Logistic Regression-Based Systematic Trading: Performance on the S&P 500

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Abstract

This paper examines the performance of a Logistic Regression-Based Systematic Trading (LRST) strategy, applied to stocks in the S&P 500 from November 1983 to July 2023. The LRST strategy uses logistic regression to predict stock price movements based on historical returns, framing the problem as a binary classification task. Over the long term, the strategy achieved an annualized return of 24.61%, outperforming the S&P 500 during key periods, particularly in the 1990s and early 2000s. However, recent performance from 2021 to 2024 has been notably weak, with the strategy failing to capitalize on market gains, resulting in cumulative returns that fell behind the benchmark index. The methodology incorporates a rolling logistic regression model with a 10-year window and normalizes cumulative returns across various time frames. This enables the model to adapt to changing market conditions. The paper evaluates the strategy using financial metrics like the Sharpe and Sortino ratios, revealing significant downside risk alongside positive returns. The study concludes that while the LRST strategy has shown potential, it requires further refinement to adapt to modern market dynamics. Incorporating machine learning techniques and additional predictive factors, such as sentiment and macroeconomic indicators, could improve its robustness and future performance.

Keywords: *Logistic regression, systematic trading strategies, momentum trading, mean reversion, stock price prediction, binary classification, S&P 500, cumulative returns, rolling regression model, risk-adjusted performance, Sharpe ratio, Sortino ratio, machine learning in finance, portfolio optimization, predictive modeling, market dynamics, financial metrics, econometric methods, sentiment analysis, macroeconomic indicators.*

1 Introduction

Systematic trading strategies have become a cornerstone of modern financial markets, leveraging quantitative techniques to exploit patterns and inefficiencies in asset prices. These strategies offer a methodical approach to trading, driven by data and statistical models, reducing reliance on human intuition and emotions. Among the most prominent systematic strategies are momentum and mean reversion, both extensively studied and implemented for their ability to capitalize on predictable price movements.

Momentum strategies leverage the tendency for assets that have performed well to continue performing well, while mean reversion strategies assume that prices will eventually revert to their historical averages. Recently, logistic regression has emerged as a powerful tool for systematic trading, particularly in predicting the direction of future price movements based on historical returns. This paper introduces the Logistic Regression Portfolio (LRST) strategy, which employs logistic regression to classify future price movements, offering a systematic approach to portfolio construction.

The objective of this paper is to analyze the long-term performance of the LRST strategy using data from the S&P 500 over the period from November 1983 to July 2023. Additionally, the paper explores the robustness of the strategy, especially its recent performance from 2021 to 2024, during which it encountered significant challenges in adapting to contemporary market dynamics.

2 Literature Review

Systematic trading strategies have gained significant attention in financial markets due to their potential to exploit predictable patterns in asset prices. Among these strategies, momentum and mean reversion are two foundational approaches that have been extensively studied and applied. This literature review explores these basic approaches, followed by a discussion of simple econometric methods using price data and past returns, specifically focusing on linear regression and logistic regression.

2.1 Basic Approaches: Momentum Trading and Mean Reversion

2.1.1 Momentum Trading

Systematic trading strategies have gained significant traction in financial markets, particularly those based on momentum and mean reversion. The momentum strategy, as articulated by Jagadeesh and Titman in their seminal 1996 paper, *Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency*, posits that stocks that have performed well in the past tend to continue performing well in the future, while those that have performed poorly tend to continue underperforming [31]. This phenomenon can be attributed to investor behavior and market inefficiencies, which create a persistent trend in stock prices over time [35]. The authors provide empirical evidence supporting the existence of momentum profits over various time horizons, suggesting that the market does not fully adjust to new information, thus allowing for the exploitation of these trends through systematic trading strategies.

Building on this foundation, subsequent research has expanded the understanding of momentum strategies. For instance, studies have explored the role of behavioral biases, such as overconfidence and herding, in reinforcing momentum effects [34]. Additionally, the implementation of momentum strategies has been shown to yield significant returns across various asset classes, including equities, commodities, and currencies, further validating the robustness of this approach [32]. The momentum phenomenon has also been linked to liquidity conditions, where periods of high liquidity tend to enhance momentum returns, while low liquidity can dampen them [33]. This strategy capitalizes on the persistence of price trends, allowing traders to take long positions in rising markets and short positions in declining ones. Momentum strategies profit from both upward and downward price movements, indicating their versatility in various market conditions [9]. Moreover, empirical evidence suggests that momentum trading can yield substantial returns, particularly in trending markets [9].

2.1.2 Mean Reversion

In contrast, mean reversion strategies operate on the premise that asset prices will revert to their historical averages over time. This approach involves identifying assets that have deviated significantly from their mean price levels and taking positions that anticipate a return to equilibrium. Mean reversion traders buy assets that have fallen below their historical averages and sell those that have risen above [37]. This strategy is supported by the concept that prices oscillate around a mean, and deviations from this mean present trading opportunities. Studies indicate that mean reversion can be particularly effective in volatile markets, where price fluctuations are more pronounced [39].

The effectiveness of mean reversion strategies is often attributed to the behavioral biases of market participants. Investors may overreact to news, leading to excessive price movements that eventually correct themselves. This phenomenon is particularly evident in periods of high volatility, where the likelihood of price reversals increases [38]. Empirical evidence suggests that mean reversion can be observed across various asset classes, including equities, commodities, and currencies, indicating its broad applicability in financial markets [36]. Furthermore, the mean reversion effect has been documented in both developed and emerging markets, highlighting its relevance across different market conditions [36].

2.2 Econometric Methods Using Price Data

To implement these trading strategies, econometric methods can be employed using price data and past returns as independent variables. Linear regression is one such method that can be utilized to model the relationship between past returns and future price movements. By regressing future returns on past returns, traders can identify patterns and make informed decisions based on historical data. This approach has been shown to provide insights into the predictability of asset returns, although it may not fully capture the complexities of market dynamics [36].

Another method, logistic regression, is particularly useful for modeling binary outcomes, such as whether an asset's price will increase or decrease. This method can be employed to assess the likelihood of price movements based on historical return data. The logistic regression model estimates the probability of a particular outcome, allowing traders to make decisions based on the predicted probabilities of price changes. This approach is advantageous in capturing the non-linear relationships often present in financial data [36].

2.3 Logistic Regression in Systematic Trading

Logistic regression has emerged as a powerful tool in systematic trading strategies, particularly for its ability to handle binary classification problems. By modeling the probability of an asset's price movement based on past returns, traders can develop robust trading signals. The logistic regression model can be expressed as:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}}$$

where $P(Y = 1|X)$ represents the probability of a price increase, β_0 is the intercept, and $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the independent variables $X_1, X_2, \ldots, X_n$ (past returns) [36].

The application of logistic regression in trading strategies allows for the incorporation of various independent variables, such as different time frames of past returns, which can enhance the model's predictive power. For instance, by analyzing returns over multiple periods, traders can identify patterns that may not be evident when considering a single time frame. This multi-period approach can lead to more accurate predictions of price movements, thereby improving trading performance [36].

Moreover, logistic regression can be combined with other techniques, such as machine learning algorithms, to create hybrid models that leverage the strengths of both approaches. This integration can lead to more sophisticated trading strategies that adapt to changing market conditions [36]. The flexibility of logistic regression in handling various types of data and its ability to provide probabilistic outputs make it a valuable tool for systematic trading.

In conclusion, systematic trading strategies, particularly momentum and mean reversion, provide a framework for exploiting market inefficiencies. The use of econometric methods, especially logistic regression, enhances the ability to predict price movements based on historical data, thereby informing trading decisions. As financial markets continue to evolve, the integration of advanced statistical techniques will likely play a crucial role in the development of effective trading strategies.

3 Data and Methodology

3.1 Data

The dataset utilized for this study comprises stocks listed on the S&P 500 index, covering the time frame from January 1985 to July 2024. This extensive period allows for a comprehensive analysis of stock performance across various market conditions, including bull and bear markets, thereby enhancing the robustness of the findings. The data was sourced from Bloomberg ensuring a high level of reliability in the information used for analysis.

To mitigate the effects of survival bias, the dataset includes stocks that have been added to or removed from the S&P 500 index during the specified timeframe. This approach is crucial, as it allows for a more accurate representation of the market dynamics and ensures that the analysis reflects the actual trading environment experienced by investors. The inclusion of stocks that have exited the index helps to account for the performance of companies that may have underperformed, thus providing a more balanced view of the overall market behavior [13].

The choice of the S&P 500 index is particularly relevant, as it is widely regarded as a benchmark for the U.S. equity market, encompassing a diverse range of sectors and industries. This diversity allows for the examination of various trading strategies across different market segments, enhancing the generalizability of the results. Furthermore, the S&P 500's composition is regularly updated, reflecting changes in the market and providing a dynamic environment for testing systematic trading strategies [12].

3.2 Methodology

The objective of this study is to predict the next month's return of stocks based solely on historical return data. To achieve this, the problem is framed as a classification task rather than a regression task. This approach aligns with the findings of Kumar and Lee [18], who emphasize the importance of investor sentiment and its impact on stock returns, suggesting that understanding the probability of outperformance can be more beneficial than focusing solely on predicted returns. This decision is grounded in the desire to identify stocks that are most likely to outperform the market in the upcoming month, rather than merely selecting stocks based on the highest predicted return.

3.2.1 Dependent Variable

The dependent variable in this analysis is a categorical variable that indicates whether the monthly return for a specific stock is above or below the median return for that month. This binary classification allows for a clearer interpretation of the model's output, as it directly relates to the performance of the stock relative to its peers. The use of median returns as a threshold is supported by research indicating that median-based measures can provide a robust benchmark in financial contexts, as they are less sensitive to outliers compared to mean returns [21].

3.2.2 Feature Selection

For the feature set, this study follows the methodology proposed by Poh et al. [19], which involves utilizing cumulative returns over various time frames leading up to the month being predicted. Specifically, cumulative returns from the past 20 days and the past 12 months are used, allowing the model to learn which periods are most predictive of future performance. This flexible approach to feature selection is consistent with findings that advocate for the use of multiple time frames in developing systematic trading strategies, enhancing the model's ability to capture relevant market dynamics. To enhance the performance of the machine learning models and improve data handling, predictors are normalized using z-scores. Normalization ensures that all features contribute equally to the model's learning process, a practice supported by the literature for improving convergence rates and model accuracy [15].

3.2.3 Machine Learning Approach

Several algorithms were tested, but the study implements a rolling logistic regression model with a rolling window of 10 years. This choice ensures that the model reflects market conditions relevant to the time of the backtest, which dates back to 1984. Logistic regression is particularly suitable for this classification task, as it provides probabilistic outputs that can be interpreted as the likelihood of a stock's return exceeding the median. This aligns with the work of Zhang and Zhang [21], who highlight the effectiveness of logistic regression in capturing the dynamics of feedback trading in financial markets. The rolling window approach allows for the adaptation of the model to changing market conditions, crucial in financial markets influenced by various external factors. This methodology is consistent with findings by Fama and French [16], who argue that market conditions significantly impact the relationships between historical returns and future performance.

3.2.4 Mathematical Formulation and Regression Model

As the framework is designed to classify whether a stock's return for the upcoming month exceeds the median return of that month, the dependent variable, $Y_{i,t}$, is defined as:

$$Y_{i,t} = \begin{cases} 1 & \text{if } R_{i,t+1} > \text{Median}(R_{t+1}) \\ 0 & \text{otherwise} \end{cases}$$

where $R_{i,t+1}$ represents the monthly return of stock i in month $t+1$, and $\text{Median}(R_{t+1})$ is the median return across all stocks in month $t+1$.

The logistic regression model estimates the probability $P(Y_{i,t} = 1)$ using the equation:

$$P(Y_{i,t} = 1) = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{k} \beta_j X_{i,t}^{(j)})}},$$

where β_0 is the intercept term, β_j represents the coefficient for the j-th predictor, $X_{i,t}^{(j)}$ is the j-th feature for stock i in month t, and k is the total number of predictors.

The predictor variables $X_{i,t}^{(j)}$ include cumulative returns over different time periods, capturing short-term momentum and long-term trends. Specifically, short-term cumulative returns ($CR_{20,i,t}$) are calculated as the cumulative return of stock i over the past 20 trading days:

$$CR_{20,i,t} = \prod_{d=t-20}^{t} (1 + r_{i,d}) - 1,$$

where $r_{i,d}$ is the daily return of stock i on day d. Long-term cumulative returns ($CR_{12M,i,t}$) are calculated as the cumulative return of stock i over the past 12 months:

$$CR_{12M,i,t} = \prod_{m=t-12}^{t} (1 + R_{i,m}) - 1,$$

where $R_{i,m}$ is the monthly return of stock i in month m. Additionally, the market-wide median return ($\text{Median}(R_t)$) is included as a feature to normalize for market-wide performance variations.

The final logistic regression equation is expressed as:

$$\log\left(\frac{P(Y_{i,t}=1)}{1-P(Y_{i,t}=1)}\right) = \beta_0 + \beta_1 CR_{20,i,t} + \beta_2 CR_{12M,i,t} + \beta_3 \text{Median}(R_t) + \epsilon_{i,t}.$$

The error term $\epsilon_{i,t}$ represents unexplained variability due to factors not captured by the selected features, such as unpredictable external events or idiosyncratic stock-specific dynamics that influence returns.

To account for temporal market dynamics, the model employs a rolling window of 10 years. For each window, the logistic regression is re-estimated using data from the prior 120 months. This ensures that the model adapts to evolving market conditions, as older data is excluded, reflecting the relevance of recent historical patterns. The rolling nature of the window mitigates overfitting and improves the model's robustness in out-of-sample predictions.

3.2.5 Model Evaluation

The performance of the classification model is assessed using a portfolio simulation on the holdout data. This simulation involves selecting the 20 stocks with the highest predicted probabilities of outperforming the market and constructing an equally weighted portfolio. The performance of this portfolio is evaluated using various financial metrics, such as the geometric return, standard deviation, Sharpe ratio and Sortino ratio widely used indicators of investment performance [17, 20].

4 Returns Comparison and Findings

The performance of the Logistic Regression Portfolio (LRST) strategy can be evaluated through its monthly return data and cumulative return metrics, which provide valuable insights into its long-term strengths and short-term weaknesses. Over the historical period

Table 1: Performance Metrics of the LRST Strategy and the SP 500 (1984 – 2024)

Performance Metrics	LRST Strategy	S&P 500
Geo Mean Monthly Return	0.0185	0.0102
Max Return	0.3518	0.1243
Min Return	-0.3247	-0.1987
Monthly Standard Deviation	0.0754	0.0512
Monthly Downside Deviation	0.0776	0.0489
Monthly Upside Deviation	0.0785	0.0525
Annualized Return	0.2461	0.1288
Annualized Standard Deviation	0.2611	0.1775
Annualized Downside Deviation	0.2689	0.1703
Annualized Upside Deviation	0.2721	0.1822
Sharpe Ratio	0.7738	0.7254
Sortino Ratio	0.7514	0.7098

from July 1984 to July 2024, the LRST strategy consistently outperformed the S&P 500 (ĜSPC) during several market phases. However, the strategy's performance has notably weakened in recent years, particularly over the last three years, as evidenced by the cumulative returns from 2021 to 2024 3, where it failed to capitalize on significant market gains [23].

From a long-term perspective, the LRST strategy has demonstrated considerable success, with strong outperformance relative to the S&P 500 during key periods, especially in the 1990s and early 2000s. As illustrated in 2 , the cumulative logarithmic returns of both the LRST strategy and the S&P 500 indicate that the LRST strategy was able to generate excess returns across various market conditions. For instance, during the early 1990s, the strategy's cumulative returns increased significantly, significantly outpacing the S&P 500. This long-term performance is reflected in the strategy's annualized return of 24.61%, which is a robust figure for a systematic trading strategy [30]. However, this high return is accompanied by substantial risk, as indicated by the annualized standard deviation of 26.11%, signaling significant variability in returns over time [28] 1.

In terms of risk-adjusted performance, the LRST strategy's Sharpe ratio of 0.7738 and Sortino ratio of 0.7514 suggest that while the returns are attractive, they are accompanied by considerable risk 1. The Sharpe ratio, which falls below the optimal threshold of 1, indicates that the returns are not sufficiently high to fully compensate for the associated volatility [26]. This is further evidenced by the monthly downside deviation of 7.76%, highlighting the strategy's exposure to downside risk during periods of market decline. Additionally, the Sortino ratio, which focuses specifically on downside risk, aligns with the Sharpe ratio, indicating that both upside and downside volatility are significant contributors to the strategy's overall risk profile [22].

The LRST strategy's performance in the last three years has been particularly concerning. From July 2021 to July 2024, the strategy struggled to generate positive returns, significantly underperforming the S&P 500. As shown in 3, which depicts cumulative returns based on an initial $100 investment, the LRST strategy consistently trailed behind the S&P 500. By

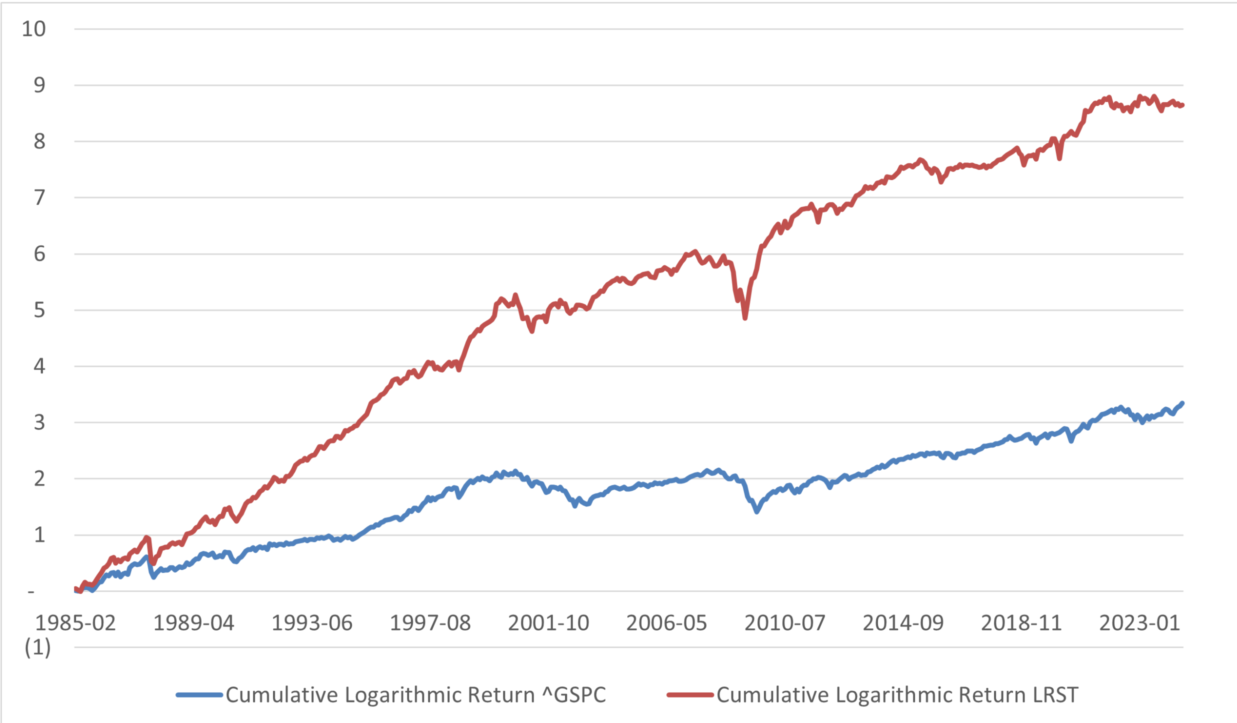

Figure 1: Excess returns of the LRST strategy over the S&P500 and cumulative return of the S&P500 (1/1985 – 7/2024).

July 2024, the cumulative return of the S&P 500 had grown to approximately \$140, while the LRST strategy remained around the \$100 mark, with periods where its cumulative return dipped below the initial investment [24]. This trend is further corroborated by 1, where the excess returns of the LRST strategy over the S&P 500 are shown to be consistently negative or flat during this period.

This recent underperformance could be attributed to several factors, including the changing market landscape, the rise of algorithmic trading, and macroeconomic shifts that the LRST strategy may not have been designed to capture [27]. The strategy's inability to track or outperform the S&P 500 during this time points to potential structural weaknesses. Its volatility in excess returns, particularly during a period of strong market growth, suggests that the LRST strategy might not be well-suited to current market conditions or that it requires additional refinement to adapt to contemporary challenges [25].

In conclusion, the LRST strategy exhibits strong potential over the long term, with attractive returns and reasonable risk-adjusted performance. However, its failure to adapt to recent market conditions, as evidenced by its underperformance from 2021 to 2024, highlights the need for further refinement. The high volatility and downside risk associated with the strategy suggest that adjustments are necessary to enhance its resilience and improve its ability to generate consistent returns in the face of evolving market dynamics. Without these changes, the strategy may continue to face challenges in periods of high volatility and shifting market environments.

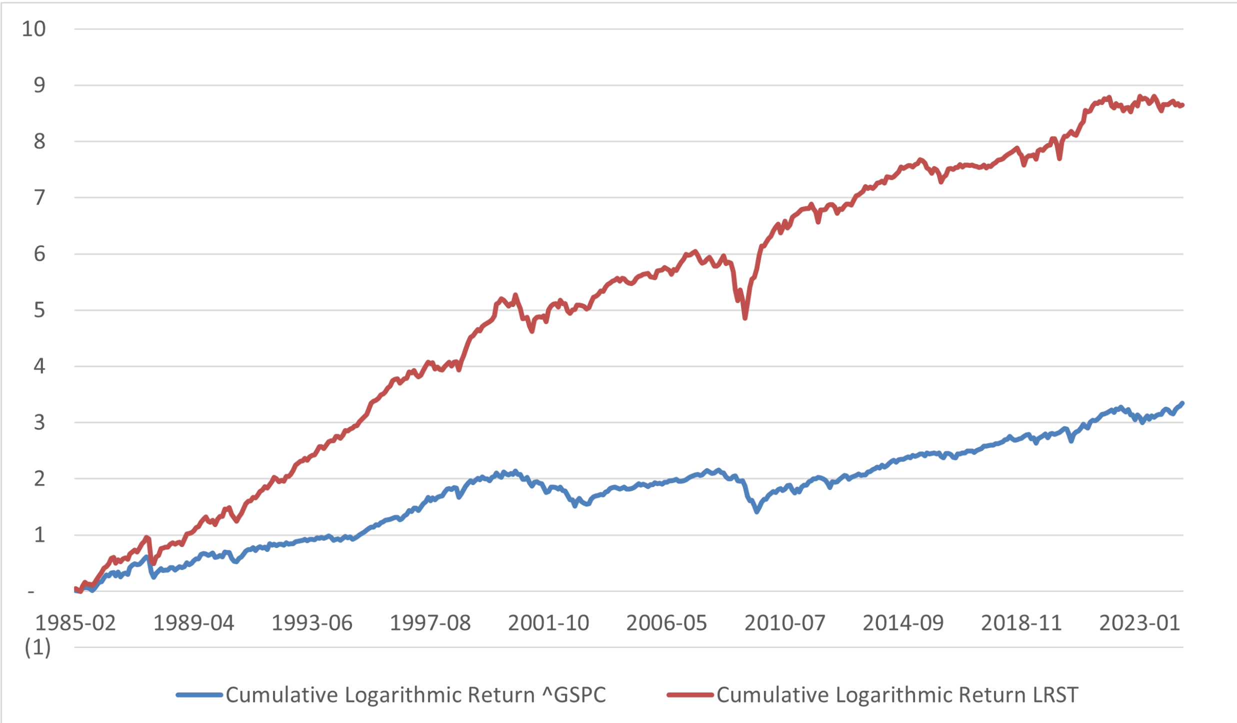

Figure 2: Cumulative returns of LRST strategy and S&P 500 (1/1985 – 7/2024)

5 Conclusion and Interpretation

The findings of this study provide valuable insights into the performance of the LRST (Logistic Regression Portfolio) strategy within the context of systematic trading strategies. The analysis reveals that while the LRST strategy has demonstrated considerable long-term success, particularly during the 1990s and early 2000s, it has struggled to adapt to recent market conditions, particularly from 2021 to 2024. This underperformance raises important questions about the robustness and adaptability of systematic trading strategies in the face of evolving market dynamics.

The LRST strategy's annualized return of 24.61% over the historical period indicates its potential for generating excess returns compared to the S&P 500. However, the accompanying high volatility, as evidenced by an annualized standard deviation of 26.11%, suggests that the strategy is not without significant risk. The Sharpe ratio of 0.7738, while indicative of positive risk-adjusted returns, falls below the optimal threshold of 1, highlighting the need for further refinement to enhance the strategy's risk-return profile. This aligns with the findings of Avramov et al. [42], who noted that the relationship between liquidity and excess returns is often not statistically significant, suggesting that factors beyond traditional metrics may influence performance.

Moreover, the recent struggles of the LRST strategy could be attributed to several factors, including the rise of algorithmic trading and macroeconomic shifts that it may not have been designed to capture. This observation resonates with the work of Liu et al. [40], which emphasizes the importance of adapting trading strategies to changing market conditions to maintain profitability. The inability of the LRST strategy to capitalize on market gains dur-

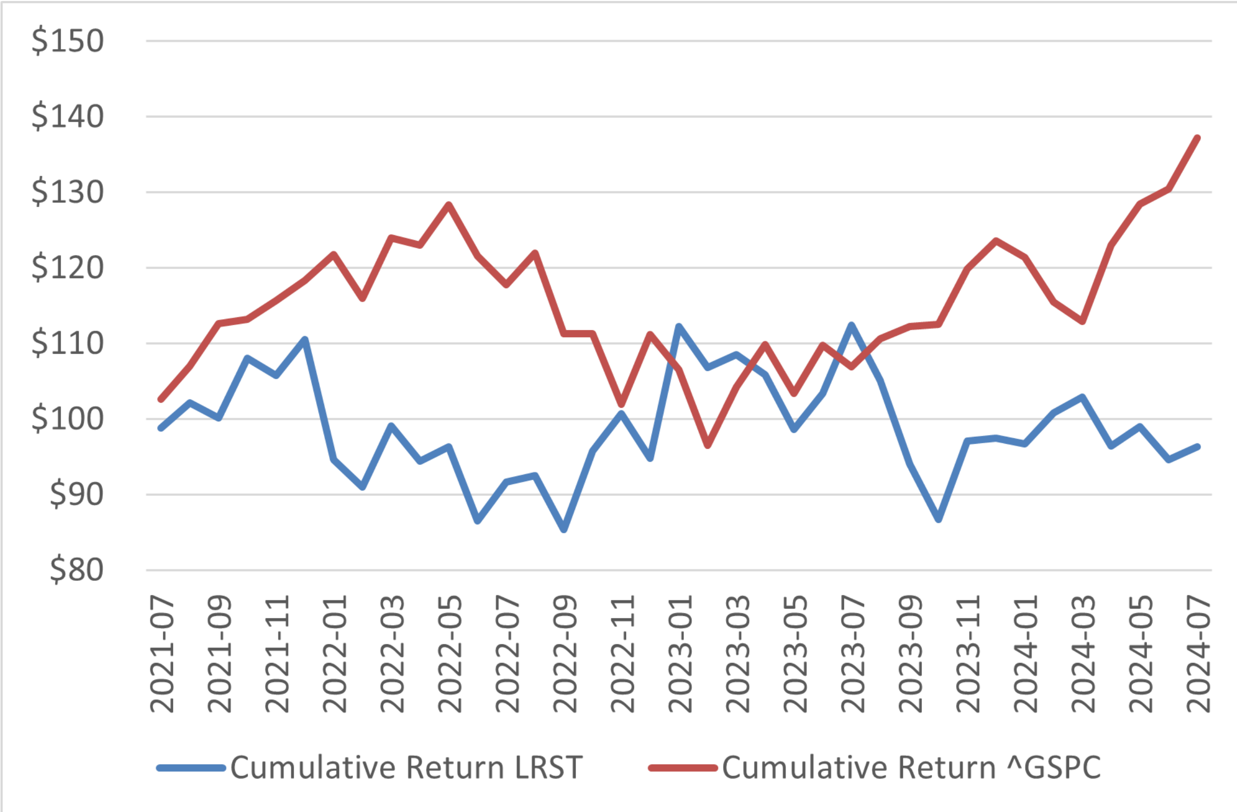

Figure 3: Cumulative returns of LRST strategy and S&P 500 (7/2021 – 7/2024)

ing a period of strong growth suggests potential structural weaknesses that warrant further investigation.

Future research could explore the integration of additional predictive variables, such as macroeconomic indicators or sentiment analysis, to enhance the model's adaptability to changing market conditions. For instance, incorporating sentiment indices could provide valuable insights into market psychology and its impact on stock returns. Additionally, examining the effects of market liquidity and volatility on the LRST strategy's performance could yield further insights into its risk profile and potential areas for improvement.

Another avenue for future research could involve the application of machine learning techniques to refine the LRST strategy. The use of advanced algorithms, such as Long Short-Term Memory (LSTM) networks, could enhance the model's ability to capture complex patterns in historical data and improve predictive accuracy, as discussed by Sebastião and Godinho [41]. This approach aligns with the growing trend in finance to leverage machine learning for portfolio optimization and return forecasting.

In conclusion, while the LRST strategy exhibits strong potential over the long term, its recent underperformance highlights the need for continuous refinement and adaptation to evolving market dynamics. By exploring additional predictive variables and incorporating advanced machine learning techniques, future research can contribute to the development of more resilient systematic trading strategies that can navigate the complexities of modern financial markets. The insights gained from this study not only enhance our understanding of the LRST strategy but also contribute to the broader literature on systematic trading and portfolio management.

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