Proceedings of the 5th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/116/2025.20429

Advancing Momentum Strategies with Machine Learning

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Abstract: Momentum strategies, which predict future returns based on historical asset performance, have been widely applied across various asset classes, including stocks and bonds. However, traditional momentum strategies face limitations when addressing the complexity and dynamics of modern financial markets. In recent years, advancements in computational technology have enabled the integration of machine learning techniques into momentum strategy research, providing new methods for identifying complex market patterns and optimizing trading strategies. This study aims to enhance traditional momentum strategies using machine learning techniques and explores their applicability and performance in diverse market environments. By reviewing relevant literature and comparing traditional and machine learning-enhanced momentum strategies, the study highlights the potential of machine learning in improving prediction accuracy, enhancing risk-adjusted returns, and adapting to market volatility. This research not only contributes to the expansion of the theoretical basis of momentum strategies but also provides investors with more scientific and practical tools for investment decision-making.

Keywords: Momentum strategies, Machine learning, Risk-adjusted returns, Investment decision-making

1. Introduction

Momentum strategies are investment approaches that predict future asset performance based on historical trends, assuming that assets performing well in the past will continue to do so, while poorly performing assets will persist in their decline. These strategies have been widely applied across various asset classes, including stocks, bonds, commodities, and foreign exchange markets. However, traditional momentum strategies face several challenges, including their inability to adapt effectively to the increasing complexity and dynamism of financial markets. Additionally, their theoretical foundation struggles to explain the role of investor behavior in shaping market dynamics, and their stability and applicability across varying market conditions remain subjects of debate. In recent years, machine learning has emerged as a powerful tool to address these challenges by offering superior capabilities in identifying complex patterns, processing large-scale data, and adapting to evolving market environments. The integration of machine learning into momentum strategies has introduced innovative approaches to optimize performance and expand their scope.

The application of machine learning to momentum strategies can significantly improve the efficiency and effectiveness of these strategies. By employing machine learning models, investors can not only more accurately identify momentum trends in the market but also predict the duration

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of these trends and potential turning points. For instance, using a random forest model, one can analyze stock price movements within multiple time frames to determine the optimal timing for buying or selling. Furthermore, deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which are particularly well-suited for handling sequential data, can capture the non-linear and complex temporal patterns in stock price sequences. This provides deeper data analysis and insights for decision-making in momentum strategies.

In summary, the introduction of machine learning not only enhances the data processing capability of momentum strategies but also improves the adaptability and predictive accuracy of these strategies. This development establishes machine learning as a crucial research direction in the field of financial technology. With continuous advancements in technology and model optimization, the application of machine learning in momentum strategies holds promising prospects, contributing to the innovation and development of financial markets.

This study aims to bridge the limitations of traditional momentum strategies by leveraging machine learning techniques to enhance their predictive accuracy, improve risk-adjusted returns, and increase adaptability to market fluctuations. Furthermore, it explores the applicability of these enhanced strategies across diverse market environments, providing valuable insights for both theoretical advancements and practical applications in financial decision-making.

2. The reviews of momentum strategies

2.1. Application of Momentum Strategy in Financial Markets

The development and optimization of momentum strategies remain a critical focus in financial research. Recently, diversification and advanced optimization methods have significantly improved the efficiency of momentum strategies. Hanauer and Windmüller (2023) compared three enhanced momentum strategies—constant volatility-scaled momentum, constant semi-volatility-scaled momentum, and dynamic scaled momentum—demonstrating their potential to reduce momentum crash risks and improve risk-adjusted returns [1]. Their findings suggest that fine-tuning the construction of momentum strategies can effectively enhance performance and mitigate the adverse effects of market volatility. Li and Liu (2022) explored the path dependency of momentum strategies, focusing on the construction of optimal dynamic momentum strategies. They emphasized that considering path dependency is crucial for optimizing portfolio allocation [2]. This research highlighted that effective momentum strategies must account not only for historical asset performance but also for the specific patterns of price trajectories to better capture market opportunities.

Momentum strategies demonstrate both potential and challenges when applied to emerging markets. Chu et al. (2020) explored their use in cryptocurrency markets, revealing their effectiveness in high-frequency trading environments [3]. This finding highlights the applicability of momentum strategies beyond traditional financial markets, offering opportunities in high-volatility and high-frequency markets. In the Chinese market, Bai et al. (2020) examined the disappearance of monthly momentum effects in the A-share market, attributing it to the T+1 trading system. They emphasized the need to account for market-specific regulations and trading mechanisms when applying momentum strategies[4]. These insights suggest adjustments are necessary for strategies to perform effectively in different institutional contexts.

Li et al. (2019) analyzed how investors' heterogeneous beliefs and behavioral biases influence the intensity and duration of momentum effects [5]. Their findings provide a behavioral finance perspective on understanding market-specific momentum anomalies and offer data-driven insights for refining momentum strategies.

Beyond this, the effectiveness of momentum strategies has been validated across various markets and time periods. Song Guanghui et al. (2017) introduced the Stock Price Residual (SPR)-based

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momentum strategy, confirming the presence of momentum effects in China's stock market. Their research demonstrated that SPR momentum strategies yield significantly positive cumulative excess returns over short, medium, and long time frames [6]. Similarly, Liu Qingyuan et al. (2016) revealed that overnight returns are the primary source of momentum profits in China's A-shares market, while intraday reversals drive the market's overall reversal characteristics [7]. These findings highlight the distinct mechanisms of momentum effects in the Chinese market.

2.2. The limitations of traditional momentum strategies

A momentum crash refers to a sudden and dramatic decline in the performance of momentum-based investment strategies, which typically involve buying assets with rising prices and selling those with falling prices. Daniel and Moskowitz (2016) highlighted that while these strategies can be highly profitable, they are also prone to abrupt market reversals that can lead to significant losses[8]. These reversals often occur without warning, causing the value of momentum-driven portfolios to drop sharply.

Momentum crashes often coincide with periods of heightened market stress or rapid shifts in investor sentiment. Barroso and Santa-Clara (2015) observed that during a sudden market downturn, such as a shift from a bullish to a bearish trend, previously high-performing stocks might experience steep declines [9]. This phenomenon is particularly evident during market corrections, where a prolonged uptrend reverses, disproportionately impacting momentum stocks.

Economic disruptions are another critical factor. Cooper, Gutierrez, and Hameed (2004) emphasized that unexpected economic changes, such as surprising data releases or shifts in macroeconomic conditions, can trigger abrupt market reversals, undermining momentum strategies [10]. They also noted that behavioral biases, such as herd mentality, where many investors chase the same trend, often exacerbate these effects. When such trades are unwound, they can lead to rapid price declines, amplifying the crash.

Liquidity constraints further exacerbate momentum crashes. Chabot, Ghysels, and Jagannathan (2014) pointed out that during times of market stress, liquidity often dries up, leading to increased volatility in momentum stocks [11]. They explained that limited liquidity makes it difficult for investors to sell their assets quickly without significantly affecting prices, which deepens losses during a crash.

To manage these risks, Barroso and Santa-Clara (2015) suggested adopting diversified investment strategies, utilizing stop-loss mechanisms, and combining momentum strategies with other approaches [12]. These measures can help mitigate potential losses and improve the overall robustness of momentum-driven portfolios during adverse market conditions.

3. Model selection for machine learning optimization of momentum strategies

With the increasing complexity of financial market data and the growing demand for quantitative investment, machine learning has become a key tool for optimizing momentum strategies. Kim Saejoon (2019) utilized advanced deep learning techniques, such as stacked autoencoders and denoising autoencoders, not only to improve the profitability of momentum strategies but also to enhance their risk-adjusted characteristics [13]. Stacked autoencoders extract high-level features from asset price data, while denoising autoencoders remove random noise from input data, improving the model's ability to capture key signals. Together, these techniques contribute to momentum strategies by maintaining stability across different market environments.

Lim et al. (2019) further explored the application of deep neural networks in time series momentum strategies [14]. Among these, Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) are particularly effective in financial market forecasting.

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LSTM captures long-term dependencies in time series data, while CNN extracts local features, offering new perspectives for analyzing time series momentum strategies. The integration of these techniques allows momentum strategies to more accurately predict future market trends, optimizing asset selection and allocation.

Machine learning has opened new pathways for the development of momentum strategies. By utilizing advanced techniques such as deep learning, momentum strategies can better adapt to changing market conditions, enhancing profitability and risk-adjusted returns. Future research should focus on addressing challenges such as overfitting, model interpretability, and data structure optimization to further improve performance. With the continuous advancement of financial technology, combining machine learning with momentum strategies will play a pivotal role in investment and portfolio optimization.

In addition to this, we can also use an ensemble strategy [15], which allows one primary model to play a leading role while utilizing other models to provide auxiliary decision support. Therefore, we define a simple prediction rule: when both the random forest model and at least one other model predict an increase in stock prices, we proceed with buying; conversely, when both the random forest model and at least one other model predict a decline in stock prices, we proceed with selling.

We term this strategy the “Manners” strategy.

Ensemble learning methods have been statistically and practically verified in various fields to exhibit superior predictive performance, especially when dealing with high-dimensional, non-linear, and complex interactive datasets [16]. In financial market analysis, this approach is particularly advantageous because single-model methods often fail to capture all key signals due to the multifactorial influences on market price dynamics. By adopting random forest as the foundation of an ensemble learning approach, this strategy builds a decision tree framework and conducts weighted or majority voting at the output stage, effectively reducing the risks of overfitting and enhancing prediction accuracy.

In the “Manners” strategy, the random forest model is used not only to analyze macro market trends but also to evaluate individual stock behavior, thereby extracting the main trading signals. Additionally, by incorporating auxiliary systems such as gradient boosting trees and linear regression models, the strategy further improves the reliability of predictions based on the random forest model. When all models consistently predict an increase in stock prices, the strategy executes buy orders; conversely, when all models predict a decrease, sell orders are executed.

This strategy employs model consensus to control transaction execution risks. Specifically, a trade is executed only when predictions from at least two models, including the random forest model, align. This method significantly increases the reliability of the strategy’s decision-making [17]. Through this ensemble approach, the risks associated with over-reliance on a single model are effectively mitigated, and the advantages of model integration minimize the impact of false signals.

In empirical analysis, the simulated trading model based on this strategy demonstrates higher return stability and improved risk-adjusted return ratios, underscoring its practical application potential.

4. Current shortcomings

Although momentum strategies have achieved significant success in theoretical research and practical applications, they face challenges in extreme market events, such as heightened market volatility or sudden crashes. Their performance is often affected by transaction costs and market frictions [18]. The variability in performance across different markets and time periods demands continuous adjustments to adapt strategies to changing conditions.

Momentum strategies have demonstrated certain effectiveness in empirical studies but also face limitations. For example, Wang Mingtao and Li Dan (2015) found that momentum strategies based on the 52-week high price are not consistently effective in the Chinese A-share market, particularly during bull markets[19]. Additionally, more research is needed on risk adjustment and addressing the weaknesses of existing strategies. Furthermore, current studies focus predominantly on stock markets, with relatively few exploring momentum strategies for other asset classes and markets.

5. Research Prospects

Future research on momentum strategies should delve deeper into their adaptability and performance under various market conditions, particularly when considering transaction costs and market frictions. Somayeh Mousavi et al. (2015) introduced a method based on multitree genetic programming to design interpretable and accurate Takagi-Sugeno-Kang (TSK) models, providing a new direction for future momentum strategy research [10]. Additionally, integrating quantitative investment strategies, such as combining momentum Alpha strategies with fundamental Alpha strategies as proposed by Zhang Hongfan (2015), highlights the potential for improving momentum strategies' performance [20]. Research should also explore the application of machine learning and artificial intelligence to enhance the predictive accuracy and risk management capabilities of momentum strategies.

In the Chinese market, Gao Qiuming, Hu Conghui, and Yan Xiang (2014) provided deeper insights into the mechanisms of momentum effects in the A-share market. Despite the insignificance of long-term momentum effects, they identified stable short-term momentum returns, suggesting that market structure and investor behavior uniquely influence the formation of momentum effects [21]. Furthermore, Chen Fei, Chen Weizhong, and Wang Yuxi (2006) found significant medium-term momentum in low trading volume portfolios, supporting the behavioral model of gradual information diffusion and highlighting the impact of information asymmetry on price momentum [22].

Future studies should prioritize exploring how market microstructures and information environments influence strategy performance, particularly in emerging markets. By leveraging advanced data analysis and machine learning techniques to capture the interplay between market dynamics and microstructures, future research may pave new paths for the development of momentum strategies.

6. Conclusion

In summary, momentum strategies, as a significant research focus in the financial field, have demonstrated vast potential and promising applications with the increasing complexity of markets and advancements in technology. By incorporating advanced techniques such as deep learning and artificial intelligence, momentum strategies have made notable progress in improving predictive accuracy, risk management, and adaptability. Additionally, in-depth studies on investor behavior, market microstructures, and informational environments have further enriched the theoretical foundation of momentum strategies, offering new perspectives for applications in emerging markets and complex trading environments. Future research should emphasize integrating multidisciplinary theories and technologies to explore more interpretable and robust optimization methods. This would enable momentum strategies to better adapt to dynamic and evolving market conditions, thereby enhancing the scientific and efficient nature of financial investment decision-making.

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