

An Exploration of Different Strategies and Applications of Quantitative Investment under Different Models

Peiyao Ouyang*

Faculty of Science, Kunming University of Science and Technology, Kunming, 650500, China

*Corresponding author: ouyangpy12@gmail.com

Abstract. With the rapid development of financial markets and the surge in data volume, quantitative investment has gradually become an important tool for investment decision-making. Traditional investment strategies often rely on experience and qualitative analysis, which is difficult to cope with complex market environments. Therefore, exploring quantitative investment models based on machine learning and deep learning has become a hot topic of research. This study aims to analyze the different applications of various models in quantitative investment, focusing on areas such as factor models, statistical arbitrage, and sentiment analysis. Through a comprehensive analysis of relevant literature in recent years, the results show that the future development of quantitative investment will increasingly rely on advanced algorithms and big data analysis techniques. Under the application of different models, there are diverse ideas and tools for the analysis and decision-making of financial markets. The combination of these models will promote the diversity and flexibility of investment strategies. At the same time, policymakers and financial institutions need to pay attention to the transparency and interpretability of the model to reduce potential risks. Looking forward, further research can focus on the combination optimization of models and the improvement of real-time data processing capabilities to cope with the changing market environment and provide stronger support for the practice of quantitative investment.

Keywords: Quantitative Investment; Factor Models; Machine Learning.

1. Introduction

In recent years, the complexity and dynamism of financial markets have continued to increase. As an emerging investment method, quantitative investment has attracted widespread attention from academia and investors. Quantitative investment uses mathematical models, statistical analysis and computer algorithms to process massive amounts of data to achieve data-driven investment decisions. Compared with traditional investment methods, quantitative investment can more effectively identify potential opportunities and risks in the market.

Different quantitative investment models are suitable for different market environments and investment objectives. The rapid development of technology has greatly reduced the cost of data acquisition and processing. The introduction of new technologies such as machine learning and artificial intelligence has provided new impetus for quantitative investment, and model technology has improved the predictive ability of quantitative investment. According to Hu's research, machine learning models can keep pace with market changes and continuously provide investment insights [1]. At the same time, Zhai et al. pointed out that multi-factor models use a more comprehensive and scientific approach to explain the complexity of the capital market and analyze the source of asset returns through multiple dimensions [2]. He et al. showed that AI big models enable quantitative investment in the financial market to predict asset prices, market trends and volatility, demonstrating its potential value in generating stock investment signals [3]. The application of so many models has brought great convenience to quantitative investment. By combining these models, investors can formulate scientific and rational investment strategies in complex and changing financial markets and pursue stable returns and risk management.

The research results of this paper are mainly to reduce the possible deviations and errors of a single model by integrating and analyzing multiple models of quantitative investment. Different models may perform differently under different market conditions. Multiple models can better capture the diversity and complexity of the market, more comprehensively identify and manage risks, and

improve the adaptability and flexibility of the overall system. This multi-model integration can give full play to the advantages of each model and achieve new results through mutual complementation and optimization.

2. Definition of Quantitative Investment

Quantitative investment is an investment method that uses quantitative models and algorithms to make trading decisions by analyzing a large amount of historical data and market trends [4]. The rise of quantitative investment stems from changes in financial markets and technological advancements. Because global financial markets continue to evolve, the amount of information and complexity faced by investors has increased significantly. With the rapid development of computer technology, data processing and analysis capabilities have been greatly improved, making it possible to implement many models. In addition, the popularity of the Internet has significantly improved the availability of financial data such as historical prices, trading volumes, and financial statements, providing a solid foundation for the construction of quantitative models.

Quantitative investment helps improve the efficiency of financial markets. By using systematic trading strategies and models, it reduces the impact of human emotions, thereby improving the accuracy and efficiency of trading decisions [5]. Methods such as regression analysis, high-frequency trading algorithms, and machine learning are widely used in investment decision-making. These models not only provide investors with a scientific basis for decision-making, but also help them find inefficiencies in the market under the framework of the efficient market hypothesis (EMH), thereby obtaining excess returns.

The study of quantitative investment is not only a frontier field of financial engineering, but also an important driving force for the development of modern financial markets. In-depth research on different quantitative investment models can improve market understanding, help investors better understand market dynamics, provide investors with more accurate strategy options, reduce risks and increase returns. In addition, studying the diversity of quantitative investment models also has important academic value and practical significance. By comparing and analyzing different models, researchers can identify the advantages and disadvantages of each model, thereby providing guidance for future research. This integration of models not only enriches some theoretical systems of the financial market, but also provides a more comprehensive tool for actual investment, which has broad application prospects and far-reaching impact.

3. Current Status of Quantitative Investment

As a method of investment decision-making that relies on mathematical and statistical models, big data technology, machine learning, and artificial intelligence continue to advance, and the complexity and accuracy of quantitative investment models have significantly improved. Quantitative investment has made great progress in the financial market in recent years. Significant development. Currently, quantitative investment models include machine learning models, factor models, AI large models, and HMM models., PS0-BP neural network stock selection and so on. At the same time, classic models such as mean regression and cointegration analysis are still widely used.

The development of models used in quantitative investment is influenced by many factors. Data availability helps investors obtain market data, including historical prices, trading volumes, financial statements, and social media sentiment, which provides a basis for model construction. Computing power, such as cloud computing and graphics processing units (GPUs), makes it possible to train complex models and trade in real time, changing the efficiency and accuracy of quantitative investment. The regulatory environment also has an impact on the models of quantitative investment strategies. Certain markets are strictly regulated, which limits the application of some models. At the same time, the update of financial markets requires investors to constantly innovate, adjust and optimize models to cope with the nonlinearity and randomness of the market.

4. The Impact of Different Models on Quantitative Investment

4.1. Model 1: Machine Learning Model

Machine learning models can effectively handle complex nonlinear relationships and extract valuable information from massive historical data, thereby providing investors with accurate decision support. For example, a novel alpha mining framework Alpha Evolve based on Auto ML. Alpha Evolve generates the new class of alphas. This class has the advantages of simplicity and generalization ability similar to formulaic alphas, and the ability to be trained by data similar to machine learning alphas. These advantages result in better performances in generating weakly correlated high returns [6]. In quantitative investment, various machine learning techniques such as supervised learning, unsupervised learning and reinforcement learning are widely used in price prediction, signal generation and risk management. Supervised learning methods such as linear regression and support vector machines are used to predict stock prices and classify trading signals, while unsupervised learning uses clustering algorithms to identify assets with similar characteristics and optimize investment portfolios. In addition, reinforcement learning automatically adjusts strategies to maximize long-term returns through interaction with the market environment. Prominent large language models (LLMs) have demonstrated impressive capabilities in understanding and producing human-like text, such as ChatGPT and GPT-4. Investigating financial LLMs makes sense since they have the potential to transform the finance sector and enable more precise trading and investment decisions [7].

4.2. Model 2: Factor Model

Factor models play an important role in quantitative investing, mainly used to explain the sources of asset returns and construct investment portfolios. Factor models are based on the assumption that asset returns can be explained by a set of systematic factors (such as market risk, scale effect, value effect, etc.). In practical applications, investors first identify significant factors through historical data, and then build a multi-factor model to evaluate the contribution of each factor to asset returns. For example, MLP and RNN-based simulated portfolios lookahead factor methods outperform conventional factor models in comparable ways [8]. It can create lookahead factor models that substantially outperform equities portfolios based on traditional factors by using deep learning to predict foundational data [9]. Investors can use these factors to build investment portfolios and select assets with high factor exposure to achieve excess returns. Factor models can also be used for risk management, helping investors optimize asset allocation by monitoring and controlling factor risks.

4.3. Model 3: AI Big Model

While traditional quantitative investment typically divides the workflow into a few sub-tasks, such as stock trend prediction and portfolio optimization, AI technologies allow for the creation of an end-to-end solution that generates the final portfolio directly [10].

AI big models are gradually being introduced into the quantitative investment field to improve the accuracy and flexibility of investment decisions. These big models, especially deep learning networks, can process massive amounts of unstructured data, such as news, social media comments, and market data, and extract potential investment signals from them. Through natural language processing (NLP) technology, AI big models analyze market sentiment and identify key factors that affect asset price fluctuations. Reinforcement learning algorithms optimize investment strategies and maximize long-term returns through simulated transactions and feedback learning in a dynamic market environment. AI-enhanced models can simultaneously optimize multiple objectives. This is particularly important in the context of portfolio optimization, where investors often have to balance conflicting goals, such as achieving high returns while maintaining a low level of risk [11].

4.4. Model 4: HMM Model and PSO-BP Neural Network Stock Selection

The Markov model (HMM) is widely used in quantitative investment to capture the dynamic changes of market status and its impact on asset returns. The basic idea is to infer potential hidden states from observed market data, which represent different states of the market, such as bull market, bear market or shock period. Investors can use HMM to classify market states and formulate corresponding trading strategies. In addition, HMM can also predict future market changes through state transition probability, providing a basis for dynamic adjustment of investment portfolios.

The rationality and application of the model building have advantages in the prediction of the stock market's nonlinear system, and they can offer a larger spectrum of development for the nonlinear prediction system [12]. The combination of particle swarm optimization (PSO) and back propagation (BP) neural network provides an innovative approach to stock selection strategies in quantitative investment. The PSO algorithm optimizes the weights and biases of the BP neural network by simulating the group behavior of particles in the search space, thereby improving the prediction accuracy of the model. In the stock selection process, the PSO-BP model first uses historical market data and financial indicators to construct a feature space, and the PSO algorithm is responsible for finding the optimal parameter combination in this space to minimize the prediction error. The optimized BP neural network can more effectively identify potential investment opportunities and capture complex nonlinear relationships. In addition, the PSO-BP model shows strong adaptability in a dynamic market environment and can adjust the stock selection strategy in real time to cope with market fluctuations. The HMM-based timing and PSO-BP neural network stock selection models show excess returns compared to the market, and the cumulative annualized rate of return is also better than a single timing or stock selection strategy [13].

5. Development Trends and Challenges of Quantitative Investment under Different Models

Through multiple papers, it is concluded that quantitative investment shows significant development trends under various models. First of all, the widespread application of deep learning and machine learning technology enables quantitative investment to improve prediction accuracy and promote the formation of intelligent investment decisions. Secondly, the combination of sentiment analysis and natural language processing enables investors to extract sentiment information from social media, news and financial reports, providing a new perspective for quantitative analysis of market sentiment. In addition, the application of models such as Hidden Markov Model (HMM) and Particle Swarm Optimization-Backpropagation (PSO-BP) neural network enhances the dynamic adaptability to market conditions and asset selection. Techniques for risk management and portfolio creation need to change to take into account a greater range of potential outcomes, reflect the dynamic and ever-changing character of the global capital markets [14].

At the same time, quantitative investment actually faces many challenges in the application of these models. First, data quality and accessibility issues are still key factors that restrict model performance, especially in high-frequency trading and sentiment analysis, where noisy data may lead to wrong decisions. Second, the contradiction between the complexity and interpretability of the model makes it difficult for investors to understand the decision-making process of the model in practical applications, increasing investment risks. In addition, rapid changes in the market environment may cause the model to perform well on historical data but fail in future markets, that is, the "overfitting" problem. Therefore, quantitative investors need to continuously optimize models, combine multiple analytical tools, and establish a sound risk management system to meet these challenges and seize market opportunities.

6. Conclusion

In recent years, quantitative investment has rapidly emerged in the financial market and has become an important tool for obtaining excess returns. With the improvement of data analysis technology and computing power, quantitative investment has gradually transformed into advanced methods such as deep learning and machine learning. The application of different models provides different ideas and tools for the analysis and decision-making of the financial market. The combination of these models will promote the diversification and flexibility of investment strategies. The interpretability and risk management of models have become the focus of research. In order to promote the healthy development of quantitative investment, it is recommended that regulators formulate a policy framework to encourage financial technology innovation, ensure market fairness and transparency, and promote data sharing and standardization to reduce data acquisition costs. At the same time, there are still parts that need to be improved in existing research, mainly focusing on the application of specific models, lacking a systematic analysis of model combinations, and data quality and diversity are still constraints. Future research should explore new data sources and model combinations to promote further development in the field of quantitative investment.

References

- [1] Hu, S. (2024). Fundamental quantitative investment strategy based on machine learning models (Master's thesis, Inner Mongolia University of Finance and Economics).
- [2] Zhai, C., Zhao, L., & Hang, X. (2024). Theory and technical system of fundamental quantitative investment based on multi-factor models. *Modern Commerce and Industry*, 45(13), 127-129.
- [3] He, Y., Jiao, L., Yang, Y., et al. (2024). AI large models empower quantitative investment in financial markets: Research based on alternative and traditional financial data. *Journal of Econometrics*, 4(03), 761-783.
- [4] Zhang, X., & Zhang, Y. (2022). Development and impact analysis of quantitative investment in China. *Tsinghua Financial Review*, (01).
- [5] Tang, J. (2024). Research on the development and impact of quantitative investment in China. *Guangdong Economy*, (12), 22-24.
- [6] Cui, C., et al. (2021). Alphaevolve: A learning framework to discover novel alphas in quantitative investment. In *Proceedings of the 2021 International Conference on Management of Data*.
- [7] Liu, Y.-Y., et al. (2023). Fingpt: Democratizing internet-scale data for financial large language models.
- [8] Alberg, J., & Lipton, Z. C. (2017). Improving factor-based quantitative investing by forecasting company fundamentals.
- [9] Chauhan, L., Alberg, J., & Lipton, Z. (2020). Uncertainty-aware lookahead factor models for quantitative investing. In *International Conference on Machine Learning (PMLR)*.
- [10] Yang, Y., et al. (2020). Qlib: An AI-oriented quantitative investment platform.
- [11] Kasaraneni, R. K. (2021). AI-enhanced portfolio optimization: Balancing risk and return with machine learning models. *African Journal of Artificial Intelligence and Sustainable Development*, 1(1), 219-265.
- [12] Zhang, D., & Lou, S. (2021). The application of neural network and BP algorithm in stock price pattern classification and prediction. *Future Generation Computer Systems*, 115, 872-879.
- [13] Qiu, Y. (2024). Research on timing based on HMM model and stock selection with PSO-BP neural network quantitative strategy (Master's thesis, Guangzhou University).
- [14] Li, X., & Sullivan, R. N. (2011). A dynamic future for active quant investing. *The Journal of Portfolio Management*, 37, 29-36.