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

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Abstract

This paper examines the performance of the Logistic Regression Portfolio (LRP) strategy, applied to stocks in the S&P 500 from November 1983 to July 2023. The LRP 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 LRP 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.

Logit Price Trading

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, which reduce reliance on human intuition and emotions. Among the most prominent systematic strategies are momentum and mean reversion, both of which have been extensively studied and implemented due to their ability to capitalize on predictable price movements. Momentum strategies take advantage of 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.

In recent years, logistic regression has emerged as a powerful tool for systematic trading, particularly in predicting the direction of future price movements based on historical returns. Logistic regression, typically used in binary classification problems, provides probabilistic predictions that traders can use to make informed decisions about whether an asset's price is likely to rise or fall. This paper introduces the Logistic Regression Portfolio (LRP) strategy, which employs logistic regression to classify future price movements, offering a systematic approach to portfolio construction. By framing the prediction of future returns as a classification task, the LRP strategy attempts to predict which assets are most likely to outperform the market in the short term.

The objective of this paper is to analyze the long-term performance of the LRP 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. Through this analysis, the paper aims to contribute to the ongoing discourse on systematic trading and provide insights into how logistic regression can be applied in financial markets.

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 will explore 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.

Basic Approaches: Momentum Trading and Mean Reversion

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. This phenomenon can be attributed to investor behavior and market inefficiencies, which create a persistent trend in stock prices over time (Turnbull, 2017). 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 (Hameed et al., 2010). 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 (Altay et al., 2017). 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 (Avellaneda & Lee, 2008). is predicated on the idea that assets that have performed well in the past will continue to do so in the future, while those that have performed poorly will continue to decline. This strategy capitalizes on the persistence of price trends, allowing traders to take long positions in rising markets and short positions in declining ones. highlight that momentum strategies profit from both upward and downward price movements, indicating their versatility in various market conditions (Wu et al., 2016). Moreover, empirical evidence suggests that momentum trading can yield substantial returns, particularly in trending markets (Wu, 2010).

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. describes how mean reversion traders buy assets that have fallen below their historical averages and sell those that have risen above (Enow, 2023). 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 (Liu et al., 2023; Bian, 2023).

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 (Firoozye & Koshiyama, 2019).

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 (Kakushadze, 2014).

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 mathematically as:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_nX_n)}}$$

where $P(Y=1|X)$ represents the probability of a price increase, β_0 is the intercept, and $\beta_1, \beta_2, ..., \beta_n$ are the coefficients for the independent variables $X_1, X_2, ..., X_n$ (past returns) (Li et al., 2013).

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 (Li et al., 2012).

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 (Gu, 2021). 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. *Table 1* compares the performance of individual strategies based on the above-described strategies and summarizes relevant literature.

Data

The dataset utilized for this study comprises stocks listed on the S&P 500 index, covering the time frame from November 1983 to July 2023. 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 and Yahoo Finance (yfinance), which are reputable platforms for financial data, 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 Poterba & Summers (1988).

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 (Maheshwari & Dhankar, 2017).

Methodology

In this study, the objective is to predict the next month's return of stocks based solely on historical return data. To achieve this, I have opted to frame the problem as a classification task rather than a regression task. . This approach aligns with the findings of (Kumar & Lee, 2006), 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 (Kumar & Lee, 2006 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

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 (Zhang & Zhang, 2011).

Feature Selection: For the feature set, I have chosen to follow the methodology proposed by (Poh et al., 2020), which involves utilizing cumulative returns over various time frames leading up to the month being predicted. Specifically, ~~I will input~~ cumulative returns from the past 20 days and the past 12 months, allowing the model to learn which periods are most predictive of future performance. This flexible approach to feature selection is consistent with the findings of (Poh et al., 2020), who advocate for the use of multiple time frames in developing systematic trading strategies, as it can enhance the model's ability to capture relevant market dynamics (Poh et al., 2020). To enhance the performance of the machine learning models and improve data handling, I will normalize the predictors using z-scores. Normalization is a critical step in preparing data for machine learning, as it ensures that all features contribute equally to the model's learning process. This practice is supported by the literature, which indicates that normalization can lead to improved convergence rates and model accuracy (Broussard & Vaihekoski, 2012).

Model Evaluation: The performance of the classification model will be assessed using confusion matrices, which provide a comprehensive view of the model's predictive capabilities by detailing true positives, true negatives, false positives, and false negatives. This statistical evaluation is essential for understanding the model's effectiveness in distinguishing between outperforming and underperforming stocks. Additionally, I will conduct a financial performance assessment through a portfolio simulation on the holdout data. This simulation will involve selecting the 20 stocks with the highest predicted probabilities of outperforming the market and constructing an equally weighted portfolio. The performance of this portfolio will be evaluated using various financial metrics, such as the Sharpe ratio and cumulative returns, which are widely recognized in the finance literature as indicators of investment performance (Gibson et al., 2000; Ze-To, 2015).

Machine Learning Approach: In terms of the machine learning approach, I have tested several algorithms; however, I have chosen to implement a rolling logistic regression model with a rolling window of 10 years. This choice is motivated by the need to ensure that the model reflects the market conditions relevant to the time of the backtest, which dates back to 1983. 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 & Zhang, 2011), who highlight the effectiveness of logistic regression in capturing the dynamics of feedback trading in financial markets (Zhang & Zhang, 2011). The rolling window approach allows for the adaptation of the model to changing market conditions, which is crucial in the context of financial markets that are influenced by various external factors. This methodology is consistent with the findings of (Fama & French, 1992), who argue that market conditions can significantly impact the relationships between historical returns and future performance (Fama & French, 1992). By employing a rolling logistic regression model, I aim to create a robust framework for predicting stock performance that can adapt to the evolving nature of financial markets. In summary, this methodology combines a classification framework with a focus on cumulative returns, normalization of features, and a robust evaluation strategy to predict stock performance. By leveraging the insights from existing literature and employing a rolling logistic regression model, this study aims to provide a comprehensive analysis of stock returns based on historical data.

Returns Comparison and Findings

The performance of the LRP (Logistic Regression Portfolio) 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 from February 1985 to July 2024, the LRP strategy consistently outperformed the S&P 500 (^GSPC) 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, where it failed to capitalize on significant market gains Dadakas et al. (2016).

From a long-term perspective, the LRP 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 Figure 2, the cumulative logarithmic returns of both the LRP strategy and the S&P 500 indicate that the LRP strategy was able to generate excess returns across various market conditions. For instance, during the early 1990s, the strategy's cumulative returns increased significantly, at times 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 (Xiong et al., 2019). 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 (Lynch et al., 2003).

In terms of risk-adjusted performance, the LRP 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. 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 (Huu & Faff, 2012). 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 (Cullen et al., 2011).

The LRP 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 Figure 3, which depicts cumulative returns based on an initial $100 investment, the LRP strategy consistently trailed behind the S&P 500. By July 2024, the cumulative return of the S&P 500 had grown to approximately $140, while the LRP strategy remained around the $100 mark, with periods where its cumulative return dipped below the initial investment (Downs & Ingram, 2000). This trend is further corroborated by Figure 1, where the excess returns of the LRP 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 LRP strategy may not have been designed to capture (Kamalov et al., 2021). 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 LRP strategy might not be well-suited to current market conditions or that it requires additional refinement to adapt to contemporary challenges (Goh, 2024).

In conclusion, the LRP 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 (Tchatoka et al., 2019).

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Conclusion and Interpretation

The findings of this study provide valuable insights into the performance of the LRP (Logistic Regression Portfolio) strategy within the context of systematic trading strategies. The analysis reveals that while the LRP 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 LRP 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. Avramov et al. (2006), 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 LRP 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 Xu et al. (Xu et al., 2021), which emphasizes the importance of adapting trading strategies to changing market conditions to maintain profitability. The inability of the LRP strategy to capitalize on market gains during 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, as suggested by Xu et al. (Xu et al., 2021), could provide valuable insights into market psychology and its impact on stock returns. Additionally, examining the effects of market liquidity and volatility on the LRP 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 LRP 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 Yıldız and Yildiz (Yıldız & Yildiz, 2020). This approach aligns with the growing trend in finance to leverage machine learning for portfolio optimization and return forecasting.

In conclusion, while the LRP 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 LRP strategy but also contribute to the broader literature on systematic trading and portfolio management.

References

Avellaneda, M. and Lee, J. (2010). Statistical arbitrage in the us equities market. Quantitative Finance, 10(7), 761-782. https://doi.org/10.1080/14697680903124632

Balvers, R. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. The Journal of Finance, 55(2), 745-772. https://doi.org/10.1111/0022-1082.00225

Balvers, R. and Wu, Y. (2006). Momentum and mean reversion across national equity markets. Journal of Empirical Finance, 13(1), 24-48. https://doi.org/10.1016/j.jempfin.2005.05.001

Gârleanu, N. and Pedersen, L. (2013). Dynamic trading with predictable returns and transaction costs. The Journal of Finance, 68(6), 2309-2340. https://doi.org/10.1111/jofi.12080

Li, B., Hoi, S., Sahoo, D., & Liu, Z. (2015). Moving average reversion strategy for on-line portfolio selection. Artificial Intelligence, 222, 104-123. https://doi.org/10.1016/j.artint.2015.01.006

Li, B., Zhao, P., Hoi, S., & Gopalkrishnan, V. (2012). Pamr: passive aggressive mean reversion strategy for portfolio selection. Machine Learning, 87(2), 221-258. https://doi.org/10.1007/s10994-012-5281-z

Miao, G. (2014). High frequency and dynamic pairs trading based on statistical arbitrage using a two-stage correlation and cointegration approach. International Journal of Economics and Finance, 6(3). https://doi.org/10.5539/ijef.v6n3p96

Song, Q. and Zhang, Q. (2013). An optimal pairs-trading rule. Automatica, 49(10), 3007-3014. https://doi.org/10.1016/j.automatica.2013.07.012

Stübinger, J. and Endres, S. (2018). Pairs trading with a mean-reverting jump–diffusion model on high-frequency data. Quantitative Finance, 18(10), 1735-1751. https://doi.org/10.1080/14697688.2017.1417624

Wu, Y. (2010). Momentum trading, mean reversal and overreaction in chinese stock market. Review of Quantitative Finance and Accounting, 37(3), 301-323. https://doi.org/10.1007/s11156-010-0206-z

Bae, M., Seo, M., Ko, H., Ham, H., Kim, K., & Lee, J. (2023). The efficacy of memory load on speech-based detection of alzheimer’s disease. Frontiers in Aging Neuroscience, 15. https://doi.org/10.3389/fnagi.2023.1186786

Duan, L. (2024). Exploring efficient quantitative trading strategies: a comprehensive comparison of momentum, smas and machine learning. Advances in Economics Management and Political Sciences, 86(1), 43-48. https://doi.org/10.54254/2754-1169/86/20240940

Maheshwari, S. and Dhankar, R. (2017). Profitability of volume-based momentum and contrarian strategies in the indian stock market. Global Business Review, 18(4), 974-992. https://doi.org/10.1177/0972150917692401

Poterba, J. and Summers, L. (1988). Mean reversion in stock prices. Journal of Financial Economics, 22(1), 27-59. https://doi.org/10.1016/0304-405x(88)90021-9

Wang, F. and Zheng, L. (2022). Do fund managers time momentum? evidence from mutual fund and hedge fund returns. European Financial Management, 30(1), 55-91. https://doi.org/10.1111/eufm.12406

Broussard, J. and Vaihekoski, M. (2012). Profitability of pairs trading strategy in an illiquid market with multiple share classes. Journal of International Financial Markets Institutions and Money, 22(5), 1188-1201. https://doi.org/10.1016/j.intfin.2012.06.002

Fama, E. and French, K. (1992). The cross-section of expected stock returns. The Journal of Finance, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Gibson, S., Safieddine, A., & Titman, S. (2000). Tax-motivated trading and price pressure: an analysis of mutual fund holdings. Journal of Financial and Quantitative Analysis, 35(3), 369. https://doi.org/10.2307/2676209

Kumar, A. and Lee, C. (2006). Retail investor sentiment and return comovements. The Journal of Finance, 61(5), 2451-2486. https://doi.org/10.1111/j.1540-6261.2006.01063.x

Poh, D., Lim, B., Zohren, S., & Roberts, S. (2020). Building cross-sectional systematic strategies by learning to rank.. https://doi.org/10.48550/arxiv.2012.07149

Ze-To, S. (2015). Cross-section stock return and implied covariance between jump and diffusive volatility. Journal of Forecasting, 34(5), 379-390. https://doi.org/10.1002/for.2348

Zhang, X. and Zhang, L. (2011). Internet-facilitated feedback trading.. https://doi.org/10.1109/hicss.2011.250

Cullen, G., Gasbarro, D., Monroe, G., & Zumwalt, J. (2011). Investor sentiment and momentum and contrarian trading strategies: mutual fund evidence. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1911010

Dadakas, D., Karpetis, C., Fassas, A., & Varelas, E. (2016). Sectoral differences in the choice of the time horizon during estimation of the unconditional stock beta. International Journal of Financial Studies, 4(4), 25. https://doi.org/10.3390/ijfs4040025

Downs, T. and Ingram, R. (2000). Beta, size, risk, and return. The Journal of Financial Research, 23(3), 245-260. https://doi.org/10.1111/j.1475-6803.2000.tb00742.x

Goh, J. (2024). The role of arbitrage risk in the max effect: evidence from the korean stock market. Journal of Derivatives and Quantitative Studies 선물연구, 32(2), 159-180. https://doi.org/10.1108/jdqs-09-2023-0031

Huu, B. and Faff, R. (2012). Are pairs trading profits robust to trading costs?. The Journal of Financial Research, 35(2), 261-287. https://doi.org/10.1111/j.1475-6803.2012.01317.x

Kamalov, F., Gurrib, I., & Rajab, K. (2021). Financial forecasting with machine learning: price vs return. Journal of Computer Science, 17(3), 251-264. https://doi.org/10.3844/jcssp.2021.251.264

Lynch, A., Wachter, J., & Boudry, W. (2003). Does mutual fund performance vary over the business cycle?. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.470783

Tchatoka, F., Masson, V., & Parry, S. (2019). Linkages between oil price shocks and stock returns revisited. Energy Economics, 82, 42-61. https://doi.org/10.1016/j.eneco.2018.02.016

Xiong, X., Luo, C., Zhang, Y., & Lin, S. (2019). Do stock bulletin board systems (bbs) contain useful information? a viewpoint of interaction between bbs quality and predicting ability. Accounting and Finance, 58(5), 1385-1411. https://doi.org/10.1111/acfi.12448

Altay, S., Colaneri, K., & Eksi, Z. (2017). Pairs trading under drift uncertainty and risk penalization. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2954762

Avellaneda, M. and Lee, J. (2008). Statistical arbitrage in the u.s. equities market. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1153505

Boguslavskaya, E., Boguslavsky, M., & Muravey, D. (2020). Trading multiple mean reversion.. https://doi.org/10.48550/arxiv.2009.09816

Coval, J. and Shumway, T. (2005). Do behavioral biases affect prices?. The Journal of Finance, 60(1), 1-34. https://doi.org/10.1111/j.1540-6261.2005.00723.x

Cox, R. and Zwinkels, R. (2016). Mortgage insurance adoption in the netherlands. Real Estate Economics, 47(4), 977-1012. https://doi.org/10.1111/1540-6229.12157

Finucane, T. (2000). A direct test of methods for inferring trade direction from intra-day data. Journal of Financial and Quantitative Analysis, 35(4), 553. https://doi.org/10.2307/2676255

Fouque, J. and Hu, R. (2018). Optimal portfolio under fractional stochastic environment. Mathematical Finance, 29(3), 697-734. https://doi.org/10.1111/mafi.12195

Garvey, R. and Murphy, A. (2005). Entry, exit and trading profits: a look at the trading strategies of a proprietary trading team. Journal of Empirical Finance, 12(5), 629-649. https://doi.org/10.1016/j.jempfin.2004.10.002

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. The Journal of Finance, 65(1), 257-293. https://doi.org/10.1111/j.1540-6261.2009.01529.x

Hsieh, P., Kim, Y., & Yang, J. (2009). The magnet effect of price limits: a logit approach. Journal of Empirical Finance, 16(5), 830-837. https://doi.org/10.1016/j.jempfin.2009.06.002

Schmitz, P. and Weber, M. (2012). Buying and selling behavior of individual investors in option-like securities. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2055088

Turnbull, D. (2017). Market fragmentation, market quality and clientele effects. International Journal of Financial Research, 9(1), 74. https://doi.org/10.5430/ijfr.v9n1p74

Tables

Table 1

Different Trading Strategies in Literature

Strategy	Type of Strategy	Ann. Ret. (%)	Reference
Momentum	Trend-following	22.20%	Wu (2010)
Mean Reversion	Contrarian	Varies (typically 5-15%)	Enow (2023); Liu et al. (2023)
Mean Reversion (DDAIF)	Contrarian	10.50%	Bian (2023)
Linear Regression	Predictive	Varies (dep. on model)	Firoozye & Koshiyama (2019)
Logistic Regression	Predictive	Varies (dep. on model)	Li et al. (2013); Gu (2021)
Confidence Weighted Mean Reversion	Adaptive	12.30%	Li et al. (2013)
Passive Aggressive Mean Reversion	Adaptive	15%	Li et al. (2012)
Deep Reinforcement Learning (Mean Reversion)	Adaptive	18%	Gu (2021)

Table 2

Performance Metrics of the LRP Strategy (1984 - 2024)

LRP Strategy Performance Metrics	
Geo Mean Monthly Return:	0.0185
Max Return:	0.3518
Min Return:	-0.3247
Monthly Standard Deviation:	0.0754
Monthly Downside Deviation:	0.0776
Monthly Upside Deviation:	0.0785
Annualized Return:	0.2461
Annualized Standard Deviation:	0.2611
Annualized Downside Deviation:	0.2689
Annualized Upside Deviation:	0.2721
Sharpe Ratio:	0.7738
Sortino Ratio:	0.7514

Figures

Figure 1

Excess returns of LRP strategy over ^GSPC and cumulative return of ^GSPC (1/1985 – 7/2024)

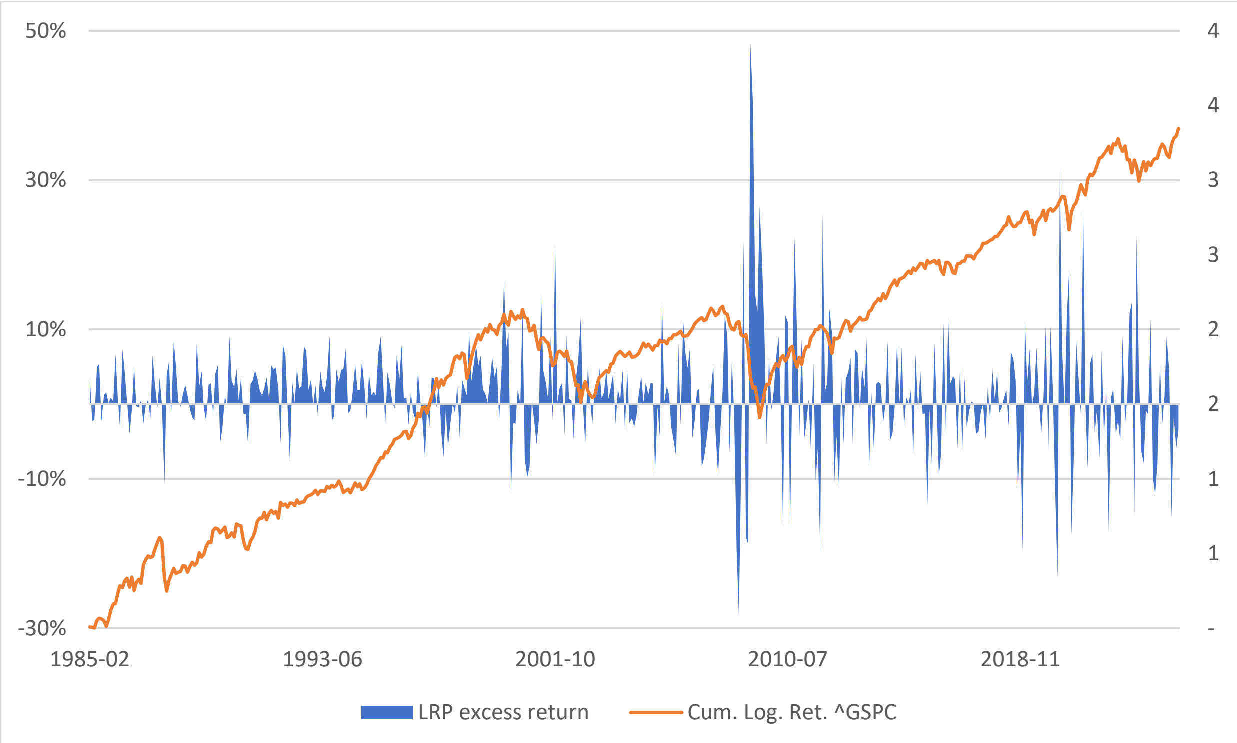

Figure 2

Excess returns of LRP strategy over ^GSPC and cumulative return of ^GSPC (1/1985 – 7/2024)

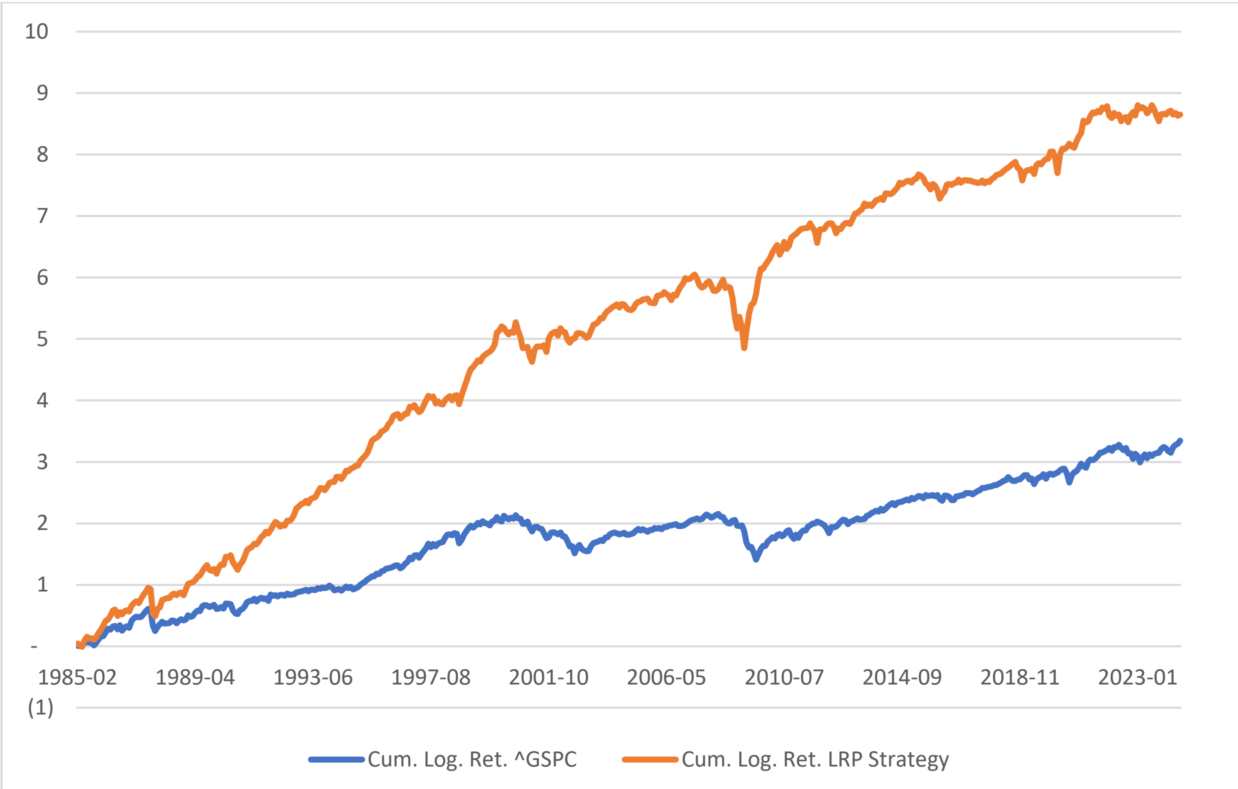

Figure 3

Cumulative returns of LRP strategy and cumulative return of ^GSPC (7/2021 – 7/2024)