (Murphy 2004). This approach recognizes that markets do not operate in isolation; shifts in one market can have ripple effects across others, offering a broader perspective on potential trading opportunities (Perry 2010).

Cycle Theory explores recurring market cycles to predict future price movements, suggesting that markets are influenced by various cyclical factors including economic indicators, seasonal trends, and even planetary cycles (Hurst 1970). While the identification of precise cycles remains challenging due to market complexity, proponents argue that recognizing cyclical patterns can enhance timing strategies (Murphy 1999).

Chaos Theory and Fractal Theory bring a scientific lens to technical analysis, proposing that financial markets exhibit properties of chaotic systems and fractal geometry (Peters 1991; Mandelbrot 1997). These theories suggest that seemingly random market movements have underlying order and self-similarity across different time frames (Peters 1994). Although practical application can be challenging due to the complexity of mathematical models, these theories have contributed to a deeper understanding of market volatility and risk assessment (Calvet & Fisher 2002).

Technical analysts rely heavily on indicators and oscillators to interpret market data and generate trading signals. Momentum indicators like the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) measure the speed and change of price movements, assisting in identifying overbought or oversold conditions (Jegadeesh & Titman 1993). Mean Reversion Theory complements momentum strategies by suggesting that prices will eventually return to their historical averages, with tools like Bollinger Bands highlighting potential reversal zones (Poterba & Summers 1988).

Other notable indicators include the Commodity Channel Index (CCI), which measures a security's deviation from its statistical mean, and the Average Directional Index (ADX), which assesses the strength of a trend without indicating its direction (Lambert 1980; Wilder 1978). The Parabolic SAR (Stop and Reverse) provides potential reversal signals by placing points above or below price bars, guiding traders on when to exit or enter trades (Wilder 1978).

Innovations in charting have led to the development of alternative methods that filter out market noise and focus on significant price movements. Heikin-Ashi charts modify traditional candlesticks by averaging price data, resulting in smoother visual trends (Yasuke 2004). Renko, Kagi, and Three Line Break charts, originating from Japan, disregard time and volume to emphasize substantial price changes, aiding in the identification of key support and resistance levels (Nison 1994; Schwager 1996).

Ichimoku Kinko Hyo, developed by Goichi Hosoda, offers a comprehensive charting system that simultaneously displays support, resistance, trend direction, and momentum (Hosoda 1969). By utilizing five lines—Tenkan-sen, Kijun-sen, Senkou Span A and B, and Chikou Span—the Ichimoku system provides a multifaceted view of the market, though its complexity can be a barrier for some traders (LeBlanc 2011).

The advent of technology has ushered in algorithmic trading theories, where computer algorithms execute trades based on predefined criteria, often at speeds beyond human capability (Chaboud et al. 2014). High-frequency trading and quantitative models leverage statistical and mathematical techniques to exploit market inefficiencies, significantly impacting market dynamics (Aldridge 2013). While algorithmic trading offers advantages in speed and efficiency, it has raised concerns about increased volatility and the potential for systemic risks (Jones 2013).

The Efficient Market Hypothesis (EMH) developed by Eugene Fama proposes that it is impossible to consistently achieve returns that outperform the overall market through either technical analysis or fundamental analysis, as any new information that could influence a stock's price is already incorporated into the current price (Fama, 1970).

The EMH is grounded in the notion of rational expectations and rational behavior among investors. It assumes that market participants are rational actors who make decisions based on all available information, leading to optimal pricing of securities. The hypothesis has been influential in shaping modern portfolio theory and investment strategies, promoting passive investment approaches like index fund investing.

Fama (1970) delineated the EMH into three forms based on the degree of information reflected in asset prices:

Weak Form Efficiency: In weak form efficiency, all past trading information is fully reflected in stock prices. This includes historical prices, trading volumes, and other market-generated data. Under this form, technical analysis is deemed ineffective because any patterns or trends in historical prices have already been exploited, rendering them useless for predicting future price movements.

Semi-Strong Form Efficiency: The semi-strong form posits that all publicly available information is reflected in stock prices. This encompasses not only past trading data but also financial statements, news releases, and other publicly accessible information. Consequently, neither technical analysis nor fundamental analysis can consistently yield abnormal returns since all public information is already priced in.

Strong Form Efficiency: Strong form efficiency asserts that stock prices fully reflect all information, both public and private (inside information). Under this form, even insider trading cannot result in consistent abnormal profits because the market has already accounted for all information. This form is considered the most extreme and is often criticized for being unrealistic due to legal and practical barriers to accessing insider information.

The EMH, particularly in its weak and semi-strong forms, presents significant challenges to the validity of technical analysis. If markets are efficient in the weak form, historical price data cannot provide any predictive power, rendering technical analysis tools like chart patterns and indicators ineffective. The semi-strong form further undermines the potential benefits of fundamental analysis.

Under the EMH framework, any attempt to outperform the market through analysis or market timing is futile in the long run. The hypothesis supports the idea of random walk theory, where price changes are random and unpredictable due to the immediate incorporation of new information. As a result, passive investment strategies, such as buying and holding a diversified portfolio, are advocated over active trading based on financial analysts' skills.

Fama (1965) conducted one of the first empirical tests of the EMH by examining the serial correlation of stock prices. He found little evidence of autocorrelation, suggesting that past prices do not predict future prices.

Ball and Brown (1968) analyzed the impact of earnings announcements on stock prices and found that prices adjusted rapidly to new information, supporting semi-strong form efficiency.

Jensen (1968) evaluated the performance of mutual fund managers and concluded that they did not outperform the market after accounting for fees and expenses, indicating that professional investors could not consistently achieve abnormal returns.

Despite its widespread acceptance, the EMH has faced substantial criticism, particularly in light of market anomalies and behavioral finance research.

Market Anomalies: Market anomalies are patterns or occurrences that cannot be explained by the EMH. They suggest that markets are not fully efficient and that opportunities for abnormal profits may exist.

Calendar Effects: January Effect: Keim (1983) documented that small-cap stocks tended to outperform in January, particularly in the first few trading days, challenging the EMH's assertion that such predictable patterns should not exist.

Weekend Effect: French (1980) observed that stock returns were systematically lower on Mondays compared to other weekdays, indicating a predictable pattern in returns.

Short-Term Momentum Effect: Jegadeesh and Titman (1993) found that stocks that performed well in the past 3 to 12 months tended to continue performing well in the subsequent 3 to 12 months, suggesting that past price trends can predict future performance.

Long-Term Reversal Effect: De Bondt and Thaler (1985) discovered that stocks that performed poorly over the past few years tended to outperform in the subsequent years, indicating a mean-reversion tendency.

Size Effect: Banz (1981) identified that small-cap stocks consistently outperformed large-cap stocks, even after adjusting for risk, contradicting the EMH.

Value Effect: Fama and French (1992) showed that stocks with high book-to-market ratios (value stocks) outperformed those with low book-to-market ratios (growth stocks).

These anomalies present significant challenges to the EMH, suggesting that predictable patterns exist and can be exploited for profit.

The Adaptive Market Hypothesis, proposed by Andrew Lo, integrates principles of the Efficient Market Hypothesis with behavioral finance, suggesting that market efficiency evolves as participants adapt to changing environments (Lo 2004). This perspective acknowledges the dynamic nature of markets and the influence of human behavior, offering a more flexible framework for technical analysis.

Despite the extensive array of tools and theories, technical analysis faces criticism regarding its empirical validity and reliability. Critics argue that many technical patterns and indicators are subjective, leading to inconsistent interpretations among analysts (Malkiel 2019). The Efficient Market Hypothesis contends that all available information is already reflected in prices, rendering technical analysis ineffective (Fama 1970). However, proponents of technical analysis maintain that markets are not perfectly efficient and that patterns do emerge due to human psychology and behavior (Murphy 1999).

Another limitation is the potential for self-fulfilling prophecies, where patterns and indicators work because a significant number of traders act upon them, rather than due to inherent market properties (Hudson & Urquhart 2015). The rise of algorithmic trading and high-frequency trading has also altered traditional volume and price patterns, challenging the applicability of some technical analysis techniques (Murphy 2019).

The evolution of technical analysis reflects the ongoing quest to understand and predict financial market behavior. From foundational theories like Dow Theory and trend analysis to advanced mathematical models and algorithmic strategies, technical analysis offers a diverse set of tools for traders and analysts. While no single theory guarantees success, the integration of multiple approaches can enhance decision-making by providing a comprehensive view of market dynamics. Recognizing the strengths and limitations of each theory is crucial for effective application in the ever-changing landscape of financial markets.

2.2 Empirical Investigations into RSI Effectiveness

While the RSI's utility in signaling overbought and oversold conditions has been extensively studied, the divergence aspect has received comparatively little attention. Key studies (e.g., Wong, Manzur & Chew 2003; Chong & Ng 2008; Chong, Ng & Liew 2014) often yielded mixed results, with the RSI's performance varying across different markets and time periods. Additionally, limitations such as look-ahead bias, lack of transaction cost considerations, and short analysis periods have been noted (Nor & Wickremasinghe 2014; Ţăran-Moroşan 2011).

2.2.1 Wong, Manzur, and Chew's (2003) Examination of RSI in the Singapore Stock Market

Wong, Manzur, and Chew (2003) conducted a seminal study evaluating the efficacy of the Relative Strength Index (RSI) in generating profitable trading signals within the Singapore stock market. Over a comprehensive 21-year period from 1974 to 1994, the researchers analyzed daily closing prices of the Singapore Straits Times Industrial Index (STII), dividing the data into three sub-periods of seven years each to capture different market conditions.

The study focused on various forms of RSI application, including the RSI Centerline (50) Crossover and the classic overbought (above 70) and oversold (below 30) signals. The primary objective was to assess the effectiveness of these RSI signals in different market environments, testing their ability to produce significantly positive returns.

RSI '50 Crossover' method emerged as the most robust and consistently effective strategy. It involved triggering a buy signal when the RSI crossed above 50 from below and a sell signal when it crossed below 50 from above. The '50 Crossover' method produced consistently impressive results, with a majority of the statistics being significant at the 5% and 1% levels across all sub-periods.

Techniques such as 'Touch,' 'Peak,' and 'Retracement' yielded mixed results. Their effectiveness varied across different market conditions, and they did not consistently generate significant positive returns.

The study concluded that the RSI, particularly the '50 Crossover' method, could be a valuable tool in timing stock market entries and exits. This finding supports the general utility of RSI in technical analysis within the Singapore market.

A significant limitation was the absence of data to distinguish between trending and range-bound markets. All tests were conducted across both types of market conditions, potentially contributing to the mixed results observed with some RSI methods.

Due to the data limitation, the study primarily focused on the '50 Crossover' method, which proved effective despite the inability to segregate market conditions.

2.2.2 Chong and Ng's (2008) Evaluation of RSI on the London Stock Exchange

Chong and Ng (2008) extended the exploration of RSI effectiveness to the London Stock Exchange, examining whether the RSI and Moving Average Convergence Divergence (MACD) indicators could generate excess returns. The study analyzed the Financial Times – Institute of Actuaries 30 (FT30) index over a 59-year period from 1935 to 1994, dividing the data into three sub-periods to mitigate data snooping biases.

The 14-day RSI was utilized, following its popularity among traders. The classical interpretation was applied, where an RSI reading above 70 suggests an overbought condition, and below 30 indicates oversold.

A buy signal was triggered when the RSI crossed the center line (50) from below, indicating a bullish trend. Conversely, a sell signal was generated when the RSI crossed the center line from above.

The study focused on 10-day returns following each signal, ignoring any additional signals within that period to concentrate on the primary trading signals.

For the full sample period, the RSI buy signal generated a 10-day return of 0.779% (annualized at 22.44%), while the sell signal yielded -0.127% (annualized at -3.36%). The buy return was significant at the 5% level, and the sell return at the 10% level.

- 1975–1994: The buy return was significant at the 10% level, and the combined buy-sell return was significant at the 5% level, indicating effectiveness during this period.

- 1935–1954: Only the combined buy-sell return was significant at the 10% level.
- 1955–1974: All returns were insignificant, suggesting the RSI was less effective during this period.

The combined buy and sell signals resulted in an annual return of 4.48%, which outperformed the buy-and-hold strategy.

The varying performance across different sub-periods was not fully explained, leaving questions about the consistency of RSI effectiveness under different market conditions.

The study did not account for transaction costs, which could reduce the net returns of the RSI strategies.

2.2.3 Chong, Ng, and Liew's (2014) Cross-Market Analysis of RSI Effectiveness

Chong, Ng, and Liew (2014) further expanded the scope by analyzing the effectiveness of RSI and MACD indicators across five OECD countries: Italy, Canada, Germany, the United States, and Japan. The study covered daily closing prices from January 1976 to December 2002, aiming to determine whether these technical indicators could generate excess returns in different international markets.

Similar to previous studies, 10-day returns were calculated, focusing on primary trading signals and ignoring additional signals within the holding period.

A 1% transaction cost was included to reflect the minimum round-trip cost of executing trades.

The RSI(14, 50) rule exhibited some predictability and profitability across various indices. The RSI(21, 50) rule outperformed the buy-and-hold strategy in the Milan Comit General and S&P/TSX Composite indices, even after accounting for transaction costs.

The RSI(7, 30/70) rule generated negative returns in most series, particularly significant losses in the Milan Comit General. The RSI(14, 30/70) and RSI(21, 30/70) rules also resulted in negative returns in certain indices, indicating that these strategies were less effective in some markets.

The effectiveness of RSI and MACD rules was not consistent across different markets, highlighting geographical limitations.

Inclusion of transaction costs reduced the profitability of some strategies, emphasizing the importance of considering trading expenses in practical applications.

This study underscored the variability of technical indicator effectiveness across different international markets. It suggested that strategies successful in one market might not be directly applicable to others, highlighting the need for market-specific analysis when employing technical trading rules.

2.2.4 Ţăran-Moroşan's (2011) Reexamination of RSI Interpretations

Ţăran-Moroşan (2011) revisited the effectiveness of RSI by comparing its classic interpretation with an adjusted form that incorporates trading volume. The study focused on the S&P 500 index from March 2004 to April 2010, aiming to test the accuracy of RSI signals at extreme points and explore whether incorporating volume data could enhance predictive capabilities.

The study analyzed the following forms of RSI:

- Classic RSI: Based solely on price data, using standard overbought (70) and oversold (30) levels.
- Adjusted RSI (RSIM): Incorporated trading volume, with adjusted signal levels at 62.5 (overbought) and 37.5 (oversold).

The RSIM generated higher gains than the classic RSI when applying the reverse interpretation, suggesting that incorporating volume enhances RSI's predictive power.

Both RSI forms yielded better results under the reverse interpretation, indicating that extreme RSI values may signal trend continuation rather than reversal.

The study concluded that the traditional interpretation of RSI signals at extreme points was ineffective during the examined period.

The analysis was based on a relatively brief six-year period, limiting the generalizability of the findings.

The author acknowledged that the data was insufficient and recommended that future research include a more extended period for comprehensive validation.

2.2.5 Nor and Wickremasinghe's (2014) Consideration of Look-Ahead Bias

Nor and Wickremasinghe (2014) investigated the effectiveness of RSI and MACD indicators in the Australian All Ordinaries Index (XOA) from January 1996 to June 2014. The study aimed to address criticisms of previous research, particularly the issue of look-ahead bias, by ensuring that trading signals were executed based on information available at the time.

The study analyzed 4,685 daily observations, dividing the data into four non-overlapping sub-periods for robustness. The 14-day RSI period was used, adhering to Wilder's original recommendation.

Buy and sell trades were executed at the next day's index value following the generation of trading signals to avoid look-ahead bias. A 10-day holding period was applied, consistent with methodologies in prior studies.

The effectiveness of RSI in the Australian market was not consistently superior to a buy-and-hold strategy. The results varied across different sub-periods, and no definitive conclusion was reached regarding RSI's predictive capabilities.

By avoiding look-ahead bias, the study presented a more realistic assessment of the performance of RSI strategies.

The study did not provide specific statistical significance levels or the magnitude of returns, limiting the ability to assess the practical profitability of the strategies.

Transaction costs were not considered, which could impact the net returns and practical applicability of the strategies.

2.2.6 Anderson and Li's (2015) Investigation of RSI in the Currency Market

Anderson and Li (2015) contributed to the discourse on the effectiveness of technical indicators by focusing specifically on the Relative Strength Index (RSI) within the context of the currency market. Their study examined the trading profitability of RSI-based strategies using daily data for the Swiss Franc/US Dollar (CHF/USD) exchange rate over an 11-year period from January 1998 to May 2009.

The primary objective was to assess whether the RSI could generate profitable trading signals in the currency market, particularly when using standard and alternative parameter configurations. The study also aimed to contribute to the ongoing debate on market efficiency by exploring if the well-known RSI indicator still offered profit opportunities or if its effectiveness had diminished due to widespread usage.

The researchers utilized daily closing prices of the CHF/USD exchange rate, comprising 2,955 observations.

The standard 14-day RSI was calculated using Wilder's original formula. The RSI values were derived by computing the exponential moving averages (EMAs) of up and down price changes over the 14-day period. The conventional RSI thresholds of 30 (oversold) and 70 (overbought) were initially employed to generate buy and sell signals.

The study also experimented with alternative RSI thresholds, including 20/80, 15/85, 25/75, 35/65, 40/60, and 10/90, to assess if deviations from standard parameters could yield profitable trading opportunities.

A position was opened when an RSI threshold was crossed and remained open until an opposite signal was generated. Profits or losses were calculated in pips by taking the difference between the entry and exit exchange rates for each trade. Trades were executed at the exchange rate corresponding to the RSI signal on the day it was generated.

The strategy using standard thresholds resulted in a total loss of 3,009 pips over 53 trades. The lack of profitability suggested that the widely known and commonly used RSI parameters no longer provided a trading edge, likely due to market adaptation and the elimination of easily exploitable inefficiencies.

20/80 Thresholds generated a small profit of 2,387 pips over 23 trades. Observation: Although profitable, the largest single trade loss was significant at 2,442 pips, indicating high risk. 15/85 Thresholds yielded a profit of 4,616 pips over 10 trades. The strategy required enduring substantial drawdowns, with the largest loss being 1,946 pips. 10/90 Thresholds produced a smaller profit of 1,094 pips over 6 trades. The largest loss increased to 3,622 pips, suggesting diminishing returns and increased risk at extreme thresholds. 25/75 Thresholds achieved a modest profit of 863 pips over 41 trades. The maximum loss per trade was 1,380 pips. 35/65 Thresholds recorded a higher profit of 6,621 pips over 93 trades. The largest loss per trade decreased to 1,461 pips, and the increased number of trades suggested more frequent trading opportunities. 40/60 Thresholds attained the highest profit of 5,206 pips over 125 trades. Despite a large maximum loss of 1,876 pips, the increased trade frequency contributed to overall profitability.

The study suggested that the inefficiency exploited by the standard RSI thresholds had been arbitraged away due to widespread usage, rendering the traditional 30/70 strategy ineffective.

While alternative thresholds provided profitability, they also entailed significant drawdowns, with individual trades experiencing substantial losses.

The research was confined to the CHF/USD exchange rate, limiting the generalizability of the findings to other currency pairs or markets.

The study did not account for transaction costs, such as spreads, commissions, or slippage, which could significantly affect net profitability.

The research did not perform statistical tests to determine if the observed profits were significantly different from zero or could be attributed to chance.

2.2.7 Hari and Dewi's (2018) Forecasting System Using RSI

Hari and Dewi (2018) contributed to the field of technical analysis by developing a forecasting system that integrates the Relative Strength Index (RSI) and Moving Average (MA) indicators to assist investors and traders in the Indonesian stock market. Recognizing the growing interest in stock investment within Indonesia, fueled by government initiatives such as the national movement "to love stock market," the authors aimed to address the challenges faced by individuals lacking analytical tools and knowledge. Their study focused on creating a decision support system to help users determine optimal times to buy and sell stocks by providing recommendations based on RSI and MA indicators.

The primary objective of the study was to produce an application that could analyze stock trends and offer actionable advice to investors and traders. The authors observed that many people entered the stock market hoping for high returns but often suffered losses due to a lack of understanding of fundamental principles like "high return means high risk." To mitigate this issue, they proposed using technical indicators—specifically, RSI and MA—to enhance the ability to analyze stock transactions.

The forecasting system was designed to retrieve historical stock price data from online sources such as Bloomberg and Yahoo Finance using web scraping techniques. Users could input a stock code listed on the Indonesia Stock Exchange, and the system would process the historical data using the RSI and MA indicators. The RSI calculation followed the standard approach, where daily changes in price were used to compute the RSI value, indicating momentum and potential reversal points. The Moving Average, particularly the 10-day Simple Moving Average (SMA), was utilized to analyze price trends, with the period chosen for its balance between responsiveness and noise reduction.

In their methodology, Hari and Dewi emphasized the importance of selecting appropriate periods for the indicators. They noted that a 14-day RSI and a 10-day MA provided more accurate and reliable signals for their system. By combining these indicators, the system aimed to filter out false signals and improve the accuracy of buy and sell recommendations. The RSI would identify overbought and oversold conditions, while the MA would confirm the overall trend direction.

The system underwent both internal and external evaluations. Internal testing involved functionality assessments to ensure that the system operated as intended, retrieving data accurately and performing the necessary calculations. The external evaluation consisted of distributing questionnaires to users who were active stock traders.

The feedback indicated that the system was user-friendly and provided valuable guidance. Users rated aspects such as ease of use, content clarity, feature utility, user interaction, and helpfulness in providing recommendations. The scores suggested that the system was generally well-received, with room for further enhancements.

In practical application, the system was tested using 90 days of historical data for the stock code BBRI (Bank Rakyat Indonesia). The results showed an accuracy rate of 76.7%, with 69 out of 90 events correctly predicted. This indicated that the system could effectively assist investors in identifying favorable trading opportunities. The authors acknowledged that while the system could indicate optimal times to buy or sell, it could not predict exact timing or guarantee profitability due to the inherent volatility of stock prices. They emphasized that the final decision rested with the user, and the system served as a tool to support, not replace, investor judgment.

Hari and Dewi's study highlighted the potential of combining RSI and MA indicators in a forecasting system to aid investors and traders. Their approach differed from previous studies by focusing on the development of a practical application rather than solely analyzing the indicators' effectiveness. By providing a user-friendly interface and real-time data processing, the system bridged the gap between complex technical analysis and accessible investment tools.

However, the authors recognized limitations in their work. The system's accuracy was tested on a single stock over a limited period, which might not generalize to other stocks or longer time frames. The volatile nature of stock prices meant that the system could not predict profits or losses with certainty. Additionally, the reliance on historical data without incorporating real-time market dynamics or fundamental analysis could affect the system's effectiveness in rapidly changing market conditions.

For future research, Hari and Dewi suggested expanding the system's testing to include a broader range of stocks and extended periods to validate its generalizability. They also recommended integrating more advanced analytical methods, such as artificial intelligence and machine learning, to enhance predictive capabilities and adapt to evolving market trends. By doing so, the system could provide more robust support to investors and potentially increase its accuracy and utility.

2.2.8 Gurrib and Kamalov's (2019) Implementation of an Adjusted RSI Model

Gurrib and Kamalov (2019) conducted a comprehensive study to enhance the predictive power of the Relative Strength Index (RSI) by proposing an adjusted RSI model (AdRSI). Their research focused on the application of this new model to both foreign currency and energy markets in emerging and developed economies. The primary objective was to address inherent weaknesses in the traditional RSI model and to test the effectiveness of the AdRSI model over different market conditions, specifically before and after the 2008 global financial crisis.

The authors recognized that while technical analysis tools like the RSI are widely used, they possess certain limitations that could reduce their effectiveness in volatile markets such as foreign exchange and energy commodities. The traditional RSI does not account for the underlying price of an asset relative to another, is overly sensitive to minor price movements in stable stocks, and exhibits asymmetrical behavior concerning changes in relative strength (RS) values. Gurrib and Kamalov aimed to refine the RSI to overcome these issues, thereby improving its utility as a market-timing tool and enhancing its predictive capabilities.

The study utilized daily data spanning from September 2001 to September 2015, covering pre- and post-global financial crisis periods. The authors selected the most actively traded USD-based currency pairs, including both developed (e.g., EUR/USD, JPY/USD, GBP/USD) and emerging market currencies (e.g., CNY/USD, INR/USD, BRL/USD). They also incorporated two major energy markets—crude oil and natural gas—due to their significant volatility and economic importance.

To address the shortcomings of the traditional RSI, the authors introduced the Adjusted RSI (AdRSI) model. The AdRSI modifies the calculation of the relative strength (RS) by incorporating the security's price and a calibration constant (α), as follows: AdRS = [α+(Sg/p)] / [α+(S l/p)] where:

- Sg is the sum of gains over the period,
- Sl is the sum of losses over the period,
- p is the price of the security at the beginning of the period,
- α is the calibration constant.

The adjusted RSI is then calculated using the standard RSI formula but substituting the adjusted RS: AdRSI = 100 − (100 / [1+AdRS])

By including the security's price and the calibration constant, the AdRSI aims to normalize the impact of price movements and reduce sensitivity to minor fluctuations, particularly in stable markets.

The authors conducted extensive back-testing of the AdRSI model, comparing its performance against the traditional RSI and a buy-and-hold strategy. They analyzed the models over the entire period and separately for pre- and post-financial crisis periods. The performance metrics included annualized returns, annualized risk (volatility), and reward-to-volatility ratios.

The AdRSI model generally produced higher annualized returns than the traditional RSI model. The buy-and-hold strategy often outperformed both RSI-based models in terms of reward-to-volatility ratios.

Energy markets (crude oil and natural gas) exhibited higher volatility and, in some cases, higher returns compared to currency markets. The Chinese yuan (CNY/USD) had the lowest annualized risk among all markets studied. The performance of currency and energy markets shifted notably between pre- and post-financial crisis periods. An inverse relationship was observed between energy and currency markets' returns before and after the crisis.Emerging market currencies generally displayed higher risk and lower returns compared to developed market currencies within each region.

The AdRSI model improved the performance of some developed market currencies, yielding positive annualized returns for the JPY/USD and CHF/USD pairs. While the AdRSI model addressed some limitations of the traditional RSI, it did not consistently outperform the buy-and-hold strategy. The adjusted model resulted in fewer trades and aimed to reduce transaction costs associated with frequent trading signals from the traditional RSI.

The study acknowledged several limitations:

The choice of the calibration constant significantly affects the AdRSI's sensitivity to price movements. Determining the optimal α requires careful consideration and may vary across different markets.

The effectiveness of the AdRSI model varied across different market conditions and asset classes, suggesting that its utility may be context-dependent.

While the AdRSI model aimed to reduce the number of trades, the study did not explicitly account for transaction costs, which could impact net returns.

The analysis focused on a select group of currency pairs and energy commodities. The generalizability of the findings to other assets or markets remains uncertain.

2.2.9 Bansal’s (2023) Retest & Correction of Research Direction

Addressing the gaps in prior research, Bansal (2023) conducted an extensive study of over 21 years (2000–2021) using daily close and open price data from the NIFTY 50 index. The study stands out by evaluating RSI periods of 7, 14, and 21 days to determine their effectiveness, assessing 33 different RSI strategies, including those based on divergence detection, rather than focusing solely on traditional threshold levels or centerline crossovers, and Employing python for data preprocessing and analysis, enhancing the robustness and reproducibility of the results.

Analysis revealed that, RSI strategies based on divergence (referred to as RSI (14, D)) demonstrated positive performance for buy decisions, effectively capturing potential uptrends and mitigating timing risks. Popular RSI strategies using overbought/oversold levels of 70/30 or 20/80 often resulted in negative returns, suggesting these thresholds may not be optimal for the NIFTY 50 index.

Divergence strategies exhibited favorable statistical characteristics, with acceptable levels of standard deviation and positive skewness, indicating a propensity for significant positive returns.

The findings underscore the potential of RSI divergence as a more reliable tool compared to traditional RSI applications:

Divergence strategies provided clearer signals for market entries, aligning with Wilder's original assertion about the RSI's capabilities in forecasting trend reversals.

The study highlights the importance of incorporating risk management techniques, such as stop-loss orders, due to the variability in standard deviation and the presence of kurtosis in return distributions.

Traders and analysts are encouraged to integrate RSI divergence into their analytical frameworks, considering customized RSI periods and divergence criteria tailored to specific markets.

While Bansal advances the understanding of RSI divergence, certain limitations should be acknowledged:

The research is confined to the NIFTY 50 index, and results may not be directly transferable to other markets or asset classes without further validation.

Factors such as transaction costs, market impact, execution delays, and slippage were not accounted for, which could affect the practical applicability of the strategies.

Bansal suggests that subsequent studies should incorporate these real-world considerations and explore the effectiveness of divergence strategies across different markets and longer time frames.

2.2.10 Khatavkar's (2024) Investigations of RSI Divergence

Building upon the foundation laid by Bansal (2023), Khatavkar (2024) under the supervision of Bansal, conducted a comprehensive empirical study to evaluate the efficacy of Relative Strength Index Divergence (RSID) as a predictive tool within the NIFTY 50 index. Recognizing the need for a nuanced understanding of RSI divergences, Khatavkar's research offers significant insights into their formation characteristics, reliability, and practical applications in trading strategies.

Khatavkar analyzed daily price data from the NIFTY 50 index over a 24-year period (2000–2024), encompassing diverse market conditions, including major financial crises and economic events. By employing a systematic case study approach and dividing the data into three distinct eight-year periods, the study ensured a robust analysis of RSI divergences across varied market environments.

The study tested several hypotheses concerning the predictive power and formation characteristics of RSI divergences:

H1.1: Reliability in Predicting Trend Reversals: RSI divergences forming in the 14–21 day range and beyond 21 days exhibited the highest success rates, confirming their reliability in predicting stock trend reversals. Bullish divergences demonstrated higher immediate success rates compared to bearish divergences, indicating a stronger predictive impact on positive market momentum.

H1.2: Duration for Divergence Formation: The typical formation period for RSI divergences was confirmed to be within an 8–14 day range, aligning with the hypothesis and providing traders with a critical timeframe for monitoring potential trend reversals.

H1.3: Types of Divergences: The study validated that bullish divergences generally possess higher predictive reliability than bearish divergences. Bearish divergences showed higher instances of delayed success and occasional failures, especially during market downtrends and periods of heightened volatility.

H1.4: Impact of Transaction Costs: By incorporating brokerage fees and other transactional costs, the research affirmed that RSI divergence strategies remain profitable, underscoring their practical viability in real-world trading scenarios.

Apart from these, the study provided the following insights:

RSI divergences predominantly formed within an 8–14 day range, with bullish divergences exhibiting slightly longer formation durations and higher kurtosis, indicating more extreme values. The positive skewness in formation durations suggests a common occurrence of short-duration divergences.

Divergences forming in the 15–21 day and beyond 21-day ranges demonstrated near-perfect reliability, providing robust benchmarks for traders. Even the more common

1–7 and 8–14 day periods showed considerable reliability, particularly for bullish divergences.

In a real-world validation phase, eight trades were executed based on bullish RSI divergences in Reliance Industries Ltd. during the first quarter of FY23–24. Overseen by expert technical analyst Jyoti Bansal, these trades yielded a cumulative return on investment of 15.34%, affirming the practical applicability and profitability of RSI divergence strategies.

Khatavkar's (2024) study advances the understanding of RSI divergence. The manual identification of divergences, despite potential biases, allowed for nuanced detection of patterns that automated tools might miss. This approach ensured a higher accuracy in capturing subtle divergences.

By analyzing data across three distinct periods, the study provided a thorough understanding of RSI divergences under different market scenarios, enhancing the robustness of the findings.

Unlike some previous studies, Khatavkar accounted for transactional costs, offering a more realistic assessment of net profitability and the practical implications for traders.

While the study offers significant contributions, certain limitations were acknowledged:

The reliance on manual observation introduces potential human error and subjectivity. Despite cross-verification efforts, these biases cannot be entirely eliminated.

The research is confined to the NIFTY 50 index, and the effectiveness of RSI divergences may vary across different markets and asset classes. Therefore, results may not be directly transferable without further validation.

The study primarily utilized the 14-day RSI period as recommended by Wilder. Different RSI settings, as suggested by Bansal (2023), were not explored and might yield varying results.

Khatavkar (2024) suggests several avenues for future exploration:

- Creating sophisticated algorithms and machine learning models could improve the accuracy and efficiency of RSI divergence detection, reducing subjectivity.
- Extending the analysis to other indices, asset classes, and international markets would help determine the generalizability of RSI divergence efficacy.
- Investigating the impact of different RSI periods and combining RSI divergence with other technical indicators might enhance predictive accuracy.
- Implementing back-testing strategies and real-time simulations could provide practical insights, refining divergence-based trading strategies.
- Further research could examine the influence of economic events, regulatory changes, and technological advancements on the effectiveness of RSI divergences.

2.3 Gap Analysis of Existing Research on RSI

The existing body of literature provides a comprehensive examination of the Relative Strength Index (RSI) and its effectiveness across various markets and time periods. Despite the depth of research, several significant gaps persist, particularly in the context of RSI divergence strategies. These gaps highlight the need for further investigation to enhance the understanding and practical application of RSI in technical analysis.

One prominent gap identified is the limited focus on RSI divergence strategies across diverse markets. The majority of studies have concentrated on traditional RSI applications, such as overbought/oversold thresholds and centerline crossovers. There is a notable scarcity of extensive research on RSI divergence strategies applied to different markets and asset classes beyond specific indices like the NIFTY 50. This underrepresentation raises concerns about the generalizability of findings from studies centered on a single market. Markets vary in their volatility patterns, liquidity levels, and participant behaviors, all of which can influence the effectiveness of RSI divergence strategies. To address this gap, there is an opportunity to conduct cross-market analyses that apply RSI divergence strategies to a broader range of markets, including equities, commodities, forex, and emerging markets. Comparative studies between developed and emerging markets could also illuminate significant differences or similarities in the effectiveness of these strategies.

Another significant gap is the inadequate consideration of transaction costs and real-world trading constraints in many studies. Several researchers did not account for transaction costs, slippage, market impact, or execution delays in their analyses. Ignoring these factors can lead to an overestimation of a strategy's net returns, presenting a misleading picture of its profitability. This omission raises practical applicability concerns, as strategies that appear profitable in theoretical models may not be viable when real-world trading expenses are considered. Future research should incorporate realistic transaction costs to assess the net profitability of RSI strategies accurately. Implementing models that simulate actual market conditions, including liquidity constraints and execution challenges, would enhance the practical relevance of these studies.

The reliance on specific markets and indices in existing research limits the generalizability of findings. Many studies have focused on particular markets or indices, such as the Singapore STII, London FT30, S&P 500, or the NIFTY 50. This narrow focus can result in conclusions that are not universally valid, as market-specific anomalies might skew results. The risk of bias increases when findings are based on confined study samples, making it challenging to apply these results to other markets with different regulatory environments, participant structures, or economic conditions. To overcome this limitation, future research should expand to include a diverse range of markets, sectors, and asset classes. Conducting meta-analyses that aggregate data from multiple studies could also help identify overarching patterns and insights, enhancing the robustness of conclusions.

There is also an insufficient exploration of different RSI periods and settings in the literature. Most studies adhere to standard RSI settings, typically a 14-day period with 30/70 thresholds, with minimal experimentation with alternative configurations. This limited parameter testing may lead to suboptimal strategies, as standard settings might not be optimal for all markets or timeframes. The potential for improved predictive power through alternative periods and thresholds remains largely unexplored. Future research should focus on parameter optimization, systematically testing various RSI periods and thresholds to identify the most effective settings for different markets and conditions. Developing adaptive models that adjust RSI parameters dynamically based on market volatility or other indicators could further enhance strategy performance.

The lack of integration of RSI with other technical indicators represents another gap in the research. Many studies have analyzed RSI in isolation without considering the potential benefits of combining it with other indicators. This isolated approach may limit the predictive power of RSI, as sole reliance on it might not capture the full spectrum of market signals necessary for reliable trading decisions. By exploring combined indicator strategies, researchers could investigate how the RSI works in conjunction with other technical tools like Moving Averages, MACD, or Bollinger Bands. Employing multivariate analysis to assess the combined impact of multiple indicators could reveal synergies that enhance predictive accuracy and trading performance.

A prevalent issue in existing studies is the predominant use of manual identification methods for detecting RSI divergences. Manual identification introduces human error and subjectivity, potentially affecting the reliability and consistency of results. Different analysts may interpret divergences differently, leading to inconsistent findings, and manual methods are not scalable for large datasets or real-time analysis. To address this, future research should focus on automating the detection process by developing algorithms and machine learning models. Automation would reduce subjectivity, enhance consistency, and allow for the analysis of larger datasets, making it feasible to apply RSI divergence strategies in real-time trading environments.

Short analysis periods and limited data samples constitute another gap in the literature. Some studies have utilized relatively brief timeframes, limiting the robustness and statistical power of their conclusions. Short periods may not capture the full range of market cycles, such as bull and bear markets, which is essential for assessing the long-term effectiveness of RSI strategies. To enhance the validity of findings, future research should employ extended time horizons, utilizing longer historical data that encompasses various market conditions. Data enrichment through the incorporation of additional data sources can also increase sample sizes and improve the statistical reliability of analyses.

There is a need for more rigorous statistical validation and robustness checks in RSI research. Several studies have not performed statistical tests to determine the significance of their results, leaving uncertainty about the reliability of observed profits.

Without statistical validation, it is difficult to ascertain whether the success of a strategy is due to skill or random chance, and strategies may be vulnerable to overfitting. Future studies should apply appropriate statistical tests, such as t-tests or chi-squared tests, to assess the significance of results. Conducting out-of-sample testing by validating strategies on separate datasets can also evaluate their predictive power and robustness, ensuring that findings are not artifacts of specific data samples.

The limited examination of economic and market regime influences on RSI effectiveness is another gap in the current research. Few studies have analyzed how different economic events, regulatory changes, or market regimes impact the predictive power of RSI. Understanding these contextual factors is crucial, as the effectiveness of RSI may vary across different market conditions, such as volatile versus stable periods. Future research should incorporate regime-switching models that adjust RSI strategies based on market condition indicators. Event studies that analyze the impact of specific economic events on RSI performance could also identify patterns and enhance the adaptability of RSI strategies to changing market environments.

Lastly, there is a need for real-time implementation and practical validation of RSI strategies. Many studies remain theoretical and do not test RSI strategies in live trading environments, leading to potential implementation challenges when applied in practice. Without practical validation, traders may be hesitant to adopt these strategies due to uncertainties about their performance under real market conditions. Future research should focus on live testing and simulation, implementing RSI strategies in simulated or actual trading environments to assess real-world performance. Collaborating with market practitioners to refine strategies based on practical experiences and challenges could bridge the gap between theory and practice, enhancing the adoption and effectiveness of RSI-based trading strategies.

In conclusion, while significant progress has been made in understanding the RSI and its applications, particularly regarding divergence strategies, these identified gaps highlight critical areas for future research. Addressing these gaps will lead to more robust, generalizable, and practically applicable RSI-based trading strategies. Researchers are encouraged to explore these areas to enhance the utility of RSI in technical analysis and contribute to more effective and reliable trading practices.

2.4 Chapter Summary

The chapter commences with an overview of the historical progression of technical analysis, highlighting the foundational role of Dow Theory in trend analysis. It delves into the utilization of patterns such as Head and Shoulders, Double Tops, and charting techniques such as candlesticks and Heikin-Ashi for market movement prognostication, providing practical insights for traders and researchers.

The chapter explores the introduction of numerical theories such as Fibonacci Retracements, Elliott Wave Theory, and modern methodologies like the Wyckoff Method and fractal analysis. These approaches, particularly the Wyckoff Method and fractal analysis, offer more intricate means of interpreting market behavior and enhancing forecast precision.

Besides, the chapter delves into pioneering advancements in charting methods, including Renko and Kagi charts, designed to eliminate market noise, as well as the Ichimoku Cloud, an extensive system that exhibits trend, support, resistance, and momentum.

The rapid advancement of technology has elevated algorithmic trading to a pivotal position in market dynamics. This chapter meticulously assesses the influence of algorithmic strategies on market efficiency, speed, and volatility, while also addressing concerns related to systemic risks.

In addition, the chapter delves into the conundrum presented by the Efficient Market Hypothesis (EMH), which posits that consistently outperforming the market through technical or fundamental analysis is unattainable. The Adaptive Market Hypothesis, proposed by Andrew Lo, is also examined as a counterpoint, emphasizing the adaptability of the market and instilling a sense of optimism about the future of trading.

Also, critics draw attention to the subjective nature of interpreting technical patterns and indicators, as well as the potential for self-fulfilling prophecies. The impact of algorithmic trading on traditional technical analysis methods is carefully scrutinized within this discourse.

The chapter provides an in-depth analysis of empirical studies pertaining to the Relative Strength Index (RSI), examining its strengths and weaknesses across various markets and timeframes. Notable studies from Singapore, Australia, Indonesia, and India are reviewed, shedding light on the practical applications and constraints of the RSI indicator, thereby providing a realistic view of its use in different markets and timeframes.

Furthermore, recent research on RSI divergence is scrutinized, focusing on its efficacy in predicting trend reversals and the implementation of divergence strategies. The chapter also suggests potential avenues for future research, proposing the integration of machine learning and back-testing models, thereby engaging the audience in the ongoing evolution of technical analysis.

This comprehensive examination of technical analysis presents the evolution, current applications, and ongoing debates surrounding its effectiveness, offering traders valuable insights for navigating financial markets.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter provides a comprehensive overview of the research methodology employed to assess the effectiveness of the Relative Strength Index (RSI) Divergence as a predictive tool in the NIFTY 50 stocks as well as Non-NIFTY 50 stocks.

3.1 Research Design

The research design of this study is formulated to systematically investigate the reliability of the Relative Strength Index (RSI) divergence as a trend reversal indicator across different categories of stocks in the Indian stock market. The study adopts a quantitative research approach with a descriptive and analytical design, focusing on the empirical analysis of historical stock price data to test the formulated hypotheses.

3.1.1 Research Paradigm

This study is grounded in the positivist research paradigm, which emphasizes objectivity, measurability, and the use of statistical methods to analyze observable phenomena. The positivist approach is appropriate for this research as it involves testing hypotheses through empirical data analysis, aiming to discover generalizable patterns and relationships in financial markets.

3.1.2 Research Approach

A quantitative research approach is employed, utilizing numerical data and statistical techniques to assess the efficacy of RSI divergence as a trend reversal indicator. This approach allows for objective measurement and analysis of stock price movements and RSI values, facilitating the testing of hypotheses through statistical inference.

3.1.3 Research Type

The study utilizes a non-experimental, correlational research design. It does not manipulate any variables but instead observes and analyzes existing data to identify relationships between RSI divergences and subsequent stock price movements. The correlational design is suitable for examining the association between technical indicators and market behavior without introducing experimental interventions.

3.1.4 Research Strategy

An observational longitudinal study is conducted, analyzing stock price data over an extended period from January 2000 to January 2024. This strategy enables the examination of RSI divergence patterns and their reliability over time, capturing various market conditions and trends.

3.1.5 Justification of the Research Design

The chosen research design is justified by the following considerations. The quantitative, correlational design aligns with the research objectives of empirically testing the reliability of RSI divergences across different stock categories.

The availability of extensive historical data allows for a longitudinal analysis without the need for experimental manipulation.

The non-experimental design is appropriate for financial market studies where variables cannot be controlled or manipulated. The manual identification of RSI divergences enables a detailed and nuanced analysis that automated methods may not capture.

3.2 Data Collection

This section provides a detailed account of the rationale for selecting stocks and time frame and explains the procedures ensuring the research is grounded in a robust and transparent data collection process.

3.2.1 Selection of Stocks

The selection of stocks is a pivotal component of this research, as it directly influences the validity, reliability, and applicability of the findings. This study focuses on two specific stocks: RELIANCE Industries Limited (RELIANCE), representing NIFTY 50 stocks, and Liberty Shoes Limited (LIBERTSHOE), representing non-NIFTY 50 stocks. The rationale behind choosing these particular stocks is grounded in their ability to effectively address the research objectives and hypotheses, thereby facilitating a comprehensive comparative analysis of RSI divergence as a trend reversal indicator across different stock categories.

The primary rationale for selecting RELIANCE and LIBERTSHOE lies in their representative characteristics of their respective stock categories. RELIANCE, being one of the largest companies in India by market capitalization and a constituent of the NIFTY 50 index, epitomizes large-cap stocks with high liquidity and significant market influence. Its inclusion allows for the examination of RSI divergence within well-established indices, aligning with the objective to retest the findings of Khatavkar (2024) over an extended period from 2000 to 2024. Additionally, RELIANCE's diverse operations across multiple industries such as energy, petrochemicals, textiles, natural resources, retail, and telecommunications offer a comprehensive dataset that reflects varied market conditions and trends.

On the other hand, LIBERTSHOE represents mid-cap companies not included in the NIFTY 50 index, thereby providing insights into the applicability of RSI divergence beyond well-known indices. As a footwear manufacturing and retail company, LIBERTSHOE introduces industry diversification into the study, contrasting with the conglomerate nature of RELIANCE. The selection of LIBERTSHOE aims to extend the exploration of RSI divergence to less scrutinized areas, fulfilling the research objective of assessing the indicator's efficacy across a broader spectrum of market capitalizations.

The criteria for stock selection were meticulously formulated to ensure that the chosen stocks are not only representative of their categories but also possess attributes conducive to a meaningful analysis. Firstly, representation was paramount; RELIANCE and LIBERTSHOE were selected to embody NIFTY 50 and non-NIFTY 50 stocks, respectively. This dichotomy allows the study to investigate whether the reliability of RSI divergence is consistent across different market segments. Secondly, the availability of extensive historical data was crucial. Both stocks have comprehensive price data spanning from January 2000 to January 2024, which is essential for analyzing long-term trends and capturing multiple market cycles.

Industry diversification was another critical consideration. By selecting stocks from different sectors—RELIANCE from a conglomerate spanning various industries and LIBERTSHOE from the consumer goods sector—the study accounts for sector-specific factors that may influence RSI divergence patterns. This diversification enhances the robustness of the findings by ensuring that they are not unduly influenced by industry-specific dynamics.

Liquidity and trading volume were also integral to the selection process. RELIANCE, with its high liquidity and substantial trading volume, ensures that the findings are relevant for both institutional and retail traders. LIBERTSHOE, while a mid-cap company, has sufficient liquidity for retail trading, making the results applicable to individual investors. This consideration is vital for the practical applicability of the research, as it aims to inform trading strategies that can be implemented in real-world scenarios.

The selection of RELIANCE aligns with previous studies, particularly Khatavkar (2024), where RELIANCE was utilized in the validation phase. Retesting the results using RELIANCE over a broader period not only strengthens the validity of previous findings but also facilitates a direct comparison with earlier research. Conversely, the inclusion of LIBERTSHOE, a stock not previously analyzed in Khatavkar (2024), extends the scope of the research and contributes original insights into the effectiveness of RSI divergence in non-NIFTY 50 stocks.

Aligning with the research objectives and hypotheses, the selection of these stocks serves multiple purposes. For Objective 1, retesting Khatavkar's (2024) findings using RELIANCE over an extended period enhances the credibility and reliability of the results. For Objective 2, analyzing LIBERTSHOE addresses the under-investigated area of RSI divergence applicability in non-NIFTY 50 stocks, thereby filling a notable gap in the existing literature. The chosen stocks enable the testing of Hypothesis H1.1 by examining the reliability of RSI divergence across different stock categories. Hypotheses H1.2 and H1.3 are addressed through the comparative analysis of divergence formation timeframes and the identification of the most accurate types of RSI divergences in both stocks. Hypothesis H1.4 is explored by assessing the profitability of trading strategies based on RSI divergences after accounting for transactional costs in both NIFTY 50 and non-NIFTY 50 stocks.

While the selection process was rigorous, certain considerations and limitations are acknowledged. The analysis of only two stocks may limit the generalizability of the findings. However, the depth of analysis and the representative nature of the selected stocks aim to provide a foundation for future studies with larger samples. Additionally, the unique characteristics of RELIANCE and LIBERTSHOE, such as their industry sectors and market behaviors, may influence RSI divergence patterns. The study accounts for these factors by incorporating industry diversification and acknowledging that results may vary with different stocks and market conditions.

3.3.2 Time Frame

The selection of the time frame for this study is a critical factor that significantly influences the validity and robustness of the research findings. The period chosen for analysis spans from January 2000 to January 2024, encompassing a comprehensive range of market conditions, economic cycles, and geopolitical events that have affected the Indian stock market over nearly a quarter of a century. This extensive time frame is intentionally selected to ensure that the study captures a wide spectrum of market behaviors, thereby enhancing the generalizability and applicability of the results.

The rationale behind selecting such an extended period is multifaceted. Firstly, the time frame includes multiple bull and bear markets, periods of high volatility, and significant financial events such as the global financial crisis of 2008, the European debt crisis, the taper tantrum of 2013, the demonetization event in India in 2016, and the COVID-19 pandemic starting in 2020. Analyzing data across these diverse periods allows for a thorough examination of how Relative Strength Index (RSI) divergence performs under varying market conditions, which is essential for assessing its reliability as a trend reversal indicator.

Secondly, the period from 2000 to 2024 represents a phase of significant growth and development in the Indian financial markets. The liberalization policies initiated in the 1990s began to manifest more prominently in the early 2000s, leading to increased foreign investment, technological advancements in trading systems, and greater market participation from both institutional and retail investors. By including this transformative period, the study can analyze how structural changes in the market may have influenced the effectiveness of RSI divergence.

Moreover, extending the analysis up to January 2024 ensures that the most recent data is included, capturing the latest market trends and technological advancements in trading. This is particularly relevant given the rapid evolution of algorithmic trading, high-frequency trading, and the increased use of artificial intelligence and machine learning in market analysis. Incorporating data up to 2024 allows the study to remain current and relevant to contemporary trading practices.

Another critical aspect of selecting this time frame is its alignment with the availability of reliable and high-quality data. Both RELIANCE and LIBERTSHOE have sufficient historical data available from reputable financial databases starting from the year 2000. This consistency in data availability ensures that the analysis for both stocks is conducted over the same period, facilitating a fair and accurate comparative analysis.

The chosen time frame also aligns with the research objectives and hypotheses. For instance, one of the research objectives is to retest the results of Khatavkar (2024) using RELIANCE over a broader period. By extending the analysis back to 2000, the study not only retests previous findings but also examines whether the efficacy of RSI divergence has remained consistent over time. This longitudinal approach enables the investigation of any temporal patterns or shifts in the indicator's reliability, which could be attributed to changes in market dynamics or investor behavior.

Additionally, analyzing such an extensive period allows for a sufficient number of RSI divergence instances to be identified and studied. This is crucial for statistical significance, as a larger sample size enhances the reliability of the results and the robustness of the conclusions drawn. It also enables the examination of different types of divergences and their frequency over time, contributing to a more detailed understanding of which divergences are most effective under specific market conditions.

Furthermore, the time frame selection acknowledges potential limitations related to data accuracy and relevance. While historical data is generally reliable, older data may be subject to discrepancies due to changes in accounting standards, reporting practices, or data recording methods. The study mitigates this risk by sourcing data from reputable and consistent financial databases and by cross-verifying data where possible.

3.3.3 Manual Data Collection and Observation

The methodology for data collection is a critical component of this research, particularly given the specific challenges associated with identifying RSI divergences. Manual data collection and observation have been employed as the primary methods for gathering data on RSI divergences in both RELIANCE and LIBERTSHOE over the selected time frame. This section elaborates on the rationale for choosing manual methods, the procedures implemented to ensure accuracy and reliability, and the measures taken to mitigate potential biases and errors inherent in manual data collection.

The decision to utilize manual data collection and observation stems from the absence of automated tools capable of accurately identifying RSI divergences with the precision required for this study. While there are software programs and algorithms designed to detect technical indicators, they often lack the nuanced judgment that human analysts can provide when interpreting chart patterns and divergences. RSI divergences can be subjective and may require contextual understanding of market conditions, price action, and the specific characteristics of the stock being analyzed. Therefore, manual observation is deemed necessary to achieve a level of accuracy and insight unattainable by current automated systems.

The manual data collection process involves several meticulous steps. Firstly, historical price data for both RELIANCE and LIBERTSHOE is obtained from reputable financial databases such as NSE (in this case purchased from National Stock Exchange of India). This data includes daily closing prices, high and low prices, and volume traded for each trading day within the study period. Using this data, the RSI is calculated for each stock using the standard 14-period formula, which is widely accepted in technical analysis. The RSI values are computed using built-in indicator on TradingView to ensure accuracy.

Once the RSI values are established, the process of identifying RSI divergences begins. Analysts meticulously examine the price charts and corresponding RSI charts for both stocks throughout the entire time frame. The identification of divergences involves looking for instances where the price makes a new high or low that is not confirmed by the RSI, indicating a potential trend reversal. Four types of divergences are considered: regular bullish and regular bearish. Each identified divergence is documented, noting the date, type of divergence, price levels, RSI values, and any subsequent price movements that confirm or invalidate the divergence.

To ensure consistency and reduce subjective bias, the study adheres strictly to predefined criteria for divergence identification, following the methodologies outlined by Bansal (2023) and Khatavkar (2024).

Recognizing the potential for human error and subjective bias in manual observation, several measures are implemented to enhance the reliability and validity of the data collected. Firstly, a double-entry verification system is employed, wherein an independent analyst also performed the divergence identification process. The results are then compared, and any discrepancies are discussed and reconciled. This cross-validation helps to catch errors and ensures that divergences are not overlooked or misidentified.

Secondly, to further mitigate bias, the analyst conducting the observations was not informed about the specific hypotheses or the stock category (NIFTY 50 or non-NIFTY 50) of the stocks he was analyzing. This blind analysis approach reduces the risk of confirmation bias, where the researcher might subconsciously look for patterns that support the expected outcomes. Additionally, the analyst is trained in technical analysis and are familiar with the standard practices for identifying RSI divergences, ensuring that they possess the requisite expertise to perform the observations accurately.

Moreover, expert consultation is sought to validate the identified divergences. Technical analysis experts with extensive experience in the field review a sample of the identified divergences to confirm their validity. This external validation adds an additional layer of scrutiny and enhances the credibility of the data collected.

With each identified divergence logged in a structured database. The database includes detailed information such as the date of occurrence, type of divergence, subsequent price movements, and any other relevant notes. This systematic documentation facilitates efficient data analysis and allows for transparency and reproducibility in the research.

Despite these measures, the study acknowledges the inherent limitations of manual data collection and observation. Humans are subject to fatigue, oversight, and cognitive biases that may affect the accuracy of the data. To address fatigue, the data collection process is scheduled in manageable sessions, allowing the researcher and independent analyst to maintain focus and reduce the likelihood of errors. Regular breaks and a reasonable workload are emphasized to ensure that analysts remain attentive throughout the process.

Additionally, the potential for ignorance or lack of knowledge is mitigated by providing thorough training and resources to the analyst. He was equipped with comprehensive guidelines, examples of divergences, and access to support from more experienced colleagues if uncertainties arise during the observation process.

In conclusion, manual data collection and observation are integral to this study due to the nuanced and subjective nature of identifying RSI divergences. While acknowledging the challenges and limitations associated with manual methods, the study implements rigorous procedures and safeguards to ensure the accuracy, reliability, and validity of the data collected. By combining meticulous documentation, double-entry verification, blind analysis, and expert validation, the research endeavors to minimize errors and biases, thereby enhancing the overall integrity of the findings. This approach ultimately contributes to a more precise and meaningful assessment of the reliability of RSI divergence as a trend reversal indicator across different stock categories.

3.4 Data Analysis Methods

The data analysis methods employed in this research are designed to systematically evaluate the efficacy of RSI divergence as a trend reversal indicator across both NIFTY 50 and non-NIFTY 50 stocks. This section delineates the analytical procedures, statistical techniques, and methodological frameworks utilized to address the research questions and test the formulated hypotheses. The analysis is structured to provide a comprehensive examination of RSI divergence patterns, their predictive reliability, and the profitability of trading strategies based on these indicators, while accounting for transactional costs.

3.4.1 Identification of RSI Divergences

The foundational step in the data analysis involves the meticulous identification of RSI divergences within the selected stocks, RELIANCE and LIBERTSHOE, over the period from January 2000 to January 2024. RSI divergences are instances where the price of a stock and its Relative Strength Index (RSI) move in opposite directions, potentially signaling an upcoming trend reversal. The identification process adheres to standard criteria established in technical analysis literature and aligns with methodologies outlined in previous studies by Bansal (2023) and Khatavkar (2024).

3.4.1.1 Types of RSI Divergences

Two primary types of RSI divergences are analyzed:

- Regular Bullish Divergence occurs when the stock price forms lower lows while the RSI forms higher lows, indicating potential upward reversal.
- Regular Bearish Divergence occurs when the stock price forms higher highs while the RSI forms lower highs, suggesting potential downward reversal.

3.4.1.2 Criteria for Divergence Identification

The identification of divergences is conducted using the following criteria:

- Daily closing prices and RSI values are used to ensure consistency across the dataset.
- Divergences are confirmed only when both the price and RSI meet the criteria within a reasonable proximity in time.

- Minor price and RSI movements that do not represent significant trends are excluded to reduce noise in the data.
- The identification process is performed manually due to the lack of automated tools capable of achieving human-level accuracy in detecting RSI divergences. Each identified divergence is recorded with details such as the date of occurrence, type of divergence, RSI values, price levels, and subsequent price movements.

3.4.2 Statistical Analysis

Following the identification of RSI divergences, statistical analyses are conducted to evaluate their predictive reliability and to compare their characteristics between the NIFTY 50 and non-NIFTY 50 stocks.

3.4.2.1 Frequency and Success Rate Analysis

The frequency of each type of RSI divergence is calculated for both RELIANCE and LIBERTSHOE. The success rate is determined by analyzing the proportion of divergences that correctly predicted a trend reversal. Both immediate success and extended success are recorded as valid attributes. A divergence is deemed a failure if no trend reversal occurs before the RSI goes on the other side of centerline.

3.4.2.2 Timeframe Comparison

To address the research question regarding the timeframes for divergence formation and trend reversals, statistical comparisons are made between the two stocks. The average time between the identification of a divergence and the subsequent trend reversal is calculated for each type of divergence and for both stocks. Apart from this standard deviation & kurtosis is also calculated to judege the shape of the distribution. This analysis assesses whether RSI divergences signal trend reversals within similar timeframes across different stock categories.

3.4.2.3 Analysis of Divergence Types

An examination of which types of RSI divergences demonstrate higher predictive reliability is conducted. The success rates of regular bullish, regular bearish and both types are compared. These comparisons are consistent with Khatavkar (2024) to ensure comparability. This analysis aims to identify the most accurate types of RSI divergences and whether their effectiveness is consistent across NIFTY 50 and non-NIFTY 50 stocks.

3.4.3 Profitability Assessment

To evaluate whether trading strategies based on RSI divergences remain profitable after accounting for all transactional costs, a simulated trading analysis is conducted.

3.4.3.1 Trading Simulation Parameters

The trading simulation is designed with realistic parameters to reflect actual trading conditions. Following the recommendation by Khatavkar (2024), Trades are initiated upon confirmation of an RSI divergence and closed as per the analyst skills. All calculations account for brokerage fees, taxes, and duties to ensure that net profitability is assessed. 100% of the portfolio is allocated to each trade to calculate a realistic compounded return. Stop-loss orders of 2% are placed to limit potential losses on each trade along with maximum 20% target levels to avoid outliers on the plus side.

3.4.3.2 Return on Investment (ROI) Calculations

The ROI for each trade is calculated, and compounded returns are assessed over the study period for both stocks. The total net profit or loss is determined after subtracting all transactional costs. Returns are annualized to facilitate comparison between the stocks and with other investment benchmarks.

3.4.4 Ethical Considerations in Data Analysis

Ethical standards are upheld throughout the data analysis process. All analytical methods and procedures are documented thoroughly to allow for replication and verification by other researchers. Although the data used are publicly available, care is taken to handle all information responsibly and ethically. Proper credit is given to original sources, and any adaptations of existing methodologies are clearly indicated.

3.4.5 Limitations of the Research Methodology

While the research methodology is designed to be rigorous, certain limitations are acknowledged.

- Reliance on manual identification of divergences may introduce human error despite efforts to mitigate it.
- Findings based on two stocks may not be generalizable to other international markets and asset classes.

3.5 Chapter Summary

This **chapter discussed** the the research methodology utilized to evaluate the effectiveness of RSI divergence as an indicator of trend reversal. It commence**d** by rationalizing the research framework, which encompasses a longitudinal observational analysis employing a manual approach to identify RSI divergences in two representative stocks. The chosen timeframe of 2000 to 2024 yields a comprehensive dataset, encompassing market cycles and transitions, which ensures the thoroughness of the study. The process of stock selection is delineated, with RELIANCE and LIBERTSHOE selected to epitomize NIFTY 50 and non-NIFTY 50 stocks, ensuring that the study's outcomes are pertinent to both the large-cap and mid-cap segments of the Indian stock market. Criteria such as liquidity, data availability, and representative attributes were instrumental in guiding the selection process to ensure rigorous analysis.

The chapter delve**d** into the complexities associated with detecting divergences and elucidates the use of manual methods to address the limitations of automated tools. It outlines procedures aimed at minimizing errors, such as double-entry verification and blind analysis, to ensure the robustness of the study. The robustness of the study, ensured through these procedures, reassures the audience about the reliability of the findings. Furthermore, it introduce**d** data analysis techniques, including statistical comparisons of divergence success rates and trading simulations, to assess the predictive capability of RSI divergences in relation to market trends.

By adhering to a rigorous methodological framework, this chapter establishe**d** the groundwork for subsequent empirical testing and analysis.

CHAPTER 4: RESULTS

This chapter presents a comprehensive empirical examination of RSID for two specific stocks: Reliance Industries (RELIANCE) and Liberty Shoes (LIBERTSHOE). By scrutinizing the duration, statistical attributes, and outcomes of these divergences, this study aims to provide practical insights for traders and financial analysts, offering them a roadmap to refine their trading strategies based on empirical evidence.

4.1 Results On RELIANCE

This section discusses the results of the RSI divergence analysis for RELIANCE stock. The examination includes time taken for divergence formation, statistical analysis, delayed success, and overall performance outcomes.

Table 4.1a provides a detailed analysis of the time it takes for RSI divergences to form, categorized by duration and separated into bullish and bearish divergences.

Formation Duration	Both	Bullish	%	Bearish	%
1-7 days	24	8	33.33	16	66.67
8-14 days	54	14	25.93	40	74.07
15-21 days	17	4	23.53	13	76.47
>21 days	12	0	0.00	12	100.00
Total	**107**	**26**	**-**	**81**	**-**

Table 4.1a: Time It Takes To Form An RSI Divergence On RELIANCE

For divergences forming within 1-7 days, there were 24 total instances, with 8 being bullish (33.33%) and 16 being bearish (66.67%).

In the 8-14 days range, there were 54 instances, with 14 being bullish (25.93%) and 40 being bearish (74.07%).

For divergences forming within 15-21 days, there were 17 total instances, with 4 being bullish (23.53%) and 13 being bearish (76.47%).

For divergences extending beyond 21 days, there were 12 instances, all of which were bearish, making up 100% of this category, with no bullish divergences recorded.

In total, across all durations, there were 107 RSI divergences observed for Reliance stock, with 26 being bullish and 81 being bearish. This distribution highlights a predominance of bearish divergences, especially as the formation duration increases, with all instances beyond 21 days being bearish.

Table 4.1b provides a detailed breakdown of the statistical characteristics for the formation duration of RSI divergences, differentiating between bullish and bearish instances.

Formation Duration	**Both**	**Bullish**	**Bearish**
Count	107	26	81
Mean	12.7103	10.1538	13.5309
Standard Deviation	6.8570	4.4694	7.2974
Skewness	1.3247	0.6647	1.2133
Kurtosis	1.6684	-0.3439	1.0861

Table 4.1b: Statistical Analysis of RSI Divergence Formation Durations On RELIANCE

There was a total of 107 instances of RSI divergences for Reliance stock, with 26 being bullish and 81 being bearish divergences.

The mean formation duration for all divergences was 12.7103 days. Bullish divergences had a mean formation duration of 10.1538 days, while bearish divergences had a longer mean formation duration of 13.5309 days.

The standard deviation, which measures the variability of the formation durations, was 6.8570 days for all divergences. Bullish divergences had a standard deviation of 4.4694 days, indicating less variability compared to bearish divergences, which had a standard deviation of 7.2974 days.

The skewness values indicate the asymmetry of the distribution of formation durations. For all divergences, the skewness was 1.3247, suggesting a right-skewed distribution with more instances having shorter formation durations. Bullish divergences had a lower skewness of 0.6647, indicating a less pronounced right skew. Bearish divergences had a skewness of 1.2133, also indicating a right-skewed distribution but more pronounced than bullish divergences.

The kurtosis values show the "tailedness" of the distribution. For all divergences, the kurtosis was 1.6684, indicating a distribution with heavier tails than a normal distribution. Bullish divergences had a negative kurtosis of -0.3439, suggesting a distribution with lighter tails and fewer extreme values. Bearish divergences had a kurtosis of 1.0861, indicating a slightly heavier-tailed distribution compared to bullish divergences.

This statistical analysis highlights that bearish divergences tend to take longer to form compared to bullish divergences for Reliance stock, and the variability is higher in bearish divergences. Both types of divergences exhibit right-skewed distributions, with bearish divergences having a more pronounced right skew and heavier tails compared to bullish divergences.

Table 4.1c provides an analysis of RSI divergences that initially formed but required additional time to achieve the expected price movement, indicating delayed success. The table distinguishes between bullish and bearish divergences across different extended duration ranges.

Extended Duration	**Both**	**Bullish**	**%**	**Bearish**	**%**
1-7 days	8	2	25.00	6	75.00
8-14 days	11	2	18.18	9	81.82
15-21 days	0	0	-	0	-
>21 days	2	0	0.00	2	100.00

Table 4.1c: Time By Which An RSI Divergence Extends On RELIANCE

For divergences that extended by 1-7 days, there were 8 instances in total. Of these, 2 were bullish (25.00%), while 6 were bearish (75.00%).

In the 8-14 days extended range, there were 11 instances in total. Of these, 2 were bullish (18.18%), while 9 were bearish (81.82%).

For divergences extending by 15-21 days, there were no recorded instances, indicating that within this timeframe, no divergence exhibited delayed success.

For divergences extending beyond 21 days, there were 2 instances, both of which were bearish, making up 100% of this category. There were no bullish divergences recorded within this extended duration.

This analysis highlights that bearish divergences are more prone to delayed success, particularly in the 1-14 days and beyond 21 days ranges, with no bullish divergences requiring an extended duration beyond 21 days to achieve the expected outcome.

Table 4.1d provides a detailed breakdown of the statistical characteristics for divergences that extend before achieving success, distinguishing between bullish and bearish instances.

Extended Duration	Both	Bullish	Bearish
Count	21	4	17
Mean	1.9907	1.3462	2.1975
Standard deviation	4.8262	3.5546	5.1706
Skewness	2.8367	2.7361	2.7465
Kurtosis	8.5229	6.7218	7.8286

Table 4.1d: Statistical Analysis of Extended Duration for RSI Divergences On RELIANCE

There was a total of 21 instances where divergences extended before success. Among these, 4 were bullish and 17 were bearish divergences.

The mean extended duration for all divergences was 1.9907 days. Bullish divergences had a mean extended duration of 1.3462 days, while bearish divergences had a longer mean extended duration of 2.1975 days.

The standard deviation, which measures the variability of the extended durations, was 4.8262 days for all divergences. Bullish divergences had a standard deviation of 3.5546 days, indicating less variability compared to bearish divergences, which had a standard deviation of 5.1706 days.

The skewness values indicate the asymmetry of the distribution of extended durations. For all divergences, the skewness was 2.8367, suggesting a right-skewed distribution with more instances having shorter extended durations. Bullish divergences had a skewness of 2.7361, indicating a pronounced right skew. Bearish divergences had a skewness of 2.7465, also indicating a pronounced right-skewed distribution.

The kurtosis values show the "tailedness" of the distribution. For all divergences, the kurtosis was 8.5229, indicating a distribution with very heavy tails. Bullish divergences had a kurtosis of 6.7218, suggesting a heavy-tailed distribution with a higher likelihood of extreme values. Bearish divergences had a kurtosis of 7.8286, also indicating a heavy-tailed distribution but less extreme than the overall sample.

This statistical analysis highlights that bearish divergences tend to extend longer before achieving success compared to bullish divergences, and the variability is higher in bearish divergences. Both types of divergences exhibit right-skewed distributions with heavy tails, particularly pronounced in the overall and bearish divergence samples.

Table 4.1e provides a comprehensive analysis of the success and failure rates of RSI divergences, distinguishing between bullish and bearish divergences.

All Observations	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	107	100.00%	26	100.00%	81	100.00%
Failed	23	21.50%	3	11.54%	20	24.69%
Success	84	78.50%	23	88.46%	61	75.31%
Immediate Success	63	75.00%	19	82.61%	44	72.13%
Delayed Success	21	25.00%	4	17.39%	17	27.87%

Table 4.1e: Outcome Analysis of RSI Divergences On RELIANCE

Out of 107 total observations, 26 were bullish divergences and 81 were bearish divergences, each making up 100% of their respective categories.

The failure rate for all divergences was 21.50%, with 23 instances failing to achieve the expected outcome. Among these, 3 were bullish (11.54%) and 20 were bearish (24.69%).

The success rate for all divergences was 78.50%, with 84 instances achieving the expected outcome. Bullish divergences had a higher success rate of 88.46%, with 23 successful instances. Bearish divergences had a success rate of 75.31%, with 61 successful instances.

Further analysis of the successful divergences reveals that 75.00% of the total successful instances were immediate successes, with 63 immediate successes overall. Among these, 19 were bullish (82.61%) and 44 were bearish (72.13%).

Delayed successes accounted for 25.00% of the total successful instances, with 21 delayed successes overall. Of these, 4 were bullish (17.39%) and 17 were bearish (27.87%).

This analysis highlights that RSI divergences for Reliance stock have a high overall success rate, particularly for bullish divergences. Immediate success is more common than delayed success for both bullish and bearish divergences, although bearish divergences have a slightly higher proportion of delayed successes. The data indicates that while bearish divergences are more prone to failure compared to bullish divergences, they still have a substantial success rate, especially in the immediate term.

Table 4.1f provides an analysis of the success and failure rates of RSI divergences within the 1-7 day duration, distinguishing between bullish and bearish divergences.

1-7 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	24	100.00%	8	100.00%	16	100.00%
Failed	6	25.00%	0	0.00%	6	37.50%
Success	18	75.00%	8	100.00%	10	62.50%
Immediate Success	16	88.89%	8	100.00%	8	80.00%
Delayed Success	2	11.11%	0	0.00%	2	20.00%

Table 4.1f: Outcome Analysis of RSI Divergences for 1-7 Days On RELIANCE

Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
19/02/2001	01/03/2001	7	Sell	Yes	0	NA	02/03/2001
31/07/2003	08/08/2003	5	Sell	No	0	No	Failed
01/02/2005	11/02/2005	7	Sell	No	0	No	Failed
21/09/2005	29/09/2005	5	Sell	Yes	0	NA	30/09/2005
08/02/2007	19/02/2007	5	Sell	Yes	0	NA	20/02/2007
25/09/2007	05/10/2007	6	Sell	No	0	No	Failed
17/04/2008	29/04/2008	7	Sell	No	4	Yes	07/05/2008
01/02/2011	10/02/2011	6	Buy	Yes	0	NA	11/02/2011
23/05/2013	04/06/2013	7	Buy	Yes	0	NA	05/06/2013
21/10/2013	31/10/2013	7	Sell	Yes	0	NA	01/11/2013
17/12/2015	29/12/2015	6	Sell	No	0	No	Failed
27/09/2016	06/10/2016	6	Sell	Yes	0	NA	07/10/2016
20/03/2018	28/03/2018	5	Buy	Yes	0	NA	02/04/2018
01/08/2018	09/08/2018	5	Sell	No	0	No	Failed
03/01/2019	14/01/2019	6	Buy	Yes	0	NA	15/01/2019
18/04/2019	03/05/2019	7	Sell	Yes	0	NA	06/05/2019
09/03/2020	19/03/2020	6	Buy	Yes	0	NA	20/03/2020
04/05/2021	12/05/2021	5	Buy	Yes	0	NA	14/05/2021
28/01/2022	07/02/2022	4	Buy	Yes	0	NA	08/02/2022
24/02/2022	08/03/2022	5	Buy	Yes	0	NA	09/03/2022
19/12/2023	28/12/2023	5	Sell	No	0	No	Failed
14/02/2024	23/02/2024	6	Sell	No	6	Yes	04/03/2024
23/02/2024	04/03/2024	6	Sell	Yes	0	NA	05/03/2024
22/04/2024	30/04/2024	5	Sell	Yes	0	NA	02/05/2024

Table 4.1g: List of Observations In 1-7 Days Duration On RELIANCE

For divergences forming within 1-7 days, there were 24 total instances, with 8 being bullish and 16 being bearish, each making up 100% of their respective categories.

The failure rate for all divergences in this duration was 25.00%, with 6 instances failing to achieve the expected outcome. All failures were bearish divergences, accounting for 37.50% of bearish instances. There were no failures among bullish divergences.

The success rate for all divergences in this duration was 75.00%, with 18 instances achieving the expected outcome. Bullish divergences had a success rate of 100.00%, with all 8 instances being successful. Bearish divergences had a success rate of 62.50%, with 10 successful instances.

Further analysis of the successful divergences reveals that 88.89% of the total successful instances were immediate successes, with 16 immediate successes overall. Among these, all 8 bullish divergences were immediate successes (100.00%), while 8 of the 10 successful bearish divergences were immediate successes (80.00%).

Delayed successes accounted for 11.11% of the total successful instances, with 2 delayed successes overall. Both delayed successes were bearish divergences, accounting for 20.00% of successful bearish instances. There were no delayed successes among bullish divergences.

This analysis highlights that RSI divergences for Reliance stock within the 1-7 day duration have a high overall success rate, particularly for bullish divergences, which experienced no failures and all were immediate successes. Bearish divergences, while having a lower success rate, still showed a majority of immediate successes, with a smaller portion experiencing delayed success.

Table 4.1h provides an analysis of the success and failure rates of RSI divergences within the 8-14 day duration, distinguishing between bullish and bearish divergences.

8-14 Days	Both	%	Bullish	%	Bearish	%
Total	54	100.00%	14	100.00%	40	100.00%
Failed	9	16.67%	3	21.43%	6	15.00%
Success	45	83.33%	11	78.57%	34	85.00%
Immediate Success	33	73.33%	8	72.73%	25	73.53%
Delayed Success	12	26.67%	3	27.27%	9	26.47%

Table 4.1h: Outcome Analysis of RSI Divergences for 8-14 Days On RELIANCE

Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
07/01/2000	28/01/2000	13	Sell	No	9	Yes	11/02/2000
18/06/2001	04/07/2001	11	Buy	No	0	No	Failed
19/11/2001	05/12/2001	10	Sell	No	2	Yes	10/12/2001
06/06/2003	20/06/2003	9	Sell	No	0	No	Failed
13/10/2003	03/11/2003	14	Sell	Yes	0	NA	04/11/2003
04/10/2004	19/10/2004	9	Sell	Yes	0	NA	20/10/2004
25/11/2004	17/12/2004	14	Buy	Yes	0	NA	20/12/2004
04/01/2006	20/01/2006	10	Sell	No	9	Yes	06/02/2006
20/04/2006	10/05/2006	12	Sell	Yes	0	NA	11/05/2006
29/10/2007	14/11/2007	11	Sell	No	12	Yes	03/12/2007
14/11/2007	03/12/2007	12	Sell	Yes	0	NA	04/12/2007
04/03/2008	18/03/2008	8	Buy	Yes	0	NA	19/03/2008
15/04/2009	07/05/2009	13	Sell	No	0	No	Failed
01/06/2009	12/06/2009	9	Sell	Yes	0	NA	15/06/2009
09/09/2009	30/09/2009	12	Sell	Yes	0	NA	01/10/2009
30/09/2009	16/10/2009	9	Sell	Yes	0	NA	20/10/2009
05/02/2010	25/02/2010	13	Buy	Yes	0	NA	26/02/2010
19/03/2010	07/04/2010	10	Sell	Yes	0	NA	08/04/2010
06/05/2010	21/05/2010	10	Buy	Yes	0	NA	24/05/2010
26/10/2010	08/11/2010	8	Sell	Yes	0	NA	09/11/2010

25/11/2011	12/12/2011	9	Buy	No	13	Yes	30/12/2011
12/12/2011	30/12/2011	13	Buy	Yes	0	NA	02/01/2012
19/06/2012	29/06/2012	8	Sell	No	6	Yes	10/07/2012
16/05/2013	29/05/2013	8	Sell	Yes	0	NA	30/05/2013
01/07/2013	19/07/2013	12	Sell	Yes	0	NA	22/07/2013
02/09/2013	19/09/2013	11	Sell	Yes	0	NA	20/09/2013
13/11/2013	27/11/2013	8	Buy	Yes	0	NA	28/11/2013
11/02/2014	28/02/2014	11	Buy	Yes	0	NA	03/03/2014
02/04/2014	22/04/2014	11	Sell	Yes	0	NA	23/04/2014
19/05/2014	09/06/2014	14	Sell	Yes	0	NA	10/06/2014
16/12/2014	06/01/2015	13	Buy	No	5	Yes	14/01/2015
19/06/2015	06/07/2015	11	Sell	No	11	Yes	22/07/2015
06/07/2015	22/07/2015	11	Sell	Yes	0	NA	23/07/2015
19/10/2015	03/11/2015	9	Sell	Yes	0	NA	04/11/2015
03/11/2015	26/11/2015	14	Sell	Yes	0	NA	27/11/2015
26/11/2015	17/12/2015	14	Sell	No	0	No	Failed
09/03/2016	22/03/2016	8	Sell	No	0	No	Failed
20/07/2016	09/08/2016	13	Sell	Yes	0	NA	10/08/2016
14/12/2016	03/01/2017	13	Sell	Yes	0	NA	05/01/2017
06/04/2017	25/04/2017	11	Sell	Yes	0	NA	26/04/2017
17/07/2017	03/08/2017	12	Sell	Yes	0	NA	04/08/2017
07/03/2018	20/03/2018	8	Buy	No	5	Yes	28/03/2018
05/10/2018	25/10/2018	12	Buy	Yes	0	NA	26/10/2018
21/01/2019	06/02/2019	11	Sell	Yes	0	NA	08/02/2019
13/03/2019	01/04/2019	11	Sell	Yes	0	NA	02/04/2019
24/06/2019	08/07/2019	10	Buy	No	0	No	Failed
28/11/2019	19/12/2019	14	Sell	Yes	0	NA	20/12/2019
19/06/2020	06/07/2020	9	Sell	No	0	No	Failed
05/10/2021	19/10/2021	8	Sell	Yes	0	NA	21/10/2021
30/03/2022	21/04/2022	13	Sell	No	4	Yes	28/04/2022
10/05/2023	29/05/2023	12	Sell	No	0	No	Failed

25/09/2023	09/10/2023	8	Buy	No	0	No	Failed
15/01/2024	29/01/2024	8	Sell	No	25	Yes	04/03/2024
29/01/2024	14/02/2024	11	Sell	No	13	Yes	04/03/2024

Table 4.1i: List of Observations In 8-14 Days Duration On RELIANCE

For divergences forming within 8-14 days, there were 54 total instances, with 14 being bullish and 40 being bearish, each making up 100% of their respective categories.

The failure rate for all divergences in this duration was 16.67%, with 9 instances failing to achieve the expected outcome. Among these, 3 were bullish divergences (21.43%) and 6 were bearish divergences (15.00%).

The success rate for all divergences in this duration was 83.33%, with 45 instances achieving the expected outcome. Bullish divergences had a success rate of 78.57%, with 11 successful instances. Bearish divergences had a success rate of 85.00%, with 34 successful instances.

Further analysis of the successful divergences reveals that 73.33% of the total successful instances were immediate successes, with 33 immediate successes overall. Among these, 8 were bullish divergences (72.73%) and 25 were bearish divergences (73.53%).

Delayed successes accounted for 26.67% of the total successful instances, with 12 delayed successes overall. Among these, 3 were bullish divergences (27.27%) and 9 were bearish divergences (26.47%).

This analysis highlights that RSI divergences for Reliance stock within the 8-14 day duration have a high overall success rate for both bullish and bearish divergences. The majority of successful instances were immediate successes for both types, with a significant portion also experiencing delayed success. Bearish divergences had a slightly higher success rate compared to bullish divergences in this duration, but both showed strong performance.

Table 4.1j provides an analysis of the success and failure rates of RSI divergences within the 15-21 day duration, distinguishing between bullish and bearish divergences.

15-21 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	17	100.00%	4	100.00%	13	100.00%
Failed	5	29.41%	0	0.00%	5	38.46%
Success	12	70.59%	4	100.00%	8	61.54%
Immediate Success	7	58.33%	3	75.00%	4	50.00%
Delayed Success	5	41.67%	1	25.00%	4	50.00%

Table 4.1j: Outcome Analysis of RSI Divergences for 15-21 Days On RELIANCE

Start Date	**Confirmation Date**	**Formation Duration**	**Trade Type**	**Immediate Success**	**Extended Duration**	**Delayed Success**	**Trade Date**
11/12/2000	05/01/2000	17	Sell	No	0	No	Failed
26/11/2002	26/12/2002	20	Sell	Yes	0	NA	27/12/2002
03/11/2003	04/12/2003	21	Sell	Yes	0	NA	05/12/2003
31/05/2004	23/06/2004	17	Buy	Yes	0	NA	24/06/2004
03/01/2005	01/02/2005	18	Sell	No	0	No	Failed
30/08/2006	26/09/2006	18	Sell	No	0	No	Failed
15/01/2007	08/02/2007	15	Sell	No	5	Yes	19/02/2007
25/04/2007	22/05/2007	15	Sell	Yes	0	NA	23/05/2007
05/10/2007	29/10/2007	15	Sell	No	24	Yes	03/12/2007
23/06/2008	16/07/2008	16	Buy	Yes	0	NA	18/07/2008
06/12/2012	04/01/2013	19	Sell	No	0	No	Failed
06/03/2017	06/04/2017	18	Sell	Yes	0	NA	07/04/2017
30/10/2019	28/11/2019	19	Sell	No	14	Yes	19/12/2019
11/05/2020	05/06/2020	17	Sell	No	0	No	Failed

20/11/2020	22/12/2020	20	Buy	No	12	Yes	11/01/2021
07/09/2021	05/10/2021	18	Sell	No	8	Yes	19/10/2021
07/05/2024	04/06/2024	19	Buy	Yes	0	NA	05/06/2024

Table 4.1k: List of Observations In 15-21 Days Duration On RELIANCE

For divergences forming within 15-21 days, there were 17 total instances, with 4 being bullish and 13 being bearish, each making up 100% of their respective categories.

The failure rate for all divergences in this duration was 29.41%, with 5 instances failing to achieve the expected outcome. All failures were bearish divergences, accounting for 38.46% of bearish instances. There were no failures among the bullish divergences.

The success rate for all divergences in this duration was 70.59%, with 12 instances achieving the expected outcome. Bullish divergences had a success rate of 100.00%, with all 4 instances being successful. Bearish divergences had a success rate of 61.54%, with 8 successful instances.

Further analysis of the successful divergences reveals that 58.33% of the total successful instances were immediate successes, with 7 immediate successes overall. Among these, 3 were bullish divergences (75.00%) and 4 were bearish divergences (50.00%).

Delayed successes accounted for 41.67% of the total successful instances, with 5 delayed successes overall. Among these, 1 was a bullish divergence (25.00%) and 4 were bearish divergences (50.00%).

This analysis highlights that RSI divergences for Reliance stock within the 15-21 day duration show a relatively high success rate, especially for bullish divergences, which experienced no failures. However, the success rate for bearish divergences was lower, with a notable portion of successful instances being delayed rather than immediate. The data suggests that bearish divergences within this timeframe are more prone to both failure and delayed success compared to bullish divergences.

Table 4.1l provides an analysis of the success and failure rates of RSI divergences extending beyond 21 days, specifically focusing on bearish divergences, as no bullish divergences were recorded within this timeframe.

>21 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	12	100.00%	0	#DIV/0!	12	100.00%
Failed	3	25.00%	0	#DIV/0!	3	25.00%
Success	9	75.00%	0	#DIV/0!	9	75.00%
Immediate Success	7	77.78%	0	#DIV/0!	7	77.78%
Delayed Success	2	22.22%	0	#DIV/0!	2	22.22%

Table 4.1l: Outcome Analysis of RSI Divergences Beyond 21 On RELIANCE

Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
11/02/2000	10/04/2000	38	Sell	Yes	0	NA	11/04/2000
05/12/2001	09/01/2002	22	Sell	Yes	0	NA	10/01/2002
02/09/2003	13/10/2003	26	Sell	No	14	Yes	03/11/2003
03/11/2003	04/12/2003	21	Sell	Yes	0	NA	05/12/2003
02/01/2004	18/02/2004	30	Sell	Yes	0	NA	19/02/2004
05/08/2004	17/09/2004	30	Sell	No	0	No	Failed
22/06/2005	02/08/2005	27	Sell	Yes	0	NA	03/08/2005
02/08/2005	12/09/2005	26	Sell	No	12	Yes	29/09/2005
20/01/2006	07/03/2006	29	Sell	No	0	No	Failed
03/08/2017	13/09/2017	26	Sell	Yes	0	NA	14/09/2017
23/10/2017	27/11/2017	24	Sell	Yes	0	NA	28/11/2017
18/06/2018	20/07/2018	23	Sell	No	0	No	Failed
28/07/2020	11/09/2020	32	Sell	Yes	0	NA	14/09/2020

Table 4.1m: List of Observations Beyond 21 Days Duration On RELIANCE

For divergences forming beyond 21 days, there were 12 total instances, all of which were bearish, making up 100% of the category.

The failure rate for all divergences in this duration was 25.00%, with 3 instances failing to achieve the expected outcome. Since all instances were bearish, this failure rate applies entirely to the bearish divergences.

The success rate for all divergences in this duration was 75.00%, with 9 instances achieving the expected outcome. Again, since all instances were bearish, this success rate applies entirely to the bearish divergences.

Further analysis of the successful divergences reveals that 77.78% of the total successful instances were immediate successes, with 7 immediate successes overall.

Delayed successes accounted for 22.22% of the total successful instances, with 2 delayed successes overall.

This analysis indicates that for RSI divergences forming beyond 21 days in Reliance stock, the bearish divergences have a relatively high success rate, with most successes occurring immediately. However, there is still a notable portion of delayed successes, reflecting that some bearish divergences may take longer to achieve the expected outcome. The 25% failure rate suggests a moderate risk associated with these longer-term bearish divergences.

Table 4.1n provides an analysis of profitability of RSI divergences in RELIANCE after accounting for all transactional costs.

Parameter	Value
Total Number of Trades	107

Successful Trades	84
Failed Trades	23
Stock Price at 01/01/2000	39
Stock Price at 01/01/2024	2580
Annual Return From Passive Investment	19.08%
Balance at 01/01/2000	100
Balance at 01/01/2024	341,424
Annual Return From RSI Divergence	40.35%

Table 4.1n: Profitability Analysis of All RSI Divergences On RELIANCE

The stock price significantly increased from 39 in 2000 to 2580 in 2024, reflecting strong long-term growth. The annual return from passive investment was 19.08%, showcasing a solid performance over the years. During the simulation with RSI Divergence based trading, starting with a balance of 100, the investment grew to 341,424 by 2024. The annual was substantially higher at 40.35%, illustrating the efficacy of utilizing RSI divergences as a trading strategy, which outperformed passive investment returns.

4.2 Results On LIBERTSHOE

This section discusses the RSI divergence analysis for LIBERTSHOE stock. The examination is comprehensive, covering the duration required for divergence formation, statistical evaluations, occurrences of delayed success, and overall performance outcomes, categorized into bullish and bearish divergences.

Table 4.2a provides an analysis of the duration over which RSI divergences formed, with a distinction between bullish and bearish divergences.

Formation Duration	Both	Bullish	%	Bearish	%
1-7 days	18	8	44.44	10	55.56
8-14 days	30	13	43.33	17	56.67
15-21 days	9	4	44.44	5	55.56
>21 days	3	2	66.67	1	33.33
Total	**60**	**27**	**-**	**33**	**-**

Table 4.2a: Time It Takes To Form An RSI Divergence On LIBERTSHOE

For divergences forming within 1-7 days, there were 18 total instances, with 8 being bullish (44.44%) and 10 being bearish (55.56%).

In the 8-14 days range, there were 30 instances, with 13 being bullish (43.33%) and 17 being bearish (56.67%).

For divergences forming within 15-21 days, there were 9 total instances, with 4 being bullish (44.44%) and 5 being bearish (55.56%).

For divergences extending beyond 21 days, there were 3 instances, with 2 being bullish (66.67%) and 1 being bearish (33.33%).

In total, across all durations, there were 60 RSI divergences observed for Liberty Shoes stock, with 27 being bullish and 33 being bearish. The distribution shows a relatively balanced occurrence of bullish and bearish divergences, with a slight predominance of bearish divergences, particularly in the shorter durations of 1-14 days. However, in the extended duration beyond 21 days, bullish divergences became more prevalent, making up two-thirds of the observed instances.

Table 4.2b provides an overview of key statistical measures for the formation duration of RSI divergences, distinguishing between bullish and bearish divergences.

Formation Duration	Both	Bullish	Bearish
Count	60	27	33
Mean	10.7500	11.0741	10.4848
Standard Deviation	5.6377	5.6564	5.6961
Skewness	2.0437	1.6120	2.4985
Kurtosis	5.1670	2.5253	8.4498

Table 4.2b: Statistical Analysis of RSI Divergence Formation Durations On LIBERTSHOE

For all 60 observed instances of RSI divergences, the mean duration is 10.75 days, indicating the average time it takes for a divergence to form. The standard deviation is 5.64 days, reflecting the variability in the formation duration. The skewness is 2.04, suggesting a right-skewed distribution where most divergences form within a shorter duration, but a few take significantly longer. The kurtosis is 5.17, indicating a leptokurtic distribution with more instances of extreme values compared to a normal distribution.

For the 27 bullish divergences, the mean duration is 11.07 days, slightly higher than the overall mean, indicating that bullish divergences tend to take slightly longer to form. The standard deviation is 5.66 days, showing similar variability to the overall sample. The skewness is 1.61, indicating a moderate right skewness, with most bullish divergences forming relatively quickly. The kurtosis is 2.53, suggesting a distribution closer to normal, with fewer extreme values.

For the 33 bearish divergences, the mean duration is 10.48 days, slightly lower than the overall mean, indicating that bearish divergences tend to form a bit faster. The standard deviation is 5.70 days, showing a similar level of variability as the overall sample and bullish divergences. The skewness is 2.50, indicating a stronger right-skewed distribution, with most bearish divergences forming quickly, but some taking much longer. The kurtosis is 8.45, indicating a highly leptokurtic distribution with a significant presence of extreme formation durations.

This analysis highlights that while the formation duration for both bullish and bearish divergences in Liberty Shoes stock is relatively similar, bearish divergences exhibit a more pronounced tendency towards extreme durations, with some forming much faster or slower than average.

Table 4.2c provides an analysis of divergences that required additional time to achieve the expected price movement, indicating delayed success. The table distinguishes between bullish and bearish divergences across different extended duration ranges.

Extended Duration	Both	Bullish	%	Bearish	%
1-7 days	3	0	0.00	3	100.00
8-14 days	3	2	66.67	1	33.33
15-21 days	2	1	50.00	1	50.00
>21 days	0	0	0	0	0

Table 4.2c: Time By Which An RSI Divergence Extends On LIBERTSHOE

For divergences that extended by 1-7 days, there were 3 instances in total. All 3 of these were bearish, making up 100% of this category, with no bullish divergences recorded within this timeframe.

In the 8-14 days extended range, there were 3 instances in total. Of these, 2 were bullish (66.67%), while 1 was bearish (33.33%).

For divergences extending by 15-21 days, there were 2 instances. Of these, 1 was bullish (50.00%) and 1 was bearish (50.00%), indicating an equal distribution between the two.

For divergences extending beyond 21 days, there were no recorded instances, indicating that within this timeframe, no divergence exhibited delayed success.

This analysis suggests that while bearish divergences are more likely to extend by 1-7 days, bullish divergences are more prevalent in the 8-14 days range. There is also a balanced occurrence of bullish and bearish divergences in the 15-21 days range, with no instances of extended divergences beyond 21 days.

Table 4.2d provides an analysis of divergences that required additional time to achieve the expected price movement, indicating delayed success. The table distinguishes between bullish and bearish divergences across different extended duration ranges.

Extended Duration	**Both**	**Bullish**	**Bearish**
Count	8	3	5
Mean	1.2667	1.3333	1.2121
Standard deviation	3.8438	4.1971	3.5948
Skewness	3.3551	3.4857	3.3225
Kurtosis	11.1215	12.6935	10.8210

Table 4.2d: Statistical Analysis of Extended Duration for RSI Divergences On LIBERTSHOE

For divergences that extended by 1-7 days, there were 3 instances in total. All 3 of these were bearish, making up 100% of this category, with no bullish divergences recorded within this timeframe.

In the 8-14 days extended range, there were 3 instances in total. Of these, 2 were bullish (66.67%), while 1 was bearish (33.33%).

For divergences extending by 15-21 days, there were 2 instances. Of these, 1 was bullish (50.00%) and 1 was bearish (50.00%), indicating an equal distribution between the two.

For divergences extending beyond 21 days, there were no recorded instances, indicating that within this timeframe, no divergence exhibited delayed success.

This analysis suggests that while bearish divergences are more likely to extend by 1-7 days, bullish divergences are more prevalent in the 8-14 days range. There is also a balanced occurrence of bullish and bearish divergences in the 15-21 days range, with no instances of extended divergences beyond 21 days.

Table 4.2e summarizes the outcomes of 60 observed divergences, divided between bullish and bearish scenarios, with further distinction between immediate and delayed success.

All Observations	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	60	100.00%	27	100.00%	33	100.00%
Failed	14	23.33%	7	25.93%	7	21.21%
Success	46	76.67%	20	74.07%	26	78.79%
Immediate Success	38	82.61%	17	85.00%	21	80.77%
Delayed Success	8	17.39%	3	15.00%	5	19.23%

Table 4.2e: Outcome Analysis of RSI Divergences On LIBERTSHOE

Out of the total 60 divergences, 14 failed to produce the expected price movement, accounting for 23.33% of all cases. Of these, 7 were bullish (25.93% of all bullish cases), and 7 were bearish (21.21% of all bearish cases). 46 succeeded in achieving the expected price movement, representing 76.67% of the total. Of these, 20 were bullish (74.07% of all bullish cases), and 26 were bearish (78.79% of all bearish cases).

Among the successful divergences, 38 achieved immediate success, accounting for 82.61% of all successful cases. Of these, 17 were bullish (85.00% of all successful bullish cases), and 21 were bearish (80.77% of all successful bearish cases). 8 exhibited delayed success, representing 17.39% of all successful cases. Of these, 3 were bullish (15.00% of all successful bullish cases), and 5 were bearish (19.23% of all successful bearish cases).

This analysis reveals that while the overall success rate of RSI divergences for Liberty Shoes stock is high, with a slight edge for bearish divergences, immediate success is more common than delayed success. Both bullish and bearish divergences exhibit similar patterns in terms of success and failure, though delayed success is slightly more prevalent among bearish divergences.

Table 4.2f details the performance of divergences that formed within this short timeframe, distinguishing between bullish and bearish cases.

1-7 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	18	100.00%	8	100.00%	10	100.00%
Failed	4	22.22%	3	37.50%	1	10.00%
Success	14	77.78%	5	62.50%	9	90.00%
Immediate Success	11	78.57%	4	80.00%	7	77.78%
Delayed Success	3	21.43%	1	20.00%	2	22.22%

Table 4.2f: Outcome Analysis of RSI Divergences for 1-7 Days On LIBERTSHOE

Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
29/08/2002	12/09/2002	7	Buy	No	0	No	Failed

08/07/2003	16/07/2003	5	Sell	No	0	No	Failed
22/01/2004	04/02/2004	6	Buy	Yes	0	NA	05/02/2004
06/10/2006	16/10/2006	5	Sell	Yes	0	NA	17/10/2006
20/11/2006	28/11/2006	5	Buy	Yes	0	NA	29/11/2006
06/08/2007	17/08/2007	7	Sell	No	2	Yes	22/08/2007
25/05/2009	04/06/2009	7	Sell	Yes	0	NA	05/06/2009
22/09/2009	06/10/2009	7	Sell	Yes	0	NA	07/10/2009
12/08/2010	24/08/2010	7	Sell	Yes	0	NA	25/08/2010
09/08/2011	19/08/2011	6	Buy	Yes	0	NA	22/08/2011
26/06/2013	08/07/2013	7	Buy	No	0	No	Failed
27/04/2015	07/05/2015	6	Buy	No	0	No	Failed
02/09/2016	14/09/2016	5	Buy	Yes	0	NA	15/09/2016
27/01/2017	06/02/2017	6	Sell	Yes	0	NA	07/02/2017
05/11/2018	14/11/2018	5	Sell	Yes	0	NA	15/11/2018
25/11/2019	03/12/2019	5	Sell	Yes	0	NA	04/12/2019
15/02/2023	27/02/2023	7	Buy	No	19	Yes	28/03/2023
12/06/2024	24/06/2024	6	Sell	No	12	Yes	11/07/2024

Table 4.2g: List of Observations In 1-7 Days Duration On LIBERTSHOE

Out of 18 total divergences formed in 1-7 days, 4 failed, accounting for 22.22% of all cases in this range. Among these, 3 were bullish (37.50% of bullish cases), while only 1 was bearish (10.00% of bearish cases). 14 succeeded, representing 77.78% of the total. Of these, 5 were bullish (62.50% of bullish cases), and 9 were bearish (90.00% of bearish cases).

Among the successful divergences, 11 achieved immediate success, comprising 78.57% of all successful cases. This includes 4 bullish divergences (80.00% of successful bullish cases) and 7 bearish divergences (77.78% of successful bearish cases). 3 exhibited delayed success, making up 21.43% of all successful cases. Of these, 1 was bullish

(20.00% of successful bullish cases), and 2 were bearish (22.22% of successful bearish cases).

This analysis suggests that divergences forming within 1-7 days are more likely to succeed, particularly in bearish scenarios. Immediate success is more common than delayed success, especially among bearish divergences. Bullish divergences, however, show a higher failure rate and a relatively balanced occurrence of immediate and delayed success within this timeframe.

Table 4.2h provides insights into the performance of divergences that took 8-14 days to form, categorizing them into bullish and bearish scenarios.

8-14 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	30	100.00%	13	100.00%	17	100.00%
Failed	4	13.33%	1	7.69%	3	17.65%
Success	26	86.67%	12	92.31%	14	82.35%
Immediate Success	21	80.77%	10	83.33%	11	78.57%
Delayed Success	5	19.23%	2	16.67%	3	21.43%

Table 4.2h: Outcome Analysis of RSI Divergences for 8-14 Days On LIBERTSHOE

Start Date	**Confirmation Date**	**Formation Duration**	**Trade Type**	**Immediate Success**	**Extended Duration**	**Delayed Success**	**Trade Date**
25/04/2000	10/05/2000	9	Buy	No	8	Yes	23/05/2000
10/05/2000	23/05/2000	8	Buy	Yes	0	NA	24/05/2000
09/08/2002	29/08/2002	11	Buy	No	0	No	Failed
20/06/2003	08/07/2003	11	Sell	No	0	No	Failed
05/04/2004	22/04/2004	10	Sell	Yes	0	NA	23/04/2004
25/01/2005	11/02/2005	11	Sell	Yes	0	NA	14/02/2005
08/10/2007	22/10/2007	9	Sell	No	0	No	Failed
01/07/2008	16/07/2008	10	Buy	Yes	0	NA	17/07/2008

10/10/2008	27/10/2008	10	Buy	Yes	0	NA	28/10/2008
23/07/2009	05/08/2009	8	Sell	Yes	0	NA	06/08/2009
03/09/2009	22/09/2009	11	Sell	No	7	Yes	06/10/2009
24/02/2011	15/03/2011	11	Buy	Yes	0	NA	16/03/2011
05/05/2011	26/05/2011	14	Buy	Yes	0	NA	27/05/2011
14/06/2011	30/06/2011	11	Sell	No	16	Yes	25/07/2011
27/07/2012	14/08/2012	10	Buy	Yes	0	NA	16/08/2012
10/09/2012	01/10/2012	13	Sell	Yes	0	NA	03/10/2012
20/05/2013	04/06/2013	10	Sell	Yes	0	NA	05/06/2013
07/07/2014	22/07/2014	10	Sell	Yes	0	NA	23/07/2014
24/08/2015	08/09/2015	11	Buy	Yes	0	NA	09/09/2015
22/12/2015	06/01/2016	9	Sell	Yes	0	NA	07/01/2016
30/05/2016	10/06/2016	8	Sell	Yes	0	NA	13/06/2016
14/09/2016	29/09/2016	10	Buy	Yes	0	NA	30/09/2016
06/08/2018	23/08/2018	10	Sell	Yes	0	NA	24/08/2018
12/02/2019	27/02/2019	10	Buy	Yes	0	NA	28/02/2019
01/07/2021	16/07/2021	10	Sell	No	3	Yes	23/07/2021
11/04/2022	26/04/2022	8	Sell	Yes	0	NA	27/04/2022
10/08/2022	26/08/2022	10	Sell	No	0	No	Failed
27/02/2023	14/03/2023	9	Buy	No	9	Yes	28/03/2023
14/03/2023	28/03/2023	9	Buy	Yes	0	NA	29/03/2023
03/10/2023	16/10/2023	8	Sell	Yes	0	NA	17/10/2023

Table 4.2i: List of Observations In 8-14 Days Duration On LIBERTSHOE

Out of the 30 divergences that formed within 8-14 days, 4 failed, representing 13.33% of all cases in this range. Among these, 1 was bullish (7.69% of bullish cases), and 3 were bearish (17.65% of bearish cases). 26 succeeded, accounting for 86.67% of the total. Of these, 12 were bullish (92.31% of bullish cases), and 14 were bearish (82.35% of bearish cases).

Among the successful divergences, 21 achieved immediate success, comprising 80.77% of all successful cases. This includes 10 bullish divergences (83.33% of successful bullish cases) and 11 bearish divergences (78.57% of successful bearish cases). 5 exhibited delayed success, making up 19.23% of all successful cases. Of these, 2 were bullish (16.67% of successful bullish cases), and 3 were bearish (21.43% of successful bearish cases).

This analysis reveals that divergences forming within 8-14 days have a high likelihood of success, especially in bullish scenarios where the success rate is notably higher. Immediate success is the dominant outcome, with bearish divergences showing a slightly higher tendency for delayed success compared to bullish ones. Overall, both bullish and bearish divergences exhibit strong performance within this timeframe, with only a small percentage resulting in failure.

Table 4.2j illustrates the performance of divergences that took 15-21 days to form, with distinctions made between bullish and bearish scenarios.

15-21 Days	**Both**	**%**	**Bullish**	**%**	**Bearish**	**%**
Total	9	100.00%	4	100.00%	5	100.00%
Failed	3	33.33%	1	25.00%	2	40.00%
Success	6	66.67%	3	75.00%	3	60.00%
Immediate Success	6	100.00%	3	100.00%	3	100.00%
Delayed Success	0	0.00%	0	0.00%	0	0.00%

Table 4.2j: Outcome Analysis of RSI Divergences for 15-21 Days On LIBERTSHOE

Start Date	**Confirmation Date**	**Formation Duration**	**Trade Type**	**Immediate Success**	**Extended Duration**	**Delayed Success**	**Trade Date**
24/09/2002	25/10/2002	19	Buy	Yes	0	NA	28/10/2002

28/02/2003	25/03/2003	15	Sell	Yes	0	NA	26/03/2003
08/07/2004	29/07/2004	15	Buy	Yes	0	NA	30/07/2004
19/07/2005	22/08/2005	21	Sell	No	0	No	Failed
12/12/2007	04/01/2008	15	Sell	Yes	0	NA	07/01/2008
23/11/2011	20/12/2011	16	Buy	Yes	0	NA	21/12/2011
11/01/2012	06/02/2012	16	Sell	No	0	No	Failed
19/06/2019	11/07/2019	15	Buy	No	0	No	Failed
08/06/2020	03/07/2020	18	Sell	Yes	0	NA	06/07/2019

Table 4.2k: List of Observations In 15-21 Days Duration On LIBERTSHOE

Out of the 9 divergences formed within 15-21 days, 3 failed, representing 33.33% of all cases in this range. This includes 1 bullish divergence (25.00% of bullish cases) and 2 bearish divergences (40.00% of bearish cases). 6 succeeded, accounting for 66.67% of the total. Among these, 3 were bullish (75.00% of bullish cases) and 3 were bearish (60.00% of bearish cases).

All successful divergences in this duration achieved immediate success, with, 6 cases showing immediate success, making up 100.00% of all successful cases. This includes 3 bullish divergences (100.00% of successful bullish cases) and 3 bearish divergences (100.00% of successful bearish cases).

There were no instances of delayed success in this timeframe, highlighting that any successful divergences in this period tend to manifest their impact immediately. Overall, while the success rate is lower than in shorter formation durations, the fact that all successes are immediate suggests that once a divergence formed over 15-21 days triggers a price movement, the effect is prompt and decisive. However, the higher failure rate indicates caution when relying on divergences within this timeframe, especially for bearish scenarios.

Table 4.2l highlights the outcomes of divergences that took more than 21 days to form.

>21 Days	Both	%	Bullish	%	Bearish	%
Total	3	100.00%	2	100.00%	1	100.00%
Failed	3	100.00%	2	100.00%	1	100.00%
Success	0	0.00%	0	0.00%	0	0.00%
Immediate Success	0	0	0	0	0	0
Delayed Success	0	0	0	0	0	0

Table 4.2l: Outcome Analysis of RSI Divergences Beyond 21 On LIBERTSHOE

Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
17/08/2007	08/10/2007	34	Sell	No	0	No	Failed
09/12/2010	17/01/2011	26	Buy	No	0	No	Failed
09/05/2019	19/06/2019	27	Buy	No	0	No	Failed

Table 4.2m: List of Observations Beyond 21 Days Duration On LIBERTSHOE

For divergences within this duration, 3 cases were recorded in total, comprising 2 bullish and 1 bearish divergence, each representing 100.00% of their respective categories. All 3 instances failed, with no successful divergences observed. This means that 100.00% of both bullish and bearish divergences failed to result in the anticipated price movement.

There were no immediate or delayed successes within this timeframe, as all attempts to capitalize on divergences formed over this extended duration did not yield favourable results.

This data suggests a significant challenge when relying on RSI divergences that take longer than 21 days to form for Liberty Shoes stock, as none of these instances have led to a successful price reversal or continuation. Consequently, traders may want to exercise caution or avoid taking positions based on divergences that extend beyond this period.

Table 4.2n provides an analysis of profitability of RSI divergences in LIBERTSHOE after accounting for all transactional costs.

Parameter	Value
Total Number of Trades	60
Successful Trades	46
Failed Trades	14
Stock Price at 01/01/2000	52
Stock Price at 01/01/2024	280
Annual Return From Passive Investment	7.27%
Balance at 01/01/2000	100
Balance at 01/01/2024	13,359
Annual Return From RSI Divergence	22.62%

Table 4.2n: Profitability Analysis of All RSI Divergences On LIBERTSHOE

The stock price increased from 52 in 2000 to 280 in 2024, reflecting strong long-term growth. The annual return from passive investment was 7.27%, showcasing a solid performance over the years. During the simulation with RSI Divergence based trading, starting with a balance of 100, the investment grew to 13,359 by 2024. The annual was substantially higher at 22.62%, illustrating the efficacy of utilizing RSI divergences as a trading strategy, which outperformed passive investment returns.

4.3 Chapter Summary

This chapter presented the empirical findings for both RELIANCE and LIBERTY. The analysis underscores the potential of RSI divergences as effective trading signals, empowering traders with valuable insights. Bullish divergences generally demonstrate higher immediate success and lower failure rates, making them particularly promising. Traders leveraging this strategy for both RELIANCE and LIBERTSHOE stocks could benefit from the insights provided by this statistical analysis. However, caution is advised for longer-duration divergences, particularly bearish ones.

CHAPTER 5: DISCUSSION & CONCLUSION

Th**is chapter discusses the results and provides answers to the questions and hypotheses of the study.** By comparing a highly liquid large-cap stock (RELIANCE) to a smaller and more volatile non-NIFTY 50 stock (LIBERTSHOE), this study explores the impact of liquidity, market capitalization, and investor **behaviour** on the formation and resolution of RSI divergences. The results offer a nuanced understanding of how technical analysis tools such as RSI divergences can be tailored for different stock categories, providing traders with practical and actionable insights to optimize their trading strategies.

5.1 How does the timeframe for divergence formation and extension compare between NIFTY 50 and non-NIFTY 50 stocks?

The comparative analysis of RSI divergence formation durations between NIFTY 50 and non-NIFTY 50 stocks reveals significant insights into the temporal dynamics of technical indicators in different market segments. Specifically, the examination of RELIANCE (a NIFTY 50 stock) and LIBERTSHOE (a non-NIFTY 50 stock) provides a nuanced understanding of how divergence patterns manifest and evolve over time in stocks with differing liquidity and market capitalization.

In analysing the formation durations of RSI divergences, RELIANCE exhibited a total of 107 divergences, with a mean formation duration of approximately 12.71 days. The standard deviation was 6.86 days, indicating moderate variability around the mean. Notably, bearish divergences were more prevalent, accounting for 81 out of the 107 cases, and they tended to form over longer periods compared to bullish divergences. For instance, in durations exceeding 21 days, only bearish divergences were observed, comprising 100% of that category. The skewness of 1.32 and kurtosis of 1.67 for the overall divergences suggest a distribution with a long right tail and a tendency towards more extreme formation durations.

Conversely, LIBERTSHOE demonstrated a total of 60 RSI divergences with a slightly lower mean formation duration of 10.75 days and a standard deviation of 5.64 days. The distribution between bullish and bearish divergences was more balanced in LIBERTSHOE, with bearish divergences making up 33 instances and bullish divergences accounting for 27. Interestingly, the skewness and kurtosis values for LIBERTSHOE were higher (2.04 and 5.17, respectively), indicating a distribution with an even longer right tail and more pronounced peaks. This suggests that while most divergences in LIBERTSHOE formed within a relatively short timeframe, there were instances of significantly longer formation durations, although these were less frequent.

The differences in formation durations between the two stocks can be attributed to their distinct market characteristics. RELIANCE, being a large-cap stock with high liquidity, may experience more gradual price movements, leading to longer periods for divergence patterns to form, especially for bearish divergences. The dominance of bearish divergences in longer durations could reflect prolonged market skepticism or slow transitions in investor sentiment regarding the stock's performance. In contrast, LIBERTSHOE, as a smaller-cap stock, is more susceptible to rapid price changes due to lower liquidity and higher volatility. This can result in quicker formation of both bullish and bearish divergences, as reflected in the higher proportion of divergences forming within 1-14 days.

Examining the extended durations—periods required for the expected price movement to materialize after divergence confirmation—further accentuates the contrasts between the two stocks. RELIANCE had 21 instances where divergences extended before achieving the anticipated price reversal, predominantly bearish divergences (17 out of

21). The mean extended duration was approximately 1.99 days, with a high standard deviation of 4.83 days, indicating significant variability. The skewness and kurtosis values were notably high (2.84 and 8.52, respectively), suggesting that while most extended durations were short, there were outliers with substantially longer delays in price reversal.

In LIBERTSHOE, only 8 divergences required extended durations, with a mean of 1.27 days and a standard deviation of 3.84 days. The distribution of bullish and bearish divergences in this context was relatively even, and the higher skewness and kurtosis values (3.36 and 11.12, respectively) indicate a pronounced presence of extreme values despite the smaller sample size. The shorter mean extended duration implies that price reversals following divergence confirmations occur more swiftly in LIBERTSHOE compared to RELIANCE, aligning with the stock's higher volatility profile.

These findings suggest that the timeframes for divergence formation and subsequent price reversals are influenced by the stock's position within the market hierarchy. NIFTY 50 stocks like RELIANCE, characterized by higher liquidity and institutional investor presence, may exhibit more prolonged periods of divergence formation and delayed price reversals due to the significant capital required to influence price movements. The prevalence of extended durations in bearish divergences may reflect institutional investors gradually adjusting their positions in anticipation of market downturns, leading to slower transitions in price trends.

In contrast, non-NIFTY 50 stocks such as LIBERTSHOE may respond more rapidly to technical signals due to their lower trading volumes and susceptibility to market sentiment shifts among retail investors. The relatively quick formation and resolution of divergences in LIBERTSHOE could be attributed to the agility of retail traders in reacting to technical indicators, as well as the impact of smaller trades on the stock's price.

From a trading strategy perspective, these insights underscore the necessity for investors to tailor their approaches based on the stock category. In NIFTY 50 stocks, traders might need to exercise patience when relying on RSI divergences, accounting for longer formation and confirmation periods. Additionally, the higher likelihood of extended durations before price reversals suggests the importance of incorporating risk management strategies to mitigate potential delays. For non-NIFTY 50 stocks, traders could capitalize on the quicker formation and resolution of divergences but should remain cognizant of the heightened volatility and potential for abrupt market movements.

Moreover, the statistical characteristics of divergence durations highlight the significance of distributional properties in technical analysis. The higher skewness and kurtosis values observed, particularly in the extension durations, indicate that extreme events, although infrequent, can substantially impact trading outcomes. This emphasizes the need for traders to not only consider average durations but also prepare for atypical scenarios where divergences may take significantly longer to manifest or resolve.

Now to answer the question, the comparative analysis reveals that the timeframes for RSI divergence formation and extension differ notably between NIFTY 50 and non-NIFTY 50 stocks. The larger, more liquid NIFTY 50 stock tends to exhibit longer divergence formation and extension durations, especially for bearish signals, reflecting gradual shifts in market sentiment and the influence of large institutional investors. In contrast, the non-NIFTY 50 stock demonstrates quicker divergence dynamics, likely due to its higher volatility and sensitivity to retail investor behaviour. These differences highlight the importance of contextualizing technical analysis within the specific market environment of each stock and adapting trading strategies accordingly to optimize performance and manage risk effectively.

5.2 How does the accuracy of RSI divergences compare between NIFTY 50 and non-NIFTY 50 stocks?

In assessing the overall success rates of RSI divergences, both stocks exhibit remarkably similar performance. RELIANCE recorded a success rate of 78.5%, with 84 out of 107 divergences leading to the expected price movement. LIBERTSHOE closely mirrors this, with a 76.67% success rate, as 46 out of 60 divergences were successful. This indicates that RSI divergences are a generally reliable indicator for predicting price reversals in both NIFTY 50 and non-NIFTY 50 stocks.

Delving deeper into the nature of these divergences, there is a noticeable difference in the distribution of bullish and bearish signals between the two stocks. In RELIANCE, bearish divergences are more prevalent, constituting 81 out of 107 observations (75.7%), whereas LIBERTSHOE has a more balanced distribution, with 33 bearish and 27 bullish divergences. This disparity may stem from the inherent characteristics of the stocks and the sectors they represent, affecting how investors perceive and react to overbought or oversold conditions signalled by the RSI.

When examining the success rates of bullish versus bearish divergences, both stocks show that bullish divergences have a slightly higher success rate. In RELIANCE, bullish divergences succeeded 88.46% of the time compared to 75.31% for bearish divergences. LIBERTSHOE presents a similar trend, with bullish divergences succeeding 74.07% of the time versus 78.79% for bearish divergences. This suggests that bullish divergences might be marginally more reliable indicators of upcoming price increases, possibly due to market participants' propensity to respond more vigorously to oversold conditions.

The analysis of immediate versus delayed successes provides further nuance to the efficacy of RSI divergences. In RELIANCE, 75% of the successful divergences resulted in immediate price reversals, while 25% experienced delayed success. Bullish divergences were more likely to lead to immediate success (82.61%) compared to bearish divergences (72.13%). LIBERTSHOE exhibited a higher proportion of immediate successes at 82.61%, with bullish and bearish divergences resulting in immediate reversals 85% and 80.77% of the time, respectively. The higher rate of immediate successes in LIBERTSHOE could be indicative of the stock's greater volatility and responsiveness to technical indicators.

Analysing the impact of divergence formation duration on success rates reveals insightful patterns. For divergences forming within 1-7 days, both stocks show high success rates, with RELIANCE at 75% and LIBERTSHOE at 77.78%. This suggests that shorter formation durations might be associated with stronger and more reliable signals. Notably, in RELIANCE, all bullish divergences within this timeframe were successful, highlighting the potency of quick-forming bullish signals in highly liquid stocks.

In the 8-14 day formation duration, both stocks maintain high success rates, with RELIANCE at 83.33% and LIBERTSHOE at 86.67%. This indicates that divergences forming over this moderate timeframe are still effective predictors of price movements. The proportion of delayed successes increases slightly in this category, particularly in RELIANCE, where delayed successes account for 26.67% of successful divergences, compared to 19.23% in LIBERTSHOE. This could reflect a more cautious market response to divergences that take longer to form.

For divergences forming over longer durations (15-21 days), the success rates begin to decline. RELIANCE's success rate drops to 70.59%, and LIBERTSHOE's to 66.67%. Additionally, all successful divergences in LIBERTSHOE during this period resulted in immediate success, whereas RELIANCE still exhibited a significant proportion of delayed successes (41.67%). This suggests that in non-NIFTY 50 stocks, longer formation durations might not diminish the immediacy of the market's reaction to divergences as much as in NIFTY 50 stocks.

An interesting observation emerges when considering divergences that take more than 21 days to form. In RELIANCE, all divergences in this category were bearish, with a success rate of 75%. However, in LIBERTSHOE, none of the divergences extending beyond 21 days were successful. This stark contrast could be due to the differing market dynamics and investor behaviours in large-cap versus small-cap stocks. In NIFTY 50 stocks like RELIANCE, prolonged bearish divergences might still carry weight with investors, potentially due to the extensive analysis and deliberation that often accompany investment decisions in such stocks. In contrast, the lack of success in LIBERTSHOE's long-duration divergences might reflect the market's diminishing confidence in signals that take excessive time to form, possibly due to the rapid information flow and quick trading cycles in smaller-cap stocks.

The higher failure rates associated with longer formation durations underscore the importance of considering the timing aspect in technical analysis. Traders relying on RSI divergences in NIFTY 50 stocks should be cautious with signals that take longer to develop, especially bearish ones, as they may still yield successful outcomes but possibly with delays. In non-NIFTY 50 stocks, prolonged divergences, particularly those exceeding 21 days, may warrant scepticism due to their lower likelihood of success.

The distribution of immediate versus delayed successes also provides practical implications for trading strategies. The higher proportion of immediate successes in both stocks, especially in shorter formation durations, suggests that traders can capitalize on prompt price reversals following divergence confirmations. However, the presence of delayed successes indicates that patience and effective risk management are essential, as some divergences may take additional time to influence price movements.

Furthermore, the slightly higher overall success rates of bearish divergences in LIBERTSHOE (78.79%) compared to bullish ones (74.07%) could imply that traders might achieve marginally better results by focusing on bearish signals in non-NIFTY 50 stocks. This could be attributed to the market's propensity to react more swiftly to negative news or overbought conditions in smaller-cap stocks, where sentiment can shift rapidly.

In contrast, the higher success rate of bullish divergences in RELIANCE (88.46%) suggests that upward price reversals signalled by bullish divergences are particularly reliable in NIFTY 50 stocks. This might reflect the general long-term upward trend in large-cap stocks due to consistent institutional investment and overall market growth, making bullish signals more dependable.

The comparative analysis highlights that while RSI divergences are generally effective predictors of price movements in both NIFTY 50 and non-NIFTY 50 stocks, subtle differences exist in their accuracy and timing based on the stock category. NIFTY 50 stocks exhibit a higher success rate for bullish divergences and a greater incidence of delayed successes, especially in divergences with longer formation durations. Non-NIFTY 50 stocks demonstrate slightly higher success rates for bearish divergences and a tendency for immediate successes, reflecting their volatility and the rapid response of the market to technical signals.

These findings emphasize the necessity for traders and analysts to adapt their use of RSI divergences based on the specific characteristics of the stock in question. In NIFTY 50 stocks, greater emphasis might be placed on bullish divergences and accounting for potential delays in price reversals. In non-NIFTY 50 stocks, traders might focus more on bearish divergences and expect quicker market reactions, adjusting their strategies accordingly.

Moreover, the influence of divergence formation duration on success rates suggests that traders should consider the timeframe over which a divergence forms as a factor in their analysis. Shorter formation durations generally correlate with higher success rates and more immediate price reversals, offering opportunities for swift trading actions. Longer formation durations, while still potentially successful, may require more cautious approaches and robust risk management to accommodate possible delays or failures.

Now to answer the question, the accuracy of RSI divergences shows notable similarities between NIFTY 50 and non-NIFTY 50 stocks, with overall success rates hovering around 77-78%. However, differences emerge in the distribution of bullish and bearish divergences, the impact of formation duration on success rates, and the immediacy of price reversals following divergence confirmations. These variations underscore the importance of tailoring technical analysis strategies to the specific market context, considering factors such as stock liquidity, market capitalization, and typical investor behaviour associated with different stock categories. By doing so, traders and analysts can enhance the effectiveness of RSI divergences as a tool for predicting price movements and making informed trading decisions.

5.3 Does RSI divergence, while accounting for all transactional costs, lead to profitable outcomes in both NIFTY 50 and non-NIFTY stocks?

The simulation results indicate that trading strategies based on RSI divergences are profitable for both NIFTY 50 and non-NIFTY 50 stocks, even after accounting for all transactional costs. However, the magnitude of profitability differs between the two stocks, with RELIANCE generating an annualized return of approximately 40.35%, compared to 22.62% for LIBERTSHOE.

A major reason behind this can be that RELIANCE had a higher number of trading opportunities (107 trades) compared to LIBERTSHOE (60 trades). This increased frequency allowed for greater capital turnover and the compounding of returns, thereby enhancing overall profitability. In other words, while both stocks exhibited similar success rates (78.5% for RELIANCE and 76.67% for LIBERTSHOE), the absolute number of successful trades was higher for RELIANCE, contributing to greater cumulative gains.

Secondary reason that may explain such results can be that RELIANCE, as a NIFTY 50 stock, benefits from higher liquidity and tighter bid-ask spreads, which can reduce the impact of transactional costs and slippage. This efficiency in execution may enhance net returns compared to less liquid stocks like LIBERTSHOE.

Apart from this, the stop loss was standardized at 2% and target level at 20% to filter outliers. However, the underlying volatility and price movement patterns may differ, influencing the ease with which target profits are achieved or stop loss is hit.

Transactional costs play a significant role in determining net profitability. These costs erode gross profits and exacerbate losses, especially in failed trades where the stop-loss is triggered. For example, the gross loss on a failed trade is 2% due to the stop-loss, but the net loss becomes 2.78% after including transactional costs.

The high success rates of RSI divergences help mitigate the impact of transactional costs. The consistent generation of profits from successful trades outweighs the cumulative costs and losses from failed trades. This underscores the importance of maintaining a high accuracy rate in trading strategies to ensure profitability after expenses.

Allocating 100% of the portfolio capital to each trade amplifies the effects of compounding. Profits from each successful trade are reinvested, leading to exponential growth in capital over the study period. However, this approach also increases exposure to risk, as a series of failed trades could significantly deplete the portfolio. The inclusion of stop-loss orders helps manage this risk by capping potential losses on any single trade.

The annualized returns of 40.35% for RELIANCE and 22.62% for LIBERTSHOE outperform traditional investment benchmarks such as fixed deposits, government bonds, and even some mutual funds. For context, the average annual return of the NIFTY 50 index over the past decade has been approximately 14%. The trading strategy based on RSI divergences thus offers superior returns, albeit with higher associated risks.

The profitability demonstrated in the simulation suggests that traders can potentially achieve significant returns by employing RSI divergence strategies, provided they adhere to disciplined risk management practices. The higher returns in RELIANCE indicate that NIFTY 50 stocks may offer more lucrative opportunities due to their liquidity and the reliability of technical signals. However, traders should remain cognizant of the risks involved, including market volatility, the potential for unexpected price movements, and the limitations of technical indicators.

Moreover, the success of the strategy hinges on timely and accurate identification of RSI divergences, as well as effective execution of trades. Delays in entering or exiting positions can erode profitability, especially in fast-moving markets. Therefore, traders should ensure they have access to real-time data and efficient trading platforms.

Now to answer the question, The trading simulation demonstrates that RSI divergence strategies can lead to profitable outcomes in both NIFTY 50 and non-NIFTY 50 stocks after accounting for all transactional costs. The higher annualized returns achieved with RELIANCE suggest that such strategies may be more effective with highly liquid, large-cap stocks. However, profitability is also attainable with non-NIFTY 50 stocks like LIBERTSHOE, albeit to a lesser extent.

5.4 Concluding The Research Hypotheses

Based on the comprehensive analysis conducted in this study, we can draw definitive conclusions regarding the proposed hypotheses concerning the effectiveness and characteristics of RSI divergences in predicting stock trend reversals and their profitability in both NIFTY 50 and non-NIFTY 50 stocks.

H1.1: RSI divergence reliably predicts stock trend reversals in both NIFTY 50 and non-NIFTY 50 stocks.

The investigation into the predictive reliability of RSI divergences revealed that both NIFTY 50 and non-NIFTY 50 stocks exhibit high success rates when utilizing this technical indicator. Specifically, the analysis of RELIANCE (a NIFTY 50 stock) demonstrated an overall success rate of 78.5%, with 84 out of 107 observed divergences leading to the expected price movement. Similarly, LIBERTSHOE (a non-NIFTY 50 stock) showed a success rate of 76.67%, with 46 out of 60 divergences resulting in successful trend reversals.

These high success rates indicate that RSI divergences are robust predictors of stock trend reversals across different market segments. The minor variation in success rates between the two stocks is negligible, suggesting that the reliability of RSI divergences is consistent irrespective of a stock's inclusion in the NIFTY 50 index.

Conclusion: The findings support H1.1, confirming that RSI divergence reliably predicts stock trend reversals in both NIFTY 50 and non-NIFTY 50 stocks.

H1.2: RSI divergences typically form and signal trend reversals within similar timeframes in both NIFTY 50 and non-NIFTY 50 stocks.

The comparative analysis of formation durations for RSI divergences revealed some similarities as well as notable differences between the two stock categories. The mean formation duration for RELIANCE was approximately 12.71 days, while LIBERTSHOE exhibited a slightly shorter mean duration of 10.75 days. Although the difference of roughly two days suggests a degree of similarity, the distribution of formation durations indicates variations in how divergences develop over time.

RELIANCE showed a higher frequency of divergences forming over longer durations, particularly in the 8-14 day and >21 day categories, with bearish divergences dominating the longer timeframes. In contrast, LIBERTSHOE had a more balanced distribution of divergences across shorter durations, with fewer instances extending beyond 21 days and none successfully predicting trend reversals in that category.

Despite these differences, the overall pattern indicates that RSI divergences in both stock types generally form within a comparable range of timeframes, predominantly within 1-14 days. The slight discrepancies can be attributed to inherent market characteristics such as liquidity and volatility.

Conclusion: H1.2 is partially supported. While RSI divergences in both NIFTY 50 and non-NIFTY 50 stocks typically form within similar timeframes, some differences exist in the distribution and duration of divergences, influenced by the specific characteristics of each stock.

H1.3: Certain types of RSI divergences demonstrate higher predictive reliability in both NIFTY 50 and non-NIFTY 50 stocks.

The analysis identified variations in the predictive reliability of bullish versus bearish RSI divergences within each stock category. In RELIANCE, bullish divergences exhibited a higher success rate of 88.46%, compared to 75.31% for bearish divergences. This suggests that bullish divergences are more reliable predictors of upward trend reversals in NIFTY 50 stocks.

Conversely, in LIBERTSHOE, bearish divergences demonstrated a slightly higher success rate of 78.79%, compared to 74.07% for bullish divergences. This indicates that in non-NIFTY 50 stocks, bearish divergences may be marginally more reliable in forecasting downward trend reversals.

These findings imply that certain types of RSI divergences indeed have higher predictive reliability, and this trend is observable in both stock categories, although the specific type (bullish or bearish) with higher reliability differs between NIFTY 50 and non-NIFTY 50 stocks.

Conclusion: The evidence supports H1.3, affirming that certain types of RSI divergences demonstrate higher predictive reliability in both NIFTY 50 and non-NIFTY 50 stocks, with the specific type varying based on stock characteristics.

H1.4: Trading strategies based on reliable RSI divergences remain profitable after accounting for all transactional costs in both NIFTY 50 and non-NIFTY 50 stocks.

The profitability assessment conducted through a simulated trading analysis revealed that RSI divergence-based trading strategies yield positive returns in both stock categories, even after factoring in all transactional costs.

For RELIANCE, the trading strategy resulted in an annualized return of approximately 40.35%. This substantial return indicates that the strategy is highly profitable for NIFTY 50 stocks.

In the case of LIBERTSHOE, the annualized return was approximately 22.62%. While lower than that of RELIANCE, this return still signifies a profitable outcome, outperforming traditional investment benchmarks.

These results confirm that trading strategies based on RSI divergences can remain profitable in both NIFTY 50 and non-NIFTY 50 stocks, despite the differences in market dynamics and stock-specific factors. The consistent profitability across both categories underscores the effectiveness of RSI divergences as a foundation for trading strategies when proper risk management and cost considerations are in place.

Conclusion: The findings substantiate H1.4, confirming that trading strategies based on reliable RSI divergences remain profitable after accounting for all transactional costs in both NIFTY 50 and non-NIFTY 50 stocks.

5.5 RSI Divergence Within the EMH Framework

The Efficient Market Hypothesis (EMH) posits that financial markets are "informationally efficient," meaning that asset prices fully reflect all available information at any given time (Fama, 1970). Under the EMH, especially in its weak form, past price movements and trading volumes should have no bearing on future price movements because any patterns or trends would already be exploited by market participants. This presents a theoretical challenge to the effectiveness of technical analysis tools, such as the Relative Strength Index (RSI) and its divergence patterns, which rely on historical price data to predict future movements.

However, the EMH assumes that all market participants have equal access to information and interpret it rationally and instantaneously. In practice, this is rarely the case. Information asymmetry, cognitive biases, and varying levels of analytical expertise can lead to situations where not all available information is fully reflected in asset prices. This creates opportunities for technical analysis methods to identify inefficiencies and potential trading opportunities.

RSI divergence occurs when the momentum of an asset's price, as indicated by the RSI, moves in a different direction from the actual price trend. For example, during a bullish divergence, the price makes lower lows while the RSI makes higher lows, suggesting a potential reversal from a downtrend to an uptrend. This divergence between price and momentum indicates that the underlying strength of the price movement is weakening, even if the price has not yet reflected this change.

Within the context of the EMH, the existence of RSI divergence implies that all information may not be fully integrated into the asset's price, or that market participants have not recognized or acted upon this information. If markets were perfectly efficient, such divergences would not persist because rational investors would immediately trade on this information, correcting any mispricing. However, the presence of RSI divergence suggests that inefficiencies exist, allowing traders who can identify and interpret these signals to potentially achieve above-average returns.

5.6 Reconciling EMH with RSI Divergence Findings

The apparent contradiction between the EMH and the positive results of RSI divergence studies can be reconciled by considering several factors:

The EMH assumes that all investors process information rationally and instantaneously, but in reality, there are limitations to human cognition and information processing capabilities. Behavioral finance studies have shown that investors often exhibit cognitive biases, such as overconfidence, anchoring, and herd behavior, which can lead to suboptimal decision-making (Barberis & Thaler, 2003). These biases can delay the incorporation of new information into asset prices, creating short-term inefficiencies that technical analysis can exploit.

Financial markets consist of a diverse range of participants, including institutional investors, retail traders, algorithmic trading systems, and others. This diversity means that not all participants have equal access to information or the same ability to interpret and act on it. For example, institutional investors may have sophisticated models and resources to identify RSI divergence, while retail traders may lack the expertise or tools to do so. This heterogeneity among market participants can lead to temporary inefficiencies that persist until the information is fully disseminated and acted upon.

RSI Divergence can extend to long periods of time before a reversal actually happens. Market acts irrationally and can keep doing to till an average investor goes bankrupt. A rational investor may choose not to act, allowing the inefficiency to persist (Grossman & Stiglitz, 1980). This provides a window of opportunity for traders who are willing to accept higher risks and go against the trend.

5.7 Reasons for Limited Empirical Studies on RSI Divergence

Despite the potential significance of RSI divergence in predicting market movements, only a few studies, notably Bansal (2023) and Khatavkar (2024), have emphatically tested its effectiveness. Several reasons may explain the limited number of empirical studies:

The dominance of the EMH in academic finance has historically led to skepticism towards technical analysis. Many scholars have regarded technical analysis as unscientific or akin to pseudoscience, focusing instead on fundamental analysis or quantitative models based on financial statements and macroeconomic indicators. This skepticism has resulted in fewer academic studies exploring technical indicators like RSI divergence.

Analyzing RSI divergence requires high-quality, high-frequency data and sophisticated analytical methods to accurately identify divergence patterns. Collecting and processing such data can be resource-intensive, potentially limiting the number of researchers who undertake such studies. Moreover, the subjective nature of identifying divergence patterns may introduce methodological challenges and inconsistencies across studies.

There may be a publication bias in academic journals favoring studies that support established theories like the EMH. Research that contradicts these theories or supports technical analysis may face higher scrutiny or be deemed less rigorous, reducing the likelihood of publication (Malkiel, 2003). This bias can discourage researchers from pursuing or submitting studies on RSI divergence.

Financial markets have evolved significantly with advancements in technology, algorithmic trading, and increased market globalization. Studies conducted in earlier periods (Wilder, 1976) may not reflect current market dynamics, leading to a temporal gap in the literature. Researchers may hesitate to draw conclusions from outdated data or may find it challenging to compare results across different time periods.

5.8 Implications for Traders and Future Research

It's important to recognize that the effectiveness of RSI divergence does not necessarily invalidate the EMH entirely. Instead, it highlights the limitations of the hypothesis in accounting for real-world complexities, such as behavioral biases, information asymmetries, and market frictions. By acknowledging these limitations, researchers and practitioners can develop more nuanced models that integrate elements of both efficient market theory and behavioral finance.

Traders should be aware that while RSI divergence can signal potential trend reversals, it is not foolproof. Incorporating risk management strategies, such as stop-loss orders and position sizing, is essential.

Using RSI divergence in conjunction with other technical indicators or fundamental analysis may improve the reliability of trading signals.

Understanding the market conditions and characteristics of specific stocks (e.g., liquidity, volatility) can help traders determine where RSI divergence is more likely to be effective.

5.9 Future Research

Future studies could explore RSI divergence across different markets, asset classes, and time periods to assess its generalizability.

Investigating the behavioral factors that contribute to the persistence of RSI divergence signals can deepen the understanding of market inefficiencies.

Developing standardized methods for identifying and measuring RSI divergence can enhance the comparability and robustness of empirical studies.

5.10 Closing Thoughts

The analysis conducted throughout this study provides strong evidence in support of the proposed hypotheses. RSI divergences have been demonstrated to be reliable predictors of stock trend reversals in both market segments, with high success rates affirming their effectiveness. While there are minor differences in the formation durations and the types of divergences that exhibit higher reliability, the overarching conclusion is that RSI divergences function as a valuable tool for traders across different stock categories.

Moreover, the profitability assessment affirms that strategies based on RSI divergences can yield substantial returns after accounting for all transactional costs. This profitability holds true for both NIFTY 50 and non-NIFTY 50 stocks, highlighting the practical applicability of RSI divergences in real-world trading scenarios.

These conclusions reinforce the utility of technical analysis and RSI divergences in particular, advocating for their inclusion in trading strategies and investment decision-making processes. The findings encourage further exploration and refinement of such strategies to enhance their effectiveness and adaptability to various market conditions.

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