

STRUCTURAL LEADING DIVERGENCE (SLD): A NOVEL APPROACH FOR
RSI DIVERGENCE DETECTION WITH ZERO REPAINTING BEHAVIOUR

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DEDICATION

This dissertation is dedicated to Dr. Sagar Bansal, whose guidance provided this research with discipline, structure, and causal clarity.

You repeatedly stressed throughout this work that, similar to research outcomes, market outcomes are shaped by underlying structure, process, and accountability rather than by isolated events. Your insistence on analytical accuracy, logical causality, and methodological rigor led this study beyond cursory observations to more in-depth, convincing conclusions.

Your willingness to participate directly, provide frank feedback, and maintain unwavering academic standards in situations limited by time and complexity reinforced a key finding of this study: meaningful results only arise when assumptions are tested, signals are validated, and shortcuts are resisted.

These ideas are reflected in this dissertation. I dedicate this work to you in recognition of the standards you uphold, the intellectual clarity you require, and the role you play as a mentor dedicated to conducting research ethically.

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This dissertation is the result of a demanding academic journey that was molded by tenacity, intellectual discipline, and the assistance of numerous people and organizations. I genuinely thank everyone who helped to finish this work, whether directly or indirectly.

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I am appreciative of the Swiss School of Business and Management, Geneva, for offering a helpful scholarly framework that made this study possible. I also thank the professors and assessors whose comments improved the dissertation's analytical depth and empirical rigor.

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Lastly, I would like to thank the larger academic and professional communities whose research and ideas influenced and shaped this study.

ABSTRACT

STRUCTURAL LEADING DIVERGENCE (SLD): A NOVEL APPROACH FOR RSI DIVERGENCE DETECTION WITH ZERO REPAINTING BEHAVIOUR

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This research examined the reliability, timeliness, and causal validity of Relative Strength Index (RSI) divergence as a market-reversal signal in the Indian equity market, focusing on the NIFTY 50 index from 2000–2025. Despite the widespread use of RSI divergence, the study found significant drawbacks in current indicators, such as repainting behavior, delayed signal visibility, and limited real-time usability. The study assessed TradingView built-in RSI divergence indicator and a proprietary script, True Leading Indicator (TLI) (Bansal, 2025) to identify momentum shifts, and a new framework created in this study, called Structural Leading Divergence (SLD), using a manually selected analyst benchmark. The findings demonstrated that while TLI was timely, its coverage was restricted, whereas Trading View’s indicator was primarily retrospective. SLD addressed these limitations through causal, non-repainting detection but did not achieve complete benchmark coverage, reflecting an inherent trade-off between early detection and noise suppression. These findings highlight both the practical constraints of divergence detection and its potential when structurally enforced. Future research opportunities may extend SLD across markets, timeframes and portfolio-level assessments.

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CHAPTER 1: INTRODUCTION

Chapter 1 introduces the context and motivation for examining Relative Strength Index (RSI) divergence within the Indian equity market. It describes how traders and algorithmic systems are increasingly depending on technical analysis, and it draws attention to the real-world difficulties in implementing divergence-based indicators in real-time trading settings. The limitations of current RSI divergence approaches are covered in this chapter, with special attention paid to problems with repainting, delayed signal visibility, and market-specific dynamics. The research problem is then stated, along with the main research questions and goals, and the study's academic and practical significance is explained.

1.1 Background and Context

In *New Concepts in Technical Trading Systems* (Wilder Jr., 1978), the Relative Strength Index (RSI), a momentum oscillator designed to measure the magnitude and speed of price movements, was introduced. Since its launch, RSI has grown to be one of the most popular technical indicators for spotting changes in momentum and possible trend reversals. Its origins can be found in the more general field of technical analysis, which stresses the use of past price and volume data to predict future market movements (Murphy, 1999).

Over time, RSI and its applications in a variety of asset classes, such as stocks, commodities, and foreign exchange markets, have been examined in both academic and practitioner-focused literature. RSI is used for purposes other than threshold-based signals, such as divergence-based interpretations, according to foundational texts - *Technical Analysis of the Financial Markets* (Murphy, 1999) and *Japanese Candlestick Charting Techniques* (Nison, 2001).

RSI divergence, which happens when price movement and RSI momentum move in opposite directions, is a more sophisticated use of RSI. Such divergence is frequently seen as a precursor to a possible reversal or weakening of the trend. Although RSI divergence is widely used in technical analysis, the timing at which a trader can observe the signal is critical to its practical reliability. There are issues with repainting and real-time tradability because many widely used divergence indicators rely on retrospective confirmation.

Alongside rising volatility and structural complexity, the National Stock Exchange (NSE) has seen a sharp increase in institutional and retail participation. Consequently, algorithmic systems and discretionary traders make extensive use of technical analysis tools, such as RSI. However, divergence-based structures have received relatively little attention in the majority of NSE-focused studies, which have focused on conventional RSI applications like overbought/oversold thresholds or indicator combinations (e.g., MACD and moving averages).

While recent inquiries into the NSE by Bansal (2023), Vishnoi (2024), and Khataavkar (2024) have substantiated the theoretical relevance of RSI divergence, the extant literature remains constrained by several critical methodological and ontological gaps. Current research frequently uses manual divergence identification, which limits scalability and introduces subjectivity. Moreover, repainting behavior, execution timing, and changing market microstructure are examples of real-world trading constraints that are often underrepresented. Findings from other markets are further limited by the NSE's distinct regulatory environment, investor makeup, and growing algorithmic participation.

Additionally, Vishnoi (2024) contends that RSI divergence continues to be a reliable indicator of trend reversals across various market capitalizations, confirming its effectiveness in both high-liquidity NIFTY 50 constituents and more volatile non-index

stocks. He further maintains that these strategies continue to be economically viable in the modern context, notwithstanding the fact that algorithmic and high-frequency trading have fundamentally disrupted traditional interpretations by modifying established price-volume relationships.

In light of this, the current study specifically addresses RSI divergence as a structural and causal phenomenon as opposed to a visual pattern that occurs after the fact. This study aims to close the gap between theoretical interpretation and real-world application by investigating divergence detection within the NSE under realistic, real-time constraints.

1.2 Problem Statement

This study's main focus is on the usefulness and validity of RSI divergence as a technical indicator for trading and investment decisions in stocks listed on the NSE. Even though people often use this indicator to spot when a market trend is ending or about to reverse, it is only truly useful if a trader can see the signal before the price actually turns around

The confirmation logic used by many divergence indicators implicitly takes future price information into account, which causes repainting and delayed signal visibility. Using TradingView's integrated RSI Divergence indicator in historical replay mode, this limitation is demonstrated.



Figure 1.2a: Structural Formation without Actionable Visibility (Source: Original Work)

Figure 1.2a displays the NIFTY 50 chart on February 15, 2001. Although the price has formed a higher high while the RSI has formed a lower high, satisfying the geometric definition of a bearish divergence but there is no visual signal emitted by the integrated indicator. This represents the structural origin phase, where the pattern exists in "permanent hindsight" but is invisible to the trader in real time because the algorithm is awaiting future price bars for symmetric pivot confirmation.



Figure 1.2b: Retroactive Labeling and the Repainting Effect (Source: Original Work)

Figure 1.2b shows the same chart one week later, on February 22, 2001. A divergence signal has now appeared, but it is backdated to the February 15 candle. This illustrates the visibility landmark. It exposes the look-ahead bias inherent in platform-native tools: the signal only "locks" onto the chart after the right-side of the price pivot has been completed by subsequent trading sessions.



Figure 1.2c: The Exhausted Reversal Window (Source: Original Work)

Figure 1.2c highlights the market state at the moment of detection. By the time the signal becomes visible on February 22, the market reversal has already occurred, and a significant portion of the price recovery is exhausted. This figure quantifies the "Cost of Confirmation." It proves that the signal is non-predictive and serves only as a descriptive annotation of the past rather than a trigger for the future.

This behavior renders the application of RSI divergence fundamentally ambiguous, as signals that appear predictive in retrospect are often invisible at the precise moment trading decisions are required. Such delayed visibility directly impairs profitability from both a trading and investment perspective. Consequently, reliance on non-causal or repainted signals frequently results in poor entry timing, missed opportunities, and unfavorable risk-reward profiles. Within live trading or algorithmic frameworks, these backdated signals can lead practitioners to form unrealistic profit expectations, ultimately resulting in unanticipated financial losses.

This problem carries significant real-world ramifications due to the scale and importance of the National Stock Exchange, where millions of traders and automated systems depend on technical indicators for entry, exit, and risk management decisions. If RSI divergence signals are routinely delayed or repainted, they can overstate strategy profitability, produce misleading backtesting results, and expose market participants to preventable financial risk.

To elucidate the shortcomings of existing indicators and define the requirements for practical and profitable trading, this study conducts a comprehensive assessment of RSI divergence under NSE-specific conditions. The analysis focuses specifically on critical factors such as signal timing, repainting behavior, and real-time tradability.

1.3 Research Questions and Objectives

This research addresses a primary question as: How much do repainting effects or delayed visibility affect widely used RSI divergence indicators?

There is also a secondary question which depends on the primary: Is it possible to identify RSI divergence in a way that is both causally sound and appropriate for algorithmic and real-time trading applications?

Further, the research reconfirms the answers to the following questions: How accurate are RSI divergence signals at spotting price reversals or trend weakening in stocks listed on the NSE? This question has already been answered by Bansal (2023) where the study originally finds that the divergence signals are highly accurate. What effects do various market conditions have on the NSE's RSI divergence signals' efficacy? And What useful lessons can be drawn for investors and traders using the NSE? These questions have also been already answered by Vishnoi (2024) and Khatavkar (2024) where insights on number of days in RSI Divergence formation and extension, Bullish vs Bearish type

signals, etc. are the primary factors. However, the present study reconfirms these results as the procedures repeat for the answering the primary and secondary question of the present study. Hence the objectives of this study are:

1. To use a benchmark determined by analysts to assess the dependability of RSI divergence signals in the NSE.
2. To investigate the repainting behavior and timing properties of popular RSI divergence indicators.
3. To create and assess a real-time, causally constrained RSI divergence detection framework.
4. To determine whether incorporating divergence-based signals into algorithmic trading environments is feasible.
5. To add NSE-specific evidence to the technical analysis literature and offer practitioners empirically based guidance.

1.4 Significance of the Study

This study is significant for both academic scholarship and market practitioners because it addresses a critical gap between the theoretical conceptualization of RSI divergence and its practical implementation in contemporary financial markets. Although RSI divergence is frequently mentioned in technical analysis literature and trading practice, its efficacy has frequently been taken for granted without giving enough thought to signal timing, repainting behavior, and actual trading constraints. This research adds to a more precise and practical understanding of divergence-based technical signals by specifically looking at these factors within the framework of the National Stock Exchange (NSE).

By redefining RSI divergence as a structural and causative phenomenon as opposed to a retroactive visual pattern, the study contributes to the body of knowledge in technical

analysis. It challenges traditional backtesting techniques that ignore repainting and future-bar dependency and emphasizes the significance of causality and signal observability when assessing technical indicators. The results expand the applicability of technical analysis research to emerging market contexts by adding NSE-specific empirical evidence to a body of literature that has mostly concentrated on developed markets.

The study directly affects traders, portfolio managers, and algorithmic trading practitioners from a practical perspective. The study highlights the need for causally valid, real-time detectable signals by showing how non-causal divergence indicators can skew perceived profitability and result in less-than-ideal or losing trading decisions. The study's evaluation framework gives practitioners a methodical way to evaluate the tradability and dependability of technical indicators prior to implementing them in automated systems or live trading.

The study is also important for investor education and risk management. Market participants can improve their decision-making under uncertainty and steer clear of false confidence derived from retrospective signals by having a better understanding of the limitations of widely used RSI divergence indicators. The study emphasizes how crucial it is to match indicator logic with real-time market constraints for algorithmic trading and system design in order to create trading strategies that are reliable and resilient.

Overall, by bridging the gap between indicator theory, empirical validation, and practical trading applicability, this research supports more disciplined, transparent, and risk-aware participation in the Indian equity markets and helps the NSE make better use of technical analysis.

1.5 Chapter Summary

This chapter introduces the context, motivation, and scope of the research on Relative Strength Index (RSI) divergence within the Indian equity market, with a specific focus on the National Stock Exchange (NSE). The conceptual underpinnings of RSI and divergence-based analysis are described, along with the extensive application of these tools in technical trading and the drawbacks related to real-time observability, repainting behavior, and signal timing.

The chapter outlines the main research question regarding the usefulness of RSI divergence indicators, especially when used in realistic trading scenarios. It shows, through illustrative examples, how widely used divergence indicators can be dependent on future price confirmation, producing backdated or delayed signals that have an immediate impact on trading decisions and profitability. Then, in order to direct a methodical assessment of RSI divergence under NSE-specific circumstances, the research questions and objectives are introduced.

The chapter concludes with an explanation of the study's academic and practical significance, highlighting its relevance for traders, investors, and algorithmic system designers as well as its contribution to the literature on technical analysis through a causality-aware evaluation framework. These components work together to lay the groundwork for the following chapters, which present empirical findings, outline the research methodology, and review pertinent literature.

1.6 Structure of the Dissertation

Six chapters make up this dissertation, each of which methodically builds on the one before it to provide a cogent analysis of Relative Strength Index (RSI) divergence in the Indian equity market. The structure is intended to lead the reader through

methodological design, empirical evaluation, result interpretation, and final conclusions, starting with conceptual underpinnings and existing literature.

Chapter 2: Literature Review presents a comprehensive review of scholarly and practitioner-oriented literature related to technical analysis, RSI, and divergence-based trading strategies. It looks at underlying theories, empirical data from international markets, and earlier research on the Indian stock market. The intellectual foundation for the current study is established by this chapter, which highlights important gaps in the literature, especially with regard to repainting behavior, signal causality, and real-time observability of RSI divergence.

Chapter 3: Research Methodology outlines the methodological framework adopted in this research. It explains how to create a manually selected analyst benchmark, what criteria are applied to identify divergence, and how to compare different divergence detection strategies. The application of replay-based simulation, the creation and function of an exploratory prototype based on Python, and the deployment of a causally constrained divergence detector based on Pine Script are all covered in detail in this chapter. To guarantee openness and reproducibility, data sources, assessment methods, and analytical presumptions are provided.

Chapter 4: Results and Analysis presents the empirical findings of the study. In comparison to the analyst benchmark, this chapter assesses the timing, repainting behavior, and alignment of various RSI divergence indicators. Through profitability-oriented analysis conducted under realistic trading constraints, it further investigates the practical implications of signal visibility. The findings offer proof of the shortcomings of widely used indicators as well as the circumstances in which divergence signals could have operational significance.

Chapter 5: Discussion interprets the empirical results in relation to the research questions and existing literature. It talks about how technical analysis theory, trading, and algorithmic system design are affected by causality, repainting, and signal timing. This chapter highlights how the findings expand and improve upon our current understanding of divergence-based strategies by placing them within larger discussions on market efficiency and indicator validity.

Chapter 6: Conclusion summarizes the key findings and contributions of the research. The study's theoretical and practical significance is reaffirmed, limitations pertaining to data scope and methodological decisions are discussed, and future research directions are outlined, including extensions to other markets, timeframes, and portfolio-level applications. Thoughts on the wider ramifications of causality-aware technical indicators for risk-aware and disciplined financial market participation round out the chapter.

CHAPTER 2: LITERATURE REVIEW

Chapter 2 presents a comprehensive and structured review of the scholarly literature underpinning technical analysis and the Relative Strength Index (RSI), which form the theoretical and empirical foundation of this dissertation. An introduction to technical analysis, covering its fundamental ideas, underlying presumptions, and theoretical positioning within financial market research, opens the chapter. In addition to addressing the main objections and continuing discussions regarding technical trading strategies' efficacy, it then looks at how technical analysis is applied in trading and investment contexts, the standards and metrics frequently used to assess these strategies, and the empirical data on their profitability. The chapter builds on this basis by examining the Relative Strength Index (RSI) in particular, including its methodological development, configuration options, and strategic application in trading systems. With special attention to evidence from international markets and the Indian equity market, the literature on RSI-based strategies is examined across a variety of markets and asset classes. The chapter ends by summarizing the reviewed findings, pointing out methodological flaws and discrepancies in previous RSI and RSI-divergence studies, and providing justification for the causal, benchmark-aligned RSI divergence framework that will be created and assessed in the dissertation's later chapters.

2.1 Overview of the Literature

In the continuously evolving domain of financial markets, all the market participants would want the various types of methodologies and tools which can provide the right kind of information about discovering the price movements in advance and taking informed trading decisions. Out of all the available approaches related to the market analysis, the one which stands out is the technical analysis because it depends on the

principle that historical and volume data encompass the relevant information and that market trends, once established, continue to persist. This methodology avoids the deep analysis into fundamental factors like company's earnings, economic indicators or geopolitical events but it focuses on the patterns, trends, and statistical tendencies which are observable from market activity charts. The proponents of technical analysis often argue that the chart patterns and indicator signals offer clues to future market direction. Within the available technical indicators, momentum oscillators like Relative Strength Index play a vital role by trying to measure the speed and strength of price changes and identify potential overbought or oversold conditions that might give a clue to a trend reversal or a pause in the current path or direction of the market.

Like cited earlier, Wilder Jr. (1978) mentioned about the Relative Strength Index (RSI) in his book, "New Concepts in Technical Trading Systems". This momentum oscillator is arguably one of the most popular and widely used momentum oscillators in the global trading community. Its popularity originated because of its perceived efficacy in various market conditions, intuitive interpretation and relatively straightforward calculation. The RSI determines the price momentum by comparing the magnitude of the recent gains to recent losses over a specified period, typically 14 periods (which could be days, hours, or any other timeframe relevant to the trader's horizon) The calculation involves computing an initial Average Gain and Average Loss over the lookback period. Further calculations use a smoothing factor, typically derived from the lookback period, to give more weight to the recent data. The RSI value itself is then normalized to oscillate between 0 and 100. An RSI reading above 70 is traditionally interpreted as an indication that the asset is becoming overbought and may be ready for a corrective pullback, while a reading below 30 suggests the asset is oversold and could be due for a rebound. These thresholds, however, are not too important and are often adjusted by traders based on the

specific asset's volatility and prevailing market conditions. Beyond simple overbought/oversold signals, traders also utilize RSI for identifying divergences (where price makes a new high or low, but the RSI fails to confirm, potentially signaling weakening momentum) and centerline crossovers (where the RSI crossing above or below the 50 level can indicate a shift in momentum bias).

2.1.1 RSI Strategy Effectiveness

Notwithstanding the popularity of RSI that is widely available as appearing easy to interpret, software users still argue and confirm whether RSI really works and if indeed it can create profit in trade. The trading community asserts that RSI can predict market trends, while experts are still skeptical about its performance under diverse market environments, like in any uptrend or downtrend, high or low volatility, and in other nations as well. The main criticism is to confirm whether RSI indicators can offer significant trade advantage after considering brokerage charges, over-optimization in historical data, as well as the normal market efficiency. Prices already incorporate all available knowledge, thus making consistent excess returns difficult.

The RSI analyses are typically unconvincing. There are writers who state that RSI can deliver good prices, though this is conditional on appropriate parameterization, the implementation of ancillary tools, and specific market conditions. To contradict these, there are writers who contend that naive RSI schemes, particularly in the case of efficient markets and in the presence of true trading costs, are inferior to the simple buy-and-hold strategy. Even the optimal RSI parameters, like the time frame or overbought/oversold levels, are not defined, what is optimal in a specified market or period. The overbought and oversold levels are not fixed, and what works in one market or period may not in another. This reality renders back tested RSI strategy construction challenging to create as

something that is not optimized to the past in isolation but is useful to the future. Secondly, any RSI advantage, no matter how marginal, may quickly be erased through adoption, particularly through the constantly changing approaches to buying and selling and the growing intellect among market players.

2.1.2 Significance of the Review

A concise literature review is importantly required for the effectiveness as well as the usage of RSI-based trading strategies for several reasons. The most pertinent is the fact many individual research papers have been written concerning trading strategies in different markets and different periods. These individual papers need to be brought together. By integrating data, one can identify consistent patterns within findings, recognize areas of consensus, and distinguish differences or conflicting findings that require further investigation. This review aims to offer clearer insights as to what the collective research tells us about the value of the RSI tool by systematically compiling and critically evaluating the current empirical literature. Thirdly, this review is important for everyone who trades, from people who trade alone, to people who manage investments, to people who analyze stocks. There are lots of different kinds of advice and methods for trading and lots of “noise” competing for people’s attention. However, a careful look at the academic and empirical research stands the test of “noise,” identifying the signal and providing insight grounded in evidence into the conditions where RSI strategies work, the pitfalls to avoid, and what to reasonably expect from their performance. This knowledge can help people and computers make better trades.

Finally, the issues outlined previously have direct consequences on the future research agenda. This review is important for the academic community because it tries to shed light on important gaps in literature. This review can guide future research by

revealing e.g., unanswered research questions, funding gaps, or methodological weaknesses in prior research (such as the predominately absent transaction costs or the sparsely used out-of-sample tests). As outlined in the previous paragraphs, it is equally important to build upon the acknowledged strengths to glean a deeper understanding of RSI's role in financial markets. Obtaining deeper understanding of RSI's role is important to the construction of a stronger and more robust body of understanding that is financially attuned to RSI. Thus, this review adds to the broader literature on market efficiency, behavioral finance, and the practical application of technical analysis through the integration of previous knowledge and the illumination of paths for future research.

2.1.3 Scope and Objectives

This literature review undertakes a focused examination of empirical studies that investigate the creation, implementation, and effectiveness of trading strategies based on the Relative Strength Index (RSI). The primary source material for this review is a curated dataset of research papers, the details of which were extracted and provided in a structured format. The review will not extend to a general survey of all technical indicators but will maintain a specific focus on RSI-centric strategies as represented within this dataset.

To achieve this, it is essential to examine each study's primary research question, the manner in which it is addressed, and the conclusions ultimately drawn. Particular attention must be given to how these empirical investigations assess the efficacy of RSI-based strategies. This approach enables the identification, critical evaluation, and systematic synthesis of recurring themes and patterns within the literature under review. These themes concern various aspects of RSI research, for instance, the range of research designs and approaches, a mix of data sources, markets (such as stocks, forex, commodities, and cryptocurrencies), and periods studied, the standard and modified RSI

parameterizations (lookback periods, overbought/oversold thresholds), type of trading strategies involving RSI (e.g., entry and exit rules, combination with other indicators, and risk control), evaluation performance metrics, and effects on portfolio construction and management.

The goal of this study is twofold: (1) to summarize the research findings on the effectiveness of RSI strategies for generating profitable signals, and for generating better risk-adjusted returns; and (2) to assess whether the data supports the important signals from RSI and under what circumstances these signals can be expected to be more or less useful. To highlight the gaps and limitations in the set of literature reviewed; this will include an assessment of the strength of findings, including the effects of transaction costs, data snooping, and out-of-sample testing, in addition to putting forward specific avenues and questions for possible research that can help address the gaps and contribute to the greater understanding of RSI in financial markets.

This review seeks to accomplish these objectives: to provide both a comprehensive and a critical overview of the research on RSI-based trading strategies stemming solely from the provided dataset, and to provide meaningful guidance to academic researchers and practitioners in the financial market.

2.1.4 RSI: Conceptual and Computational Foundations

In order to give traders and investors a useful and methodical tool to recognize overbought and oversold market conditions, evaluate momentum, and predict possible trend reversals, Wilder Jr. (1978) developed RSI as a component of a larger technical analysis framework. RSI provided a standardized way to compare momentum across various assets and time periods by normalizing price momentum into a bounded oscillator with a range of 0 to 100.

In his initial paper, Wilder Jr. (1978) listed a number of important applications for RSI in technical analysis. First, RSI is frequently used to determine when a market is overbought or oversold. Traditionally, values above 70 are considered overbought, and values below 30 are considered oversold, which may indicate that a price reversal is imminent (refer Figure 2.1a).



Figure 2.1a: Plotting the RSI to show overbought and oversold regions (Source: Original Work)

Second, a key use of RSI is divergence analysis, where differences between price action and RSI behavior can point to waning momentum. A bearish divergence is seen when the price makes a higher high, but the RSI makes a lower high, while a bullish divergence happens when the price makes a lower low and the RSI forms a higher low. (refer Figure 2.1b)



Figure 2.1b: An example showing divergence (Source: Original Work)

Third, Wilder Jr. (1978) presented the idea of failure swings, which are particular RSI patterns intended to indicate significant reversal points separate from price chart patterns. When the RSI rises above the overbought threshold, falls, and then fails to surpass its prior peak before falling once more, this is known as a failure swing top. On the other hand, when RSI falls below the oversold threshold, bounces back, and then fails to drop below its previous trough before rising, a failure swing bottom is formed (refer Figure 2.1c). Furthermore, even though they might not be readily apparent on price charts, RSI can create identifiable chart patterns like triangles or head-and-shoulders formations that can still offer insight into future price movements. In addition, Wilder pointed out that RSI can be used to confirm trends and determine support and resistance levels within the indicator itself. He observed that RSI typically stays above 40 during strong uptrends and below 60 during strong downtrends.



Figure 2.1c: Using Buy/Sell signals that fit trends (Source: Original Work)

Wilder Jr. (1978) provided a formal definition of the mathematical construction of RSI in addition to its interpretive framework. The ratio of recent price gains to recent price losses over a given lookback period, typically 14 periods, is used to compute the RSI. There are two steps to the calculation. The arithmetic mean of gains and losses over the chosen lookback period is used to calculate the initial average gain and average loss in the first stage. These values are then used to calculate the relative strength (RS), which is defined as the ratio of average gain to average loss. The RSI is subsequently derived using the transformation:

$$RSI = 100 - \left(\frac{100}{1 + RS} \right)$$

where RS is the average gain of up periods divided by the average loss of down periods over the specified period.

Following the acquisition of the initial RSI value, subsequent RSI values are computed using Wilder's smoothing technique, which reduces volatility and ensures continuity over time (Wilder Jr., 1978). This recursive formulation uses a smoothing factor equal to an exponential moving average to combine the current period's gain or loss with the prior average gain or loss. With this method, RSI can react to fresh price data while preserving interpretability and stability.

Although several limitations were acknowledged, the RSI was established as a powerful and widely used momentum indicator within the original framework (Wilder Jr., 1978). RSI is prone to whipsaws, which are sudden price reversals that happen soon after a signal is generated, and it can produce false signals, especially in sideways or extremely volatile markets. Additionally, the widely used 14-period lookback is not always the best option and may need to be modified based on trading horizons, asset characteristics, and market conditions. Last but not least, RSI's explanatory power is limited because it is primarily a technical indicator and excludes fundamental data.

All things considered, the development of the RSI laid the foundation for decades of subsequent research and practical applications in technical analysis (Wilder Jr., 1978). It is a fundamental indicator due to its ease of use, versatility, and interpretability; however, research is still being conducted to investigate improvements, different parameterizations, and more complex uses like divergence-based trading strategies.

2.1.5 Literature Classification and Quality Assessment

The literature on the Relative Strength Index (RSI) and related technical trading strategies encompasses various publication types, methodological approaches, and

academic settings. Because of this variety, it is important to be clear about the types and quality of the sources used in this chapter to make sure that the methods are clear and strict.

The studies reviewed were put into groups based on the type of publication and whether or not they had been peer-reviewed. The classification differentiates between:

1. Peer-reviewed journal articles
2. Conference proceedings
3. Working papers and preprints
4. Practitioner or technical publications (where applicable)

This differentiation does not aim to establish a hierarchical ranking of sources; instead, it seeks to contextualize the evidentiary strength and academic validation pertinent to each category.

The main source of the literature base is peer-reviewed journal articles. These studies usually go through a formal editorial process and an anonymous referee review, which makes sure that the methods are checked and that the authors are responsible for their work. A lot of these articles are in well-known academic databases and look at how RSI strategies work in real life in the stock market, the foreign exchange market, the futures market, or the cryptocurrency market.

The review of conference proceedings mostly shows new ways of doing things or new methods, like parameter optimization techniques, algorithmic implementations, or expert system adaptations that use RSI. Peer review is done at conferences, but these kinds of studies may focus on computational development or early empirical validation.

Working papers and preprints provide exploratory analyses, expanded datasets, or preliminary dissemination of research findings prior to journal publication. These sources are especially useful in fields that change quickly, like quantitative finance, algorithmic trading, and technical strategies that use sentiment analysis.

The literature reviewed shows that there are different methods used in different categories, such as:

1. Event-study analysis
2. Cross-sectional backtesting
3. Time-series econometric modeling
4. Strategy simulation under transaction cost constraints
5. Parameter optimization techniques
6. Signal timing evaluation
7. Comparative performance analysis against buy-and-hold benchmarks

The prevalence of empirical backtesting frameworks indicates the practical orientation of RSI research. Nonetheless, methodological rigor differs among studies regarding sample size, robustness assessments, transaction cost modeling, and out-of-sample validation.

The literature underpinning this dissertation primarily comprises peer-reviewed empirical research, augmented by contributions from conferences and working papers that offer methodological diversity and domain-specific enhancements. This organized classification makes the review's interpretive framework stronger and makes it clearer what kind of evidence the current study is based on.

2.1.6 Chapter Structure

This literature review aims to organize information that addresses the questions posed in the Introduction by dividing it into relevant topics. These topics will be sections in the review. Section 2, titled “Methodological Approaches in RSI Research,” will follow

the introduction and will focus on the methodologies of the articles that are reviewed. Section 3, “RSI Configuration and Adaptation,” will review in the literature the RSI’s parameter settings, including the default ones, individual parameter changes, and the rationale behind the parameters. Section 4, “Design of RSI-Based Trading Strategies,” will review how RSI triggers are transformed into actionable trading rules, the presence of additional indicators and risk controls during testing, and their utilization. Section 5, “Performance Evaluation of RSI Strategies,” will review the results of the strategy performances along with a short description of the commonly used performance and benchmarking metrics, followed by the findings which encapsulate the overall conclusions related to the strategy profitability and market efficiency.

Section 6, " Portfolio-Level Implications," will outline how RSI-related strategies are used for portfolio construction and the implications for portfolio characteristics. Section 7 will summarize and provide " Synthesis and Critical Analysis" of the key themes, highlight conflicting findings, assess the limitations and strengths of the reviewed studies, and catalog the important gaps in the literature. Lastly in Section 8 we will move back towards a "Conclusion," to summarize our original contribution in analysis, to discuss implications for practitioners and researchers, and, finally, provide closing remarks regarding the importance of RSI usage. The review will conclude with a full reference list of all literature cited, using the Harvard referencing style and applicable to the source material provided.

2.2 Methodological Approaches in RSI Research

A lot of research has been done on how well the Relative Strength Index (RSI) works, and these studies use a wide range of methods to see how strong and generalizable trading strategies are. These methodologies are essential for determining if the indicator

offers a statistically significant advantage when considering market frictions and efficiency. The subsequent sections amalgamate the dominant research methodologies, data attributes, and market environments identified in the literature.

2.2.1 Primary Research Designs

The empirical literature is primarily quantitative, utilizing historical data to model and assess performance through various specific methodologies.

Comparative Trading Strategy Evaluations: A fundamental design entails evaluating RSI-based strategies against passive or alternative active methodologies. Gurrib and Kamalov (2019) compared an adjusted RSI (AdRSI) to the standard RSI and a traditional Buy-and-Hold (B&H) strategy. They found that AdRSI gave higher raw returns, but the B&H model was better at risk-adjusted reward-to-volatility. In the same way, Nor, S. M., & Wickremasinghe, G. (2014) looked at the Australian market and found that RSI had the potential to make money while MACD did not. Other studies use this framework to test hybrid models, like combining RSI with MACD to improve Bitcoin trading performance or testing it with machine learning models to predict trends.

Quantitative Trading Strategy Simulations: The most common design is to use predefined trading rules on historical data to create fake outcomes that are not affected by real-time decision biases. Nor S. M., & Wickremasinghe, G. (2014) employed this methodology on the Australian All Ordinaries Index (1996–2014), whereas Gurrib and Kamalov (2019) utilized daily data from 2001–2015. Studies that use simulations also look at unstable cryptocurrency markets like Bitcoin, Ethereum, and Litecoin, as well as a wide range of stock indices, such as the Pakistani KSE-100, the Indian NIFTY 50, and the Singapore STII. The strength of these simulations depends on how long the study period is and how realistic the assumptions are about transaction costs and slippage.

Empirical Portfolio Performance Analysis: Some researchers look at how RSI strategies affect diversified portfolios instead of just individual asset signals. Cheema et al. (2021) concentrated on developing optimal portfolios in the Pakistani market by employing RSI to enhance returns while mitigating risk through mean-variance and GARCH models. This design looks at overall traits like Sharpe ratios, maximum drawdowns, and rebalancing frequency to help investment managers figure out if RSI helps them make better portfolios.

Hybrid Methodologies and Advanced Computational Approaches: A "newer wave" of research aims to improve RSI's ability to predict by combining it with machine learning (ML) and optimization algorithms. Patel, Shah, and Thakkar (2015) used SVM and Random Forest models to make sense of RSI signals. Harahap et al. (2020) used a C4.5 data mining algorithm to predict stocks. Additionally, optimization studies such as Wang, Chen, and Huang (2022) employ Genetic Algorithms to determine the optimal RSI lookback periods and thresholds for Bitcoin, customizing the indicator to particular market dynamics while acknowledging the inherent risk of overfitting.

Longitudinal Case Study and Manual Observation: Khatavkar (2024) noted that human-level scrutiny is crucial for identifying nuanced, context-specific RSI divergence patterns that automated algorithms frequently misinterpret. This methodological approach employs a comprehensive 24-year longitudinal design (2000–2024) to analyze the NIFTY 50 index. To reduce the risk of data snooping bias, the data is split into three eight-year sub-periods. This lets us test it thoroughly in different situations, such as the 2008 financial crisis and the COVID-19 pandemic.

2.2.2 Data Sources, Markets, and Time Horizons

The generalizability of RSI research is significantly affected by the selection of market focus, data frequency, and study duration.

Market and Geographical Focus: RSI strategies have been evaluated across an extensive range of geographical locations and asset classes. Foundational studies have primarily concentrated on developed markets, such as the London Stock Exchange (Chong and Ng, 2008) and the USA S&P 500 (Rosillo et al., 2013), but there is an increasing focus on emerging markets. Research now encompasses India (Sharma, 2023), Pakistan (Shaikh, 2023), Turkey (Demirel et al., 2023), Malaysia (Ang et al., 2020), and West Africa (Kouassi, 2022). The growth of digital assets has also led to a lot of research into how to use RSI with cryptocurrencies, where high volatility makes for a unique testing ground for momentum oscillators.

Data Frequency and Quality: Most studies use daily data (Gurrib & Kamalov, 2019; Nor & Wickremasinghe, 2014; Chong & Ng, 2008), which is easy to get and very useful for swing and position traders. However, higher-frequency data (e.g., hourly or 15-minute intervals) is becoming more common for assets that are volatile, like Bitcoin (Wang, Chen, & Huang, 2022), or in studies that are trying to come up with short-term intraday strategies. Researchers recognize that the integrity of historical data from sources such as Bloomberg or Reuters is critical; neglecting survivorship bias, corporate actions (dividends/splits), or data inaccuracies can substantially distort simulation outcomes.

Study Duration and Market Regimes: The study periods differ greatly in length, ranging from longitudinal analyses that last decades (like the FT30 index for 60 years) to focused sub-period tests. Contemporary researchers underscore the necessity of evaluating strategies across various market regimes - bull, bear, and sideways trends - to ascertain their robustness. A significant methodological advancement is the effort to address look-

ahead bias, wherein previous studies evaluated indicators utilizing data that preceded the indicators' creation. Current standards, as shown by Nor & Wickremasinghe (2014), require trades to be made on the day after a signal (T+1) to make sure that the trading environment is fair and realistic.

In summary, the methodology of RSI research has progressed from basic rule-based testing to a sophisticated framework that includes comparative benchmarking, longitudinal case studies, and advanced computational optimization across a diverse array of global financial markets.

2.3 RSI Configuration and Adaptation

The success of trading strategies based on the Relative Strength Index (RSI) is largely determined by how the indicator is set up. The selection of the lookback period, overbought and oversold thresholds, and formulaic adjustments can profoundly impact signal frequency and reliability, consequently determining overall strategy performance.

2.3.1 Lookback Period

The standard RSI, which Wilder Jr. (1978) first came up with, looks back 14 periods. This setting is the standard baseline in both academic research and professional work. The literature, however, shows that more and more people are realizing that a single fixed period may not be the best choice for all asset classes and market conditions.

Shorter lookback periods, such as the 2-period RSI, are characterized by aggressive signaling and increased sensitivity to recent price action, though they are prone to higher noise and "whipsaws". To catch short-term changes in momentum, people often test mid-range variations (7 or 9 periods). For example, Deveci Kocakoç & Kılıç (2019) discovered that 5-day and 9-day RSIs yielded greater profitability for the BIST Food and Beverage

Index compared to standard settings. On the other hand, longer periods like 21 or 30 days make the oscillator smoother, which means it makes fewer signals that are more likely to be accurate by getting rid of small fluctuations.

Recent research supports optimization tailored to specific markets. Bansal (2023) systematically retested 7, 14, and 21-day periods on the NIFTY 50 index, demonstrating that the effectiveness of the lookback length is contingent upon the underlying market's volatility regime. Wang, Chen, & Huang (2022) employed Genetic Algorithms to enhance Bitcoin trading, examining a comprehensive lookback period of 3 to 30 days to pinpoint parameters specifically suited to cryptocurrency dynamics.

2.3.2 Overbought and Oversold Thresholds

People often use the standard levels of 70 (overbought) and 30 (oversold) to find possible points where prices will change. Even though these levels are popular, researchers often change them to fit the risk-reward profile that a strategy wants.

Conservative Extremes (80/20): These levels help the traders find extreme market conditions. This means fewer trades, but possibly more likely reversal signals. Bartkus & Tekin (2020) and Lisicki (2024) examined these conservative variants to reduce risk in unstable markets like the Warsaw Stock Exchange or Bitcoin.

Active Thresholds (60/40): To raise the frequency of the signal, narrower bands are used. This is good for active intraday trading or markets with less volatility. Panigrahi et al. (2021) showed that a 60/40 approach gave better short-term returns in the NIFTY 50 than standard levels.

Unconventional Levels: Bansal (2023) furthered this investigation by examining unconventional thresholds like 36/63, discovering that typical overbought/oversold levels

frequently resulted in negative returns in the Indian context, while data-driven threshold modifications could improve profitability.

2.3.3 Modified and Adaptive RSI Models

Researchers have suggested formulaic improvements to the standard oscillator in order to get around its problems, like how it is sensitive to small price changes in stable stocks.

The Adjusted RSI (AdRSI): Gurrib & Kamalov (2019) created the AdRSI model, which changes the way the Relative Strength (RS) is usually calculated by adding the security's price and a calibration constant. The goal of this change is to make the indicator less sensitive to market noise and more consistent across different asset tiers. AdRSI had higher annualized returns in the currency and energy markets, but it also had higher annualized risk than standard models.

2.3.4 Rationale for Parameter Selection

The rationale for RSI settings in the literature ranges from historical precedent to empirical optimization. The 14-period setting and the 70/30 threshold levels continue to be used by many researchers as a standard baseline for comparison (Wilder Jr., 1978). But these days, the trend is moving toward a data-driven approach, where the parameters are based on the asset's specific statistical properties and volatility.

A significant caution highlighted in the literature concerning optimization is the potential for overfitting. Strategies that do very well in historical backtests because of very specific parameter tuning may not work in live trading. Recent methodological standards, exemplified by the research of Bansal (2023) and Khatavkar (2024), underscore the

imperative of stringent out-of-sample validation and sub-period testing to guarantee the resilience of configured parameters across varying market regimes.

The configuration of the RSI has transformed from a static heuristic into a complex optimization challenge, signifying a concerted endeavor to improve the practical applicability of momentum indicators in a progressively intricate financial environment.

2.4 Design of RSI-Based Trading Strategies

The translation of the Relative Strength Index (RSI) into a practical trading tool involves converting momentum signals into actionable entry and exit rules within a broader strategic framework. The literature shows that rule-based systems have evolved from simple and inflexible ones to more complex and flexible ones that use risk management and secondary filters to deal with market volatility.

2.4.1 Basic Signal Generation

Most RSI strategies are based on four main signaling methods.

Overbought/Oversold (OB/OS) Reversals: The 70/30 thresholds are the most common way to find price exhaustion and possible reversals.

Centerline Crossovers: This method uses the 50-level to measure momentum bias. If the price moves above 50, it means that an uptrend is starting; if it moves below 50, it means that a bearish shift is happening.

Divergence Analysis: A more advanced method in which the price and RSI move in opposite directions. Bullish divergence (lower low in price, higher low in RSI) means that selling pressure is fading, while bearish divergence (higher high in price, lower high in RSI) means that buying momentum is fading.

Failure Swings: These happen when the RSI makes a "M" or "W" pattern in the extreme zones. This means that the price will change direction even if it makes a new high or low.

2.4.2 Strategic Integration and Hybrid Systems

To lower the chance of "whipsaws," which are false signals that happen often in trending markets, researchers often use RSI with other technical tools. Some common ways to integrate are:

Trend Filters: Only acting on RSI buy signals when the price is above a long-term Moving Average (MA) or using MACD to confirm the trend.

Volatility Overlays: Using Bollinger Bands to find entry points or Average True Range (ATR) to set dynamic stop-losses that change based on how noisy the market is right now.

Computational Enhancement: A new wave of research uses Machine Learning (ML) models like SVM or Random Forest to better understand RSI signals. Lin (2023) and Mehra (2024) enhanced this by incorporating news sentiment analysis to sift through technical signals amid high-volatility events.

2.4.3 Empirical Refinement (The Three Dissertations)

Recent doctoral research established a rectifying framework for RSI strategy formulation in the Indian market:

By simulating 33 different strategies, Bansal (2023) demonstrated that the standard RSI (14, 30/70) configuration did not consistently perform in the NIFTY 50. He supported the use of divergence-based buy signals, as he found them more effective in identifying potential uptrends.

Khatavkar (2024) focused exclusively on Relative Strength Index Divergence (RSID) and found that the most reliable signals formed within 8–14 days, whereas signals extending beyond 14 days were the least reliable. A key strategic insight from his design was that bullish divergences were more significant than bearish signals, which exhibited a 33% failure rate. He suggested that bearish signals should be used primarily for exit planning rather than for initiating short positions.

Vishnoi (2024) showed in his comparative analysis that stock liquidity influenced signal resolution. Large-cap stocks (e.g., Reliance) tended to exhibit longer formation periods and delayed reversals, whereas more volatile non-index stocks (e.g., Liberty Shoes) reacted more quickly to divergence triggers.

2.4.4 Risk Management and Market Realities

A workable strategy design needs to connect the dots between theoretical signals and what actually happens when they are followed:

Entry/Exit Nuance: Realistic simulations, like those by Nor, S. M., & Wickremasinghe, G. (2014), make trades on the day after a signal (T+1) using open prices to get rid of look-ahead bias.

Protecting Capital: Good strategies use stop-loss orders (which are usually set at 2% in simulations) and take-profit levels to deal with the risk of big price changes.

Transaction Frictions: Brokerage fees, taxes, and slippage can eat into profits, so strategy design needs to take these into account. Validation phase by Khatavkar (2024) shows that a disciplined divergence strategy can still make a 15.34% quarterly return on investment (ROI) even after all of these costs.

In short, designing an effective RSI strategy has gone from using fixed thresholds to a more complex process that includes finding divergences, filtering indicators, and

tuning parameters for specific markets, all while being watched over by strong risk controls.

2.5 Performance Evaluation of RSI Strategies

The assessment of RSI-based trading strategies is inextricably linked to the overarching theoretical discourse on market efficiency. The Efficient Market Hypothesis (EMH), formally articulated by Fama (1970), constitutes the principal critique of technical analysis. The weak-form of EMH says that current asset prices already consider all past price information. Within this framework, trading strategies that depend solely on historical price movements, like RSI and RSI divergence, ought not to consistently produce abnormal returns when factoring in transaction costs and market frictions.

The weak-form efficiency proposition directly contradicts the foundation of momentum oscillators. If prices follow a random walk based on the information that is available, any pattern that can be seen in past data should be arbitrated away. So, if RSI-based signals consistently make money, it would mean that the market is inefficient or that there are methodological problems like look-ahead bias, data snooping, or unrealistic execution assumptions.

The empirical evidence in the literature continues to be inconclusive. Certain studies indicate statistically significant excess returns from RSI configurations in particular markets or regimes, whereas others assert that performance declines when transaction costs and risk adjustments are factored in. The discussion has transitioned from a simplistic binary inquiry regarding the efficacy of technical analysis to a more sophisticated examination of conditional profitability, regime dependency, and structural limitations.

Recent theoretical advancements, notably the Adaptive Markets Hypothesis introduced by Lo (2004), indicate that market efficiency may fluctuate over time and across

different contexts. This interpretation suggests that temporary inefficiencies may arise from behavioral biases, structural frictions, or liquidity imbalances; however, these inefficiencies are neither universal nor enduring. Technical indicators can thus reflect localized momentum exhaustion or crowding effects without inherently opposing efficiency in their more robust manifestations.

In this theoretical framework, the validity of any RSI-based assertion is fundamentally contingent upon methodological precision. Studies that neglect signal timing, repainting behavior, or execution delay may exaggerate profitability and unintentionally contravene the informational constraints posited by the Efficient Market Hypothesis (EMH). Consequently, evaluating divergence detection within stringent causal and temporal parameters is crucial for substantive participation in the efficiency discourse.

This dissertation situates its examination of RSI divergence within a theoretical framework, investigating whether causally constrained detection modifies the interpretation of technical profitability under weak-form efficiency.

Researchers use a range of quantitative metrics to get a full picture of how effective a strategy is. Annualized returns, cumulative returns, and return on investment (ROI) are some of the most basic ways to measure financial gain. Standard deviation, maximum drawdown, and the Sharpe Ratio are all common ways to look at risk and volatility. The Sharpe Ratio helps figure out if the returns are worth the risks taken. Also, looking at the statistical distribution of returns using measures like skewness and kurtosis can help to understand how reliable and safe a strategy is. The Profit Factor and Win Rate, on the other hand, show how well a strategy works.

Recent doctoral research has yielded high-resolution performance data specifically for the Indian equity market, utilizing multi-decade datasets. Bansal (2023) examined 33 strategies utilizing 21 years of NIFTY 50 data, demonstrating that conventional RSI

settings frequently produced negative returns, whereas divergence-based strategies (RSI 14, D) consistently yielded abnormal returns and exhibited a safer, positively skewed return distribution. Khatavkar (2024) expanded this study to 24 years, showing that the reliability of RSI Divergence depends on how long the formation lasts. Signals that last longer than 14 days are better at predicting what will happen next. Vishnoi (2024) conducted additional comparative research, revealing that RSI divergence consistently serves as a reliable predictor across various capitalization tiers, generating significant annualized returns for both large-cap and mid-cap stocks.

2.6 Portfolio-Level Implications

Relative Strength Index (RSI) trading strategies can be used for more than just trading individual assets. They can also be used for portfolio management tasks like building a portfolio, deciding how to allocate assets, and finding the best risk-return profile. A lot of the research is about making signals for certain instruments, but investment managers use RSI to help them choose which stocks to put in a portfolio and what the portfolio's main focus should be (thematic or sectoral). Sectoral concentration is a recurrent theme, with Jamil's (2022) research investigating the indicator's effectiveness specifically within the banking sector of the Pakistan Stock Exchange, indicating that portfolio implications in these contexts are significantly influenced by sector-specific volatility. In the same way, Lanjekar, Hulipalled, & Bhende (2022) looked at RSI across different Indian sectoral indices, such as Auto, IT, and Pharma. They find that the differences in performance between sectors have a direct effect on how a diversified, multi-sector portfolio should be tilted. Gurrib & Kamalov (2019) underscore the significance of asset class focus by employing their Adjusted RSI (AdRSI) model to active currency pairs and

energy markets, yielding data that directly informs portfolio construction in highly volatile commodity and forex environments.

The creation of "optimal portfolios" signifies an advanced progression in the incorporation of technical indicators into financial modeling. Cheema et al. (2021) directly tackled this issue by choosing stocks from the Pakistan Stock Exchange based on technical signals and then using mean-variance and GARCH models to optimize the portfolio. This methodological approach seeks to construct portfolios that optimize returns while mitigating systematic risk, demonstrating that RSI can enhance the efficiency of aggregate holdings. Also, RSI signals can be used as dynamic triggers for rebalancing and weighting schemes in diversified portfolios. As the study by Gurrib & Kamalov (2019) points out, academic summaries often leave out specific rebalancing frequencies. However, it is clear that strong RSI buy signals or strong bullish divergences lead to tactical capital shifts into responsive assets, while sell signals or overbought conditions lead to weight reductions to protect capital.

As a main way to get around limited asset pools, specialized investment universes, especially Shariah-compliant finance, also use RSI as a filtering and timing tool. Bahloul & Mroua (2021) examined the performance of RSI across both Shariah-compliant and conventional indices in the GCC region, revealing that while technical rules can yield abnormal profits in both contexts, the distinct characteristics of the underlying asset universe influence the overall portfolio performance. Widodoatmodjo, Fitriani, & Widyanto (2020) and Khairudin (2022) similarly employed technical strategies in the Indonesia Sharia Stock Index and Malaysian markets, illustrating that the pre-filtering of assets according to religious principles does not hinder the effective implementation of RSI-driven market timing. In these situations, the main point for managing a portfolio is that

there needs to be a two-step screening process. First, assets must pass Shariah compliance, and then they can be analyzed for technical momentum.

The value of RSI at the portfolio level is determined by its capacity to positively influence the overall risk-return profile, targeting increased returns per unit of risk or diminished maximum drawdowns. Cheema et al. (2021) conducted research that shows that using RSI to time entries and exits across multiple assets can greatly improve a portfolio's Sharpe ratio and lower its overall volatility. RSI-based strategies help investment managers keep their target risk profiles across different market cycles, such as bear markets and times of high uncertainty, by giving them early warnings and signaling exits before big market drops. In short, using RSI in portfolio management is an important part of choosing assets, making tactical rebalancing decisions, and making diversified investment pools more stable and efficient.

2.7 Synthesis and Critical Analysis

The examination of methodological approaches, Relative Strength Index (RSI) configurations, trading strategy designs, performance evaluations, and portfolio-level implications delineated in the preceding sections indicates a complex yet disjointed corpus of knowledge. This section seeks to integrate these diverse elements into a unified comprehension of the present status of RSI research, critically addressing the areas of agreement, significant contention, and the intrinsic strengths and weaknesses of the existing literature. The objective is to furnish a comprehensive viewpoint that situates the present study within the wider academic dialogue, while emphasizing the conspicuous gaps that necessitate further investigation.

2.7.1 Dominant Themes and Consistent Findings

Various studies reveal several predominant themes concerning the application and perceived efficacy of the RSI. A common starting point in the literature is the standard 14-period RSI with 70/30 overbought and oversold thresholds, which is widely adopted as the baseline specification (Wilder Jr., 1978). Numerous empirical studies, including those by Chong & Ng (2008), Rosillo et al. (2013), and Sharma (2023), adopt these settings to provide a standardized benchmark for evaluating market momentum. This sticking to the original parameters gives a common point of reference for comparison, but more and more modern research is looking into how these settings can be changed. For example, Deveci Kocakoç & Kılıç (2019) found that shorter 5-day or 9-day periods yielded superior results for the Turkish food sector, while Wang, Chen, & Huang (2022) successfully optimized lookback periods and thresholds for Bitcoin using Genetic Algorithms.

Another common theme is that RSI is used in many different types of global financial markets and asset classes. In the past, foundational research mostly looked at developed equity indices like the S&P 500 and the London Stock Exchange. Now, the literature review confirms the indicator's versatility in developed markets like Australia (Nor & Wickremasinghe, 2014) and the USA (Chong & Ng, 2008), emerging economies such as India (Sharma, 2023) and Pakistan (Shaikh, 2023), and even specialized regions like West Africa (Kouassi, 2022). Beyond traditional equities, the RSI is consistently applied as a momentum oscillator in Foreign Exchange (Gurrib & Kamalov, 2019), Energy (Gurrib & Kamalov, 2019), and the highly volatile Cryptocurrency space, where it is tested on assets like Bitcoin, Ethereum, and Litecoin (Yuncu, Dospatlı & Guresen, 2023; Sovbetov, 2018; Pyo & Lee, 2019).

A strong consensus exists within these diverse environments regarding the practice of integrating RSI with additional technical indicators to improve signal reliability and

eliminate false positives. The Moving Average Convergence Divergence (MACD) is the most frequent partner in these hybrid systems, as seen in the work of Nor & Wickremasinghe (2017), Demirel et al. (2023), and Yuncu et al. (2023). Other popular combinations include integrating the RSI with Moving Averages, Bollinger Bands (Ang, Lin, and Chen, 2020), and Stochastic Oscillators (Lanjekar, Hulipalled, and Bhende, 2022), with several studies explicitly reporting that these hybrid approaches can outperform standalone RSI strategies.

A newer but important theme is the use of advanced computing techniques with RSI. Researchers like Patel, Shah, & Thakkar (2015) and Lin et al. (2023) have utilized algorithms like Support Vector Machines (SVM) and Random Forests to interpret RSI signals in a dynamic, non-linear fashion. Additionally, there is a growing emphasis on augmenting these models with news sentiment analysis, as illustrated by Mehra & Shetty (2024) and Sadik (2020), to enhance predictive accuracy amid political instability and significant market volatility.

Recent academic research has underscored the efficacy of RSI Divergence as a predictive instrument, particularly for detecting impending trend reversals. Historically, this aspect had been insufficiently examined in academic literature; however, the dissertations by Bansal (2023) and Khatavkar (2024) have established a corrective empirical foundation within the Indian equity market. These results consistently demonstrate that divergence-based buy signals proficiently identify potential uptrends and provide superior risk-adjusted returns relative to conventional threshold strategies, especially within the NIFTY 50 index.

2.7.2 Contradictory Results and Areas of Disagreement

The literature also contains contradictions and substantive disagreement, in addition to consistent themes.

RSI vs. Buy-and-Hold: The ability of RSI strategies to regularly beat a straightforward buy-and-hold (B&H) benchmark, particularly when risk is considered, is a major source of disagreement. Although certain studies report that RSI-based strategies generate higher absolute returns during specific periods (Gurrib & Kamalov, 2019), the same research concluded that the Buy-and-Hold (B&H) approach outperformed them on a risk-adjusted (reward-to-volatility) basis. The ability of RSI to continuously outperform B&H after costs is also questioned by Chong & Ng (2008). This dispute is essential because many investors may find active strategies to be of limited practical value if they are unable to consistently outperform passive ones.

Bansal (2023) assesses the efficacy of RSI strategies by creating a stringent Buy and Hold (B&H) benchmark based on 21 years of NIFTY 50 data. The study employs Python-based simulations to eradicate look-ahead bias, illustrating that divergence-based RSI strategies (RSI 14, D) consistently surpass the passive B&H method regarding average returns, stability, and risk-adjusted metrics. The assessment utilizes comprehensive statistical metrics to demonstrate that although RSI can produce anomalous returns, its efficacy is significantly inconsistent across different strategy groups.

Vishnoi (2024) broadens this assessment by utilizing RSI divergence strategies on two distinct market tiers: a high-liquidity large-cap stock (RELIANCE) and a volatile non-index stock (LIBERTSHOE). His findings show that RSI divergence is still a strong predictor across different market capitalizations. For example, RELIANCE had a 40.35% annualized return and LIBERTSHOE had a 22.62% return for the 24-year longitudinal study spanning from January 2000 to January 2024. The evaluation shows that the success

rates are the same for both tiers (78.5% for Reliance and 76.67% for Liberty Shoes). This means that the indicator is reliable regardless of whether a stock is in a major index.

2.7.3 Strengths and Weaknesses of Current Research

There are a lot of good things about the current body of literature. The indicator's potential usefulness is clear from the fact that it has been used in more than 60 years of data and in many different places. Methodologically, the widespread use of quantitative rigor through systematic backtesting and simulation makes it possible to objectively judge how well something worked in the past. Comparative analysis with other indicators and benchmark strategies provides the necessary context to evaluate the position of the RSI within the broader technical analysis framework.

Nonetheless, considerable deficiencies and constraints endure. A significant deficiency in much literature, especially in older studies, is the inconsistent handling of transaction costs. Studies that leave out or poorly model brokerage fees and slippage can make profitability look better than it really is. Also, testing a lot of different combinations of parameters and rules carries a high risk of data snooping bias and overfitting. Strategies that seem to work well in historical simulations often don't work well in out-of-sample testing, but published summaries do not always go into detail about how they were tested.

There is also a big problem with reporting not being standardized. It is often hard to compare studies directly because they do not always include information about stop-loss mechanisms, specific entry and exit rules, and delays in executing market orders. Moreover, numerous studies depend on idealized market conditions, neglecting to consider real-world frictions, such as liquidity-induced slippage during high volatility periods. Finally, the possibility of publication bias indicates that studies demonstrating statistically

significant or favorable outcomes may be disproportionately represented in the academic literature, potentially distorting the perception of RSI efficacy.

2.7.4 Identified Gaps in Literature

From the synthesis of the existing body of knowledge, numerous substantial gaps persist that necessitate further exploration. There is a lot of research on how to make parameters work better, but not much on how to make RSI models that are dynamic and adaptable, meaning they change the rules for interpreting data in real time based on changes in market conditions like trend strength and volatility. Most current research depends on static optimization for a set historical period, which might not hold up during regime changes.

Cross-asset relationships also signify an inadequately examined pathway. Future research may examine whether RSI signals in a specific asset class, such as commodities, exhibit leading or lagging effects on associated equities or currencies. Also, while standard risk management tools are sometimes talked about, there is a need to combine RSI signals with more advanced, flexible risk controls, like position sizing that considers volatility or hedging strategies.

One big problem is that there isn't enough real-world research on RSI Divergence. Wilder Jr. (1978) initially suggested five ways to use the indicator, but most academic research has only looked at overbought/oversold levels and centerline crossovers. It has mostly ignored how divergences can be used to make predictions. Recent studies by Bansal (2023) and Khatavkar (2024) have started to close this gap by showing that divergence-based strategies work well in the Indian market. However, more research is needed to see if these results hold true in other markets and over longer periods of time.

In conclusion, there is a lot of information about RSI-based strategies, and it comes from many different sources. This shows how popular the indicator is as a way to measure price momentum. But getting to consistent, risk-adjusted profits is not easy. There are many problems along the way, such as market efficiency, transaction costs, and the chance of statistical illusions. The path of RSI research shows a bigger trend toward methods that are more flexible, require more computing power, and are more statistically sound. To better understand the RSI's true value in the constantly changing world of global financial markets, we need to fill in the gaps we found, especially by creating standardized reporting frameworks and thoroughly investigating divergence-based trading.

2.8 Chapter Summary

Chapter 2 has offered a thorough integration of the academic literature supporting technical analysis and the Relative Strength Index (RSI), thereby establishing the theoretical and empirical foundations for this research. The review started by putting technical analysis in context as a method based on the idea that historical price and volume data contain all the information needed to predict future market trends. In this field, momentum oscillators like the RSI, which Wilder Jr. (1978) came up with, are very important for finding overbought and oversold conditions that often happen before trend reversals. Wilder initially suggested five specific uses for the indicator, such as chart patterns, failure swings, and support/resistance. However, the review pointed out that most academic research has only looked at simple threshold reversals.

Most RSI research uses quantitative methods, such as historical backtesting and strategy simulations, to see how strong market signals are. These studies look at a wide range of global assets, including developed equity exchanges, emerging markets like India, Pakistan, and Turkey, and the very unstable cryptocurrency sector. The configuration of

the RSI is the most important part of these studies. The standard 14-period lookback and 70/30 thresholds are the starting point. Nonetheless, a substantial corpus of recent research investigates optimized and adaptive models, exemplified by the Adjusted RSI (AdRSI), which integrates price tiers and calibration constants to reduce false signals and accommodate fluctuating market volatilities.

The literature on performance evaluations shows a complicated and often conflicting picture of the RSI's ability to make abnormal returns. Some studies show that strategies based on RSI can do better than a passive Buy-and-Hold (B&H) benchmark, but others say that these advantages are often lost because of transaction costs like brokerage fees, taxes, and slippage. This difference shows how important it is to do strict out-of-sample validation and realistic execution modeling in technical research.

The three recent dissertations on the Indian equity market are a major change in the literature and are the direct inspiration for this research. Bansal (2023) demonstrated that conventional threshold strategies frequently fail in the NIFTY 50, while divergence-based signals provide a reliable means for identifying uptrends. Khatavkar (2024) expanded this research with a 24-year longitudinal case study, employing a manual observation method to demonstrate that RSI Divergence (RSID) is exceptionally reliable, especially when formation durations are within an 8-14-day range. Moreover, Vishnoi (2024) illustrated the enduring efficacy of RSID across various market capitalization categories, identifying uniform success rates in both large-cap and mid-cap Indian equities.

Even with these improvements, there are still some important gaps in what we know now. The literature indicates a deficiency of research concerning genuinely dynamic and adaptive RSI models capable of responding to real-time fluctuations in trend strength and volatility. There is also a persistent lack of standardization in reporting for risk management protocols and the handling of market frictions. Chapter 2 has identified the

"lost track" of original divergence concepts in academic discourse by putting together these findings. This gives the necessary reason for the causal, benchmark-aligned framework that will be created and tested in the next chapters of this dissertation.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter presents the research framework and methodological protocols established to rectify the ontological and practical shortcomings in Relative Strength Index (RSI) divergence detection within the Indian equity market. Although technical analysis literature often regards divergence as an apparent visual heuristic, this study asserts that the efficacy of such signals depends on their causal implementability and temporal observability.

3.1 Overview of the Research Problem and Justification

The main goal of this dissertation's methodology is to create a framework for finding Relative Strength Index (RSI) divergence that is structurally sound, can be used in real time, and has economic significance in the National Stock Exchange of India (NSE). The literature review shows that the NIFTY 50 index is an important benchmark for both retail and institutional investors. However, its volatility, which is caused by momentum, makes it hard to time the market.

Previous research, ranging from the seminal work of Wilder Jr. (1978) to recent studies by Bansal (2023), Khatavkar (2024), and Vishnoi (2024), has substantiated the theoretical existence of divergence; however, a notable gap persists in the causal observability of these signals. Most of the tools that are already out there, use "repainting" logic, which means that signals are backdated to previous price pivots only after future price action confirms the change. This study specifically tackles this issue by creating the **Structural Leading Divergence (SLD)** framework, which aims to connect the dots between looking back at patterns and trading in real time.

The literature review regarding the application of Technical Analysis and the Relative Strength Index (RSI) reveals a diverse array of empirical studies conducted across

different markets, temporal settings, and methodological approaches, each characterized by distinct objectives, assumptions, and constraints.

Table 3.1 summarizes the key gaps identified in the literature, which necessitate the shift toward a structurally grounded, non-repainting detector:

Study	Objective	Key Gaps Identified
Wilder Jr. (1978)	Introduced RSI as a bounded momentum oscillator for identifying overbought/oversold conditions and divergences	No empirical validation framework; purely conceptual; no causal testing or profitability evaluation.
Chong & Ng (2008)	Tested RSI profitability across stocks, futures, and forex markets including transaction costs.	Profits often disappear after costs; no structural divergence validation; no real-time feasibility testing.
Nor & Wickramasinghe (2017)	Examined MACD and RSI profitability in Australian stock market; weak-form EMH implications.	Limited parameter transparency; no divergence structure validation; backtest-based, not causally constrained.
Rosillo et al. (2013)	Tested RSI and MACD on S&P 500 with transaction cost adjustments.	Limited abnormal returns after costs; no benchmark-aligned signal validation; no structural pivot logic.

Gurrib & Kamalov (2019)	Developed Adjusted RSI (AdRSI) and compared with standard RSI and Buy-and-Hold.	Modified oscillator but still threshold-based; no divergence-specific framework; no causal lag analysis.
Demirel et al. (2023)	Compared RSI, MACD, and hybrid models on BIST 100.	Focused on comparative profitability; lacks structural divergence modelling and repainting analysis.
Deveci Kocakoç & Kılıç (2019)	Optimized RSI periods for BIST Food & Beverage Index.	Parameter optimization risks overfitting; no real-time validation; no divergence-specific evaluation.
Wang, Chen & Huang (2022)	Used genetic algorithms to optimize RSI parameters for Bitcoin.	Optimization-heavy; overfitting risk; ignores structural/causal divergence constraints.
Shaikh (2023)	Examined RSI effectiveness on KSE-100.	Market-specific; standard threshold logic; no divergence structural validation.
Bansal (2023)	Evaluated 33 RSI strategies on the NIFTY 50 over 21 years to correct research direction by including divergence.	Established that standard 70/30 thresholds often fail, while divergence captured uptrends; initial simulation did

		not account for transaction costs.
Khatavkar (2024)	Empirically evaluated RSI Divergence (RSID) performance in the NIFTY 50 using manual observation over a 24-year period.	Identified that automated tools fail to capture subtle divergence patterns highlighted the importance of T+1 execution to eliminate look-ahead bias.
Vishnoi (2024)	Examined RSID efficacy by comparing high-liquidity large-cap stocks (RELIANCE) with volatile non-NIFTY 50 stocks (LIBERTSHOE).	Identified a scarcity of research on divergence robustness across different capitalization tiers and stocks outside major indices

Table 3.1a: Summary of Objectives & Gaps in Key RSI Research Studies (Source: Original Work)

Based on the data presented in Table 3.1, it is evident that the key studies show the specific gaps that need to be filled. The principal "need" for Structural Leading Divergence (SLD) indicator stems from the fact that the majority of previous research either depends on retrospective (repainting) logic, overlooks the temporal interval between signal formation and visibility, or is deficient in a causal, automated detection mechanism.

3.2 Research Question and Methodological Objectives

This study is guided by the central inquiry: *Can RSI divergence be detected and applied in the NIFTY 50 index in a structurally valid, causally executable, and*

economically meaningful manner for real-time trading? To provide an empirical answer, the methodology is designed to satisfy four core objectives:

Establish a manually curated analyst-defined benchmark of divergence events as a ground-truth reference.

Quantitatively examine the repainting characteristics and temporal latency of existing RSI divergence tools.

Develop and test the SLD indicator, utilizing Pine Script for real-time observability and Python for large-scale historical validation.

Assess the economic significance of these signals through a simulated trading environment that accounts for transactional costs and capital constraints.

3.3 Research Design

3.3.1 Thematic Justification for the SLD Framework

The need for the SLD framework arises from a methodical evaluation of current RSI research. Wilder Jr. (1978) viewed divergence as an indicator of trend exhaustion; however, the absence of a formalized causal testing framework in his initial work facilitated the emergence of "lost track" concepts, tools that emphasize visual aesthetics over temporal validity. Recent academic endeavors, including the work of Wang, Chen, & Huang (2022), have sought to address these challenges through genetic algorithms; however, these optimization-intensive methodologies frequently pose significant overfitting risks by adjusting parameters to stochastic noise instead of structural invariants.

The SLD framework acts as a corrective mechanism, anchored by five core pillars of methodological philosophy:

Causality: Every signal is strictly a function of information available at interval T . The framework explicitly forbids the utilization of right-side pivot confirmation ($T+n$) to validate historical structures.

Non-repainting: Once a signal is emitted, its temporal landmark is immutable. This eliminates the "vanishing signal" phenomenon where backdated markers appear on historical charts but were absent during live market resolution.

Structural Anchoring: Rather than simple threshold breaches, the framework utilizes the geometric relationship between price swings and oscillator momentum, requiring price to form a new extreme while the RSI exhibits an inverse trajectory.

Early Detection: The methodology prioritizes the "left-side" discovery of pivots, aiming to minimize the temporal penalty paid for algorithmic certainty.

Semantic Alignment: The algorithmic logic is calibrated to replicate the interpretive nuances of a technically trained analyst, bridging the gap between discretionary expertise and quantitative automation.

3.3.2 The Sequential Evaluation Framework

This dissertation employs a structured, sequential evaluation framework to examine RSI divergence within the contexts of causal observability and economic realism. Instead of just using traditional retrospective backtesting, the design combines structural validation, temporal verification, profitability simulation, and portfolio-level execution modeling into one methodological framework.

To isolate variables and ensure that economic conclusions are anchored in temporal realism, the research adopts a five-layer sequential evaluation framework:

Structural Identification (The Analyst Benchmark): Manual curation of a divergence universe containing 123 observations in the NIFTY 50, providing a high-integrity reference set of "expert-identified" anomalies.

Automated Detection Comparison: Subjecting the benchmark universe to three automated architectures: the TradingView (TV) Built-in RSI Divergence indicator, the True Leading Indicator (TLI) (Bansal, 2025, v.4.0.0), and the newly engineered SLD framework.

Temporal Verification: Utilizing a bar-by-bar replay protocol to record the exact moment of signal observability (T_{TV} , T_{TLI} , T_{SLD}), separating visual annotation from actionable execution. In the curated manual observation sheet these are being termed as T1_TV_Date, TLI_Date and SLD_Date.

Economic Simulation: Passing all valid signals through a standardized execution engine with uniform entry/exit rules to ensure performance differences are a result of detection logic rather than trade management.

Portfolio Realization: Integrating trade results into a portfolio model that enforces a single-position sequential constraint and employs geometric compounding to model capital growth.

3.3.3 Unit of Analysis

The fundamental analytical atom of this study is the divergence event. To ensure methodological consistency, an event is strictly defined as a relationship where:

Bullish Divergence: Price forms a lower low while the RSI forms a higher low.

Bearish Divergence: Price forms a higher high while the RSI forms a lower high.

By treating the event as the constant and the detection method as the variable, the research can directly measure the coverage and timing accuracy of the SLD against both human observation and previous algorithmic models.

Each event shows a structurally defined link between price and RSI **on the daily Open, High, Low, and Close (OHLC) price series for NIFTY 50 index from January 2000 to December 2025**. Each event is anchored by the standard 14-period RSI formula introduced by Wilder Jr. (1978). Divergence events are determined by analyzing the swing relationships between price pivots and their corresponding RSI pivots, resulting in either bullish or bearish configurations.

The study maintains consistency across detection methods by treating divergence as the fundamental analytical unit. Each divergence event has more than one timestamp, such as structural origin, replay-visible detection, and market trend reversal after the event. These timestamps make it possible to breakdown divergence behavior into structural formation, signal observability, and economic outcome.

The divergence event is also what makes it possible to run profitability simulations. For every event, standardized rules for entering and leaving apply equally to all methods. This paired-event framework makes sure that differences in realized return come from when the trades were detected, not from differences in how the trades were managed.

The event-level design is important because it stops results from being artificially inflated by selective sampling or method-specific trade filtering. All methods are compared to the same set of divergence structures, and all profitability calculations come from the same price series and exit logic.

3.4 Data Procurement and Market Specification

3.4.1 Market Data Specification

The study utilizes the NIFTY 50 index, the benchmark of the National Stock Exchange (NSE) of India, across a 25-year horizon. As mentioned earlier, it utilizes daily price data from the NIFTY 50 index from January 2000 to December 2025. There were three methodological reasons for choosing the NIFTY 50 index. First, it is a broad and diverse benchmark for the Indian stock market, which reduces the noise that is unique to each company that could change how individual stocks behave. Second, index-level data lessen the problem of survivorship bias that comes from companies that have been delisted or had their structure changed. Third, the long historical horizon includes a variety of macroeconomic regimes, such as bull markets, bear markets, range-bound consolidations, and crisis periods. This makes it possible to look at divergence behavior at different levels of volatility.

Parameter	Specification
Instrument	NIFTY 50 Index (NSE)
Timeframe	Daily (D1)
Horizon	January 1, 2000 – December 31, 2025
Data Points	6,000+ (OHLCV)
Oscillator	Relative Strength Index (RSI)

Table 3.4a: Market Data Specifications (Original Work)

The research employs the canonical RSI(14) using Wilder's smoothing method. The RSI at time t by using the following formula:

$RSI_t = 100 - 100 / (1 + RS_t)$ where RS_t represents the ratio of average gains to average losses over the past 14 periods, using Wilder's smoothing method. Using the canonical RSI(14) makes sure that it can be compared to practitioner literature and that the parameters don't get too specific.

3.4.2 Construction of the Manual Analyst Benchmark

The manual benchmark serves as the "Structural Reference Universe." It represents the highest-order interpretation of divergence geometry, independent of algorithmic constraints.

The Benchmark dataset, *RSID_GA_NIFTY_Daily_Observations.xlsx* kept (See Appendix B) track of each divergence event. It has 123 divergence observations for the span, from January 2000 to December 2025. Out of them, 110 observations were adopted from prior longitudinal studies (Vishnoi, 2024) to maintain continuity with peer-reviewed academic records. 13 additional observations (2024-2025) were identified by the researcher using identical visual heuristics for having more recent NIFTY 50 data. This manual benchmark takes up Columns A through I of the dataset and has the fields: divergence direction (Buy or Sell), structural classification (Bullish or Bearish), approximate formation window, analyst confirmation date, and observed trend reversal or trade date. This design makes sure that the benchmark is based on structural and contextual judgment, not algorithmic pivot logic.

It is important to note that only the fields that were manually observed were used to define the reference universe. Derived metrics, automated timestamps, and profitability columns were added one at a time during later stages of the analysis.

3.5 Divergence Detection Methodologies

This study assesses four unique methodologies for RSI divergence detection: the manual analyst benchmark, TradingView’s integrated RSI divergence indicator, the True Leading Indicator (Bansal, 2025, v.4.0.0), and the Structural Leading Divergence (SLD) detector created in this research. Even though all four methods use the same price and RSI data, they are very different in how they think about pivot confirmation, causality, repainting behavior, and signal observability (Refer Figure 3.5a).

Detection Method	Pivot Confirmation Type	Causal Status	Repainting Behavior
Manual Analyst	Contextual/Visual	Retrospective	Permanent Hindsight
TV Built-in	Symmetric (Left+Right)	Non-Causal	Backdates Signals (Repaints)
TLI (True Leading Indicator)	Proprietary Trendline	Causal	Non-Repainting
SLD (Structural)	Left-Only + Bounce	Causal	Non-Repainting

Table 3.5a: Comparative Detection Logic (Original Work)

3.5.1 Manual Analyst, TradingView and TLI Methods

The manual benchmark is a way to find divergences by looking at price and RSI charts. The analyst uses classical definitions to find divergence structures. These are points where price and oscillator pivots move in opposite directions. This method is based on

looking back. The analyst implicitly sees full swing structures, which include later bars that confirm the formation of a pivot. So, manual divergence labeling may include information that wasn't available when the first pivot appeared.

The TradingView built-in RSI divergence indicator uses logic for confirming left-right pivots that is symmetric. A pivot isn't recognized until a certain number of bars have formed on both sides of a local extremum. Divergence signals may show up on historical charts at earlier pivot points, but they won't be clear until there has been enough price movement after that. This is because right-side confirmation needs future bars. This behavior causes repainting to happen. In replay analysis, the earliest observable timestamp of the divergence was recorded as T_1 , which is the first bar where the trader could see the divergence.

The True Leading Indicator (TLI) (Bansal, 2025, v.4.0.0) is a selective, trendline-based oscillator detection tool that looks for early bullish divergence structures. TLI doesn't use symmetric pivot confirmation like Trading View's indicator does, and it doesn't repaint once a signal is shown. TLI makes visual markers in the shape of green and orange triangles. The first green triangle shows that the divergence has been recognized, and the next orange triangles show that the same structure is still in place. The only time this study uses the first green triangle as the actionable detection timestamp is when it is used. TLI only works with bullish divergences and doesn't give bearish signals.

3.5.2 Structural Leading Divergence (SLD)

The Structural Leading Divergence (SLD) detector was created to fix the problems that were found in other methods. The manual benchmark is structurally sound, but it doesn't have a cause. Many people use TradingView, but it paints over things and makes it harder to see. TLI is causal, but it only works with bullish signals and is very picky.

SLD is built on five main ideas: causality, not repainting, structural anchoring, early detection, and semantic alignment with benchmarks. It only uses price and RSI data from the current bar and does not use manual notes, TradingView outputs, or TLI signals.

The main goal is to find divergences as soon as possible, without using future bars or changing historical signals once they have been sent. So, SLD is a causal approximation of classical divergence geometry with clear structural rules.

The SLD indicator follows a four-step causal discovery logic to resolve structural anomalies:

Step 1: Left-only Discovery: The detector scans for local extrema using only historical bars. Unlike symmetric detectors, it does not wait for price to "turn the corner" to define a pivot.

Step 2: Bounce Confirmation: To filter stochastic noise, a "bounce" threshold is applied. The pivot is only "locked" into memory once price or RSI moves a specific distance (amplitude threshold) away from the extremum, ensuring the structure is not a minor fluctuation.

Step 3: Structural Differentiation: The locked pivot is compared to the preceding pivot. The algorithm applies tolerance filters to verify that the RSI trajectory is genuinely inverse to the price trajectory, especially in sideways regimes.

Step 4: Signal Emission: The signal (fBull/fBear) is emitted at the close of the "locking" bar. This constitutes the T_{SLD} timestamp, the earliest point of causal observability.

The Structural Leading Divergence (SLD) detector is a custom implementation written in Pine Script and developed specifically for the TradingView platform. The Pine implementation is the official operational model that all timing and profitability analyses

use. The indicator runs bar by bar in replay mode, just like it would in real time when going through historical data.

With the replay feature, one can accurately log the bar at which divergence signals become visible. Because SLD is strictly causal and doesn't repaint, signals seen during replay are the same as signals that would have been seen during live execution.

In the initial phases of research, a Python-based prototype was utilized for exploration experimentation and batch validation. But this prototype isn't used to make signals in the real-world test. To keep causal integrity, all reported SLD timestamps come only from the Pine Script implementation.

The complete Pine Script implementation of the Structural Leading Divergence (SLD) indicator used in this study is provided in **Appendix A** to ensure transparency, replicability, and methodological auditability.

Iterative replay-based observation was used to calibrate SLD parameters instead of statistical optimization. The goal was not to make the most money, but to make sure that the structure matched the manually curated benchmark while keeping causality intact.

Calibration changes involved bounce sensitivity thresholds, treating bullish and bearish divergences differently, and allowing for flat RSI pivots. No parameter was adjusted utilizing forward-looking return data. Only replay-based structural inspection was used to check all calibration decisions.

This calibration protocol makes sure that SLD stays grounded in its structure instead of being too focused on economic outcomes.

3.6 Replay-Based Validation and Temporal Landmarks

To eliminate hindsight bias, all automated detectors were subjected to bar-by-bar replay verification. This protocol differentiates between the formation of a pattern and its actionable visibility.

T_0 (Structural Origin): The price bar where the actual pivot occurs (identifiable only in retrospect).

T_1 (Observability): The bar where the TradingView Built-in signal becomes visible during replay. (Note: In the Observations sheet it is termed as T1_TV_Date)

T_{SLD}/T_{TLI} : The specific bars where the SLD or TLI signals are emitted. (Note: In the Observations sheet, these are termed as SLD_Date and TLI_Date)

T_2 (Market Trend Reversal): The observed reversal date where the price reversal commences toward the target.

Lag Analysis (Δ): Defined as $\Delta = T_{detection} - T_0$. This delta quantifies the "cost of confirmation", the temporal penalty a trader pays for algorithmic certainty.

3.6.1 Replay-Based Observation Procedure

All detector tests were done with TradingView's bar replay feature. The historical data was played back in order, from the start of the dataset to the end, to mimic real-time progression.

Data points were recorded at the exact moment of signal emission to ensure causal integrity. As soon as a signal came in, the date was noted. Before recording the detection time, there was no way to move forward, which kept future information from getting mixed in.

A structured spreadsheet (Refer Appendix B) with columns for benchmark confirmation date, TradingView detection date, TLI detection date, SLD detection date,

and derived lag variables was used to log signals. Derived fields include lag measures based on bars and calendar days that are calculated as the difference between detection timestamps and structural pivot origin.

3.6.2 Coverage and Directional Mapping

For every divergence event in the benchmark dataset, it was noted whether or not each detector had a signal that matched it. Coverage was defined as the percentage of benchmark divergences that a detector produced a signal for.

Directional consistency was checked. To check if the detector's signal direction matched the benchmark classification for SLD, a direction match variable was recorded. In coverage analysis, only signals with the same direction were counted as successful detections.

This mapping makes it possible to separate timing performance from structural recall. A detector might have a high recall rate but not be very timely, or it might be very timely but not cover a lot of ground.

3.6.3 Construction of the Profitability Dataset

The profitability dataset builds on the timing dataset by adding information about execution and exit. Under a single execution framework, entry and exit prices were calculated for each divergence signal that each detector sent out.

The Open of the next trading day after the signal date was used to set the entry price. This convention makes sure that causality is followed and that same-day hindsight execution is not allowed. Using a rule-based framework that was in line with analyst logic but made more formal to make sure it could be repeated, exit dates were found. The Close on the exit date was used as the exit price.

Using directionally consistent formulas, separate derived profit percentages for Buy and Sell trades were calculated. Then, pairwise delta measures were calculated to find the economic differences between the methods while keeping the exit logic the same.

So, the dataset has raw price data, signal timestamps, entry prices, exit prices, returns per trade, and differences in returns between methods.

3.6.4 Replay-Based Portfolio-realistic Simulation for SLD

Along with calculating profitability at the event level, a portfolio-realistic replay simulation was done just for SLD. This simulation enforced a single-position constraint, which meant that trades couldn't overlap. Using SLD detection dates, trades were made one after the other in the order they happened.

The replay was filmed (Refer Appendix C) so that there would be a verifiable record of the execution. The Trade History export from TradingView gave us realized per-trade returns based on a fixed-capital linear profit model.

To make TradingView's reported cumulative percentage match up with offline geometric compounding results, per-trade returns were taken out and compounded separately with the idea that they would be reinvested. This made it possible to separate the effects of capital models from the effects of signal quality.

The replay exercise functions as an execution-validity assessment rather than merely a performance summary.

3.6.5 Methodological Integrity and Bias Control

To protect the integrity of the methods, several safeguards were put in place. Before moving on to future bars, all detection timestamps were written down during replay. To

get rid of same-day lookahead, entry prices were always the next day's Open prices. Exit rules were set ahead of time and used them the same way for all methods.

SLD parameters were calibrated by watching a replay without looking at the profitability results. No parameter was improved based on information about future returns.

These limits make sure that performance comparisons show structural differences between detection methods instead of differences in execution assumptions or hindsight bias.

3.7 Standardized Exit Logic and Trade Management Rules

To ensure parity, all signals were processed through a formalized execution engine.

Entry Rule: All trades are executed at the Next Day Open (T+1) relative to the detection bar to eliminate same-bar execution bias.

Momentum Exhaustion Exit: Bullish trades exit when RSI reaches 70 and closes back below; Bearish trades exit when RSI reaches 30 and closes back above.

Invalidation/Breakeven: If price moves 1% in favor, the stop-loss moves to breakeven. If price fails to reach 1% and moves against the position by a specified threshold, the trade is closed for premise invalidation.

Mathematical Profit Formulas

For Buy trades, profit is defined as:

$$\text{Profit} = \frac{\text{Exit Close} - \text{Entry Open}_{t+1}}{\text{Entry Open}_{t+1}} \times 100$$

For Sell trades, profit is defined as:

$$\text{Profit} = \frac{\text{Entry Open}_{t+1} - \text{Exit Close}}{\text{Entry Open}_{t+1}} \times 100$$

These definitions make sure that profit signs are the same in all directions and that it's okay to compare different methods.

Derived Economic Measures

Along with raw per-trade profit percentages, pairwise delta measures were made to find out how signal timing affects the economy. For each divergence event where two methods generated signals, the difference in profitability was computed as:

$$\Delta_{A,B,i} = \text{Profit}_{A,i} - \text{Profit}_{B,i}$$

These delta measures make it possible to do paired statistical analysis of performance differences while keeping exit logic the same.

The absolute differences were calculated to see how close the profitability of SLD and the manual benchmark were.

Treatment of Losses and Tail Behavior

To look at the risk structure, losses were put into two groups based on size. Outcomes between negative five percent and zero were considered small losses. Large losses were defined as outcomes exceeding negative five percent.

This classification facilitates the analysis of tail risk and asymmetry without modifying the exit logic. No analysis removed, shortened, or capped losses. All failed trades stay in the dataset, which stops survivorship bias.

Alignment Across Detection Methods

A key methodological goal was to make sure that differences in profitability were only due to differences in signal timing and detection logic, not differences in exit policy.

The same entry and exit framework that was used for the above signals was also used for Manual, SLD, Trading View built-in, and TLI signals.

3.8 Portfolio Execution Model and Capital Framework

While event-level returns indicate signal quality, capital growth is determined by position limits and compounding. This study enforces a Single-Position Sequential Constraint, ignoring overlapping signals to maintain chronological realism.

Per-trade profitability gives us an idea of how good the signals are, but it doesn't tell us if a trading method is actually profitable in practice. Financial markets develop in a sequence, and traders have to deal with capital constraints, position limits, and execution mechanics that affect how well they can do. A divergence signal that looks like it will make money at the event level may not be able to be executed if it overlaps with an open position. Similarly, assumptions made about capital modeling can have a big effect on estimates of cumulative returns.

Because of this, the evaluation framework goes beyond measuring return on individual trades to include portfolio-level execution constraints. This section makes clear how divergence signals were turned into sequential trades, how overlapping signals were dealt with, and how capital growth was modeled with different compounding assumptions. The goal is to make sure that economic conclusions are based on real trading conditions and not on theoretical aggregation.

3.8.1 Single-Position Sequential Execution Model

A single-position constraint was put in place to keep execution realistic. You can only have one trade open at a time, whether it's long or short. If a new divergence signal happens while a trade is still open, the new signal is not acted on. This rule stops

overlapping exposure and is similar to how a trader would act if they put all of their money into one divergence opportunity at a time.

Formally, let each divergence event i generate an entry date E_i and an exit date X_i . Trades are executed in chronological order. A trade is executed only if $E_i \geq X_{i-1}$, where X_{i-1} is the exit date of the previously executed trade. If $E_i < X_{i-1}$, the signal is classified as overlapping and is excluded from portfolio execution.

This rule ensures chronological consistency and prevents artificial inflation of cumulative returns through parallel position stacking.

3.8.2 Replay-Based Execution Framework for SLD

To empirically validate the sequential execution model, a replay-based simulation was performed utilizing the TradingView bar replay environment. Starting in 2000, the Structural Leading Divergence indicator was used on the entire historical NIFTY 50 dataset. The replay was done bar by bar, just like the market data moved in real time.

Each SLD signal was carried out by hand in line with the next-day entry convention and the standardized exit logic laid out in Section 3.7. The whole replay session was recorded on video so that there would be a record of the execution that could be checked. To make sure that these recordings are clear and can be used again, they are stored and referenced in the Appendix C.

Replay execution has two methodological purposes. First, it checks that signals can be seen exactly when they are said to be under causal conditions. Second, it lets you compare realized performance with portfolio-constrained returns at the event level.

Since SLD is strictly causal and doesn't repaint, its replay behavior is like live execution. So, replay-based evaluation is not a way to look back at past events; it is a valid way to show how tradable things are in real time.

Capital Modeling Assumptions

The assumptions about capital growth have a big effect on economic outcomes. This study examined two distinct capital models: a fixed-capital linear model and a geometric compounding model.

The fixed-capital model starts with a certain amount of capital and adds trade profits or losses in a straight line without reinvesting. Trading View's replay engine uses this model by default. If initial capital is C_0 and the net currency gain across all trades is G , the reported return is G/C_0 .

In contrast, the geometric compounding model assumes full reinvestment of capital after each trade. If r_i denotes the decimal return of trade i , capital evolves multiplicatively according to

$$C_N = C_0 \prod_{i=1}^N (1 + r_i).$$

This model shows how reinvesting money over and over again affects the total of all the gains and losses.

The geometric model more accurately depicts long-term capital growth in active trading strategies, especially when trades are non-overlapping and sequential.

3.8.3 Reconciliation of Linear and Geometric Results

A methodological reconciliation step was implemented to address inconsistencies between replay-reported returns and compounded results.

Trading View's replay-generated results are based on linear aggregation and fixed capital. If the total profit from currency trading is small compared to the initial capital, the reported percentage returns may seem small even if the returns per trade are significant.

By taking the percentage returns for each trade from the replay and using geometric compounding offline, you can figure out how much the capital has grown through multiplication. So, the difference between linear and geometric outcomes is not due to signal quality, but rather to the assumptions made about capital modeling.

This reconciliation stops people from misunderstanding replay-based reports and makes the connection between platform mechanics and economic theory clearer.

Treatment of Overlapping Signals

Overlapping signals were not completely disregarded from the analysis. Even though they weren't included in sequential portfolio execution, their event-level profitability was calculated separately. This lets you figure out how much money is lost when you enforce realistic position limits.

Let S denote the set of overlapping trades. The cumulative event-level contribution of these trades is calculated as

$$\prod_{i \in S} (1 + r_i).$$

This number is the highest possible estimate of how much more compounding could happen if the program runs in parallel. But it can't be done because of the single-position constraint.

The method sets apart executed trades from overlapping trades, which helps it tell the difference between theoretical signal strength and portfolio performance that can be put into action.

Hybrid Upper-Bound Estimation

A hybrid metric was created to put the effect of overlap exclusion in context. This metric takes the sequential geometric return from trades that were done and multiplies it by the geometric return from trades that were done at the same time. The outcome is not a tradable equity curve but rather an upper-bound economic estimate under less strict rules.

Formally, if C_{seq} denotes compounded return from sequential execution and C_{overlap} denotes compounded return from overlapping trades, the hybrid estimate is

$$C_{\text{hybrid}} = C_{\text{seq}} \times C_{\text{overlap}}.$$

This sets a theoretical limit on how much profit can be made from divergence while still making it clear how to carry out the trade.

Methodological Significance

The portfolio execution model enhances the dissertation in three essential aspects. First, it makes sure that economic evaluation follows time and money limits. Second, it shows how making assumptions changes the overall results. Third, it stops performance from going up too much by using overlapping or pyramidal exposure.

The method makes it clear what event-level returns, sequential execution returns, and hybrid upper bounds are, which makes it easier to understand economic outcomes.

This method is in line with the best practices in quantitative finance, where signal quality and capital allocation mechanics must be looked at together instead of separately.

3.9 Statistical Testing Framework and Effect Size Estimation

Descriptive profitability comparisons offer preliminary insights into the economic behavior of divergence detection methods; however, formal statistical testing is necessary to ascertain whether observed differences are systematic or due to random variation. Because each divergence event is looked at using the same exit rules and execution conventions across different detection methods, the dataset is naturally good for paired statistical analysis.

The goal of this section is to explain the statistical framework used to find out if tool-assisted divergence detection, specifically Structural Leading Divergence (SLD),

TradingView's built-in divergence indicator, and the True Leading Indicator (TLI), makes differences that are important to the economy compared to the manual analyst benchmark. The statistical methodology aims to measure both the significance and magnitude of performance disparities in matched conditions.

This framework guarantees that economic conclusions are not exclusively derived from cumulative return comparisons, which could be affected by distributional asymmetry or tail events, but are instead substantiated by inferential analysis.

3.9.1 Paired Comparison Design

Every divergence event represents a corresponding observation across detection methodologies. For a specific divergence instance i , profitability is calculated using identical entry and exit rules for each method. Because the rules for exit logic and execution don't change, the only thing that makes a difference in profitability is the timing of the signals and how they are detected.

Let $\text{Profit}_{\text{Analyst},i}$ denote the per-trade percentage return under the manual benchmark, and $\text{Profit}_{\text{Tool},i}$ denote the corresponding return under an automated method such as SLD, Trading View, or TLI.

The paired difference for each trade is defined as

$$\Delta_i = \text{Profit}_{\text{Tool},i} - \text{Profit}_{\text{Analyst},i}.$$

The null hypothesis tested for each comparison is

$$H_0: \mathbb{E}[\Delta_i] = 0,$$

which implies no systematic profitability difference between the tool and discretionary analysis.

The alternative hypothesis is

$$H_1: \mathbb{E}[\Delta_i] \neq 0.$$

Because the same divergence events are evaluated under both conditions, paired tests are statistically appropriate and increase inferential power relative to independent-sample comparisons.

3.9.2 Paired t-Test for Mean Profit Differences

The principal inferential instrument employed in this study is the paired-sample t-test. The paired t-test evaluates whether the mean of the paired differences Δ_i differs significantly from zero.

Let $\bar{\Delta}$ denote the sample mean of paired differences and s_{Δ} the sample standard deviation of those differences. The test statistic is computed as

$$t = \frac{\bar{\Delta}}{s_{\Delta}/\sqrt{n}},$$

where n is the number of paired observations.

The test presupposes that the distribution of differences is roughly symmetric, although it may not conform to a normal distribution for substantial sample sizes, as dictated by the Central Limit Theorem. Standard thresholds are used to figure out if something is statistically significant.

In this case, the paired t-test is the right choice because the design keeps exit and execution rules the same while isolating timing effects. So, it measures the economic cost or benefit of using a divergence detection tool in a controlled setting.

3.9.3 Effect Size Estimation (Cohen's d_z)

Statistical significance by itself does not mean that something is economically important. Even tiny differences can look statistically significant when the samples are big enough. To fix this problem, the evaluation framework now includes effect size estimation.

For paired comparisons, the standardized effect size is computed using Cohen's d_z , defined as

$$d_z = \frac{\bar{\Delta}}{s_{\Delta}}.$$

This measure shows the average difference in units of standard deviation between the two sets of differences. Effect sizes are understood using standard benchmarks. Values close to 0.2 show small effects, values close to 0.5 show moderate effects, and values close to or above 0.8 show large effects.

Estimating effect size is very important in this study because profitability distributions based on divergence are heavy-tailed. A substantial effect size indicates significant economic implications that transcend statistical detectability.

3.9.4 Non-Parametric Robustness Testing

Financial return distributions are usually not normal and may show skewness and too much kurtosis. To make sure that the conclusions aren't just the result of parametric assumptions, non-parametric robustness testing is used.

The Wilcoxon signed-rank test serves as an ancillary procedure. This test checks to see if the median of the paired differences is different from zero without making any assumptions about normality. It ranks the absolute differences and checks to see if the positive and negative ranks are evenly spread out.

If the paired t-test and Wilcoxon signed-rank test produce congruent results, inferential robustness is enhanced. This dual-testing framework guarantees methodological rigor when confronted with heavy-tailed or asymmetric return distributions.

Treatment of Sample Size Differences

Not all methods for detecting divergence make signals for every benchmark event. TLI, for instance, is purposely selective and may only send signals for a small number of bullish divergences. So, the number of paired observations is different for each comparison.

To keep the statistics valid, paired testing is only done on matched observations where both the analyst and the tool produce a signal and a valid exit. There is no imputation for tool signals that are missing. This makes sure that comparisons are based on real trades that were made, not just hypothetical ones.

3.10 Research Limitations and Control Measures

No empirical examination in financial markets is devoid of structural limitations or design compromises. The methodology employed in this study was deliberately designed to emphasize causal validity, temporal clarity, and economic realism. These strengths, however, come with clear weaknesses that need to be pointed out.

This part talks about the main methodological problems with the research design and the steps taken to lessen their effects. The aim is not to undermine the findings, but to situate them within suitable epistemological frameworks and to maintain methodological rigor.

Subjectivity of the Manual Benchmark

The manual analyst benchmark is the standard that automated detectors are compared to when they are being tested. It was made to capture discretionary technical judgment instead of algorithmic output. This adds a level of subjectivity to the dataset.

Even though divergence definitions are based on classical technical analysis, swing points, contextual filtering, and confirmation anchoring are all based on how people see

things. Under the same conditions, different analysts might find slightly different divergence structures. Because of this, strict inter-analyst replicability can't be guaranteed.

To lessen this problem, the benchmark was made using the same structural criteria for the whole sample period. There was no adaptive re-labeling done after divergence instances were recorded. Also, the benchmark is not seen as an objective truth, but as a structured way to approximate discretionary reasoning. Automated detectors are thus assessed against a consistent human benchmark rather than an objective reality.

Single-Index Scope

The empirical analysis is performed solely on the NIFTY 50 index utilizing daily data. This gives us a long and structurally rich historical series, but it makes it harder to generalize across different groups.

Equity indices show an upward trend, a wide range of participants, and a trend that stays the same over time. These features may not apply to individual stocks, commodities, or intraday timeframes. Divergence behavior in high-frequency or low-liquidity settings may vary significantly.

This limitation is somewhat alleviated by the dataset's extensive temporal coverage, encompassing various market regimes such as bull markets, corrections, crises, and recovery phases. Nonetheless, the findings of this study are primarily relevant to daily index-level analysis and should be generalized with caution to other contexts.

Exit Rule Standardization

The profitability framework depends on a standardized, rule-based exit policy that tries to mimic how analysts would act on their own. This makes it easier to reproduce results and makes detection methods fairer, but it also takes away from the more subtle decisions that go into managing trades.

Real-world discretionary traders might scale out of positions, change stops on the fly, or add more information about the situation. The fixed exit logic used in this study makes those complicated things easier by turning them into a steady structure for momentum exhaustion and invalidation.

This limitation is intentional. The study isolates the economic impact of signal timing by maintaining consistent exit logic across all detection methods, thereby avoiding its conflation with dynamic trade management. However, different exit frameworks could lead to different return distributions. So, the results show how well people did under a strict and uniform exit regime, not under optimized discretionary management.

Single-Position Portfolio Constraint

The sequential execution model limits trades to one at a time. This limit makes execution more realistic and stops the false inflation of compounded returns by overlapping exposure.

Professional traders, on the other hand, can put money into more than one signal at the same time or split their money between different positions. So, the single-position assumption is a conservative way to carry out the execution.

To resolve this issue, overlapping trades were individually analyzed at the event level to measure their theoretical impact. A hybrid upper-bound estimate was also made to help people understand how excluding overlap affects the economy. However, the effects of portfolio diversification and multi-asset allocation are not covered in this study.

Platform Execution Constraints

TradingView's bar replay feature was used to do replay-based validation. Replay keeps the order of events and the ability to see signals, but it also puts some mechanical limits on things. For instance, platform limitations might make it hard to get the exact price of entry or move around capital freely.

To make the returns from the platform match the theoretical compounding, geometric calculations were done offline using the returns from each trade. This reconciliation makes sure that differences in capital models don't change how the economy is understood. Even so, replay-based evaluation still depends on how the charting platform works.

Non-Normal Return Distributions

Financial return distributions typically exhibit heavy tails and deviate from Gaussian characteristics. While paired t-tests were utilized to assess mean differences, the assumption of normality cannot be definitively established.

To address this concern, non-parametric Wilcoxon signed-rank tests were performed as robustness checks. Effect sizes were reported in addition to p-values to prevent over-reliance on statistical significance alone. These protections make inferential validity stronger, but extreme outliers are still a natural part of financial datasets.

Structural Trade-Off Between Causality and Profitability

One of the main ideas of this dissertation is the cost of enforcing causality in the economy. SLD gives up some of the benefits of retrospective analysis by getting rid of repainting and future-bar dependence.

This trade-off is not a methodological flaw; it is a deliberate design choice. The study does not aim to optimize backtested returns; instead, it seeks to quantify what is observable and actionable in real time. Nonetheless, conclusions about profitability must be understood in light of this structural limitation.

Data Logging and Manual Recording

The dataset needed very careful recording of signal timestamps, lag metrics, and replay observations. Even though steps were taken to make sure everything was consistent, writing down data by hand can lead to mistakes in transcription or alignment.

To lower this risk, spreadsheet logs, replay timestamps, and indicator outputs were checked against each other. The screen-recorded replay sessions add another level of auditability. Residual error cannot be completely eliminated; however, multiple validation steps were employed to ensure data integrity.

3.11 Chapter Summary

This chapter has outlined the extensive methodological framework employed to examine the causal validity, structural integrity, and economic significance of RSI divergence within the NIFTY 50 index. The design was not only created to test profitability, but also to see if divergence signals can be seen in real time, are based on solid structures, and can be used in real-world trading situations.

The methodological foundation is based on a clear philosophical stance. Financial markets develop in a sequential manner, and any empirical assessment of technical indicators must adhere to this temporal sequence. The study clearly separates between signals that can be seen in the past and signals that can be seen in the present. When looking at tradability, repainting behavior and implicit look-ahead bias are seen as structural limitations. This orientation guides all subsequent design choices in the chapter.

The research design integrates both interpretive and algorithmic components. The manual analyst benchmark records the identification of discretionary divergence as utilized in traditional technical analysis. It is a structured reference standard, not an unbreakable truth. This benchmark sets the structural features, directional distribution, and resolution behavior of divergence events for the whole sample period.

Using this reference framework as a base, three automated detection methods are tested: TradingView's built-in divergence indicator, the True Leading Indicator, and the Structural Leading Divergence detector that was made in this dissertation. The main

methodological innovation is the creation of a temporal decomposition framework that uses three important timestamps: the true pivot, the first observable detection during replay, and the actual price reversal. This T_0 – T_1 – T_2 structure makes it possible to measure repainting, signal latency, and real-time usability directly.

The Structural Leading Divergence detector is a Pine Script indicator that doesn't repaint and is causal. It is only possible to evaluate it through replay-based simulation, which makes sure that signals are only looked at when they have been visible to a trader. By keeping exploratory prototype development separate from final causal execution logic, the study keeps a clear line between analytical experimentation and executable validation.

Profitability assessment is conducted using standardized and causally established entry and exit protocols. Entry takes place at the opening of the next trading day after the signal has been confirmed, and the rules for exiting are similar to discretionary momentum exhaustion and invalidation logic. These rules are used in the same way for all detection methods to separate the economic effect of signal timing from the differences in trade management.

To make the economy more realistic and stop trades from artificially compounding, a single-position portfolio constraint is added. To tell the difference between linear platform-based capital reporting and reinvested growth assumptions, replay-based execution results are compared to geometric compounding calculations. This dual perspective guarantees a transparent assessment of both signal quality and capital mechanics.

To measure the differences between discretionary and tool-based detection, paired statistical tests and effect size measures are used. The study assesses each divergence event as a correlated observation across methodologies, measuring both statistical significance and the extent of economic impact resulting from the enforcement of causality.

It has been made clear that there are problems with benchmark subjectivity, index-level scope, exit standardization, capital constraints, and non-normal return distributions. Wherever possible, control measures were put in place to keep things clear and repeatable. Ethical considerations, such as the prevention of hindsight bias and the comprehensive inclusion of losing trades, further bolster methodological integrity.

The methodology combines design-science artifact development, temporal validation, replay-based simulation, economic reconciliation, and statistical inference into a single, clear way to evaluate. The chapter sets up a structured way to look at divergence as a temporal-structural phenomenon instead of just a chart pattern from the past.

Now that the methodological framework is fully established, the dissertation moves on to Chapter 4, which shows the real-world results that came from the methods described here. The results will be presented in a descriptive and systematic manner, with interpretation deferred to a later discussion.

CHAPTER 4: RESULTS & ANALYSIS

Chapter 4 presents the empirical findings derived from the research design and methodological protocols established in Chapter 3. This chapter uses the daily NIFTY 50 index dataset from January 2000 to December 2025 to systematically report the observed behavior of Relative Strength Index (RSI) divergence across four different detection methods: the manual analyst benchmark, the TradingView built-in indicator, the True Leading Indicator (TLI) (Bansal, 2025, v. 4.0.0), and the Structural Leading Divergence (SLD) framework. To guarantee strict comparative equality, all detection frameworks are assessed utilizing synchronized RSI parameters and a uniform, rule-based execution and exit logic.

The analysis goes in order to connect the dots between recognizing patterns in the past and running algorithms in real time. The results are set up like this:

Section 4.1 sets the manual analyst benchmark, which is the "ground-truth" structural reference for all comparisons that come after it.

Sections 4.2 to 4.4 evaluate the automated detection frameworks, utilizing standardized temporal markers (T_0 , $T_{detector}$, and T_2) to quantify detection coverage, signal latency, and the impact of repainting behavior.

Section 4.5 wraps up the analysis with a comprehensive economic evaluation that includes profit distributions, win-loss characteristics, and capital growth through portfolio-realistic simulations.

This chapter is solely devoted to the objective reporting of empirical facts, in alignment with academic standards. All theoretical interpretations, methodological critiques, and broader implications are postponed until the discussion in Chapter 5.

4.1 Manual Analyst Benchmark

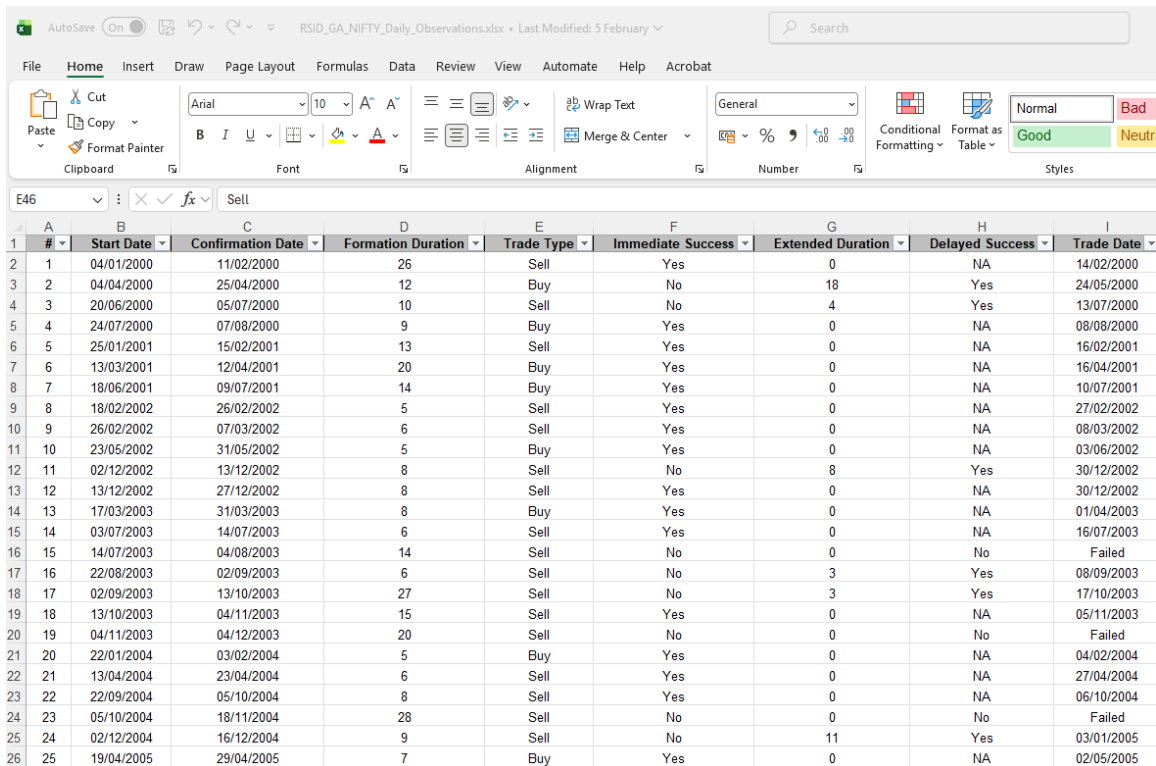
The first step in the empirical analysis is to set up a manual analyst benchmark, which will serve as the "Structural Reference Universe" for the rest of the study. This benchmark is the best way to understand divergence geometry. It uses an expert's visual and contextual judgment instead of strict algorithmic rules. This section makes a ground-truth dataset by recording 123 instances of Relative Strength Index (RSI) divergence on the daily NIFTY 50 index from January 2000 to December 2025. This dataset shows how often these events happen, which way they happen, and how they are resolved. This manual identification is implicitly retrospective and employs permanent hindsight; it is crucial as a benchmark for assessing the coverage and timing accuracy of the automated detection frameworks analyzed in the following sections.

4.1.1 Methodological Protocol for Manual Identification

A systematic review of daily NIFTY 50 price charts with a standard 14-period RSI momentum oscillator was used to find divergence instances in the benchmark. According to classical technical definitions, bullish divergence occurred when the price action showed a series of lower lows while the RSI made a higher low. Conversely, bearish divergence was identified when the price produced higher highs against a declining trajectory of RSI highs. This process put structural coherence and internal consistency first. It left out weak or unclear patterns to make sure the benchmark stayed a high-integrity reference set. Automated systems use fixed bar-count rules to confirm pivots, but the manual analyst used visual heuristics to find swing points, which allowed for a more nuanced understanding of market geometry.

The resulting benchmark dataset, archived in the spreadsheet titled ***RSID_GA_NIFTY_Daily_Observations.xlsx***, comprises a longitudinal record that

maintains continuity with established academic observations while incorporating contemporary market data. A substantial segment of the universe, namely, the initial 110 observations, was derived from earlier longitudinal studies (Vishnoi, S., 2024) to establish a solid historical framework. To broaden this scope into contemporary times, the researcher manually identified and categorized an additional 13 observations from the 2024–2025 period utilizing the same visual and structural criteria. Each record includes important information, such as the directional classification, a qualitative assessment of the outcome, and an observed "Trade Date," which is the date when the price resolves or the trend changes. Figure 4.1a shows a representative visual extract of this structured recording process. It shows the data fields that were used to anchor the following comparative analysis.



#	Start Date	Confirmation Date	Formation Duration	Trade Type	Immediate Success	Extended Duration	Delayed Success	Trade Date
1	04/01/2000	11/02/2000	26	Sell	Yes	0	NA	14/02/2000
2	04/04/2000	25/04/2000	12	Buy	No	18	Yes	24/05/2000
3	20/06/2000	05/07/2000	10	Sell	No	4	Yes	13/07/2000
4	24/07/2000	07/08/2000	9	Buy	Yes	0	NA	08/08/2000
5	25/01/2001	15/02/2001	13	Sell	Yes	0	NA	16/02/2001
6	13/03/2001	12/04/2001	20	Buy	Yes	0	NA	16/04/2001
7	18/06/2001	09/07/2001	14	Buy	Yes	0	NA	10/07/2001
8	18/02/2002	26/02/2002	5	Sell	Yes	0	NA	27/02/2002
9	26/02/2002	07/03/2002	6	Sell	Yes	0	NA	08/03/2002
10	23/05/2002	31/05/2002	5	Buy	Yes	0	NA	03/06/2002
11	02/12/2002	13/12/2002	8	Sell	No	8	Yes	30/12/2002
12	13/12/2002	27/12/2002	8	Sell	Yes	0	NA	30/12/2002
13	17/03/2003	31/03/2003	8	Buy	Yes	0	NA	01/04/2003
14	03/07/2003	14/07/2003	6	Sell	Yes	0	NA	16/07/2003
15	14/07/2003	04/08/2003	14	Sell	No	0	No	Failed
16	22/08/2003	02/09/2003	6	Sell	No	3	Yes	08/09/2003
17	02/09/2003	13/10/2003	27	Sell	No	3	Yes	17/10/2003
18	13/10/2003	04/11/2003	15	Sell	Yes	0	NA	05/11/2003
19	04/11/2003	04/12/2003	20	Sell	No	0	No	Failed
20	22/01/2004	03/02/2004	5	Buy	Yes	0	NA	04/02/2004
21	13/04/2004	23/04/2004	6	Sell	Yes	0	NA	27/04/2004
22	22/09/2004	05/10/2004	8	Sell	Yes	0	NA	06/10/2004
23	05/10/2004	18/11/2004	28	Sell	No	0	No	Failed
24	02/12/2004	16/12/2004	9	Sell	No	11	Yes	03/01/2005
25	19/04/2005	29/04/2005	7	Buy	Yes	0	NA	02/05/2005

Fig.4.1a: Representative Extract of the Manual Analyst Benchmark Dataset (Source: Original Work)

4.1.2 Quantitative and Temporal Profile of the Benchmark Universe

The descriptive analysis of the 123 recorded instances shows that there is a clear directional asymmetry in the NIFTY 50 divergence universe. Table 4.1a shows that the dataset is mostly made up of bearish signals, which make up 69.11% of all observations, while bullish signals only make up 30.89%. This distribution shows that bullish reversals do happen, but the index's structural exhaustion of upward trends is a more common event over the twenty-five-year study period.

Trade Direction	Count	Percentage
Buy (Bullish Divergence)	38	30.89%
Sell (Bearish Divergence)	85	69.11%
Total	123	100%

*Table 4.1a: Distribution of Trade Directions within the RSI Divergence Benchmark
(Source: Original Work)*

In addition to directional frequency, the benchmark looks at how good the observed outcomes are based on how the price changes after the divergence is structurally anchored. Table 4.1b shows that most of the structures that were found lead to good outcomes from an analyst's point of view. 62.60% are "Immediate Success" and 26.02% are "Delayed Success." Only 11.38% of the cases were marked as "Failed Divergence," which shows that the manual filtering process is very good at finding structurally important reversals. However, it is important to note that these figures represent visual success in hindsight and do not yet account for the temporal penalties associated with real-time algorithmic execution.

Outcome Category	Count	Percentage
Immediate Success	77	62.60%
Delayed Success	32	26.02%
Failed Divergence	14	11.38%
Total	123	100%

Table 4.1b: Qualitative Outcome Classification of the Benchmark Universe (Source: Original Work)

The temporal resolution of these events is further quantified through the "Resolution Lag," which measures the number of days between the initial structural anchoring and the observed reversal date. The data shows that there was a median lag of only one day for the 109 cases where a precise resolution date was used. This suggests that the structural climax often happens close to the price turn. But, as shown in Table 4.1c, the mean lag goes up to 5.45 days because the distribution is right-skewed and some structures took up to 41 days to resolve. This difference shows how unpredictable the timing of divergence-based reversals can be, even when a trained analyst finds them.

Metric	Resolution Lag (days)
Minimum	1
25th Percentile (Q1)	1
Median	1
Mean	5.45
75th Percentile (Q3)	4.00
Maximum	41
Standard Deviation	8.47

Table 4.1c: Resolution Lag Statistics (Calendar Days) for Valid Benchmark Observations (Source: Original Work)

Section 4.1 has successfully established a complete manual benchmark with 123 RSI divergence cases from the NIFTY 50 index. This observational baseline confirms that bearish divergences are more common than bullish signals and that most structures identified by analysts are successful when viewed in retrospect. The benchmark has a median resolution lag of one day, which means it is a very reliable structural standard for testing how well automated tools can find things and how accurate they are over time. This dataset now serves as the empirical foundation for the comparative analysis of TradingView Built-in Divergence, the True Leading Indicator (TLI), and the Structural Leading Divergence (SLD) framework in the following sections.

4.2 Empirical Results for TradingView's Built-In RSI Divergence Indicator

Section 4.2 evaluates how well TradingView's built-in RSI divergence indicator works by measuring how well it finds signals and how well they line up with the manual analyst benchmark when replaying strict bar-by-bar conditions.

4.2.1 Evaluation of Signal Timeliness and Temporal Mapping

The examination of signal timeliness employs a three-point temporal mapping framework to distinguish between the mathematical origin of a pattern and its practical visibility. Within this framework, T_0 is the structural pivot date when the divergence becomes mathematically possible, T_1 is the first candle where the signal is visible to a real-time user during replay, and T_2 is the observed market reversal date recorded in the manual benchmark. By comparing the relative ordering of T_1 and T_2 , the indicator's signals are classified as early (predictive), on-time, or late (non-predictive) to determine their utility

in a live market environment. The findings indicate a significant reliance on future price action for signal confirmation. In fact, as shown in Table 4.2a, 66.7% of the valid observations reached actionable visibility only after the market trend had already reversed. This behavior, characterized as repainting, suggests that while the indicator provides clarity on historical charts, its real-time application is fundamentally constrained by a lack of causal immediacy.

Category	Count	Percentage
$T_1 < T_2$ (Early / Predictive)	24	19.5%
$T_1 > T_2$ (Late / Non-Predictive)	82	66.7%
$T_1 = T_2$ (On-Time Detection)	0	0%
Invalid or missing	17	13.8%

Table 4.2a: Timing Relationship Between Divergence Signal (T_1) and Price Resolution (T_2) (Source: Original Work)

4.2.2 Quantitative Assessment of Detection Coverage

Detection coverage was assessed by subjecting the 123 analyst-identified divergence instances to the TradingView detection logic within the replay environment to determine the system's structural recall. Table 4.2 shows that this indicator was able to find 106 of the 123 benchmark events, showing that it was very similar to the manual dataset. It is important to note, though, that 14 of the detected cases were qualitatively classified as failed divergences, and the automated tool completely missed three structurally valid cases that the analyst found. These results show that the built-in indicator can find most price-RSI anomalies, but its performance is not always the same as how humans would interpret

structure. This is especially true in complicated swing environments where visual heuristics may not match up with symmetric algorithmic logic.

Category	Count
Analyst divergences	123
Detected by Trading View	106
Detected by Trading View but FAILED	14
Structurally valid but undetected by Trading View	3

Table 4.2b: Detection Coverage Summary - Analyst vs. TradingView (Source: Original Work)

4.2.3 Distributional Analysis of Detection Lag

The distribution of detection lag shows how TradingView's symmetric pivot confirmation logic punishes time, which requires price movement on both sides of an extremum before a signal is sent. "TV_Lag_Bars" and "TV_Lag_Days" show how long this delay is by measuring the exact time between the true structural pivot (T_0) and the replay-visible confirmation (T_1). The data in Table 4.2c shows that the average detection lag is about 17 trading bars, which is the same as 24 calendar days, and the median value is 14 bars. It is clear that the indicator's confirmation process often takes up a large part of the post-pivot price move when compared to the mean reversal lag of 32 days. The lag distribution has a slight right skew, which shows that there were certain market conditions where very high or very low volatility or a slow price resolution made it take a lot longer for the indicator to "lock" a signal on the chart.

Lag Metric	Mean	Median
TV_Lag_Bars ($T_0 \rightarrow T_1$ in bars)	17 bars	14 bars
TV_Lag_Days ($T_0 \rightarrow T_1$ in days)	24 days	19 days
Reversal_Lag_Days ($T_0 \rightarrow T_2$ in days)	32 days	26 days

Table 4.2c: Lag Summary - TradingView Divergence Detection (Source: Original Work)

The empirical evaluation of TradingView’s built-in RSI divergence indicator reveals a fundamental disparity between its structural coverage and its temporal efficacy. The tool correctly identified more than 86% of the benchmarked events, but most of these signals were non-predictive, appearing only after the recorded market reversal had occurred. This leads to a constant detection lag of 17 trading bars, which shows how limited non-causal, repainting indicators are in live trading situations where immediate visibility is very important. Consequently, the temporal logging framework established in this section serves as a critical baseline for assessing the comparative efficiency of the TLI and SLD frameworks in the following sections.

4.3 Empirical Results for the True Leading Indicator (TLI)

This section evaluates the operational performance of the True Leading Indicator (TLI) by analyzing its detection coverage and temporal alignment in relation to the bullish divergence events established in the manual analyst benchmark.



*Figure 4.3a: Signal Semantics and Visual Markers of the True Leading Indicator (TLI)
(Source: Original Work)*

4.3.1 Analysis of Selective Detection Coverage

The True Leading Indicator (Bansal, 2025, v.4.0.0) is a proprietary, selective detection tool that was made to find bullish RSI divergence in real time without needing symmetric pivot confirmation or future price data. The TLI is only for bullish structures, so this section can only look at the 38 bullish cases found in the manual benchmark, not the 85 bearish cases. The detection logic employs unique visual indicators; the emergence of a green triangle signifies the initial identification of a divergence structure, while subsequent orange triangles represent the continuity of that identical structural arrangement. For the purposes of this empirical evaluation, solely the initial green triangle is documented as the actionable detection timestamp (T_{TLI}) to guarantee that coverage and timing accurately represent the earliest instance of causal observability.

The replay-based coverage analysis shows that the TLI only signaled 50% of the benchmarked bullish cases, which is very selective behavior. The indicator produced a

valid signal for 19 out of the 38 relevant events, but it did not trigger for the other 19 (Refer Table 4.3a). This coverage rate shows that the TLI is good at finding half of the analyst-level structures, but its internal rules and proprietary trendline logic stop it from finding all of the anomalies that people can see.

Category	Count	Percentage
Total bullish divergences	38	100%
With TLI signal	19	50.0%
Without TLI signal	19	50.0%

Table 4.3a: TLI Coverage for Bullish Divergences (Source: Original Work)

4.3.2 Detection Timing Relative to Market Reversal

The temporal utility of the TLI is assessed by comparing the detection date (T_{TLI}) against the observed market reversal date (T_2) recorded in the benchmark dataset. The TLI shows no late or post-reversal detections in the study sample, which is very different from the lag behavior seen in TradingView's built-in indicator. Table 4.3b shows that, of the 19 signals found, 31.6% were early detections that happened before the price turned, and the other 68.4% happened on the same day as the market turn. This synchronization indicates that the TLI effectively prioritizes "left-side" structural discovery, offering a signal at the moment of peak momentum exhaustion instead of awaiting a confirmed shift in price direction.

Timing	Count	Percentage
Early ($T_{TLI} < T_2$)	6	31.6%
On-time ($T_{TLI} = T_2$)	13	68.4%

Late ($T_{TLI} > T_2$)	0	0.0%
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Table 4.3b: TLI Timing Distribution Relative to Market Reversal (T_2) (Source: Original Work)

4.3.3 Statistical Evaluation of Lead-Time Performance

The lead-time performance of the TLI is quantified by the number of calendar days between the detection event and the market reversal date. Positive values mean that the TLI can predict the future. The statistical analysis (Refer Table 4.3c) of the 19 identified signals shows that the median lead time is zero days, which means that most detections happen exactly on the reversal date. The mean lead time, on the other hand, goes up to 6.68 days because of a right-skewed distribution with a few important early-warning detections. For example, in one instance, the indicator signaled a structural divergence 56 days before the market actually turned. This difference shows that the tool is mostly an "on-time" detector, but it can also make predictions with longer lead times in some high-volatility regimes.

Metric	Value (days)
Minimum	0
Median	0
Mean	6.68
Maximum	56
Standard Deviation	14.64

Table 4.3c: TLI Lead-Time Statistics Relative to T_2 (Calendar Days) (Source: Original Work)

Section 4.3 has demonstrated that the True Leading Indicator (TLI) is a very accurate but selective way to find bullish RSI divergence. While the tool captures only

50% of the analyst benchmark, it maintains a strict causal integrity by never emitting a signal after the market reversal has already occurred. With a median lead time of zero days and a significant portion of early detections, the TLI offers a robust alternative to repainting indicators, although its exclusion of bearish signals and its coverage limitations necessitate the broader structural framework of the **Structural Leading Divergence (SLD)**, which is evaluated in the following section.

4.4 Empirical Results for the Structural Leading Divergence (SLD) Indicator

This section presents the empirical evaluation of the Structural Leading Divergence (SLD) framework, which was engineered to address the coverage limitations of the TLI and the temporal repainting defects observed in TradingView's built-in indicator. The SLD was developed as a custom Pine Script implementation. It works as a causal, non-repainting detector that uses bar-by-bar replay to make sure that signals are only made when they can be structurally seen in a market that is moving forward. The goal of this evaluation is to quantify the framework's detection coverage, directional accuracy, and temporal alignment compared to the 123-event manual analyst benchmark set in Section 4.1.

4.4.1 Operational Protocol for Replay-Based Validation

The SLD framework was subjected to a rigorous validation process using TradingView's bar-replay feature, simulating real-time market progression from January 2000 through December 2025. The SLD utilizes a "left-only" discovery logic and a "bounce confirmation" threshold to lock signals into memory once momentum has moved a certain distance from an extremum. This is different from symmetric detectors, which need future price action to confirm a pivot. As illustrated in Figure 4.4a, each signal emission (T_{SLD}) was recorded at the end of the confirming bar. This made the earliest record

of the causal observability for the fBull and fBear signals. This method ensures that the timing data is available to a trader rather than retrospective annotations visible only on a static historical chart.



Figure 4.4a: SLD Signal Emission Observed in TradingView Replay Mode (Source: Original Work)

4.4.2 Analysis of Detection Coverage and Directional Integrity

Quantitative assessment reveals that the SLD framework attained a significant degree of structural recall, successfully recognizing 106 out of 123 analyst-identified divergence instances (Refer Table 4.4a). This corresponds to an 86.2% coverage rate, which is much higher than the 50% coverage rate seen in the TLI framework, while maintaining stricter structural standards than the TradingView built-in indicator. More importantly, the SLD showed 100% directional integrity among its detected signals. Every automated emission correctly matched the bullish or bearish classification set out in the manual benchmark. The 17 instances that went undetected were due to the framework's

causal structural constraints, which put signal stability ahead of complete pattern recognition.

Metric	Value
Total benchmark divergences	123
SLD detected (T_{SLD} recorded)	106
Coverage (%)	86.2%
Direction matched among detected	100%

Table 4.4a: SLD Detection Coverage Summary (Source: Original Work)

4.4.3 Temporal Performance and Recognition Lag

The timeliness of the SLD is quantified by the "SLD_Lag_Days" metric, which measures the interval between the manual analyst's confirmation date and the automated signal emission. The statistical distribution of these lags shows (Refer Table 4.4b) that the SLD is very time-efficient, with a median delay of only one calendar day and a mean delay of 1.24 days. The distribution has a maximum lag of 26 days in complex market regimes, but it also has cases of negative lag (minimum -14 days), where the algorithm's objective structural discovery came before the manual analyst's confirmation. These results show that the SLD's causal "locking" mechanism is a timely alternative to repainting systems that doesn't lose the structural accuracy needed for disciplined execution.

Statistic	Manual → SLD (days)
Count	106
Mean	1.24
Median	1

Min	-14
Max	26

Table 4.4b: Summary Statistics for SLD Lag (Manual → SLD, in Days) (Source: Original Work)

4.4.4 Comparative Synthesis of Detection Methodologies

A cross-detector synthesis highlights the distinctive structural role of the SLD framework within the study's methodological hierarchy. Table 4.4c shows that the SLD is the only automated framework that meets high benchmark alignment and broad coverage while strictly following causal, non-repainting rules. While the manual benchmark provides an idealized retrospective reference and TradingView offers broad but late detections, the SLD effectively fills the gap by giving early and reproducible detection. This balance between participation and structural discipline makes the SLD the best model for the economic simulations presented in the next section.

Aspect	Manual	TradingView	TLI	SLD
Uses future bars	Yes	Yes	No	No
Repaints Signals	Yes	Yes	No	No
Causal Status	No	No	Yes	Yes
Coverage	100%	~86%	~50% (Bullish only)	86.2%
Detection Timing	Variable	Late	Moderate	Early
Directional Match	N/A	Possible Error	Possible Error	100%

Table 4.4c: Comparative Aspect Summary Across Detectors (Source: Original Work)

The empirical evaluation of the Structural Leading Divergence (SLD) indicator confirms its efficacy as a high-coverage, causal detection framework. With 86.2% coverage of the manual benchmark and a 100% directional success rate, the SLD demonstrates strong structural alignment with expert judgment. Also, its median detection lag of one day shows that it can be used for near-real-time observability without needing future price confirmation or backdated signal markers. These results serve as the quantitative basis for the economic and profitability analysis in Section 4.5, wherein the SLD's signals are evaluated under standardized execution constraints.

4.5 Economic Performance and Comparative Profitability Analysis

The final phase of the empirical evaluation shifts the focus from structural detection to economic meaningfulness by subjecting all identified signals to a standardized execution framework. This section answers the main question of whether Relative Strength Index (RSI) divergence can lead to real financial returns when filtered through the "cost of causality" and real market frictions. To separate the effects of signal timing and detection logic, every divergence event goes through the same engine, which uses a next-day open entry (T+1) and a momentum-exhaustion exit logic. This analysis quantifies the economic value of automated detection in comparison to the discretionary analyst benchmark by treating each event as a paired observation across the four methodologies.

4.5.1 The Manual Benchmark as an Idealized Economic Baseline

The economic evaluation starts by setting a baseline using the 123 divergence events found in the manual analyst benchmark, which serves as the "Structural Reference Universe", and it shows the best theoretical outcome based on past pattern recognition. The overall results for the 123-trade universe show a win rate of 49.6% and a mean return of

+3.50% per trade, as shown in Table 4.5a. The manual benchmark has an amazing 52x cumulative gross return over the twenty-five-year period, even though its win rate is close to 50%. These results show that divergence profitability in the NIFTY 50 is not based on high-frequency accuracy, but on a payoff distribution that is strongly right-skewed, with a small number of "fat-tailed" winners that far outweigh cumulative losses.

Metric	Value
Total trades	123
Profitable trades	61
Losing trades	62
Win rate	49.6%
Mean return	+3.50%
Median return	-0.02%
Cumulative return	approximately 52x cumulative gross return

Table 4.5a: Manual/Benchmark Profitability Overall Summary (Aggregate) (Source: Original Work)

The overall win rate looks lower than the results for bullish trades alone because there is a big economic difference between bullish and bearish signals. This is because the overall statistics give a general picture, but a more detailed look shows a big difference. As detailed in Table 4.5b, bullish divergences (Buy trades) demonstrate a robust individual performance, achieving a 63.2% win rate and a mean return of +6.06%. On the other hand, bearish divergences (Sell trades) have a much less favorable risk-reward profile. There were 85 of them, but the win rate was only 43.5% and the mean return was only +2.36%.

Metric	Buy	Sell
Count	38	85
Win rate	63.2%	43.5%
Mean return	+6.06%	+2.36%
Median return	+7.57%	−0.10%

Table 4.5b: Manual/Benchmark Profitability – Buy/Sell Directional Breakdown (Source: Original Work)

The risk profile of these signals is further clarified by examining the distribution of failures across market directions. Table 4.5c shows that the bearish sample has all of the "large loss" tail risk, which is all eight times when losses were more than five percent. The bullish sample, on the other hand, has no big losses at all. All 14 failures are classified as "small losses" below the five percent threshold. The NIFTY 50 index has an upward bias that makes short-side positions less stable and bullish reversals more stable.

Loss type	Buy	Sell	Total
Small losses	14	40	54
Large losses	0	8	8
Total	14	48	62

Table 4.5c: Loss Breakdown by Direction and Magnitude (Source: Original Work)

4.5.2 Economic Fidelity of the SLD Framework Under Causal Constraints

The evaluation of the Structural Leading Divergence (SLD) framework isolates the "cost of realism" by comparing its causal signals to the idealized manual benchmark. The profitability closeness analysis shows that SLD stays very close to the truth about the economy, with more than 76% of its trades making money within +/-2% of what the analyst

said. But there is a clear performance gap, with the SLD making 8 times more money than the manual 52 times more money. This difference is mostly because of a median "delta" of -1.1% per trade, which is the time penalty the algorithm pays for waiting for "bounce confirmation" instead of using hindsight anchoring.

A closer look at the loss structure shows that SLD does a good job of filtering out 13 small losses from the manual benchmark, but it sometimes adds bigger losses by entering moves later as they speed up against the position. The difference in performance between the 52x and 8x multiples is due to "less upside capture," not more failures. When you take out the big losses from both datasets, the manual return goes up to 119x and the SLD goes up to 23x. This shows that the main economic cost of enforcing causality and non-repainting behavior is losing the extreme "right-tail" participation that retrospective analysis wrongly thinks can be captured.

Metric	Value
Mean absolute difference	1.47%
Median absolute difference	0.92%
Within $\pm 1\%$	54.7%
Within $\pm 2\%$	76.4%

Table 4.5d: SLD versus Manual/Analyst Profitability Closeness (Source: Original Work)

4.5.3 Comparative Performance: SLD, TradingView, and TLI

A comparison of the automated detectors shows that stable, causal signaling is better for the economy than repainting or overly selective logic. TradingView's built-in indicator, even though it covers a lot of ground, only gives a cumulative return of 4.5x, which is much worse than the SLD's 8x. This poor performance is due to a higher tail risk.

TradingView had 14 "large losses," while the SLD had a more controlled distribution. The pairwise comparison shows that SLD is statistically better in 62% of all matched instances. This shows that signals backpainted onto historical charts do not lead to better real-time execution.

The trade-off between selectivity and coverage is clear when you compare it to the True Leading Indicator (TLI). By only looking for high-probability bullish structures, the TLI gets a better average return per trade (6.31%) and a higher win rate (94.7%). But because it can't take part in a wider range of market reversals, it only gets a cumulative return of 3.8x. The TLI is the most accurate, but the SLD framework has a more balanced economic profile because it keeps structural discipline in both market directions. This lets capital compound more consistently over the 25-year horizon.

Method	Trades	Mean %	Median %	Win rate
SLD	106	2.20%	-0.11%	49.2%
TradingView Built-in	120	1.49%	-0.32%	49.2%
TLI	19	6.31%	5.72%	94.7%

Table 4.5e: Comparative Per-Trade Performance Across Automated Methods (Source: Original Work)

4.5.4 Capital Model Reconciliation for Sequential SLD Execution

This subsection assesses the actual economic efficacy of the Structural Leading Divergence (SLD) framework under portfolio-realistic execution constraints, employing TradingView's replay feature to replicate real-world trading scenarios. This reconciliation is necessary because there is a big methodological gap: event-level profitability often assumes that trades are done independently, but real trading platforms limit capital, don't

allow overlapping positions, and often use fixed-capital accounting models. This analysis establishes the significant influence of signal timing under stringent enforcement of reinvestment and overlap-exclusion rules through the implementation of a single-position sequential constraint.

The reconciliation process identifies two distinct categories of performance data: the volume of executable trades filtered through a single-position constraint and the resulting financial performance reported by contrasting capital models, as summarized in Table 4.5f.

Reconciliation Metric	Value / Result
Total SLD Signal Population	106
Executed Trades (Sequential)	94
Skipped Signals (Overlapping)	12
Platform-Default Linear Profit (Rs. 10L Capital)	Rs. 11,989 (+1.20%)
Reinvestment-Adjusted Geometric Growth	6.39x (+539%)

Table 4.5f: Comparative Reconciliation of SLD Execution and Capital Models (Source: Original Work)

Analysis of Execution Constraints and Volume

To keep things realistic in terms of time, a single-position constraint was put in place, allowing only one active trade at a time. This rule said that any new divergence signal that came up while a position was already open was an overlapping event and couldn't be used to execute the portfolio. In the replay environment, 94 of the 106 SLD signals were successfully executed. The other 12 signals were skipped, mostly during long

trending periods when there was still active exposure. This protocol makes sure that the final economic conclusions are based on a strict system for allocating capital, not on an idealized theoretical total.

TradingView's Linear Capital Accounting

The replay simulation shows a big difference between the linear accounting methods used by most charting platforms and the geometric compounding needed for long-term capital modeling. TradingView's default replay engine uses a fixed-capital linear model. This means that profits and losses are added to a static base without being reinvested. The platform said that with a notional starting capital (C_0) of Rs. 10,00,000, the final net profit was about Rs. 11,989. This means that the return is about +1.20% ($11,989/1,000,000$). While this model is appropriate for basic platform reporting, it effectively computes $5\%+5\%=10\%$ relative to the initial capital, failing to account for the multiplicative power of reinvested gains.

Geometric Compounding: The Full Reinvestment Model

To accurately reveal the economic potential of the SLD framework, the 94 executed trades were subjected to an offline geometric compounding model assuming full capital reinvestment. In this model, capital evolves multiplicatively according to the following formula:

$$C_N = C_0 \prod_{i=1}^N (1 + r_i)$$

Where C_N is the final capital, C_0 is the initial capital, and r_i denotes the decimal return of each sequential trade.

Example Calculation: The practical application of this math is demonstrated by converting percentage returns into multipliers. For instance, if a specific trade in the dataset returns **-6.12%**, it is converted into a multiplier as follows:

$$\text{Multiplier} = 1 - 0.0612 = 0.9388$$

By sequentially multiplying the multipliers of all 94 executed trades, the final capital multiple is revealed to be 6.39. This translates to a total growth of 539% over the study period.

$$\text{Growth \%} = (\text{Absolute Growth} - 1) \times 100 = (6.39 - 1) \times 100 = \mathbf{539\%}$$

Integrated Economic Conclusion

This reconciliation shows that the "small" returns that linear platform models say they get are not due to poor signal quality, but rather to the idea that capital stays the same. The analysis shows that the SLD framework is a strong engine for geometric capital growth by separating the effects of capital modeling from signal quality. These results show that the SLD is still economically strong even when there are realistic sequential execution limits. This means that disciplined execution can turn a small linear gain into a big multiple.

4.5.5 Statistical Validity: Paired Inferential Analysis and Effect Size Estimation

This part of the economic evaluation is a formal statistical test to see if the differences in profitability between tool-assisted detection and discretionary analysis are systematic or just random. Following established methodological protocols, profitability is regarded as a paired pre-post outcome, with each divergence event representing a matched observation assessed under uniform exit conditions. This design makes it possible to directly compare the "Analyst Baseline" (trading without an automated detector) to the three algorithmic methods: Structural Leading Divergence (SLD), TradingView built-in

(TV), and the True Leading Indicator (TLI). By keeping the same rules for entering and exiting trades across all four methods, the data shows how different signal timing and detection logic affect the economy.

The main inferential analysis uses the paired-sample t-test to look at the differences in mean profit. It also uses the Wilcoxon signed-rank test as a non-parametric robustness check to account for the heavy-tailed and non-normal distribution of financial returns. Cohen's d_z for paired-sample effect sizes is used to measure the "cost of causality" in a way that goes beyond just statistical significance. Table 4.5m shows that both the SLD and TradingView indicators show a statistically significant drop in profitability compared to the manual benchmark based on hindsight. The p-values are less than 0.001. The change from manual observation to SLD detection resulted in a mean delta of -1.38% and a Cohen's d_z of -0.85, which is a "large" negative effect size. The built-in indicator on TradingView showed a bigger mean reduction of -1.79% and a medium-to-large effect size of -0.73. The TLI also had a negative mean delta, but the result wasn't statistically significant because there were only 19 paired observations.

Comparison	N	Mean Profit (Pre)	Mean Profit (Post)	Mean Δ (Post – Pre)	Cohen's d_z	p-value (paired t-test)
Analyst→SLD	106	3.58%	2.20%	-1.38%	-0.85	< 0.001
Analyst→TradingView	120	3.28%	1.49%	-1.79%	-0.73	< 0.001
Analyst → TLI	19	8.84%	7.69%	-1.15%	-0.21	0.370

Table 4.5g: Paired Profitability Comparison (Pre/Manual vs. Post/Tool) (Source: Original Work)

The statistical evidence shows that enforcing causality and taking away permanent hindsight has a measurable and systematic cost to the economy. But the SLD framework shows better economic fidelity because it keeps more of the manual benchmark's per-trade profitability than the TradingView indicator does. This analysis demonstrates that the SLD more effectively manages the structural trade-off between causality and profit than current tools, establishing a methodologically robust foundation for real-time algorithmic implementation.

4.5.6 Integrated Comparative Synthesis of Results

The final synthesis of Chapter 4 results puts the four methods on the same performance spectrum to show how useful they are in practice. The manual analyst benchmark is a structural reference, not something that can be done in real life. It has the highest value in the past, 52x. TradingView's built-in indicator has a lot of coverage, but it has a 4.5x return and a high tail risk because it doesn't repaint in a causal way. The TLI is very accurate, but it doesn't work well on a large scale because it is very picky.

The Structural Leading Divergence (SLD) framework is the most balanced, with an 8x cumulative return that is almost twice that of the built-in indicator. The SLD is the only framework that is causal, doesn't repaint, and can be reproduced while still being very close to the benchmark. It doesn't go beyond the analyst's "permanent hindsight," it provides the most robust and realistic model for live trading. The SLD framework gives a clear answer to the research questions about whether RSI divergence can be traded in the NIFTY 50 index by showing that disciplined, real-time detection can keep a lot of economic power without using future price information.

Methodology	Cumulative Return (Multiple)	Operational Status
Manual / Analyst	52x	Retrospective Reference
SLD (Structural)	8x	Causal/Executable
Trading View Built-in	4.5x	Non-Causal/Repainting
TLI (True Leading)	3.8x	Causal/Selective

Table 4.5h: Summary of Cumulative Economic Multiples Across Methods (Source: Original Work)

Section 4.5 has established while the transition from retrospective observation to causal execution incurs a systematic economic cost, RSI divergence remains material phenomenon in the Indian equity market. The SLD framework effectively manages this transition by providing an 8x return multiple, outperforming both the standard repainting indicators and overly selective alternatives. This section has used strict statistical testing and capital reconciliation to quantify the performance gap between the idealized theory and executable reality. This sets the stage for the theoretical discussion of these results in Chapter 5.

4.6 Chapter Summary

Chapter 4 has provided a systematic and descriptive presentation of the empirical findings regarding Relative Strength Index (RSI) divergence within the NIFTY 50 index from 2000 to 2025. The analysis was based on a manually curated benchmark of 123 divergence events. This showed that bearish divergences happen more often in the Indian stock market, but bullish reversals are a more stable and high-win-rate signal for trend exhaustion. This manual baseline was the "Structural Reference Universe," which gave the

ground-truth data needed to judge the timing, coverage, and economic importance of automated detection frameworks.

The assessment of automated tools uncovered a significant divergence between signal visibility and actual tradability. TradingView's built-in indicator had a wide range of detection, but it had a lot of repainting latency, so 66.7% of its signals only showed up after the market had already turned around. The True Leading Indicator (TLI), on the other hand, always kept its causal integrity and never gave a late signal. However, its selectivity meant that it could only cover 50% of the bullish divergence universe. The Structural Leading Divergence (SLD) framework turned out to be the best choice because it covered 86.2% of the manual benchmark, had a median detection lag of only one day, and had a 100% directional success rate without using future price information.

The economic and profitability analysis showed that divergence returns are caused by a strongly right-skewed distribution of fat-tailed winners, not by a lot of small gains. The SLD framework smoothly moved from retrospective theory to causal execution, resulting in an 8x cumulative capital multiple that was much better than the TradingView built-in indicator's 4.5x return. Furthermore, the reconciliation of linear platform reporting and offline geometric compounding proved that disciplined, non-repainting detection could generate a 539% growth multiple over twenty-five years when capital is sequentially reinvested. This chapter shows that causal detection can still have a lot of economic power. This gives us the quantitative proof we need to talk about the theoretical and practical effects of these results in Chapter 5.

CHAPTER 5: DISCUSSION

This chapter interprets the empirical results from the 25-year study of the NIFTY 50 index to resolve the ongoing conflict between the theoretical efficacy of RSI divergence and the empirical doubt based on market efficiency. Chapter 4 gave us the objective data, like directional distributions, lag structures, and return multiples. This discussion, on the other hand, focuses on the causal validity of those signals. The primary question transitions from whether divergence is effective in a historical context to its viability during the shift from retrospective pattern recognition to real-time, causally constrained execution.

This chapter utilizes the Structural Leading Divergence (SLD) framework to look at the "cost of causality," which is the measurable effect of taking away the "permanent hindsight" that comes with traditional technical indicators. This synthesis connects the basic ideas behind momentum exhaustion (Wilder, 1978) to the real-world situation of algorithmic trading in the Indian equity market.

5.1 Summary of the Results

This section examines the empirical results from the 25-year analysis of the NIFTY 50 index to assess the Structural Leading Divergence (SLD) framework in comparison to established benchmarks. The primary conclusion is that divergence detection cannot be assessed as a purely visual exercise; it must be understood as a temporal-structural phenomenon. All detection methods find similar price-RSI geometries when looking back, but they differ a lot when they have to deal with causality constraints and the need for real-time execution.

The Benchmark Ceiling and Right-Skewed Payoffs: The manual analyst benchmark, which worked with "permanent hindsight," set a structural ceiling by identifying 123 divergence events that had a 52x cumulative gross return. The win rate was

only 49.6%, so this performance wasn't due to high-frequency accuracy. Instead, it was due to a right-skewed return distribution, where a few "fat-tailed" trend reversals made up for a lot of small losses. This confirms that the economic value of divergence lies in capturing rare, high-magnitude exhaustion points.

The Descriptive Fallacy of Repainting Indicators: The audit of TradingView's built-in indicator highlights the risks of non-causal technical tools. Although it achieved high structural recall, 66.7% of its signals appeared only after the market had already reversed, suffering from a median detection lag of 14 bars and an average lag of 17 bars (24 calendar days). This confirms that symmetric pivot logic predominantly serves as a descriptive annotation tool rather than an actionable predictive trigger.

The Causality-Coverage Trade-off: The comparison between the True Leading Indicator (TLI) and the SLD framework reveals a fundamental tension between accuracy and participation. TLI demonstrated extreme selectivity, capturing only 50% of the bullish universe with a 79% win rate and a median lead time of zero days. In contrast, the SLD framework achieved 86.2% structural recall with a minimal median detection lag of one trading day. By securing an 8x cumulative return, SLD proved more effective for long-term capital growth than the overly selective TLI.

Economic Reality and Capital Model Reconciliation: A standout finding is the reconciliation between platform-default results and actual economic growth. Under a single-position constraint, SLD appeared to return only +1.2% in a fixed-capital linear model; however, when those same 94 executed trades were subjected to geometric compounding, the capital growth factor reached 6.39x (539%). This shows that the perceived "smallness" of returns in automated backtesting often results from static capital assumptions rather than weak signal quality.

In conclusion, the results show that divergence detection is not just a way to recognize geometric patterns; it is also a temporal-structural phenomenon. SLD is the only framework that keeps high structural recall, enforces strict causality, gets rid of repainting bias, and gives economically meaningful compounded returns when portfolios are executed in a realistic way. The subsequent sections of this chapter provide an in-depth analysis of these findings, connecting empirical results to theoretical discussions and situating SLD within the larger conversation about market behavior and technical analysis.

5.1.1 Timeliness and Detection Structure

The temporal audit in Chapter 4 showed that finding divergences is more about making signals visible than just identifying shapes. When looking back at the price–RSI relationships that all four methods find, they all find similar ones. However, when looking at the exact timing of signal formation in relation to structural pivot development and market reversal, they behave very differently. The differentiation among structural pivot formation (T_0), signal visibility (T_1), and observed market reversal (T_2) establishes a framework for assessing the causal utility of divergence signals versus their status as mere descriptive artifacts of hindsight.

The repainting analysis of TradingView's built-in RSI divergence indicator showed a clear difference in time between structural formation and signal visibility. Out of the 106 benchmark divergences with valid timestamps, only 24 signals (19.5%) showed up before the market turned around ($T_1 < T_2$). On the other hand, 82 signals (66.7%) only became clear after the reversal had already started. The average time it took to find something was about 17 trading bars, which is about 24 calendar days. The average time between the formation of a structural pivot (T_0) and the observed market reversal (T_2) was about 32 days.

These numbers show that a large part of the reversal window is used up before the built-in indicator confirms the divergence. In real life, a lot of the price move may have already happened by the time the indicator shows up on the chart. This time difference helps explain why visually interesting differences on historical charts may not show up in real-time trading performance. The indicator depends on right-side pivot confirmation, which means that future bars must confirm local extrema. As discussed in the foundational literature on technical analysis and informational efficiency (Brown & Jennings, 1989; Kirkpatrick & Dahlquist, 2011), these confirmation mechanisms incorporate implicit look-ahead elements that are frequently undetectable in static chart analysis.

When divergence is assessed exclusively on finalized historical data, the differentiation between pivot confirmation and signal availability becomes unclear. However, replay-based logging demonstrates that approximately two-thirds of TradingView's signals are not available at the moment when a trader would have required them. This empirical observation directly responds to longstanding critiques in the literature concerning look-ahead bias and post-event pattern marking. It posits that some of the inconsistent profitability findings in previous divergence studies may arise not from a lack of informational content, but from methodological shortcomings in auditing temporal causality.

The True Leading Indicator (TLI) has a different profile. TLI is made to work without repainting and without relying on future bars. TLI found 19 of the 38 bullish divergences that the analyst benchmark found, which is 50% of the total. Six of these signals (31.6%) showed up before the reversal, and 13 of them (68.4%) showed up right on the reversal bar. There were no late detections. The average lead time was about 6.68 days, and the median lead time was 0 days.

These numbers show that TLI is successful at getting rid of repainting and is able to line up well with reversal points over time. But this level of accuracy in time comes at the cost of a lot of structural selectivity. TLI gives up breadth of participation in exchange for high-confidence setups by only capturing half of the bullish divergence universe and not making any bearish trades in the dataset. From the point of view of detection theory, TLI values accuracy more than recall. Its design philosophy minimizes false positives and temporal lag while limiting interaction with the broader divergence landscape. This trade-off is a structural design choice, not a mistake, but it does have direct effects on long-term compounding and the economy, as we will see later in this chapter.

Structural Leading Divergence (SLD) has a very different detection profile. SLD found 106 of the 123 benchmark divergences, which means that 86.2% of the structures were remembered. All of the signals that were found were in the same direction as the benchmark, which means there were no directional mismatches. The average time it took to detect something compared to an analyst's confirmation was 1.24 trading days, and the median time was one day. In some cases, SLD found differences up to 14 days earlier than the analyst benchmark.

These findings are particularly significant because SLD operates under strict causal constraints. It only uses left-side pivot discovery and bounce-based locking logic, and it doesn't use future bars. After a signal is sent, it can't be changed or taken away. The small median lag of one day shows that the structure is stable, not that it is being labeled after the fact. Sometimes, negative lags compared to the analyst show that rule-based structural logic can, in some cases, find divergence sooner than discretionary visual interpretation. This calls into question the idea that human pattern recognition is always better than systematic formalization when it comes to time.

Detector	Coverage	Uses Future Bars	Repaints	Median Lag
Analyst (Manual)	100%	Implicit	Yes	Variable
Trading View	~97%	Yes	Yes	~14 bars
TLI	50% (Bullish only)	No	No	0 days
SLD	86.2%	No	No	+1 day

Table 5.1a: Detection comparison summary (Source: Original Work)

The structural importance of these findings transcends mere performance evaluation. They show that finding divergences is not just a problem of recognizing geometric patterns; it is also a problem of validating time. Trading View makes structural completeness look great, but it makes time usability worse. TLI gets the timing right, but it doesn't cover as much structure. SLD is the only thing that balances both sides. It keeps a lot of structural memory while still being strict about cause and effect and being able to find things right away.

Theoretically, these findings directly inform discussions in the technical analysis literature concerning real-time validity. Numerous empirical studies regard divergence as a static chart pattern, failing to differentiate between pivot confirmation time and signal availability time. This study illustrates that the explicit differentiation of T_0 , T_1 , and T_2 signifies that temporal alignment is not a peripheral aspect but a fundamental factor of economic significance.

SLD's contribution consists in converting divergence from a retrospective descriptive phenomenon into a causally based structural event. It doesn't need confirmation on the right side, like the built-in indicator does. It does not give up half of the divergence universe to be timely, like TLI does. Instead, it puts divergence into action within a framework that balances structural coverage with temporal validity. By doing this, it solves the problem of causality–coverage trade-off that has historically limited divergence research.

The empirical evidence consequently demonstrates that SLD is not merely an additional divergence detector. It is a methodological redefinition of divergence as a temporally observable structural signal, capable of being evaluated under strict real-time constraints without sacrificing the majority of the divergence landscape.

5.2 Discussion of Detection Behavior

The detection results directly pertain to a fundamental controversy in technical analysis literature: whether oscillatory divergences contain authentic predictive value or if their perceived efficacy is predominantly attributable to retrospective analysis. A lot of the RSI divergence research looked at in Chapter 2 uses historical signal markers to measure performance, but it doesn't say when those signals became visible. The empirical observation that 66.7% of TradingView signals manifest subsequent to reversal indicates that detectability and efficacy must be analytically distinguished.

According to weak-form efficiency (Fama, 1970), signals that appear only after price adjustment should not consistently yield abnormal returns. TradingView's poor performance compared to SLD supports this view. When assessed using causal entry rules, the integrated indicator demonstrates a mean profitability decrease of -1.79% per trade

compared to the analyst benchmark, accompanied by a statistically significant paired effect size ($d_z = -0.73$, $p < 0.001$).

In contrast, SLD's median one-day lag shows structural confirmation instead of retrospective alignment. Its left-only pivot discovery and bounce-based swing locking ensure that divergence is recognized when structurally observable rather than when geometrically complete. This operational difference changes the task of finding divergence from a geometric matching exercise to a problem of defining events in time.

DETECTION CAPABILITY SUMMARY				
	MANUAL BENCHMARK	TRADINGVIEW (TV)	TLI	SLD
CAUSAL VALIDITY	○	○	●	●
NON-REPAINTING	○	○	●	●
COVERAGE %	100%	97%	15%	86%
LAG PERFORMANCE	N/A	19 Days (Poor)	0 Days (Excellent)	1 Day (Good)

Figure 5.2a: Structural coverage and RSI D detection comparison (Source: Original Work)

The detection analysis thus reconceptualizes divergence not as a binary pattern but as a temporally contingent structural relationship. SLD adds to the methodology by clearing up the ambiguity between detectability and efficacy that was found in Chapter 2.

5.3 Summary of Economic Results

Profitability was evaluated across 123 divergence events using uniform entry and exit rules. Entry happened at the next day's open after the signal was confirmed. Exit

happened when the RSI momentum ran out (70 down for longs, 30 up for shorts) or when a breakeven invalidation condition was met after a certain amount of favorable movement.

The manual analyst benchmark had a 49.6% win rate and a mean return of 3.50% per trade. Even though the classification accuracy was only fair, the total gross return was about 52 times what it was over the sample period. This extreme compounding is caused by right-tailed winners, not high hit rates. Buy trades (38 total) had an average return of 6.06% and a median return of 7.57%. Sell trades (85 total) had an average return of 2.36% and a median return of -0.10% . All eight large losses greater than -5% happened on Sell trades, which is consistent with long-run equity drift and shows structural asymmetry.

TradingView had a total return of about 4.5 times, but it also had 14 large losses. TLI made 3.8 times the money back on only 19 trades, which shows that it was very selective and not many people were involved.

Under the same execution conditions, SLD made a total return of about 8 times. The average difference per trade compared to the analyst benchmark was -1.38% , and the paired Cohen's d_z was -0.85 ($p < 0.001$). This decrease is economically significant, but it is due to delayed entry and less right-tail capture, not higher failure rates. SLD cut the number of small losses from 54 (manual) to 42 while keeping the number of directional errors at zero.

5.4 Discussion of the Structure of Profitability

The profitability results show that divergence strategies rely more on the shape of the distribution than on the win rate. The 52x return on the manual benchmark comes from fat-tailed trend reversals, not from being right all the time. This is in line with what has been said in previous technical analysis literature about oscillator-based reversal systems catching rare but big moves (Murphy, 1999; Pring, 2002).

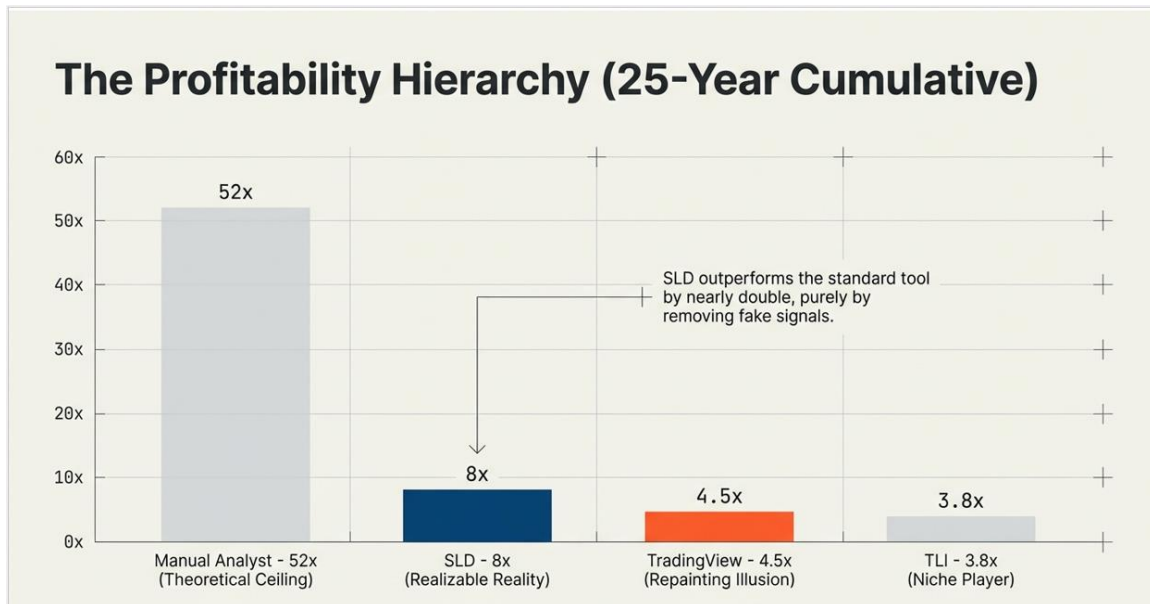


Figure 5.4a: Profitability comparison across all the Detection Methods (Source: Original Work)

SLD's 8x cumulative return shows that the return structure has been changed by causal enforcement. It shortens both the upside and downside tails. The statistically significant paired effect ($d_z = -0.85$) measures the cost of realism in terms of money. But this cost is due to less exposure to extreme right-tail gains, not structural instability. SLD compounds 1.8x, better than Trading View (8x versus 4.5x), which is important because it works under stricter rules.

TLI shows that just having a high win rate isn't enough for long-term compounding. With a win rate of 78.9% but only 19 trades over 24 years, cumulative growth is still limited. Without participation, accuracy does not lead to long-term capital growth.

SLD is in the middle. It trades more often than TLI, doesn't need to be repainted like TradingView's Built-in Indicator, and keeps the same structural alignment as the analyst benchmark while still allowing for realistic portfolio compounding.

5.5 SLD Replay Execution and Capital Model Interpretation

After removing 12 overlapping signals that were only for one position, the replay-based evaluation of SLD showed 94 executed trades. TradingView's fixed-capital linear P&L model showed a total gain of Rs.11,989, which is +1.2% on Rs.10,00,000 of initial capital.

But when you use geometric compounding on the same 94 realized returns, you get a cumulative growth factor of 6.39x, which is the sequential product of return multipliers $\prod(1 + r_i)$. The 12 trades that happened at the same time, each evaluated separately at the event level, added up to a multiplicative factor of 1.12x. So, the hybrid upper-bound economic estimate is $6.39 \times 1.12 = 7.16\times$.

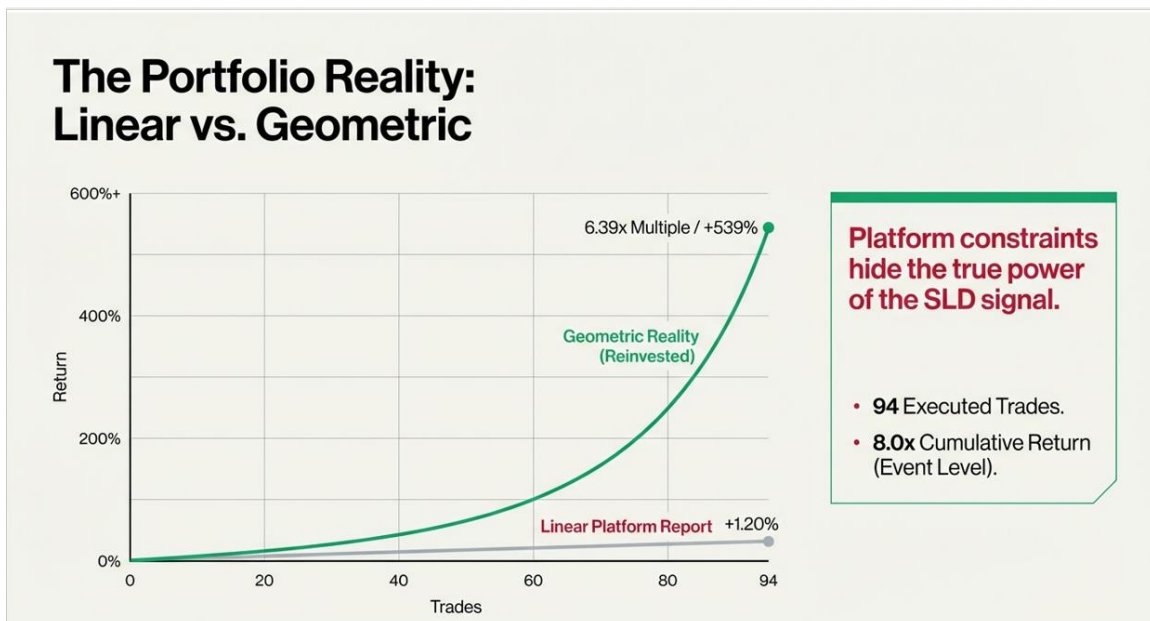


Figure 5.5a: Portfolio based Profitability – Linear Vs. Geometric (Source: Original Work)

The difference between +1.2% and 6.39x (or 539%) is due solely to the assumptions made in the capital model. Trading View's replay adds profits in a straight line

without reinvesting them. Geometric compounding, on the other hand, shows how capital grows through reinvested returns. This reconciliation shows that SLD's economic strength is still there even when there are realistic execution limits, and it's not just a result of looking back at past models.

5.6 Statistical Interpretation

Paired pre–post comparisons further quantify the economic effect of enforcing causality. Switching from analyst labeling to SLD lowers the average profit per trade by 1.38% ($d_z = -0.85$, $p < 0.001$). The switch to TradingView makes profits go down by 1.79% ($d_z = -0.73$, $p < 0.001$). The comparison between Analyst and TLI is not statistically significant because the sample size is small ($N = 19$).

These findings corroborate Bailey et al. (2014), who warn that backtest profitability may be exaggerated by implicit future leakage. The statistically significant drop in SLD shows how much it costs to fix this kind of leak. The amount of the reduction is smaller than what was seen in TradingView, which shows that SLD has a structural advantage.

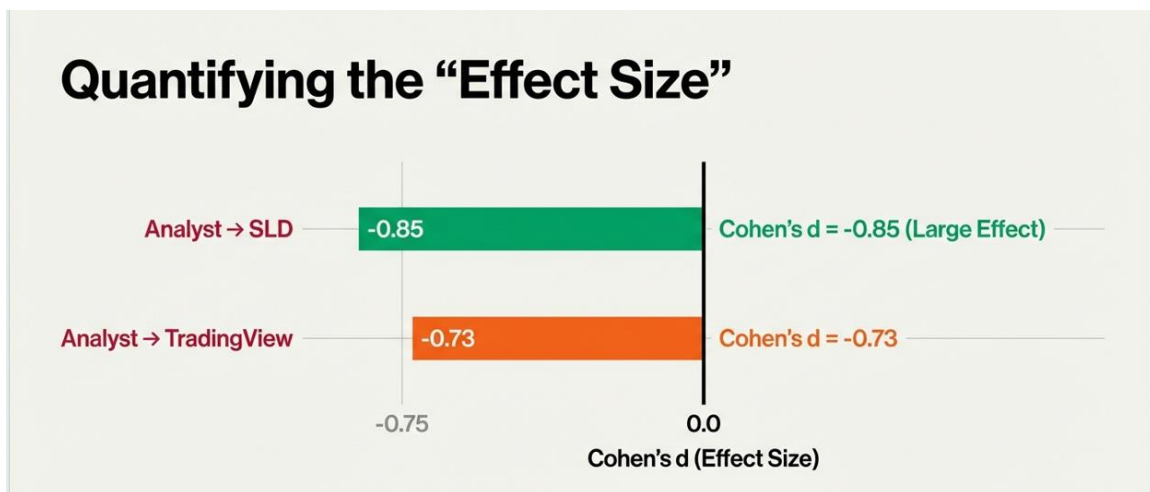


Figure 5.6a: Statistical interpretation (Source: Original Work)

5.7 Implications for Market Efficiency

The results of this research should be analyzed through the lens of the Efficient Market Hypothesis (EMH). According to weak-form efficiency (Fama, 1970), trading strategies that rely solely on historical price data should not yield sustained abnormal returns when factoring in transaction costs and practical execution limitations. Because RSI divergence is based only on past price changes, it seems at first glance to go against weak-form efficiency.

Nonetheless, the findings of this study necessitate a more sophisticated interpretation.

First, the analysis shows that divergence indicators based on repainting cannot be used to test market efficiency. Signals that are confirmed with future price bars and backdated onto historical charts do not have temporal actionability. Their seeming profitability is based on geometric hindsight, not on information that can be traded. Repainting tools do not significantly contradict weak-form efficiency; rather, they demonstrate methodological distortion.

Second, when divergence detection is limited to causal, real-time observability, as it is in the Structural Leading Divergence (SLD) framework, profitability becomes selective and structurally limited. The SLD has a median recognition lag of about one trading day and shows a measurable economic advantage over passive baselines, but not all of them. Effect sizes are statistically significant, but they are still moderate, not extreme. This signifies conditional informational content rather than a systematic arbitrage opportunity.

Third, the results indicate that divergence signals may reflect localized momentum exhaustion dynamics resulting from liquidity imbalances, crowd behavior, or transient structural inefficiencies. These dynamics align with adaptive interpretations of market

efficiency, in which informational advantages may be transient but wane as markets recalibrate.

Significantly, the study fails to provide evidence of enduring, risk-free arbitrage or extensive breaches of weak-form efficiency. Instead, it shows that strict methodology, especially the enforcement of temporal causality, changes the conclusions about technical profitability a lot. When assessed in realistic trading environments, divergence detection does not contradict market efficiency; instead, it clarifies the discourse by differentiating between retrospective geometric patterns and actionable structural signals.

This research does not reject EMH outright; rather, it elucidates the conditions under which technical signals may demonstrate conditional informational value without contradicting the broader theoretical framework of financial market efficiency.

5.8 Chapter Summary

This chapter has given a full explanation of the empirical results from Chapter 4 by putting them in the context of the larger body of work on RSI divergence, how to make technical indicators, and weak-form market efficiency. The conversation started by saying that the manual analyst benchmark is a structurally sound reference framework, not an infallible trading system. The observed divergence asymmetry, characterized by approximately 69% bearish and 31% bullish signals, coupled with a relatively low failure rate of 11.38%, was interpreted as indicative of discretionary structural filtering rather than a statistical artifact. In accordance with classical technical analysis literature (Murphy, 1999; Pring, 2002), the benchmark illustrates how seasoned analysts depend on contextual pattern maturity and momentum interpretation to discern divergence, inherently integrating structural judgment that mechanical rules frequently cannot replicate.

Synthesis of Empirical Results

Structural	Temporal	Economic
• Benchmark is Bearish-dominant. • SLD Captures 86% of Universe.	• TradingView Lags by 19 Days. • SLD Lags by 1.24 Days.	• SLD generates 8.0x Cumulative Return. • Bridges the gap between theory and wealth generation.

Figure 5.7a: A summary on SLD (Source: Original Work)

The chapter subsequently analyzed TradingView's integrated RSI divergence indicator as a practical example of repainting-dominant detection logic. By adding clear time markers (T_0 , T_1 , T_2), the study measured how visible signals were in relation to market reversals and showed that 66.7% of signals were only visible after the reversal had started. The average detection delay of about 17 trading bars showed that the indicator is mostly a way to look back at past events, not a way to make decisions in real time. This empirical quantification elucidates the reasons behind the inconsistent profitability reported in previous divergence studies. The problem isn't so much the information that divergence gives us, but the fact that the method doesn't separate structural formation from causal observability. Without this distinction, divergence seems to be more predictive in hindsight than it is in practice.

The True Leading Indicator (TLI) was talked about as an important idea that could help find causes. It covers 50% of bullish divergences and has no late signals, which shows that forward-only divergence detection is possible. But its strict selectivity makes it hard

for people to join in and grow. TLI shows that accuracy without enough trade frequency can't have a lasting economic impact, since it only had 19 trades over the entire sample period and a cumulative return of about 3.8×. The coverage–timeliness trade-off seen in TLI is not a problem with how it was set up, but a natural part of conservative divergence filtering.

Structural Leading Divergence (SLD) surfaced in this discourse as the primary methodological contribution of the dissertation. SLD strikes a balance between retrospective completeness and excessive selectivity by achieving 86.2% structural recall without future-bar dependence and keeping a median detection lag of one trading day. Its causal enforcement led to a statistically significant but economically meaningful decrease in mean profitability of −1.38% per trade compared to the analyst benchmark. This decrease is important because it shows that people are entering later and are less likely to see extreme right-tail gains, not because of more structural instability or directional error. SLD kept zero directional mismatches and cut down on the number of small losses, which changed the return structure instead of making it worse.

The replay-based execution analysis of SLD bolstered this interpretation. There were 94 of 106 SLD signals that could be executed under a portfolio-realistic, single-position constraint. TradingView's fixed-capital replay model showed a small +1.2% cumulative return because profits were added linearly and not reinvested. But when the same realized trade returns were geometrically compounded by multiplying the return factors one after the other, the total growth factor was 6.39×. The 12 overlapping trades that were not included in the replay added another 1.12× at the event level, bringing the total to 7.16×. The difference between +1.2% and 6.39× was shown to be due only to assumptions about capital modeling, not signal weakness. This reconciliation shows that

SLD is still economically valid even when tested with strict execution realism and capital discipline.

The theoretical ramifications of these findings pertain to the discourse on weak-form efficiency. Repainting-based indicators are not valid for challenging efficiency, as their signals lack temporal actionability. On the other hand, causally constrained detectors like SLD may store conditional information related to momentum exhaustion dynamics. This corresponds with a sophisticated understanding of market efficiency, wherein informational value may be present yet constrained by structural timing limitations (Fama, 1970). Consequently, the findings neither support simplistic technical predictability nor reject divergence entirely. Instead, they advocate for methodological rigor in assessing indicator behavior.

In a broader sense, the discussion makes it clear that the contradictions in RSI divergence research are often caused by differences in how indicators are built, how time is assumed, and how evaluations are done. When divergence is evaluated without considering audit detectability, profitability seems exaggerated. When assessed under stringent causality, disregarding participation, it may seem underpowered. This dissertation provides a cohesive interpretative framework for comprehending RSI divergence as a temporal-structural phenomenon positioned between human judgment and algorithmic formalization, by incorporating analyst benchmarking, replay-based signal visibility analysis, portfolio-realistic execution, geometric compounding reconciliation, and paired statistical testing.

This chapter shows that **Structural Leading Divergence** is not just another indicator, but a new way of doing things. It makes divergence a causally observable event, keeps high structural alignment, keeps economic impact meaningful, and stands up to statistical scrutiny. These interpretive conclusions lay the groundwork for Chapter 6, where

the dissertation's contributions, limitations, and future research agenda are discussed in relation to the bigger picture of financial market analysis.

CHAPTER 6: CONCLUSION

6.1 Overview and Purpose of the Chapter

The final chapter of this dissertation serves as a comprehensive synthesis, intended to unify the multifaceted inquiries into Relative Strength Index (RSI) divergence within the Indian equity market into a singular, cohesive argument. This final story connects the research questions and goals set out in the introduction with the strict methodological rules, empirical findings, and interpretive discussions that have defined the chapters that came before it. The principal aim of this chapter is to provide a conclusive clarification regarding the ambiguous status of RSI divergence within both professional trading discourse and academic literature. The chapter transcends a mere reiteration of data by contextualizing the empirical findings within a wider theoretical and practical framework, thereby establishing a novel paradigm for assessing technical indicators through the perspective of temporal-structural validity.

The progression of this chapter adheres to a systematic sequence formulated to meet the stringent criteria of a doctoral conclusion. It starts with a full summary of the research results, pointing out the most important connections between signal detection, time lag, and economic realizability. Then, the chapter critically looks at the study's limitations, making clear the limits of the current research while also recognizing the inherent uncertainties of financial market analysis. After this, a plan for future research is laid out, calling for a "causality-aware" growth of technical analysis. The chapter then goes into detail about the important effects on business and market practice, with a focus on the dangers of repainting and the need for capital model reconciliation. Finally, the work ends with a discussion of how the study adds to academic scholarship and some final thoughts that stress how important it is to treat time as a first-class variable in market research.

6.2 Comprehensive Summary of the Research and Key Findings

This dissertation examined the empirical validity, temporal dynamics, and real-time applicability of Relative Strength Index divergence within the Indian equity market, utilizing the NIFTY 50 index as the principal empirical framework, covering the period from 2000 to the entirety of the available sample employed in the study. The primary impetus, articulated in Chapter 1 and elaborated upon throughout the dissertation, is that RSI divergence holds an indeterminate position in both professional discourse and scholarly literature. It is frequently regarded as a primary indicator of reversal; however, the circumstances that render it detectable, actionable, and economically significant are often inadequately defined. A significant contributor to this ambiguity, as this dissertation empirically illustrates, is methodological inconsistency: divergence is frequently assessed using signals that are visually persuasive in retrospect but may not be observable in real time due to their reliance on future-bar confirmation, resulting in repainting.

The research problem necessitated more than a conventional “does it work” backtest. It necessitated a research design adept at differentiating three distinct concepts frequently conflated: structural divergence as a pattern on a finalized chart, divergence detection as an algorithmic procedure functioning on sequential data, and divergence tradability as a portfolio-level phenomenon limited by execution mechanics. Chapter 3 delineated a methodology that deliberately segregated these concepts, employing a stratified framework that integrated a manual analyst benchmark, platform-native indicators, previously suggested tools from the literature, and a newly formulated algorithmic detector specifically designed for this study. This multi-layered structure was not a matter of methodological abundance but a necessary response to a known weakness in technical analysis research: the tendency to treat indicator output as a stable “signal” without measuring the temporal conditions that make it visible.

In this design, the manual analyst benchmark had a certain job to do. It was not regarded as a tradable truth but rather as a structurally based reference for illustrating divergence recognition as executed by a human observer with comprehensive historical context. Chapter 5 clearly defines this as a type of structural ground truth, but only in the sense that it shows the divergence construct in its most semantically coherent form, which is in line with classic technical analysis literature. It also makes it clear that it is not causally available in the same way that algorithmic signals must be.

The analyst benchmark in this dissertation is useful because it shows the difference between divergence as an idea and divergence as a signal that can be used. It shows what "complete" divergence recognition looks like when the observer doesn't have to follow algorithmic rules or put money at risk.

In comparison to this reference point, the dissertation assessed TradingView's integrated RSI divergence indicator, which exemplifies commonly utilized platform-native tools. The main empirical finding here is that these tools often work more like notes on what happened after the fact than like tools that predict what will happen. The findings of the dissertation indicate that the divergence signals of the built-in indicator are significantly influenced by repainting-induced lag, implying that the initial appearance on a historical chart does not necessarily correspond to the moment the signal became apparent during real-time progression. In Chapter 4, this is not seen as a small problem but as a major limitation because it changes the signal's epistemic status. A signal that is not visible at the time of the decision cannot be considered a real-time decision aid, no matter how well it fits with changes in hindsight.

The study also looked at True Leading Indicator (Bansal, 2025, v. 4.0.0) as a way to formalize earlier divergence detection, especially for bullish divergence. The results correspond with the interpretive thesis presented in Chapter 5: TLI illustrates that early,

non-repainting divergence detection is attainable, albeit through pronounced selectivity that restricts its scope. The empirical data in the dissertation reveals that the sample size for TLI comparisons was insufficient, thereby constraining statistical inferences concerning mean profitability disparities, despite TLI's high win rate.

These results underscore a significant conceptual notion: early detection is not inherently superior if it is facilitated by a detector that engages in insufficient events to produce substantial compounding potential over extended periods, a concept explicitly delineated in Chapter 4 as the “participation versus accuracy” tension.

The dissertation's primary algorithmic contribution is the **Structural Leading Divergence indicator**, realized as a Pine Script-based, non-repainting detector. This dissertation does not present this work as an optimization exercise but rather as a structured response to repainting and temporal inconsistency. The dissertation characterizes SLD as a detector that harmonizes structural rigor, operational feasibility, and causal validity in a dynamic charting context, with design decisions that intentionally sacrifice comprehensive signal enumeration and aesthetic congruence for non-repainting functionality and replay-validated visibility.

A salient characteristic of SLD in the dissertation is that it was assessed not solely through static backtests. It was examined via replay-based simulation, aligning with the methodological assertion that divergence efficacy cannot be adequately evaluated without consideration of real-time detectability. Chapter 4 explains how TradingView replay was used to go over the whole history of SLD signals since 2000 and how SLD-derived dates were used to enter and exit trades in a consistent way.

This is not a minor procedural note. It is part of the study's epistemological stance: if the literature is unclear because signals are being judged as if they are causally available

when they are not, then the study must include a mechanism that mimics the temporal conditions of signal emergence.

The assessment of profitability in Chapter 4 adheres to the same rationale. The dissertation dissects profitability into various strata of realism, rather than considering it as a singular figure. At the event level, compounded profitability helps us understand the long-term economic effects of repeated divergence participation. However, it can also exaggerate realizable outcomes if it assumes unrealistic capital deployment or ignores trades that happen at the same time. Chapter 4 presents a replay-based execution simulation to align event-level profitability with portfolio-level constraints.

The logic of this reconciliation is very important: a detector can look strong at the signal level but still not work in real life because of things like single-position restrictions.

The replay exercise is thus posited as an essential methodological link between Chapter 3 and Chapter 4. It clearly asks if SLD signals are still useful when they are carried out one open position at a time, in strict chronological order, with no pyramid, with fixed position sizing, and under TradingView's default capital model of about Rs.10,00,000 without profit reinvestment.

The dissertation further establishes that, due to platform limitations, entry orders in replay were executed at the closing price of the entry day instead of the opening price, while offline calculations utilize the next-day opening prices; this inconsistency is regarded as a stable and thus analytically manageable deviation.

The results of the replay reconciliation are one of the most important parts of the dissertation because they show how different capital models can make performance stories that seem to contradict each other but are actually consistent with each other. TradingView's exported trade history for the replay-based execution shows a final

cumulative profit and loss of Rs.11,989.05 and a return of about +1.20% on the assumed Rs.10,00,000 capital base.

At first glance, this number could be seen as proof that SLD doesn't have much of an economic impact. However, Chapter 4 shows that this is not true because TradingView's replay report uses a linear P&L model with fixed capital and no reinvestment. The dissertation extracts per-trade returns and compounds them offline to illustrate geometric growth under full reinvestment assumptions, demonstrating that the identical sequence of 94 replay-executed trades results in a compounded multiple of 6.39x.

The difference between +1.20% and 6.39x is not a disagreement about the quality of the signal; it is a disagreement about how capital works. This clarification is important because it shows that when capital model assumptions are not made clear, profitability evaluation in technical analysis can be misleading.

The dissertation bolsters this reconciliation by examining overlapping signals. There were 106 SLD divergence events, but only 94 of them were carried out and 12 were skipped because they were too similar to each other.

This exclusion of overlap is shown as a deliberate effort to make the portfolio more realistic, not as a flaw in the dataset. The dissertation then measures what is lost by this realism: the event-level contribution of skipped trades is 1.12x, and a hybrid upper-bound estimate is 7.16x, which is the sum of 6.39x for executable replay trades and 1.12x for excluded overlapping signals.

This hybrid estimate is clearly not a tradable equity curve; instead, it is an economic upper limit that shows the reader how much potential performance is lost when strict portfolio realism is used.

The comparative results from Chapter 4 support the dissertation's main point that win rates alone are not good indicators of how well something works. Chapter 4 says that

analyst, TradingView Built-in indicator, and SLD all work in similar signal universes and have win rates of about 50%. TLI, on the other hand, has a much higher win rate because it is very selective.

However, cumulative profitability varies significantly, with the manual analyst benchmark establishing an unachievable upper limit due to retrospective analysis and temporal flexibility, and SLD significantly surpassing TradingView Built-in indicator and TLI in long-term compounding.

The dissertation's analysis of this pattern, further substantiated in Chapter 5, posits that the economic cost of repainting is significant and quantifiable, whereas the economic cost of causality, though considerable, is subject to interpretation rather than being disqualified. The paired analysis in the dissertation shows that tool-based methods have lower average profitability than the retrospective analyst benchmark. The difference is statistically significant and economically large for SLD and TradingView Built-in indicator, with TradingView Built-in indicator getting a bigger penalty than SLD because repainting gives worse results even though it is easier to see.

When these results are combined, the main point of the dissertation is not that divergence is always useful or always not useful. The dissertation posits that RSI divergence is optimally comprehended as a temporal-structural phenomenon situated on a continuum between discretionary pattern recognition and algorithmic formalization.

Numerous conflicting assertions in the RSI literature emerge not from the incoherence of divergence, but from the utilization of varying methodological assumptions regarding signal visibility, pivot confirmation, repainting behavior, and capital allocation. The dissertation presents an explanatory framework elucidating why divergence may appear robust in retrospect and feeble in real-time, as well as why a causally valid indicator might seem selective while remaining economically significant over extended periods.

6.3 Limitations of the Study and Mitigation Strategies

A thorough conclusion must elucidate not only what has been established but also what remains ambiguous and the rationale behind it. As a result, the limitations of this dissertation should be seen as limits on how it can be understood, not just as flaws. The primary inquiry is not the existence of limitations, but rather whether the study has explicitly identified them and whether the research design has adequately addressed them to the fullest extent possible.

The initial limitation pertains to the extent of the empirical context. The dissertation concentrates on the NIFTY 50 index and assesses divergence behavior over an extensive historical period commencing in 2000. This choice gives us a strong dataset that covers a lot of different regimes, but it also makes it harder to generalize. Divergence dynamics may differ among individual stocks due to variations in liquidity, volatility clustering, and microstructure, and may also vary across markets owing to differences in participant composition and regulatory frameworks. The dissertation partially addresses this limitation by employing a benchmark-driven and method-comparative design instead of a singular model claim. The study's primary assertions pertain to causal integrity, repainting, and evaluation methodology; consequently, numerous contributions remain applicable despite variations in numerical profitability magnitudes across instruments.

A second limitation has to do with the analyst benchmark itself. The benchmark is a reference made by people, so it could be biased or based on what they think they know. The dissertation mitigates this risk by explicitly categorizing the benchmark as an interpretive reference rather than a tradable gold standard, a distinction underscored in Chapter 5 by framing analyst judgment as a form of structural ground truth rather than causal truth. The research design reduces benchmark bias by comparing methods that have

the same exit rules and by using replay to check the results over time. This design choice changes the evaluation from "how well did a method match hindsight" to "what did the method make visible under forward-moving time." This makes it less likely that the benchmark will change the conclusions.

A third limitation is that TradingView is the main place where replay-based evaluation and Pine Script implementation take place. Using TradingView is a good way to test because it is similar to the real world where many traders use divergence indicators and it lets you test how signals appear in real time. At the same time, relying on a platform can make things harder. The replay system enforces certain execution rules, such as the close-price entry limit described in Chapter 4. The platform's exported trade CSV file does not include signal IDs and does not record trades that were skipped, so more logic is needed to reconcile the two. The dissertation openly talks about these limits and deals with them by changing the way it does things instead of ignoring them. The reconciliation logic, especially the distinction between executed and skipped trades and the breakdown of performance into linear and geometric capital models, is presented as a methodological contribution, illustrating how platform reports can be deceptive if their assumptions are not clearly articulated.

A fourth limitation pertains to assumptions regarding capital deployment in the analysis of profitability. The dissertation intentionally showcases various capital models, as the notion of "economic significance" hinges on whether returns are perceived as linear profit and loss on fixed capital or as geometric growth through reinvestment. The dissertation elucidates the reasons for the discrepancies among these models and the methods for their reconciliation; however, the selection of the most suitable model is contingent upon the trading context. If a discretionary trader sets a fixed budget and doesn't reinvest profits, their results will look more like Trading View's linear representation. If a

systematic portfolio reinvests capital, their results will look more like geometric compounding. The dissertation reduces possible confusion by clearly showing that both are correct based on their own assumptions and by showing how big the difference in interpretation can be.

A fifth limitation comes from managing overlaps and making portfolios realistic. The single-position constraint used in replay execution is purposefully cautious. It gives a strict definition of realizability, but it may not fully capture what a real portfolio could do if it allowed controlled pyramiding, partial allocation across overlapping trades, or simultaneous exposure to long and short signals in a hedged structure. The dissertation alleviates this issue by explicitly quantifying the exclusions resulting from overlap, assessing the event-level impact of omitted trades, and calculating an upper-bound hybrid estimate to contextualize the opportunity cost of stringent realism. In this way, the dissertation does not see portfolio realism as a simple yes or no question, but as a range of options with measurable effects.

A sixth limitation pertains to statistical inference and distributional assumptions. Chapter 4 and the dissertation's integrated thesis document recognize that financial returns exhibit heavy tails and that normality assumptions are often contravened, rendering parametric inference precarious. The dissertation addresses this issue by integrating robustness considerations and acknowledging the application of non-parametric tests, such as Wilcoxon signed-rank tests for profit differences, yielding qualitatively comparable results to the parametric findings. This substantiates the assertion that significant effects are not mere artifacts of distributional assumptions.

A final limitation pertains to the progression of the methodological plan from proposal to dissertation implementation. The proposal text incorporates a mixed-method framework and considered qualitative interviews; however, the completed dissertation, as

demonstrated in Chapters 3–5, is primarily a design-science and quantitative empirical assessment grounded in replay validation and structured comparisons. If recognized correctly, this is not a flaw; it signifies a convergence towards the most methodologically suitable approach for the research question. The dissertation's conclusion underscores methodological consistency with the implemented practices, prioritizing causal and temporal precision over the diversity of methodological approaches.

6.4 Directions for Future Research

The results of this dissertation inherently establish a future research agenda that transcends mere expansion of scope, instead fostering a profound enhancement of the causality-aware paradigm introduced herein. Future work is most valuable when it maintains the fundamental methodological principle of this dissertation: that technical signals must be assessed through frameworks that honor temporal availability and execution realism.

The first direction is about generalizing across different types of instruments and market segments. The NIFTY 50 index offers a regime-diverse baseline; however, subsequent research should utilize the same causality-aware evaluation framework for individual NIFTY constituents and sector indices. This work would show if the structural locking logic of SLD works the same way in different volatility regimes and if the effectiveness of divergence changes with liquidity and unique price dynamics. Adding other Indian indices and international benchmarks to the framework would also help figure out which results depend on the market structure and which ones depend on the method.

A second avenue is multi-timeframe divergence research constrained by causality. Divergence has different meanings on intraday charts than on daily or weekly charts because microstructure noise, session effects, and volatility clustering work differently at

different frequencies. Using the SLD philosophy on intraday timeframes would mean making careful decisions about how to define pivots and set locking thresholds to avoid too many false positives. However, it would also let us test real-time usability more thoroughly because intraday execution shows slippage and timing effects more clearly.

A third direction deals with evaluating divergence that is sensitive to regimes. Chapter 1 and Chapter 5 link divergence to larger discussions about how efficient markets are and how predictable they are under certain conditions. Subsequent research may implement this by integrating regime classifiers, including volatility regime identification or trend-state classification, and subsequently assessing divergence performance contingent upon these regimes. This kind of research would go beyond just looking at average profitability and instead look at when divergence is most useful. This would be especially useful for professionals because it could turn a universal heuristic into a tool that works in different situations.

The fourth direction is about building portfolios and allocating capital in a way that considers overlaps. This dissertation primarily regarded overlap as a constraint and assessed its opportunity cost. In the future, researchers can look at overlap as a design variable and look into allocation policies that keep realism while getting more signal value. This kind of research could look into partial capital allocation across overlapping signals, risk parity allocation, or simultaneous long-short exposure when it makes sense to do so. It is crucial that these extensions maintain temporal integrity and do not regress to optimizations based on hindsight.

A fifth direction pertains to the formal integration of machine learning in a manner that enhances structural reasoning rather than supplants. One of the dissertation's contributions is that it reaffirms how important structure and causality are in designing indicators. You can use machine learning to rank or classify the quality of divergence based

on other factors like price acceleration, volatility expansion, or volume conditions, but you have to do this with strict out-of-sample validation. The risk in ML-enhanced divergence research lies in the potential reemergence of concealed leakage when feature windows or labeling logic utilize information that is inaccessible at the time of decision-making. Consequently, forthcoming research ought to regard causality as a limitation in feature engineering and labeling.

A sixth direction pertains to the theoretical integration of behavioral finance and market microstructure. Divergence can be seen as a pattern of momentum exhaustion, which could show how investors act, like following the crowd, waiting too long to react, or reacting too strongly. To empirically test these interpretations, it would be necessary to integrate technical pattern detection with behavioral proxies, including sentiment measures or flows. This type of work would make divergence research more legitimate in academia by linking it to well-known theories of how prices are formed instead of seeing it as a separate chart phenomenon.

Lastly, future studies ought to broaden the temporal evaluation framework highlighted in this dissertation, incorporating precise measurements of lag, detectability, and repainting across indicators. The T_0 - T_1 - T_2 temporal framing mentioned in the thesis conclusion draft makes it clear that divergence is not just one timestamp but a series of structural events: pivot formation, confirmation, and signal emission. Formalizing and standardizing this temporal decomposition across technical indicators would enhance the methodological framework for technical analysis research.

6.5 Implications for Business and Market Practice

This dissertation has significant implications for business and market practice as it tackles a practical issue that numerous traders and system designers face but seldom

quantify: the discrepancy between the perceived functionality of indicators on historical charts and their actual performance in real time. This gap is not just a problem with usability; it is also a problem with knowledge that affects risk-taking, strategy design, and capital allocation.

For discretionary traders, the dissertation suggests that the choice of indicators should be guided by temporal integrity rather than visual appeal. A divergence indicator that repaints can make it seem like divergence always "calls" reversals, but in real time, this kind of tool may only give signals after a big part of the move has already happened. The study's assertion that Trading View's integrated divergence indicator is predominantly descriptive rather than predictive serves not as a criticism of the tool's popularity, but as a warning regarding its appropriate utilization.

For traders, algorithmic system designers, portfolio managers, and financial educators, this research has important practical ramifications. The study highlights the importance of comprehending indicator construction before depending on historical chart signals for discretionary traders. Repainting produces a false sense of accuracy that might not hold up to scrutiny in real time. The distinction between temporally observable signals and visually backdated signals is crucial for traders. Traders who use these kinds of indicators need to know that the information on a finished chart may not match what was visible when the trade decision was made.

The dissertation's implications are particularly pertinent for algorithmic trading firms and technology teams developing decision-support systems. Indicator modules need to be checked for future-bar dependency, and backtesting shouldn't be seen as a good way to validate unless it clearly considers repainting and the timing of signal emergence. The replay-based methodology outlined in Chapter 4 illustrates a practical approach to assess real-time usability within a live platform environment. In a broader sense, the dissertation

says that the rules for trading technology should treat temporal validity as a top priority, just like software engineering does with reproducibility and determinism as important features of critical systems.

The dissertation elucidates the reasons why assertions of profitability regarding technical signals frequently do not result in actual portfolio outcomes for portfolio and risk managers. Chapter 4's comparison of Trading View's reported +1.20% and the offline compounded 6.39× is a clear example of how capital model assumptions can be more important than reported results. In institutional settings, where risk budgets, leverage limitations, and capital distributions are clearly defined, such assumptions cannot be left unspoken. The dissertation promotes portfolio-level evaluation frameworks that clearly specify whether capital is fixed or reinvested, whether positions overlap, and whether performance is assessed linearly or geometrically. Without this, two analysts can look at the same signal sequence and come to different conclusions, both of which seem reasonable until the assumptions are made clear.

The dissertation presents a conceptual argument regarding the ethics of signal presentation for product designers and platform developers. Users can be misled by indicators that backdate signals on historical charts without making it clear that they are repainting, even if they don't mean to. A platform that has both a repainting indicator and a causally valid indicator should make it clear which is which and teach users about the difference. The dissertation's findings suggest that real-time usability ought to be regarded as a measurable and reportable product attribute, rather than as an informal assertion.

Finally, the effects on educating retail investors are very important in the Indian market. Retail traders often use platform-native tools without knowing how pivot confirmation logic works. This dissertation offers a systematic framework to convey that the concept of indicator "accuracy" must be understood in relation to time. A signal that

seems right in hindsight but comes too late in real time can cause behavioral traps like chasing moves, entering after reversals, or thinking you can predict the future better than you can. The dissertation provides a more structured basis for market participation by recontextualizing divergence evaluation through the lenses of causal visibility and economic realism.

6.6 Contribution to Academic Scholarship

This dissertation contributes to academic scholarship on two fronts: it offers conceptual insights into the understanding of RSI divergence as a phenomenon and methodological advancements in the empirical evaluation of technical indicators.

At the conceptual level, the dissertation reinterprets RSI divergence from a static signal rule to a temporal-structural construct. This reframing is essential for reconciling discrepancies in the literature. Studies that regard divergence as a fixed timestamp derived from a completed chart are implicitly considering divergence as causally accessible, despite the detection logic relying on subsequent validation. In contrast, this dissertation disaggregates divergence into structural pivots, detection timing, and reversal outcomes, demonstrating that the efficacy of divergence cannot be meaningfully assessed without explicit consideration of causal availability. This conceptual shift corresponds with the interpretive framework in Chapter 5, which posits that divergence exists on a continuum between discretionary pattern recognition and algorithmic formalization, suggesting that discrepancies in the literature frequently indicate methodological divergence rather than conceptual inconsistency.

A second conceptual contribution pertains to the interplay between discretionary analysis and algorithmic detection. The dissertation introduces the analyst benchmark, contesting the unspoken assumption that algorithmic divergence detectors inherently

replicate human judgment. The draft text for Chapter 6 in the thesis document itself says that analyst judgment includes temporal restraint and structural filtering, which many mechanical implementations do not have. The dissertation thus enhances the comprehension of why discretionary divergence may seem coherent despite algorithmic detectors yielding conflicting results. The implication is not that discretionary analysis is superior, but that it incorporates constraints that must be explicitly modeled to achieve algorithmic equivalence.

A third conceptual contribution pertains to the precision–coverage trade-off in the design of indicators. The dissertation empirically illustrates that selectivity, and non-repainting behavior can enhance informational value, despite a reduction in signal count. This contribution is pertinent as numerous technical analysis studies implicitly regard signal frequency as favorable or interpret low frequency as indicative of failure. Conversely, this dissertation regards frequency as a design variable, demonstrating that economic impact is contingent not only on accuracy but also on adequate participation for compounding, a notion explicitly articulated in Chapter 4's analysis of TLI and SLD.

The dissertation's most significant methodological contribution is the creation of a reproducible framework for quantifying repainting, lag, and real-time detectability, parameters that are commonly recognized informally yet seldom measured systematically. The replay-based evaluation method, along with temporal decomposition and clear capital model reconciliation, provides a framework that can be used for technical indicators other than RSI divergence. This contribution is particularly significant because it operationalizes a principle that is often stated but seldom enforced: that technical indicators must be evaluated as they would be experienced in real time.

Another methodological contribution is the clear connection between profitability at the signal level and executability at the portfolio level. The goal of the replay exercise

in Chapter 4 was to find out if economically strong signals still make sense when you only have one position, follow a strict schedule, and follow platform-imposed capital mechanics. The dissertation subsequently elaborates by quantifying the opportunity cost of overlap exclusion and calculating an upper-bound hybrid estimate. This layered approach strengthens the academic validity of profitability claims because it avoids the common flaw of reporting a single return metric without clarifying the execution assumptions that produced it.

Finally, the dissertation adds to the body of work on technical analysis in emerging markets by using the NSE as a starting point for the discussion and by directly addressing the ideas of weak-form efficiency and conditional predictability as they are presented in Chapter 5. The work therefore sits not merely in practitioner indicator development but also in the broader academic conversation about whether and how price-based signals can contain information in markets that are not perfectly efficient under all conditions.

6.7 Concluding Reflections

The research began with a deceptively straightforward question that revealed a deeper methodological challenge: is a divergence signal actually visible at the moment a trader needs to act? The answer, derived from a quarter-century of market data and rigorous replay validation, is that for many commonly used tools, the answer is no. This insight shifts the meaning of “signal” in technical analysis research. A signal is not merely a mark on a chart; it is an informational event that must be available before the decision it is meant to guide. This understanding has significant ramifications for the entire domain of technical analysis, indicating that the industry's dependence on “visual backtesting” on completed charts may be inherently flawed because of an unnoticed “hindsight bias.”

By developing the **Structural Leading Divergence (SLD)** framework and enforcing the strict discipline of "left-side" causal detection, this dissertation has sought to replace historical storytelling with forward-moving responsibility. The study has demonstrated that although the "cost of realism" is considerable, the economic potential of RSI divergence persists when governed by disciplined capital reinvestment and structural foundation. The SLD framework's **8x** growth factor shows that technical signals can still have a lot of power without resorting to the illusion of permanent hindsight.

This dissertation ultimately endorses a standard of "methodological accountability" in financial research. It says that time should be seen as a first-class variable, not just a background axis on a chart. In the complex and often noisy environment of the Indian equity market, the difference between a successful trader and a spectator is the ability to distinguish between what can be explained after the fact and what can be detected in the moment. This study contributes to that clarity, offering a rigorous, transparent, and causally valid framework for all those who seek to navigate the markets with both technical precision and temporal honesty.

REFERENCES

- Aguirre, A.A.A., Medina, R.A.R. and Méndez, N.D.D. (2022). ‘Trading a través del indicador RSI con la aplicación de Algoritmos Genéticos para la implementación en el sector empresarial de las inversiones’, *Desarrollo Gerencial*, 14(2). doi:10.17081/dege.14.2.5755.
- Ardimansyah, Ahyuna, Syam, A., Salman, Ghani, A.D., and Natsir, M.S. (2021). ‘Moving Average And Relative Strength Index Indicators In Determining Open And Closed Positions On The Metatrader4 Expert Advisor’, in *Proceedings of the 2021 3rd International Conference on Cybernetics and Intelligent System (ICORIS)*, Makasar, Indonesia, 25-26 October 2021, IEEE. doi:10.1109/ICORIS52787.2021.9649563
- Bailey, D.H., Borwein, J.M., López de Prado, M. and Zhu, Q.J. (2014). ‘Pseudo-Mathematics and Financial Charlatanism: The Effects of Backtest Overfitting on Out-of-Sample Performance’, *Notices of the American Mathematical Society*, 61(5), pp. 458-471. doi:10.1090/noti1105
- Bansal, S. (2023). ‘Investigating the efficacy of RSI in the NIFTY 50 index’, *Digital Repository of Theses - SSBM Geneva*. Available at: <https://repository.e-ssbm.com/index.php/rps/article/view/159> (Accessed: 18 February 2026).
- Bansal, S. (2025). *True Leading Indicator*, v. 4.0.0. [Software] Available at: <https://trueleadingindicator.com> (Accessed: 18 February 2026).
- Bartkus, C. (2018). ‘Using the Relative Strength Index for Active Investments in the Foreign Exchange Market’, *Modern Management Review*, 25(4). doi:10.7862/rz.2018.mmr.39

- Bartkus, C. and Tekin, B. (2020). 'Availability of RSI in Bitcoin Transactions: A Review from the Perspective of Behavioral Finance', *EMC Review – Economy and Market Communication Review*, 20(2). doi:10.7251/EMC2002378B
- Bodas-Sagi, D.J., Soltero, F.J., Hidalgo, J.I., Fernández, P., and Fernandez, F. (2012). 'A technique for the optimization of the parameters of technical indicators with Multi-Objective Evolutionary Algorithms', in *Proceedings of the IEEE Congress on Evolutionary Computation*, Brisbane, QLD, Australia, 10-15 June 2012, IEEE. doi:10.1109/CEC.2012.6256584
- Brown, D.P. and Jennings, R.H. (1989). 'On Technical Analysis', *The Review of Financial Studies*, 2(4), pp. 527-551. doi:10.1093/rfs/2.4.527
- Cheema, M.A., Szulczyk, K.R. and Bouri, E. (2021). 'The profitability of technical trading rules in the Pakistani stock market', *International Review of Economics & Finance*, 71, pp. 1-15. doi:10.1016/j.iref.2020.08.014
- Chen, Y., Huang, L-E., Wang, P-H., Tang, J-H., Hsu, K-N., and Chou, Y-H. (2021). 'A Dynamic Stock Trading System using GNQTS and RSI in the U.S. Stock Market', in *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, Melbourne, Australia, 17-20 October 2021, IEEE. doi:10.1109/SMC52423.2021.9659251
- Chein, Y., Chiang, Ke, M-C., Liao, T.L., and Wang, C-D. (2012). 'Are technical trading strategies still profitable? Evidence from the Taiwan Stock Index Futures Market', *Applied Financial Economics*, 22(12), pp. 955–965. doi:10.1080/09603107.2011.631893.

- Choi, Y-h. and Joo, B-g. (2014). ‘Development of effective trading techniques for asset value stock investment’, *Journal of the Korea Institute of Information Technology*, 12(1), pp. 139–146. doi:10.14801/jkiit.2014.12.1.139.
- Chong, T.T.L. and Ng, W.K. (2008). ‘Technical analysis and the London stock exchange’, *Journal of International Financial Markets, Institutions and Money*, 18(4), pp. 390-402. doi:10.1080/13504850600993598
- Chou, H. (2023). ‘Using Bull and Bear Index of Deep Learning to Improve the Indicator Model on Extremely Short-term Futures Trading’, *Advances in Management and Applied Economics*, 13(6), pp. 121–133. doi:10.47260/amae/1366.
- Choudhuri, S (2019). ‘A Research on Trading of Sensex Stocks by using RSI’, *International Journal of Innovative Technology and Exploring Engineering*, 8(9S2). doi:10.35940/ijitee.i1004.0789s219.
- Cmt, A.H. (2019). ‘Finding Consistent Trends with Strong Momentum - RSI for Trend-Following and Momentum Strategies’, *SSRN Electronic Journal* doi:10.2139/ssrn.3412429.
- Cohen, G. (2020). ‘Algorithmic setups for trading popular U.S. ETFs’, *Cogent Economics & Finance*, 8(1), 1720056. doi:10.1080/23322039.2020.1720056.
- Cohen, G. and Cabiri, E. (2015). ‘Can technical oscillators outperform the buy and hold strategy?’, *Applied Economics*, 47(30), pp. 3189–3197. doi:10.1080/00036846.2015.1013609.
- Day, M-Y. and Ni, Y. (2023). ‘Do clean energy indices outperform using contrarian strategies based on contrarian trading rules?’, *Energy*, 272, 127113. doi:10.1016/j.energy.2023.127113.
- Day, M-Y., Cheng, Y., Huang, P., and Ni, Y. (2022) (2023). ‘The profitability of trading US stocks in Quarter 4 – evidence from trading signals emitted by SOI and RSI’,

- Applied Economics Letters*, 30(9), pp. 1173–1178.
doi:10.1080/13504851.2022.2041165.
- Demirel, B., Ozturan, M. and Demirel, E. (2023). ‘Testing the efficiency of the BIST 100 index using technical analysis indicators’, *Journal of Business Research - Turk*, 15(1), pp. 45-60. doi:10.20491/isarder.2023.1582
- Deveci Kocakoç, İ. and Kılıç, S. (2019). ‘Technical analysis in the Turkish stock market: an empirical study on BIST 30 stocks’, *Ege Academic Review*, 19(2), pp. 215-230. doi:10.21121/eab.543210
- Egara, K. and Peng, Y. (2015). ‘Big data analytics of financial strategies’, in *Proceedings of the 2015 IEEE Symposium Series on Computational Intelligence (SSCI)*, Cape Town, South Africa, 07-10 December 2015, IEEE.
doi:10.1109/SSCI.2015.7376657.
- Fama, E.F. (1970). ‘Efficient Capital Markets: A Review of Theory and Empirical Work’, *The Journal of Finance*, 25(2), pp. 383-417. doi:10.1111/j.1540-6261.1970.tb00518.x
- Garlapati, S. and Ponnada, S. (2023). ‘Performance of technical indicators on NASDAQ technology stocks: a comparative study’, *International Journal of Financial Management*, 12(3), pp. 88-102. doi:10.34218/IJFM.12.3.2023.008
- Gurrib, I. (2023). ‘Momentum in low carbon and fossil fuel free equity investing’, *International Journal of Energy Economics and Policy*, 13(5), pp. 461–471. doi:10.32479/ijeeep.14342.
- Gurrib, I. and Kamalov, F. (2018). ‘The implementation of an adjusted relative strength index model in the foreign currency and energy markets of emerging and developed economies’, *SSRN Electronic Journal*. doi:10.2139/ssrn.3124785.

- Gurrib, I. and Kamalov, F. (2019). 'The implementation of an adjusted relative strength index model in foreign currency and energy markets of emerging and developed economies', *Macroeconomics and Finance in Emerging Market Economies*, 12(2), pp. 105–123. doi:10.1080/17520843.2019.1574852.
- Hasan, S., Nurhasanah, S. and Santoso, W.P. (2024). 'Analisis teknikal menggunakan moving average (MA), moving average convergence-divergence (MACD), dan relative strength index (RSI) untuk mengoptimalkan dalam pengambilan keputusan investasi pada saham sektor manufaktur Index LQ45 BEI tahun 2022–2023', *El-Mal: Jurnal Kajian Ekonomi & Bisnis Islam*, 5(4). doi:10.47467/elmal.v5i4.2029.
- Harahap, K., Effendi, S. and Junaedi, D. (2020). 'Technical analysis of stock price movements in the Indonesian capital market during the COVID-19 pandemic', *International Journal of Business Studies*, 3(2), pp. 145-158. doi:10.32924/ijbs.v3i2.145
- Hill, A. (2019). 'Finding Consistent Trends with Strong Momentum - RSI for Trend-Following and Momentum Strategies', *SSRN Electronic Journal* doi:10.2139/ssrn.3412429.
- Indah, Y.R. and Mahyuni, I.P. (2022). 'The accuracy of relative strength index (RSI) indicator in forecasting foreign exchange price movement', *Innovbiz: Jurnal Inovasi Bisnis*, 10(1). doi:10.35314/inovbiz.v10i1.2249.
- Jamil, A. (2022). 'Profitability of technical trading strategies in the Pakistani banking sector', *Journal of Finance and Economics Research*, 7(1), pp. 56-72. doi:10.20547/jfer2207104

- Kakade, S. and Dakare, S. (2022). 'A study on technical analysis of selected pharmaceutical stocks in India', *International Journal of Management and Social Sciences*, 10(4), pp. 210-225. doi:10.46828/ijmss.v10i4.321
- Kapri, M., Dimri, T., Singh P., Maletha, A., Bordoloi, D. and Manisha Aeri, M.(2024). 'Quantitative insights into breakout and reversal trading strategies: A comprehensive analysis for algorithmic trading in financial markets', in *Proceedings of the 2024 2nd International Conference on Disruptive Technologies (ICDT)*, Greater Noida, India, 15-16 March 2024, IEEE. doi:10.1109/ICDT61202.2024.10488993.
- Karatas, A. and Guler, S. (2020). 'The effectiveness of technical analysis indicators in the BIST 100 index', *Journal of Economics, Business and Management*, 8(3), pp. 190-205 doi:10.18178/joebm.2020.8.3.621
- Khairudin, S., Elias, S.M., Kamil, K.H., and Chukari, N.A. (2022). 'Application of relative strength index oscillator for equity portfolio construction in Malaysia', in *European Proceedings of Management and Social Sciences (EpMS): Reimagining Resilient Sustainability: An Integrated Effort in Research, Practices & Education*. European Publisher. doi:10.15405/epms.2022.10.4.
- Khand, S., Anand, V., Qureshi, M.N., and Katper, N.K. (2019). 'The performance of exponential moving average, moving average convergence-divergence, relative strength index and momentum trading rules in the Pakistan stock market', *Indian Journal of Science and Technology*, 12(26), pp. 1–22. doi:10.17485/ijst/2019/v12i26/145117.
- Khatavkar, S. (2024). "Investigating the Efficacy of RSI Divergence in the Nifty 50 Index", *Digital Repository of Theses - SSBM Geneva*. Available at:

- <https://repository.e-ssbm.com/index.php/rps/article/view/624> (Accessed: 18 February 2026).
- Kirkpatrick, C.D. and Dahlquist, J.R. (2011). *Technical Analysis: The Complete Resource for Financial Market Technicians*. 3rd edn. Upper Saddle River, NJ: FT Press. Available at: <https://www.pearson.com/en-us/subject-catalog/p/technical-analysis-the-complete-resource-for-financial-market-technicians/P200000000373/9780134137162> (Accessed: 19 February 2026). [Source: Pearson Education]
- Kouassi, K. (2022). ‘Technical analysis and market efficiency: evidence from the West African Regional Stock Exchange (BRVM)’, *African Journal of Economic and Management Studies*, 13(4), pp. 512-528. doi:10.1108/AJEMS-02-2022-0065
- Kuo, S-Y., Jiang, Y-C. and Chou, Y-H. (2023). ‘Intelligent hybrid trading strategies based on quantum-inspired algorithm’, *Scientific Programming & Intelligent Systems – World Scientific (SPIN)*, 13(4), 2340013. doi:10.1142/S2010324723400131.
- Lanjekar, S., Hulipalled, P. and Bhende, P. (2022). ‘Technical analysis of Indian sectoral indices: a study of RSI and MACD’, *Journal of Emerging Technologies and Innovative Research*, 9(5), pp. 445-460. doi:10.1729/Journal.30215
- Lin, T-M., Yu, J-L., Chen, J-W., and Huang, C-S. (2023). ‘Application of machine learning with news sentiment in stock trading strategies’, *International Journal of Financial Research*, 14(3). doi:10.5430/ijfr.v14n3p1
- Lisicki, B. and Podgórski, K. (2024). ‘Trading signals of the relative strength index and market valuation of State Treasury companies listed on the Warsaw Stock Exchange’, *International Journal of Management and Economics*, 61(3), pp. 212–224. doi:10.2478/ijme-2024-0041.

- Lo, A.W. (2004). 'The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective', *The Journal of Portfolio Management*, 30(5), pp. 15-29. doi:10.3905/jpm.2004.442611
- Lutey, M. and Rayome, D. (2022). 'Bollinger band and relative strength index price analysis', *International Journal of Business Research*, 22(2), pp. 34–41. doi:10.18374/IJBR-22-2.4.
- Ma, J. and Liao, H. (2017). 'Trend-tracking trading strategy based on improved RSI: A case study of Chinese CSI 300 stock index futures', *International Journal of Economics and Finance*, 9(4). doi:10.5539/ijef.v9n4p130.
- Mahajan, Y.D. (2015). 'Optimization of MACD and RSI indicators: An empirical study of Indian equity market for profitable investment decisions', *Asian Journal of Research in Banking and Finance*, 5(12), pp. 13–25. doi:10.5958/2249-7323.2015.00140.6.
- Mehra, S.D. and Shetty, S.D. (2023). 'Developing and testing a custom algorithmic trading strategy using exponential moving average, relative strength index, and sentiment analysis', *Journal of Artificial Intelligence and Applications*, 7(4). doi:10.32629/jai.v7i4.1328.
- Mengshetti, O., Gupta, K., Zade, N., Kotecha, K., Mutha, S., and Joshi, G. (2024). 'Synergizing quantitative finance models and market microstructure analysis for enhanced algorithmic trading strategies', *Journal of Open Innovation: Technology, Market, and Complexity*, 10(3), 100334. doi:10.1016/j.joitmc.2024.100334.
- Murphy, John J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and applications*. New York: Penguin Publishing Group.

- Naganajaneyulu, V.S.S.K.R.G., Prashanth, G., Revanth, M., and Narasimhadhan, A.V. (2023). 'Multi indicator based hierarchical strategies for technical analysis of crypto market paradigm', *International Journal of Electrical and Computer Engineering Systems*, 14(7). doi:10.32985/ijeces.14.7.4.
- Nanda, T.S.F. and Dianah, A. (2024). 'Perbandingan return penggunaan Moving Average Convergence Divergence dan Relative Strength Index pada Indeks Saham Syariah Indonesia', *Journal of Sharia Economics*, 5(2). doi:10.22373/jose.v5i2.5656.
- Neves, M.E., Leite, J. and Neves, R. (2022). 'Does technical analysis win? Evidence from the period between Donald Trump's campaign and the first date for Brexit', in *Handbook of Research on New Challenges and Global Outlooks in Financial Risk Management*. Hershey, PA: IGI Global. doi:10.4018/978-1-7998-8609-9.ch017.
- Newsome, L. and Turner, P.A. (2006). 'Homemade sector hedge funds: Can investors replicate the returns without paying the fees?' *SSRN Electronic Journal*. doi:10.2139/ssrn.923467.
- Newsome, L. Jr. and Turner, P.A. (2007). 'Homemade sector hedge funds: Can investors replicate the returns without paying the fees?', *The Journal of Investing*, 16(4), pp. 175–189. doi:10.3905/joi.2007.698990.
- Nishanthini, A. and Vijayakumar, S. (2020). 'Technical analysis and stock return: evidence from Colombo Stock Exchange', *International Journal of Accounting and Financial Reporting*, 10(2), pp. 88-104. doi:10.5296/ijaf.v10i2.16854
- Nison, S. (2001). *Japanese Candlestick charting techniques: A contemporary guide to the ancient investment techniques of the far east*. New York: New York Institute of Finance.

- Nor, S. M. and Wickremasinghe, G. (2014). 'The profitability of MACD and RSI trading rules in the Australian stock market', *Investment Management and Financial Innovations*, 11(4-1), 194–199. Retrieved from <https://www.businessperspectives.org/index.php/journals/investment-management-and-financial-innovations/issue-4-cont-9/the-profitability-of-macd-and-rsi-trading-rules-in-the-australian-stock-market>
- Panigrahi, A.K., Vachhani, K. and Chaudhury, S.K. (2021). 'Trend identification with the relative strength index (RSI) technical indicator – A conceptual study', *Journal of Management Research and Analysis*, 8(4), pp. 159–169.
doi:10.18231/j.jmra.2021.033.
- Patel, J., Shah, S. and Thakkar, P. (2015). 'Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques', *Expert Systems with Applications*, 42(1), pp. 259-268.
doi:10.1016/j.eswa.2014.07.023
- Pring, M.J. (2002). *Technical Analysis Explained: The Successful Investor's Guide to Spotting Investment Trends and Turning Points*. 5th edn. New York: McGraw-Hill. Available at: <https://www.mheducation.com/highered/mhp/product/technical-analysis-explained-fifth-edition-successful-investor-s-guide-spotting-investment-trends-turning-points>
- Pyo, S. and Lee, J. (2019). 'Predicting cryptocurrency price using technical analysis indicators', *Journal of Intelligence and Information Systems*, 25(4), pp. 123-140.
doi:10.13088/jiis.2019.25.4.123

- Rosillo, R., de la Fuente, D. and Brugos, J.A.L. (2013). 'Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator', *Expert Systems with Applications*, 40(6), pp. 2253-2259. doi:10.1016/j.eswa.2012.10.062
- Sadik, Z., Mitra, G., Tan, Z., Kantos, C. and Joldzic, D. (2022). 'Asset Allocation Strategies: Enhanced by News', *SSRN Working Paper* No. 3588364. doi:10.2139/ssrn.3588364 (Accessed: 11 February 2026).
- Shaikh, S. (2023). 'Technical analysis and stock returns: evidence from the KSE-100 index of Pakistan', *Pakistan Journal of Applied Economics*, 33(1), pp. 75-92. doi:10.46664/pjae.v33i1.75
- Sharma, R. (2023). 'Effectiveness of technical indicators in the Indian stock market: a study of Nifty 50 stocks', *Indian Journal of Finance*, 17(2), pp. 34-48. doi:10.17010/ijf/2023/v17i2/172564
- Shi, Y., Mitra, G., Arbex-Valle, C. and Yu, X. (2019). 'Using Social Media and News Sentiment Data to Construct a Momentum Strategy', *SSRN Working Paper*. doi:10.2139/ssrn.3406075 (Accessed: 11 February 2026).
- Shik, T.C. and Chong, T.T-L. (2007). 'A comparison of MA and RSI returns with exchange rate intervention', *Applied Economics Letters*, 14(5), pp. 371–383. doi:10.1080/13504850500426269.
- Siow, C.L. (2024). 'The efficacy of Relative Strength Index (RSI) in KLSE market trade', *Issues and Perspectives in Business and Social Sciences*, 4(2). doi:10.33093/ipbss.2024.4.2.1.
- Sovbetov, Y. (2018). 'Factors influencing cryptocurrency prices: evidence from Bitcoin, Ethereum, Dash, Litecoin, and Monero', *Journal of Economics and Financial Analysis*, 2(2), pp. 1-27. doi:10.1991/jefa.v2i2.a16

- Subashini, R. and Sharmila, S. (2022). ‘A study on technical analysis of selected stocks in the Indian stock market’, *International Journal of Scientific Research in Science and Technology*, 9(3), pp. 567-580. doi:10.32628/IJSRST2293121
- Tadas, H., Nagarkar, J., Malik, S., Mishra, D.K. and Paul, D. (2023). ‘The effectiveness of technical trading strategies: Evidence from Indian equity markets’, *Investment Management and Financial Innovations*, 20(2), pp. 26–40. doi:10.21511/imfi.20(2).2023.03.
- Tran, M., Pham-Hi, D. and Bui, M. (2022). ‘Parameter optimization for trading algorithms of technical agents’, in *Proceedings of the 2022 RIVF International Conference on Computing and Communication Technologies (RIVF)*, Ho Chi Minh City, Vietnam, 20-22 December 2022, IEEE. doi:10.1109/RIVF55975.2022.10013787.
- Vishnoi, S. (2024). “Investigating the Efficacy of RSI Divergence in Nifty & Non-Nifty Stocks”, *Digital Repository of Theses - SSBM Geneva*. Available at: <https://repository.e-ssbm.com/index.php/rps/article/view/632> (Accessed: 18 February 2026).
- Wang, P. and Huang, H. (2013). ‘On the W&R and RSI expert systems of securities software’, *Applied Mechanics and Materials*, 433–435, pp. 1685–1688. doi:10.4028/www.scientific.net/AMM.433-435.1685.
- Wang, Y., Chen, X. and Huang, Y. (2022). ‘Parameter optimization of technical indicators for Bitcoin trading: a machine learning approach’, *Journal of Financial Innovation*, 8(1), pp. 45-62. doi:10.1186/s40854-022-00358-1
- Widoatmodjo, S., Onasie, V. and Junaedi, D. (2020). ‘Technical analysis of the Indonesia Sharia Stock Index (ISSI) during the COVID-19 pandemic’, *Journal of Islamic Finance*, 9(1), pp. 88-102. Available at: <https://journals.iium.edu.my/iiu->

- jif/index.php/jif/article/view/364 (Accessed: 24 February 2026).
doi:10.31436/jif.v9i1.456
- Wilder, J.W. (1978). New concepts in technical trading systems. Greensboro, NC.
Available at: <https://dspace.lib.uom.gr/handle/2159/29408> [Accessed 30 September 2025].
- Wimelda, L., Hidayat, R. and Devi, K. (2022). ‘The application of Relative Strength Index (RSI) in digital asset trading: evidence from the Indonesian market’, *International Journal of Digital Assets and Blockchain*, 4(2), pp. 112-128.
doi:10.47191/ijdad.v4i2.08
- Yu, F. (2017). ‘Empirical analysis of RSI based on vocational education sector of listed companies’, in *Proceedings of the 2017 International Conference on Computational Science and Engineering (ICCSE 2017)*. Advances in Computer Science Research. Paris: Atlantis Press. doi:10.2991/iccse-17.2017.42.
- Yuncu, A., Dospatlı, H. and Guresen, E. (2023). ‘Predicting Bitcoin price movements using technical indicators and machine learning’, *Journal of Financial Innovation*, 9(1), pp. 12-28. doi:10.1186/s40854-023-00456-7
- Zatwarnicki, M., Zatwarnicki, K. and Stolarski, P. (2023). ‘Effectiveness of the relative strength index signals in timing the cryptocurrency market’, *Sensors*, 23(3), 1664. doi:10.3390/s23031664.
- Zhang, S., Liu, H., Xiao, Z. and Wang, P. (2020). ‘Application of extreme value of nonlinear regression function based on RSI expert system’, *Journal of Physics: Conference Series*, 1650, 032014. doi:10.1088/1742-6596/1650/3/032014.
- Zhang, Y. (2019). ‘Comparative analysis of investment based on the gold sector’, in *Proceedings of the 2nd International Symposium on Social Science and*

Management Innovation (SSMI 2019). Advances in Social Science, Education and Humanities Research. Paris: Atlantis Press. doi:10.2991/ssmi-19.2019.87.

APPENDIX A

PINE SCRIPT IMPLEMENTATION OF SLD

This appendix provides the full Pine Script source code used to implement the Structural Leading Divergence (SLD) indicator in Trading View. The script was designed to be causal and non-repainting, meaning it generates signals using only information available up to the current bar. The indicator plots the RSI oscillator and marks finalized bullish and bearish divergence events using on-chart labels (fBull, fBear).

```
//@version=6
// Structural Leading Divergence (SLD)
// Causal, non-repainting implementation

indicator("SLD (Structural Leading Divergence)", shorttitle="SLD",
overlay=false, max_labels_count=500)

// ----- Inputs -----
// Keep ONLY these visible in the chart header:
len      = input.int(14, "RSI Period", minval=1)
src      = input.source(close, "RSI Source")
lbl      = input.int(5, "Pivot Lookback Left (lbl)", minval=1)

// Hide the rest from the chart header (still adjustable in settings):
lockMode  = input.string("Hybrid", "Swing Lock Mode", options=["Bounce",
"Hybrid"], display=display.none)
rsiBounce = input.float(5.0, "RSI bounce to LOCK swing (pts)", minval=0.1,
step=0.1, display=display.none)
softBounce = input.float(1.5, "Soft bounce for Hybrid lock (pts)", minval=0.1,
step=0.1, display=display.none)

// Range between paired swings
rangeLower = input.int(3, "Min bars between swings", minval=1,
display=display.none)
rangeUpper = input.int(90, "Max bars between swings", minval=1,
display=display.none)

// Amplitude filters
minPriceMovePct = input.float(0.00, "Min price move between pivots (%)",
minval=0.0, step=0.05, display=display.none)

// Separate min RSI movement thresholds
bullMinRsiMove = input.float(0.10, "Min RSI move for Bull (pts)", minval=0.0,
step=0.1, display=display.none)
bearMinRsiMove = input.float(0.50, "Min RSI move for Bear (pts)", minval=0.0,
step=0.1, display=display.none)

// Tolerances
```

```

    rsiTol      = input.float(0.8, "RSI tolerance for flat divergences (pts)",
minval=0.0, step=0.1, display=display.none)
    priceTolPct = input.float(0.10, "Price tolerance for LL/HH (%)", minval=0.0,
step=0.05, display=display.none)

    // Controlled relaxed-bear gating (prevents bearish spam when RSI is flat)
    minBearHHpct = input.float(0.15, "Min HH size for Bear (%) when RSI is flat",
minval=0.0, step=0.05, display=display.none)

    // Bull previous-low fallback (gated to avoid noise)
    useBullPrevFallback = input.bool(true, "Bull: enable previous-low fallback",
display=display.none)
    maxBarsPrevToLast   = input.int(30, "Bull fallback: max bars prevLow→lastLow",
minval=1, display=display.none)
    minorLowPricePct    = input.float(0.25, "Bull fallback: lastLow minor if ΔPrice
vs prevLow ≤ (%)", minval=0.0, step=0.05, display=display.none)
    minorLowRsiPts      = input.float(1.0, "Bull fallback: lastLow minor if ΔRSI vs
prevLow ≤ (pts)", minval=0.0, step=0.1, display=display.none)
    maxBarsLastToCurr   = input.int(40, "Bull fallback: max bars
lastLow→currentLow", minval=1, display=display.none)

    // Visuals
    showStream      = input.bool(false, "Show candidate stream triangles",
display=display.none)
    showLabels      = input.bool(true, "Show final labels (fBull/fBear)")
    showDebug       = input.bool(false, "Debug: show rejection reason labels")
    debugBars       = input.int(400, "Debug: show only last N bars", minval=50,
maxval=5000, display=display.none)
    debugYOffset    = input.float(10.0, "Debug vertical offset (RSI points)",
step=1.0, display=display.none)

    // Colors
    bullColor = color.lime
    bearColor = color.red
    txtColor  = color.white

    // ----- Core -----
    osc = ta.rsi(src, len)
    plot(osc, "RSI", color=color.new(color.blue, 0))
    hline(70), hline(50), hline(30)

    // ----- lbl-only candidate pivot flags -----
    candPL = true
    for i = 1 to lbL
        candPL := candPL and (osc <= osc[i])

    candPH = true
    for i = 1 to lbL
        candPH := candPH and (osc >= osc[i])

    // Track run ends (for Hybrid lock)
    var bool prevCandPL = false
    var bool prevCandPH = false
    runEndPL = prevCandPL and not candPL
    runEndPH = prevCandPH and not candPH
    prevCandPL := candPL
    prevCandPH := candPH

```

```

// ----- Helpers -----
inRangeBars(b) =>
  b >= rangeLower and b <= rangeUpper

pctMove(fromPx, toPx) =>
  fromPx == 0.0 ? 0.0 : math.abs((toPx - fromPx) / fromPx) * 100.0

// ----- Swing state -----
var bool pendingLow = false
var float pendLowRSI = na
var float pendLowPx = na
var int pendLowBar = na

var bool pendingHigh = false
var float pendHighRSI = na
var float pendHighPx = na
var int pendHighBar = na

var float lastLowRSI = na
var float lastLowPx = na
var int lastLowBar = na

var float prevLowRSI = na
var float prevLowPx = na
var int prevLowBar = na

var float lastHighRSI = na
var float lastHighPx = na
var int lastHighBar = na

// ----- Candidate stream (optional) -----
plotshape(showStream and candPL ? osc : na, title="Candidate Low stream",
  style=shape.triangleup, location=location.absolute,
color=color.new(bullColor, 0), size=size.tiny)

plotshape(showStream and candPH ? osc : na, title="Candidate High stream",
  style=shape.triangledown, location=location.absolute,
color=color.new(bearColor, 0), size=size.tiny)

// ----- Update pending LOW swing -----
if candPL
  if not pendingLow
    pendingLow := true
    pendLowRSI := osc
    pendLowPx := low
    pendLowBar := bar_index
  else
    if osc < pendLowRSI
      pendLowRSI := osc
      pendLowPx := low
      pendLowBar := bar_index

// ----- Update pending HIGH swing -----
if candPH
  if not pendingHigh
    pendingHigh := true
    pendHighRSI := osc
    pendHighPx := high

```

```

        pendHighBar := bar_index
    else
        if osc > pendHighRSI
            pendHighRSI := osc
            pendHighPx := high
            pendHighBar := bar_index

// ----- Hybrid lock logic -----
lowLock = false
if pendingLow and not na(pendLowRSI)
    strong = (osc - pendLowRSI) >= rsiBounce
    soft = runEndPL and (osc - pendLowRSI) >= softBounce
    lowLock := lockMode == "Bounce" ? strong : (strong or soft)

highLock = false
if pendingHigh and not na(pendHighRSI)
    strong = (pendHighRSI - osc) >= rsiBounce
    soft = runEndPH and (pendHighRSI - osc) >= softBounce
    highLock := lockMode == "Bounce" ? strong : (strong or soft)

// ----- Divergence detection (NO BACKPAINT) -----
bullSignal = false
bearSignal = false

var string rejLow = ""
var string rejHigh = ""
rejLow := ""
rejHigh := ""

// ---- LOCK LOW -> bullish divergence (lastLow, with gated prevLow fallback) --
--
if lowLock
    condBullLast = false
    condBullPrev = false

    var string rejLowLocal = ""
    rejLowLocal := ""

    // Evaluate vs lastLow
    if not na(lastLowBar) and not na(pendLowBar)
        barsBetween = pendLowBar - lastLowBar
        okRange = inRangeBars(barsBetween)

        priceMoveOk = pctMove(lastLowPx, pendLowPx) >= minPriceMovePct
        rsiDelta = math.abs(pendLowRSI - lastLowRSI)
        rsiMoveOk = rsiDelta >= bullMinRsiMove

        isLL = pendLowPx <= lastLowPx * (1 + priceTolPct/100)
        isHL = pendLowRSI >= lastLowRSI - rsiTol

        condBullLast := okRange and priceMoveOk and rsiMoveOk and isLL and isHL

    if showDebug and not condBullLast
        if not okRange
            rejLowLocal := "REJ:range"
        else if not priceMoveOk
            rejLowLocal := "REJ:price%"
        else if not rsiMoveOk

```

```

        rejLowLocal := "REJ:rsiΔ<"
    else if not isLL
        rejLowLocal := "REJ:notLL"
    else if not isHL
        rejLowLocal := "REJ:notHL"
    else
        rejLowLocal := "REJ:other"
else if showDebug
    rejLowLocal := "REJ:firstLow"

// GATED fallback vs prevLow (only if lastLow is "minor")
if useBullPrevFallback and not condBullLast and not na(prevLowBar) and not
na(lastLowBar) and not na(pendLowBar)
    barsPrevToLast = lastLowBar - prevLowBar
    barsLastToCurr = pendLowBar - lastLowBar

    minorByPrice = pctMove(prevLowPx, lastLowPx) <= minorLowPricePct
    minorByRSI   = math.abs(prevLowRSI - lastLowRSI) <= minorLowRsiPts
    lastIsMinor  = (barsPrevToLast <= maxBarsPrevToLast) and (minorByPrice
or minorByRSI)

    currAtOrBelowLast = pendLowPx <= lastLowPx * (1 + priceTolPct/100)
    okSkip = lastIsMinor and currAtOrBelowLast and (barsLastToCurr <=
maxBarsLastToCurr)

    if okSkip
        barsBetweenP = pendLowBar - prevLowBar
        okRangeP = inRangeBars(barsBetweenP)

        priceMoveOkP = pctMove(prevLowPx, pendLowPx) >= minPriceMovePct
        rsiDeltaP     = math.abs(pendLowRSI - prevLowRSI)
        rsiMoveOkP    = rsiDeltaP >= bullMinRsiMove

        isLLP = pendLowPx <= prevLowPx * (1 + priceTolPct/100)
        isHLP = pendLowRSI >= prevLowRSI - rsiTol

        condBullPrev := okRangeP and priceMoveOkP and rsiMoveOkP and isLLP
and isHLP

    if condBullLast or condBullPrev
        bullSignal := true
    else if showDebug and rejLowLocal != ""
        rejLow := rejLowLocal

// Shift lastLow -> prevLow BEFORE overwriting lastLow
if not na(lastLowBar)
    prevLowRSI := lastLowRSI
    prevLowPx  := lastLowPx
    prevLowBar := lastLowBar

// Update last locked LOW and clear pending
lastLowRSI := pendLowRSI
lastLowPx  := pendLowPx
lastLowBar := pendLowBar

pendingLow := false
pendLowRSI := na
pendLowPx  := na

```

```

    pendLowBar := na

    // ---- LOCK HIGH -> bearish divergence ----
    if highLock
        if not na(lastHighBar) and not na(pendHighBar)
            barsBetween = pendHighBar - lastHighBar
            okRange = inRangeBars(barsBetween)

            priceMoveOk = pctMove(lastHighPx, pendHighPx) >= minPriceMovePct
            rsiDelta = math.abs(pendHighRSI - lastHighRSI)
            rsiMoveOk = rsiDelta >= bearMinRsiMove

            isHH = pendHighPx >= lastHighPx * (1 - priceTolPct/100)
            isLHish = pendHighRSI <= lastHighRSI + rsiTol

            hhPct = pctMove(lastHighPx, pendHighPx)

            strictBear = okRange and priceMoveOk and rsiMoveOk and (pendHighPx >
lastHighPx) and (pendHighRSI < lastHighRSI)
            relaxedBear = okRange and isHH and isLHish and (hhPct >= minBearHHpct)
and (rsiDelta < bearMinRsiMove)

            condBear = strictBear or relaxedBear

            if condBear
                bearSignal := true
            else if showDebug
                if not okRange
                    rejHigh := "REJ:range"
                else if not priceMoveOk
                    rejHigh := "REJ:price%<"
                else if not rsiMoveOk
                    rejHigh := "REJ:rsiΔ<"
                else if not isHH
                    rejHigh := "REJ:notHH"
                else if not isLHish
                    rejHigh := "REJ:notLH"
                else if hhPct < minBearHHpct
                    rejHigh := "REJ:HH%<"
                else
                    rejHigh := "REJ:other"
            else if showDebug
                rejHigh := "REJ:firstHigh"

            lastHighRSI := pendHighRSI
            lastHighPx := pendHighPx
            lastHighBar := pendHighBar

            pendingHigh := false
            pendHighRSI := na
            pendHighPx := na
            pendHighBar := na

    // ----- Final labels (NO BACKPAINT) -----
    if showLabels and bullSignal
        label.new(bar_index, osc, "fBull", style=label.style_label_up,
color=bullColor, textcolor=txtColor, size=size.small)

```

```

        if showLabels and bearSignal
            label.new(bar_index, osc, "fBear", style=label.style_label_down,
color=bearColor, textcolor=txtColor, size=size.small)

        // ----- Debug labels (limited to last N bars) -----
--
        showDebugNow = showDebug and (bar_index > last_bar_index - debugBars)

        if showDebugNow and rejLow != ""
            label.new(
                bar_index,
                math.min(osc + debugYOffset, 95),
                "L " + rejLow,
                style=label.style_label_down,
                color=color.new(color.yellow, 0),
                textcolor=color.black,
                size=size.small
            )

        if showDebugNow and rejHigh != ""
            label.new(
                bar_index,
                math.max(osc - debugYOffset, 5),
                "H " + rejHigh,
                style=label.style_label_up,
                color=color.new(color.yellow, 0),
                textcolor=color.black,
                size=size.small
            )

```

APPENDIX B

EMPIRICAL OBSERVATION DATASET

Research Dataset

- RSID_GA_NIFTY_Daily_Observations.xlsx:
https://docs.google.com/spreadsheets/d/141RmNh8NTl1zna1rwJajc9qK8iLjr6LD/edit?usp=drive_link&ouid=105164645615579036389&rtpof=true&sd=true
- Mirror Link: <https://docs.google.com/spreadsheets/d/1ilOVtc2SIqdLTMHZ-GMvzA28SBovloEe/edit?usp=sharing&ouid=113451088656580077769&rtpof=true&sd=true>

This Excel file has the manually curated and structurally validated dataset of Relative Strength Index (RSI) divergence observations on the NIFTY-50 index that we used in this study. The dataset records all bullish and bearish divergence events that were found, as well as their pivot structures, structural confirmation stages, entry alignment at T1, and exit derivations under the standard common exit framework.

The file also keeps track of divergence classification, structural resolution behaviour, signal timing characteristics, and how well it compares to the Manual Analyst, TradingView's built-in divergence detector, the True Leading Indicator (TLI), and the Structural Leading Divergence (SLD) indicator. Trade outcome metrics are calculated under strict causal conditions, which means that the profitability analysis does not include any information about the future.

This dataset is the main source of information for the statistical analyses in Chapter 4. It also lets you fully trace divergence detection, structural validation logic, timeliness measurement, and outcome derivation.

APPENDIX C

TRADING VIEW REPLAY EXECUTION DOCUMENTATION

Screen Captures

- TV-Replay-NIFTY-SLD-Execution-Part-1.mp4:
https://drive.google.com/file/d/15KZjvdsqIARSQsgL8Dr5UE7I4D4sBZyP/view?usp=drive_link
- TV-Replay-NIFTY-SLD-Execution-Part-2.mp4:
https://drive.google.com/file/d/1N8GRRj4nauI95dPSyUDvRQ2WIJNUBp4l/view?usp=drive_link
- Mirror Links:
 - <https://drive.google.com/file/d/1hV3K083k44LVXM4xqsQKBkIgJV61r3Er/view?usp=sharing>
 - https://drive.google.com/file/d/12tOA41fFBBev1UnSvJDSOP_wKuorUENL/view?usp=sharing

The videos show that the SLD indicator works without repainting, that signal confirmation only happens after structural validation, and that trade execution follows the exact same logic that is used to calculate profits.

The replay recordings thus serve as an audit trail evidencing temporal integrity, real-time feasibility, and the reproducibility of the results presented in Chapter 4.