Adaptability Analysis of Quantitative Hedging Strategies in the A-Share Market

Tianyu Huang

SWUFE-UD Institute of Data Science, Southwestern University of Finance and Economics, Sichuan 611130, China
htybb@udel.edu

Abstract. This paper examines the A-share market from January 2021 to December 2025. It applies machine learning methods, including Random Forest, AdaBoost, and Gradient Boosting to build a multi-factor quantitative hedging strategy from three dimensions: momentum, volatility, and turnover. The study systematically tests how the strategy performs under different market conditions-bull markets, bear markets, and sideways markets. The results show several findings. First, the strategy delivered an annualized return of -1.83% with a Sharpe ratio of -0.70 over the full sample period. The overall performance was unsatisfactory, mainly because the model relied solely on technical factors, the market was in a downtrend during the sample period, and transaction costs eroded returns significantly. Second, the strategy showed strong dependence on market states. It performed best in bull markets and worst in bear markets. In sideways markets, it was roughly break-even. Third, the Gradient Boosting model achieved the best prediction results. Fourth, SHAP feature importance analysis indicates that the 12-1-month momentum factor contributed the most, confirming the existence of significant medium-to-long-term momentum effects in the A-share market. The paper suggests improving the adaptability of quantitative hedging strategies through three approaches: strategy optimization, market development, and regulatory refinement.

Keywords: Quantitative Hedging, Machine Learning, Market Adaptability.

1 Introduction

In recent years, big data and artificial intelligence technologies have found increasingly wide applications in the financial sector. Quantitative investment has developed rapidly in China's capital markets. As an important type of quantitative strategy, hedging strategies aim to strip out market risk and generate stable excess returns through long-short portfolios. These strategies have attracted growing attention from institutional investors. In mature markets such as Europe and the United States, such strategies have been applied for many years and have developed relatively complete theoretical frameworks. However, the A-share market has its unique characteristics. The T+1 trading system, various short-selling restrictions, a high proportion of retail investors, and large market volatility all mean that strategies

© The Author(s) 2026
L. C. Yoong (ed.), *Proceedings of the 2026 2nd International Conference on Financial Innovation and Marketing Management (FIMM 2026)*, Advances in Economics, Business and Management Research 408,
https://doi.org/10.2991/978-94-6239-801-6_44

copied directly from mature markets often fail to work well. How to build hedging strategies suitable for local market features has become a concern for both academics and practitioners.

Scholars worldwide have conducted in-depth investigations on relevant topics. In terms of strategy construction, seven machine learning models, including random forest, have been adopted to predict the stock price trends of European listed firms, and the results verify that random forest achieves the optimal prediction performance [1]. The XGBoost algorithm has been applied to construct a multi-factor stock selection model, and empirical tests demonstrate that the model can create favorable investment returns [2]. In the research of market environment, the reversal effect in China's stock market presents significant time-varying characteristics, and the strategy yields are higher when the market is in a high-volatility upward trend [3]. Trading volume acts as a critical driving factor for the mean reversion effect and momentum effect in China's stock market [4]. Empirical analysis on the performance of market-neutral strategy funds in the A-share market indicates that most of such funds fail to maintain strict market neutrality and suffer from style factor exposure [5]. A trading strategy based on time-series momentum has been designed and empirically tested in both bull and bear market environments of the Chinese stock market [6]. From a macro perspective, the influence of quantitative hedging transactions on market liquidity has been systematically discussed [7].

Overall, existing literature has mainly studied this issue from two angles: strategy construction methods and market environment. Discussions on the adaptability mechanism of strategies under different market states remain insufficient. In particular, systematic testing of technical factor effectiveness is relatively lacking, and little attention has been paid to the specific application of machine learning models in factor selection and portfolio optimization. Given this situation, this paper takes the A-share market from 2021 to 2025 as a sample. It adopts machine learning methods, including Random Forest, AdaBoost, and Gradient Boosting to build a multi-factor quantitative hedging strategy from three dimensions: momentum, volatility, and turnover. By comparing strategy performance differences across bull, bear, and sideways markets, this paper aims to reveal the adaptability characteristics of quantitative hedging strategies in the A-share market. From a theoretical perspective, this paper enriches empirical evidence for localized quantitative strategy research and provides a new perspective for understanding factor effectiveness in the A-share market. From a practical perspective, the findings of this paper can provide some reference for institutional investors building robust hedging strategies and optimizing risk-return ratios in the A-share market.

2 Empirical Design and Model Construction

This paper examines listed companies in the A-share market from January 2021 to December 2025. The data comes from the daily stock returns file in the stock market trading series of the CSMAR database. The dataset covers core variables including daily open price, close price, high price, low price, volume, turnover, and return

adjusted for reinvestment of cash dividends [8]. This article sets the following criteria for sample screening: Exclude stocks with more than 20% missing transaction data. Exclude new stocks that have been listed for less than one year to avoid IPO effect interference. Winsorize daily yields in the first and 99th percentiles to eliminate extreme values. Remove records that lack earnings or closing prices. After the above screening, the final sample includes 78 stocks, with a total of 94,358 daily trading observations.

This paper constructs a multi-factor quantitative model, and selects 6 core factors from the three dimensions of momentum, volatility and turnover. This article uses a monthly rebalancing strategy. On the last trading day of each month, stocks are divided into 10 groups based on compound factor scores, of which 10 are long and 1 is short, thus constructing a market-neutral long-short portfolio. Each portfolio has an equal weight allocation, and the two-way transaction cost is set at 0.15% [9].

This paper selects three mainstream machine learning algorithms for profit prediction: random forest, AdaBoost, and gradient improvement. The input variables of the model are the above 6 technical factors, and the output variables are the predicted returns of the next 20 trading days [10]. For sample division, the rolling window method is adopted to split the data into a training set, a verification set and a test set, with respective proportions of 70%, 15% and 15%. In order to comprehensively evaluate the effectiveness of quantitative hedging strategies, this paper constructs a multi-dimensional performance evaluation index system including annualized return, annualized volatility, Sharpe ratio, Sortino ratio, maximum drawdown, Calmar ratio, win rate, profit-loss ratio, etc.

3 Empirical Results Analysis

3.1 Overall Performance

The overall performance of the full sample period of the quantitative hedging strategy is an annualized return of -1.83%, an annualized volatility of 6.90%, a Sharpe ratio of -0.70, a maximum drawdown of -15.71%, and a winning rate of 48.28%. From the prediction results of the machine learning model, the gradient lifting model performed best with an R^2 of 0.0161 on the test set. The random forest was the second with an R^2 of 0.0137, and the AdaBoost model performed relatively poorly with an R^2 of -0.2248. The overall unsatisfactory performance of the strategy can be explained from several aspects: the model only relies on technical factors and is not supported by fundamental information. The A-share market is in a sideways downward trend during the sample period, and the systemic risk is high. Transaction costs have a significant erosion effect on the return of the strategy. It is worth noting that compared with previous small sample studies, the sample size was expanded to 78 stocks, which reduced the annualized volatility from 11.10% to 6.90%, and the maximum drawdown narrowed from -38.63% to -15.71%, showing a clear dispersion effect.

Fig. 1 shows the cumulative return curve, monthly return distribution, and drawdown of a quantitative hedging strategy. From the perspective of the cumulative

yield curve, this strategy performed relatively well at the beginning of 2021-2022. The cumulative return once reached about 5%, but then entered the stage of continuous retracement. By the end of 2025, the cumulative return was -8.54%. The monthly return distribution shows that the strategy achieved 28 positive returns and 30 negative returns in 58 trading months, with a win rate of 48.28%. The retracement curve shows that the largest retracement occurred in the middle of 2022 to early 2023, with a retracement of -15.71%.

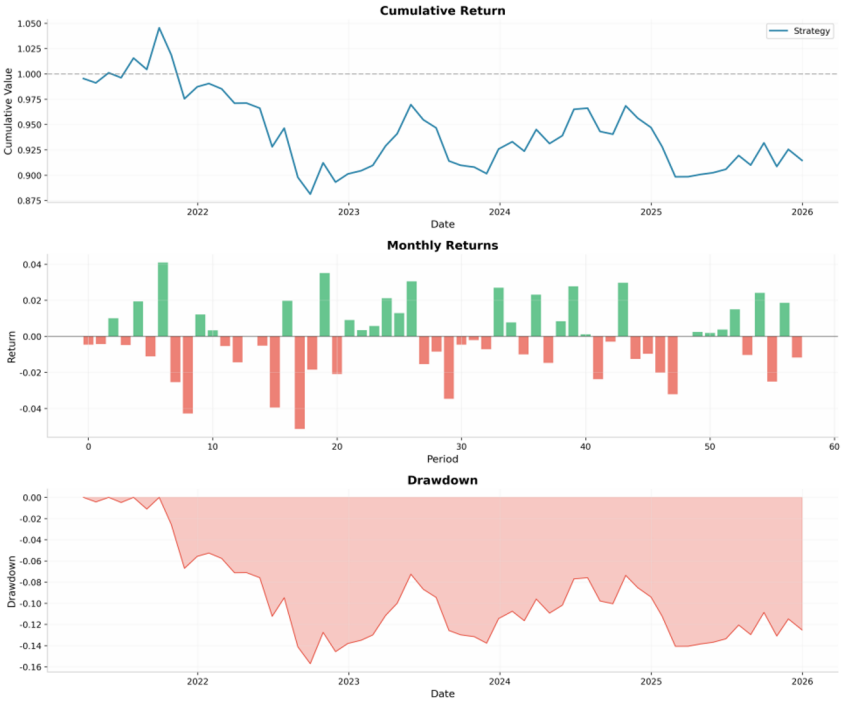

Fig. 1. The cumulative return curve (Picture credit: Original).

In order to further explore the adaptive performance of the strategy in different market environments, this paper divides the sample period into three stages: bull market, bear market and sideways according to the rolling return of the strategy. The results show that this strategy performs best in a bull market environment, with an average monthly return of 2.13% and a winning rate of 100%. It performs worst in a bear market environment, with an average monthly return of -1.41% and a winning rate of only 27.27%, in a sideways market environment, the performance is close to breakeven, with an average monthly return of -0.07% and a winning rate of 47.62%. This finding shows that quantitative hedging strategies show a clear dependence on market conditions—they can effectively capture momentum effects in an uptrend, but are difficult to achieve effective risk hedging in a downtrend.

3.2 Robustness Tests

In order to ensure the reliability of the research conclusions, this paper conducts robustness tests from four dimensions. First, data substitution. The samples are divided into training sets and test sets in chronological order. Model parameters are estimated on the training set, and strategy validity is verified on the test set. The results show that the Sharpe ratio of the test set is -0.65, a value basically consistent with the full-sample result of -0.70, which confirms that the strategy has certain out-of-sample stability. Second, a time window substitution test is performed. The lookback period parameters of the factor are adjusted, and three settings including 40 days, 60 days and 80 days are tested. The results indicate that the Sharpe ratio reaches -0.70 under the 60-day window, the highest among the three groups. The ratio stands at -0.78 under the 40-day window, ranking the second. The ratio drops to -0.85 under the 80-day window, the lowest of all. This suggests that a medium-length backtracking window can achieve a better balance between factor stability and timeliness. Third, the replacement of performance indicators. In addition to the Sharpe ratio, this paper further examines downside risk adjustment indicators such as the Sortino ratio and the Calmar ratio. The results show that the Sortino ratio is -1.08 and the Calmar ratio is -0.12, which is consistent with the conclusion of the Sharpe ratio, both indicating that the risk-adjusted return of the strategy is negative. Fourth, parameter sensitivity analysis. Transaction cost parameters are adjusted to three levels: 0.1%, 0.15% and 0.2%, and the number of groups is adjusted to three values: 5, 10 and 20. The results show that when the transaction cost decreased from 0.15% to 0.1%, the annualized return increased from -1.83% to -0.95%. When the number of groups increased from 10 to 20, the annualized volatility decreased from 6.90% to 6.12%, but the winning rate also decreased.

3.3 Feature Importance Analysis

To deeply analyze the contribution of each factor to strategy returns, this paper uses the SHAP method for feature importance analysis. It can be found that the 12-1-month momentum factor has the highest importance at 0.2638. This finding confirms the existence of significant medium-to-long-term momentum effects in the A-share market - that stocks that performed well over the past 12 months still have a relatively high probability of continuing good performance in the future. The turnover factor ranks second in importance at 0.1936. This indicates that trading activity is an important reference indicator for predicting stock returns, and stocks with lower turnover often have higher expected returns. Volatility factors and maximum daily decline factors have relatively lower importance, suggesting that in the technical factor system, momentum effects have better prediction ability than volatility effects. Fig. 2 shows the importance scores of each factor across the three machine learning models. The 12-1-month momentum factor received the highest importance score in all models, with an average importance of 0.2638, validating the robustness of medium-to-long-term momentum effects in the A-share market. The turnover factor is particularly prominent in the AdaBoost model with an importance of 0.2504,

indicating that this model pays more attention to the predictive role of trading activity for returns.

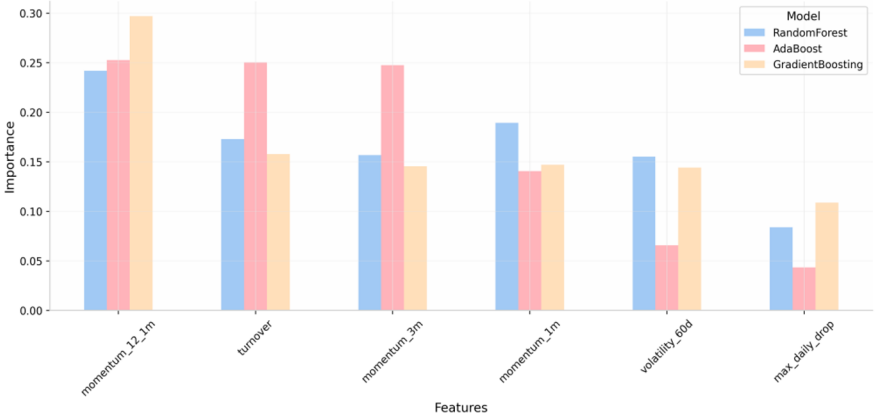

Fig. 2. Feature importance by machine learning model (Picture credit: Original).

4 Adaptability Optimization Paths and Development Suggestions

First, at the strategy level, the current model relies on technical factors. The model should incorporate valuation factors including price-to-earnings ratio and price-to-book ratio, growth factors including revenue growth rate and return on equity growth rate, and quality factors including return on assets and gross margin to establish a three-dimensional fundamental scoring framework. At the same time, alternative data such as news sentiment and northbound capital flows can be introduced, using XGBoost to dynamically adjust factor weights. Portfolio construction methods also have room for improvement. Industry-neutral constraints can be added to keep long and short portfolio weights in each industry consistent with the benchmark index. Risk Parity can replace simple equal-weight allocation, and hedge ratios can be flexibly adjusted according to market conditions. Transaction costs can be reduced, for example, by changing monthly rebalancing to bi-monthly or quarterly rebalancing, setting reasonable rebalancing thresholds to avoid frequent trading due to small fluctuations in factor scores. TWAP or VWAP algorithms can be used during execution to reduce the impact cost of large orders on the market.

Second, at the market level, the derivatives market needs further development. Considerations can be given to launching more segmented products, such as ChiNext Index futures and STAR Market 50 futures, and developing the individual stock options market to give quantitative strategies more refined risk management tools. At the same time, the scope of securities lending targets should be expanded, and a market-oriented securities lending pricing mechanism should be established to solve the current difficulty in borrowing securities. Data infrastructure also needs to keep up. Unified data format standards need to be established to reduce data cleaning costs for various institutions. Under compliant conditions, Level-2 high-frequency data can

be moderately opened, and standardized factor databases can be promoted to lower the R&D threshold for small and medium institutions. Regarding talent cultivation, universities can offer more quantitative finance-related courses to cultivate compound talents who understand both finance and programming. Industry associations can take the lead in establishing professional organizations and regularly hold technical exchange activities.

Third, at the regulatory level, the regulatory framework can be more inclusive, more flexible position limits can be adopted for true market-neutral strategies, and a "regulatory sandbox" mechanism can be established to allow innovative strategies to be tested in a controlled environment. At the same time, institutions are urged to regularly disclose key information such as strategy types and leverage levels to improve transparency. Systemic risk prevention cannot be ignored. It is necessary to establish a real-time monitoring system to track the concentration and homogeneity of quantitative transactions. When the market is extremely volatile, the trading frequency can be temporarily limited, and institutions are required to conduct regular stress tests to ensure the robustness of the model in different market environments. The industry self-discipline mechanism should also keep up, and an industry code of conduct can be issued to regulate the trading behavior of quantitative institutions. Establish a dispute mediation mechanism to resolve investor complaints in a timely manner. Strengthen investor education and let everyone rationally understand the benefits and risks of quantitative strategies.

5 Conclusion

Using A-share market data from 2021 to 2025, this study constructs a machine learning-based multi-factor quantitative hedging strategy and systematically tests its performance, market state adaptability and factor contribution. The results show that the strategy yields unsatisfactory overall performance with a negative annualized return and a Sharpe ratio of -0.70, which is caused by sole reliance on technical factors, the volatile downward market trend and significant erosion of transaction costs. The strategy presents strong dependence on market conditions, achieving positive returns in bull markets but failing to hedge effectively in bear markets. Feature importance analysis further reveals that the medium-to-long-term momentum factor is the core driver of stock return prediction, followed by the turnover factor, while volatility factors have limited predictive power. Based on the above findings, this paper proposes the following optimization suggestions: At the strategic level, fundamental factors such as valuation, growth and quality should be introduced to build a multi-dimensional scoring framework, integrate alternative data such as news sentiment and capital flow, and use risk parity methods to optimize portfolio weights. At the execution level, transaction costs can be reduced by extending the adjustment cycle, setting exchange thresholds and adopting algorithmic trading.

The main contributions of this paper are: First, it enriches the empirical evidence of quantitative strategy localization research, and provides a new observation perspective for understanding the effectiveness of A-share market factors. Second, it

systematically examines the application effect of machine learning models in factor selection and portfolio optimization, and provides an empirical reference for institutional investors to construct sound hedging strategies. Third, it reveals the adaptive mechanism of quantitative hedging strategies in different market conditions, and makes up for the lack of discussion on this issue in the existing literature. This study has certain limitations. The model uses only technical factors and fails to fully incorporate fundamental and macro-level information. The sample period covers a complete market cycle, but fails to cover more extreme market conditions. The strategy assumes idealized transaction execution and does not fully consider liquidity constraints and shock costs. Future research can be further expanded in the following directions: First, to explore the application of more advanced machine learning algorithms, such as deep learning, in quantitative investment. Second, to build a hybrid forecasting model that integrates multi-source heterogeneous data. Third, to study the interaction between quantitative trading strategies and market microstructures. Fourth, to develop a dynamic strategy framework that can adaptively adjust parameters to better respond to structural changes in the market environment.

References

1. Ballings, M., Van den Poel, D., Hespeels, N., et al.: Evaluating Multiple Classifiers for Stock Price Direction Prediction. Expert Systems with Applications 42(20), 7046–7056 (2015).
2. Praphutikul, T., Limpiyakorn, Y.: XGBoost-Based Multi-Factor Stock Selection Model for Rotational Trading. In: Proceedings of the 2023 5th International Conference on Information Technology and Computer Communications (ITCC 2023), pp. 107–115 (2023).
3. Shi, H.L., Zhou, W.X.: The Rise and Fall of Cross-sectional Momentum and Reversal Effects in the Chinese Stock Market. Physica A: Statistical Mechanics and its Applications 486, 397–407 (2017).
4. Li, Y., Liang, C., Huynh, T.L.D.: A New Momentum Measurement in the Chinese Stock Market. Pacific-Basin Finance Journal 73, 101759 (2022).
5. Huang, X., Sun, J.: Are Market-neutral Strategy Hedge Funds Really Market-neutral in China? China Finance Review International 8(1), 21–42 (2018).
6. Qin, Y., Pan, G., Bai, M.: Improving Market Timing of Time Series Momentum in the Chinese Stock Market. Applied Economics 52(43), 4711–4725 (2020).
7. Deng, H.T.: Analysis and Outlook of the Impact of Quantitative Hedging Trading on A-Shares. Economist (2), (2025).
8. Chatterjee, C., Tiwari, S.: Dividend Reduction and Stock Price Reaction in Indian Market: Is There a Role of Share Repurchase? Journal of Indian Business Research 14(4), 447–471 (2022).
9. Di Tollo, G., Fattoruso, G., Filograsso, G.: An Adaptive Evolutionary Strategy for Long–short Portfolio Construction. Decisions in Economics and Finance, 1–22 (2024).
10. Shah, A., Gor, M., Sagar, M., et al.: A Stock Market Trading Framework Based on Deep Learning Architectures. Multimedia Tools and Applications 81(10), 14153–14171 (2022).

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.