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The Evolution, Strategies, and Technologies of Quantitative Investing: A Review Focused on the Chinese Market

Meichen Lin

School of Economics and Finance, Shanghai International Studies University, Shanghai, China
linmeichencn@163.com

Abstract. This review systematically examines the transformative impact of quantitative investment technology on global financial markets, with a focus on its development, strategic applications, and evolving relationship with human expertise. It traces the theoretical evolution of quantitative finance from early mathematical models to modern machine learning techniques, highlighting key milestones such as CAPM, APT, and behavioral finance. The paper analyzes core quantitative strategies—including stock selection, market timing, long-only, long-short, and market-neutral approaches—within the context of China's rapidly growing market. It emphasizes the critical role of alternative data, AI, and rigorous risk management in sustaining alpha generation. Finally, it argues that successful quantitative investing relies not on replacing humans but on deepening collaboration between human intuition and computational power, ensuring adaptability in an increasingly complex and competitive landscape.

Keywords: Quantitative Investment, Multi-Factor Models, Technologies and Strategies, Human-Machine Collaboration

1. Introduction

Over the past two decades, global capital markets have undergone profound transformations at the intersection of three technological trends: data accessibility, computing power cost, and algorithmic complexity. The widespread availability of tick-level market data, alternative data, and cloud computing has propelled "quantitative technology" from an academic concept confined to ivory towers to a mainstream tool in the asset management industry. According to disclosures by the Asset Management Association of China (2023), the scale of quantitative private fund management in China has exceeded RMB 1.6 trillion, accounting for over a quarter of the total scale of securities private funds [1]. Simultaneously, index enhancement products, Smart-Beta ETFs, and quantitative trading desks of securities companies have also experienced explosive growth.

However, the benefits of technology are not one-sided. Events such as the retail-driven short squeeze of GameStop (GME) in the U.S. stock market in 2022 have all revealed that quantitative strategies, while enhancing market efficiency, may also amplify systemic risks.

Against this backdrop, this review article systematically synthesizes existing theoretical and practical results, aiming to address three core questions:

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1. How does quantitative technology significantly improve investment efficiency in stock selection and market timing?
2. What specific investment strategies can be formed by combining quantitative stock selection and market timing
3. What will be the relationship between quantitative technology and humans in future investment markets?

2. The development of quantitative investment

2.1. The evolution of quantitative-investment theory

The origins of quantitative investment trace back to Louis Bachelier's pioneering 1900 dissertation, "The Theory of Speculation", which first applied rigorous mathematics to finance and laid the foundation for modern option-pricing theory [2].

In the 1950s, Harry Markowitz introduced the mean–variance framework and the concept of the efficient frontier [3]. Building on these ideas, William Sharpe and his co-authors developed the Capital Asset Pricing Model (CAPM) in 1964 [4], followed by Fama’s Efficient Market Hypothesis (1970) [5]. In 1973 Fischer Black and Myron Scholes established the Black–Scholes option-pricing model, providing a rigorous foundation for derivatives valuation [6]. Stephen Ross proposed the Arbitrage Pricing Theory (APT) in 1976, forming the basis of multi-factor models [7].

Beginning in the 1980s, behavioral finance challenged traditional rational assumptions by explaining market anomalies through investor psychology, thereby inspiring new quantitative factors [8]. Since the 2000s, machine learning has further expanded the quantitative toolkit by extracting complex patterns from large-scale data to enhance forecasting and strategy design [9] [10].

2.2. The development of quantitative investment in China

Relative to mature overseas markets, China’s financial market started late and constrained by limited instruments, quantitative investment grew slowly. Yet the expansion of financial products, the diversification of asset-management demand and rising equity-market participation have since triggered explosive growth [11].

Chronologically, the development of domestic quantitative investment can be divided into four stages:

2.2.1. Inception (2002–2009)

China’s equity market was still in its infancy; only unidirectional long positions were feasible and effective hedging tools were absent, so quantitative strategies advanced slowly.

Since 2002, China's first index-enhanced funds and actively managed quantitative equity funds were introduced, bringing mature quantitative investment methodologies from overseas.

Although data, tools and market structure were limited and strategies revolved around simple multi-factor stock selection and index enhancement, these experiments laid the foundation for later growth.

2.2.2. Growth (2010–2014)

The April 2010 listing of CSI 300 index futures ushered in the hedging era. ETFs, structured funds and margin trading expanded rapidly, supplying richer instruments and greater capacity. The number

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of public quant funds surged; returnee talent accelerated the localization of multi-factor and market-neutral strategies.

Among private funds, ETF arbitrage, structured-fund arbitrage and market-neutral approaches flourished; several managers posted “zero-drawdown” track records via high-frequency arbitrage. Overall, quantitative investment evolved from theory to practice, strategy types diversified, and market participation widened.

2.2.3. Transition (2015–2018)

After the 2015 market crash, index-futures trading was severely restricted and traditional hedging strategies stalled. Managers pivoted toward high-frequency trading and statistical arbitrage, shortening holding periods and demanding faster execution and greater data-processing power.

Private funds dominated this period, specialising in T+0 reversal, event-driven and order-flow strategies while pursuing more stable returns. Machine-learning and AI techniques began to permeate factor mining and model optimisation, accumulating experience for later intelligentization [12]. Despite tighter regulation, strategy diversity and technological depth improved markedly.

2.2.4. Explosion (2019–present)

Since 2019 the gradual relaxation of index-futures rules, the expansion of ETF options and the refinement of securities-lending mechanisms have reopened the strategy space.

Approaches now span index enhancement, market-neutral, CTA, option-volatility harvesting and intraday T+0, forming a multi-strategy ecosystem. AI, deep learning and reinforcement learning are widely deployed for factor discovery, portfolio optimization and trade execution, continuously raising intellectual sophistication [13,14].

Private quant houses have scaled rapidly; several top managers now oversee RMB 100 bn-plus, becoming pivotal market participants. As competition intensifies and traditional factors decay faster, relentless innovation and technological iteration have become prerequisites for sustainable Alpha [15].

3. Quantitative investment and technology

3.1. Characteristics of quantitative investment

Generally speaking, quantitative investment is defined by the use of well-defined trading rules, implemented through computer programs, to generate execution signals.

When a trading strategy has explicit rules, it inherently possesses the ability of backtesting. Backtesting is the most important feature distinguishing quantitative techniques from subjective investment. Typically, subjective investment, whether based on fundamental analysis or technical analysis, relies on the investor's subjective judgment for final decision-making. This subjective behavior cannot be historically backtested. In contrast, quantitative techniques rely on explicit trading strategies, allowing for the backtesting of the strategy's historical investment performance using historical asset price data.

3.2. Technology of quantitative techniques in stock investment

Stock investment is one of the earliest fields where quantitative techniques were applied in financial markets. Initially, quantitative investment involved codifying some repeatable stock selection

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patterns from traditional subjective investment into simple strategies, executed repeatedly by computers. With advancements in financial theory and computer technology, the application of quantitative techniques has become increasingly widespread.

According to the Capital Asset Pricing Model (CAPM), returns from stock investment are divided into Alpha and Beta. Beta refers to the returns earned by a stock portfolio due to market movements, while Alpha represents the excess returns generated by the portfolio relative to the market. From the perspective of quantitative investment, stock selection targets Alpha returns, while market timing targets Beta returns [16].

3.2.1. Quantitative stock selection

The goal of stock selection is to choose a portfolio of stocks expected to generate excess returns relative to the market through multifactor models, which extend APT by combining multiple Alpha factors—each designed to capture sources of outperformance—into an integrated model for stock selection. These factors are generally categorized as fundamental, technical, or event-driven.

Fundamental factors are relatively traditional stock selection factors constructed based on company financial statements and operational metrics, such as company valuation, profitability, and growth. The exploration of these factors relies on investment logic and theoretical foundations such as corporate governance and financial analysis [17]. Since they depend on periodic financial reports, rebalancing occurs at low frequency (e.g., monthly or quarterly), leading to portfolios that may experience higher volatility between updates.

Technical factors, by contrast, tend to adopt perspectives from behavioral finance and statistics. Traditional economic research often assumes investor rationality, which is difficult to uphold in practical securities investment. Technical factors are indicators derived from analyzing irrational pricing anomalies present in the market [18]. The data mining capabilities of computers can analyze vast datasets to uncover market anomalies not easily detectable by humans. If these anomalies are statistically significant, the new technical factor can be incorporated into the selection model. Technical factors primarily rely on market and trading data, which is available at high frequency, allowing for higher portfolio rebalancing frequency and generally smoother factor performance.

Event-driven factors seek to exploit predictable market reactions to specific corporate or macroeconomic events—such as earnings announcements, analyst revisions, share changes, or policy updates [19]. The characteristics of these factors are that their construction depends on the frequency and impact of events; they are often empirical indicators requiring validation through statistical tests; and their influence is typically short-term and sudden, making them suitable for medium-to-high frequency strategies.

However, as quantitative investing has grown, many once-effective classic factors (such as simple low valuation or momentum factors) have exhibited significant decay and homogenization reducing their Alpha potential [20]. Therefore, to consistently achieve robust excess returns in a highly competitive market, strengthening research on novel Alpha factors and achieving iterative upgrades of the factor library has become an urgent core task in the quantitative field. This process primarily unfolds across three dimensions: data, methodology, and systematic frameworks.

Firstly, research on novel factors heavily relies on the deep mining and effective integration of alternative data. Alternative data refers to new data sources beyond traditional financial data (market data, financial reports) and traditional alternative data (research reports, news). Its core value lies in providing unique, forward-looking, incremental information not yet fully priced in by the market. Enhancing the application of such data is key to breaking through the limitations of traditional factors. For example, the novel one is sentiment factors derived from web data and Natural

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Language Processing (NLP) [21]. These apply sentiment analysis algorithms to unstructured text from social media, news, and corporate disclosures to quantify market sentiment and public attention, capturing short-term shifts or fundamental expectation gaps.

Secondly, innovation in research methodologies is another pillar for discovering novel factors. Currently, multifactor stock selection in domestic markets is still in its early stages, and existing factor construction mostly relies on linear methods. This necessitates the introduction of more powerful Machine Learning (ML) and Artificial Intelligence (AI) algorithms into the stock selection process to replace or augment traditional linear models and handle complex nonlinear relationships [22]. Algorithms such as Gradient Boosting Trees (e.g., XGBoost, LightGBM) and neural networks can automatically capture complex nonlinear interactions between factors and returns, discovering hidden patterns not easily identifiable by the human brain or linear models [23].

Finally, the exploration of novel factors must be embedded within a rigorous, systematic research framework to ensure they are not statistical flukes, but robust sources of Alpha grounded in economic logic. A robust novel factor must have a reasonable economic or behavioral finance explanation (e.g., reflecting investor cognitive biases, information dissemination delays, or risk compensation). One must resolutely avoid falling into "Data Snooping Bias," ensuring the factor remains robust in out-of-sample tests and across different phases of the economic cycle.

3.2.2. Quantitative market timing

Quantitative market timing is a key technical component within the quantitative investment system for managing market systematic risk and capturing returns from major market fluctuations. Narrowly defined, it focuses on predicting and judging the overall market trend. Broadly defined, the object of timing extends further to sector rotations, style characteristics, and the periodic rotation of significant factors, essentially representing a dynamic management and allocation of Beta. Its methodological core lies in utilizing statistical learning and artificial intelligence techniques to extract effective signals from multi-dimensional data—including market trading behavior, fund flows, and macroeconomic conditions—to make probabilistic inferences about future market states, guiding position adjustment and risk control.

Traditional timing methods adhere to the basic logic of “following the trend,” relying on technical tools like moving averages and momentum indicators (e.g., MACD) to identify and follow established price trends. These methods perform steadily in markets with clear trends but have significant limitations: signals are lagging, making it difficult to capture market turning points. To enhance the foresight and adaptability, modern quantitative timing increasingly incorporates prediction models based on machine learning. These models do not presuppose a specific form of market behavior but instead learn market characteristics by analyzing recurring patterns in historical data—such as investor sentiment cycles, patterns of fund inflows and outflows, and market reactions to extreme events. Effectively incorporating this information helps models better identify whether the market is in extreme states such as overbought/oversold or euphoria/panic, thus providing a basis for position control. Commonly used techniques include ensemble learning based on tree models, Recurrent Neural Networks (RNNs), and Hidden Markov Models (HMMs) specifically designed for processing state transitions in time series. These techniques can integrate information from multiple sources, thereby more sensitively capturing short-to-medium term market inflection points.

In terms of prediction frequency, quantitative timing strategies can be categorized into three types based on their horizon. Medium-to-long term strategies (weeks to months) rely on macroeconomic conditions and valuation levels to capture fundamental trends. Short-to-medium term approaches (days to weeks) utilize technical indicators and market sentiment for swing trading. High-frequency

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and intraday strategies (minutes to one day), often used in algorithmic trading, depend on order book data but face limitations in China’s A-share market due to the T+1 settlement rule.

It is important to note that despite continuous advancements in quantitative timing techniques, they still face the fundamental constraint of market efficiency: no model can predict the market consistently and accurately [24]. Successful timing systems often exhibit characteristics of “low win rate, high profit-to-loss ratio.” Their effectiveness depends not only on signal quality but also crucially on strict risk control and capital management rules. Therefore, in practical strategy construction, methods such as multi-signal fusion and dynamic weight adjustment are often employed to diversify risk, alongside stop-loss and take-profit mechanisms to prevent extreme losses. Quantitative timing does not seek perfect prediction but aims to enhance the discipline of investment decisions and risk-adjusted returns through systematic methods. Its value in portfolio management lies precisely in its ability to identify and respond to significant market fluctuations.

4. Application of quantitative investment strategies

In practice, quantitative equity strategies are primarily implemented through three approaches, distinguished by their exposure and management of systemic market risk.

4.1. Long-only equity strategy

The long-only strategies rely on stock selection alpha in addition to market beta. It mainly manifests in two forms: index enhancement products and active quantitative stock selection products.

Index enhancement products pursue excess returns over the benchmark. Their core risk control metric is tracking error, requiring achieving enhanced returns while controlling the degree of deviation [25]. These products suit investors who wish to obtain average market returns while also gaining stable excess returns.

Active quantitative stock selection products are not constrained by a benchmark index, offering greater flexibility in investment scope. They seek absolute returns through all-market stock selection, dynamic position adjustment, and active style rotation. Their models focus more on the effectiveness of stock selection factors, portfolio optimization, and risk control, offering high flexibility but also demanding more stringent model predictive capabilities.

4.2. Long-short equity strategy

The long-short equity strategy aims to hedge market risk and isolate stock selection Alpha by simultaneously establishing long positions and short positions. Within a quantitative framework, this strategy shorts a portfolio of stocks with low factor scores and longs a portfolio with high factor scores, thereby capturing dual Alpha from both the long and short sides. These strategies exploit historical price spread relationships, executing contrarian trades when the spread deviates, anticipating profits from its reversion.

Due to the high cost of securities lending and limitations on individual short-selling mechanisms in China’s A-share market, most domestic long-short strategies instead use derivatives like stock index futures and options for systemic hedging. Additionally, since the vast majority of investors only engage in overnight stock trading, this leaves certain profit opportunities for intraday equity trading. In recent years, intraday high-frequency trading teams, by establishing securities pools or securities lending channels, conduct intraday reversal trading (T+0) under the T+1 system. Relying on micro-market structure data and high-frequency signals for short-term operations, typically

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holding individual stocks for less than 5 minutes, they have formed a long-short strategy practice with Chinese characteristics.

4.3. Equity market neutral strategy

The market neutral strategy is a deep application of hedging techniques, aiming to completely strip the market risk from the investment portfolio, retaining only the pure Alpha returns generated by stock selection. This strategy requires not only hedging the portfolio's systemic risk through tools like stock index futures but also strictly controlling style exposures, ensuring the portfolio is neutral in style and sector, and using sufficient short positions in equity index derivatives to fully cover the Beta of the long portfolio.

Risk control is the lifeline of market neutral strategies. Historical experience shows that without strict constraints on style and sector deviations, a situation where “both the long and short sides suffer losses” can easily occur during extreme market conditions [26]. Currently, with the enrichment of index futures and options varieties such as those for the CSI 500 and CSI 1000 indices, institutions can manage risks more effectively through precise hedging using multiple tools and underlying assets. Simultaneously, the introduction of risk models for real-time exposure monitoring has become an industry standard practice.

5. The relationship between technology and humans in quantitative investing

Quantitative investing has become an indispensable force in modern financial markets, accounting for 60% of U.S. stock trading and 20%-30% in China's A-share market. This leads to two conclusions: first, the influence of quantitative investing is increasingly prominent; second, there is still room for growth for quantitative investing technology in the A-share market. However, the highly technical nature does not diminish the human role; instead, the construction of a successful quantitative system always relies on the deep integration of “human-machine collaboration.”

Human intellect remains paramount in the creative and strategic phases. The origin of strategy ideas often stems from investment managers’ or researchers’ observations and summaries of market patterns, including deep insights into fundamental logic, behavioral biases, microstructural characteristics, and more. Humans excel at “fuzzy recognition” and logical deduction, enabling them to translate complex market phenomena into testable investment hypotheses.

Once a hypothesis is formed, technology takes a central role in validation and execution. Computers can efficiently perform large-scale historical data backtesting, statistical testing, parameter optimization, and risk calculation for high-frequency trading or derivative pricing-tasks that are inefficient and impossible for humans alone. Additionally, automated execution systems can capture market opportunities in real time, swiftly complete trades, and reduce interference from human emotions.

In recent years, advancements in artificial intelligence and machine learning have further deepened the paradigm of human-machine collaboration. Machine learning models are no longer confined to human-preset linear relationships; instead, they automatically extract effective features and nonlinear patterns from vast amounts of information through data-driven approaches, such as sentiment analysis based on natural language processing (NLP) and time-series forecasting based on deep learning. This enables the capture and utilization of subtle signals that were previously difficult to identify manually.

However, model robustness and crisis response still depend on human expertise. The logical validation of quantitative strategies, the interpretation of economic implications, and ethical and

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compliance reviews all depend on human subjective judgment. It is particularly noteworthy that the market is essentially a complex adaptive system composed of participant behaviors, and its patterns constantly evolve with institutional changes, shifts in investor structure, and technological progress. Therefore, quantitative systems also require continuous iteration, and the core motivation for iteration still stems from new human understandings of the market.

Thus, the ideal model of quantitative investing is not “technology replacing humans” but rather “humans defining problems, technology solving them.” In the future, as new technologies such as explainable AI and reinforcement learning gradually mature, the depth of human-machine collaboration will further increase: humans will be responsible for strategic construction and value judgment, while machines will handle tactical execution and effect optimization. Only by combining human financial insight with machine computational power can we build a sustainable and effective quantitative investing system in an increasingly complex market.

6. Conclusion

With the rapid development of artificial intelligence technology and the continuous improvement of the financial market environment, quantitative investing is experiencing an explosive growth phase in China's securities market. Optimized trading mechanisms and enriched financial instruments have provided fertile ground for the development of quantitative investing, propelling it to become a significant force in the market.

Currently, as the number of participating institutions and the scale of capital expand rapidly, the field of quantitative investing is transitioning from a blue ocean to a red ocean market, with competition becoming increasingly intense. In this process, relying solely on traditional strategies and conventional technologies can no longer sustain a competitive advantage. Quantitative institutions that aim to thrive in the future must continuously enhance their technological innovation and strategy development capabilities, while maintaining a keen awareness of new market trends.

References

[1] China Securities Asset Management Association. (2023). Annual report of the asset management association of China 2023.
[2] Bachelier, L. (1900). Théorie de la spéculation. Annales Scientifiques de l'École Normale Supérieure, 17, 21–86.
[3] Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77–91.
[4] Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The Journal of Finance, 19(3), 425–442.
[5] Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383–417.
[6] Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. Journal of Political Economy, 81(3), 637–654.
[7] Ross, S. A. (1976). The arbitrage theory of capital asset pricing. Journal of Economic Theory, 13(3), 341–360.
[8] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.
[9] Rather, A. M., Agarwal, A., & Sastry, V. N. (2017). Stock market prediction and portfolio selection models: A survey. Opsearch, 54(3), 558–579.
[10] Subasi, A., Amir, M., Kanna, P. R., & White, B. (2021). Stock market prediction using machine learning. Procedia Computer Science, 194, 173–179.
[11] Liang, Z. (2022). Analysis on the development of quantitative investment model. In Proceedings of the 2022 7th International Conference on Financial Innovation and Economic Development (pp. 1678-1681). Atlantis Press.
[12] Luo, J., Li, Y., Wang, M., & Zhou, W. (2022). Artificial intelligent based day-ahead stock market profit forecasting. Computers & Electrical Engineering, 99, 107837.

DOI: 10.54254/2754-1169/2025.GL28096

[13] Wang, Q., Leippold, M., & Zhou, W. (2022). Machine learning in the Chinese stock market. Journal of Financial Economics, 145(2), 64–82.
[14] Zhang, L., Aggarwal, C., & Qi, G. J. (2017). Stock price prediction via discovering multi-frequency trading patterns. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2141–2149.
[15] Li, Y., & Hao, Y. (2017). A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. Expert Systems with Applications, 80, 340–355.
[16] Henriksson, R. D., & Merton, R. C. (1981). On market timing and investment performance. II. Statistical procedures for evaluating forecasting skills. Journal of Business, 54(4), 513–533.
[17] Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. The Journal of Finance, 47(2), 427–465.
[18] Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance, 48(1), 65–91.
[19] Sawhney, R., Agarwal, S., Wadhwa, A., & Shah, R. (2020). Deep attentive learning for stock movement prediction from social media text and company correlations. Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), 8275–8285.
[20] Jiang, G. J., Yao, T., & Yu, T. (2007). Do mutual funds time the market? Evidence from portfolio holdings. Journal of Financial Economics, 86(3), 724–758.
[21] Nelson, D. M. Q., Pereira, A. C. M., & de Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. 2017 International Joint Conference on Neural Networks (IJCNN), 1419–1426. IEEE.
[22] Sharpe, W. F. (1991). The arithmetic of active management. Financial Analysts Journal, 47(1), 7–9.
[23] Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273.
[24] Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. The Review of Financial Studies, 23(2), 821–862.
[25] Cremers, M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. The Review of Financial Studies, 22(9), 3329–3365.
[26] Asness, C. S., Krail, R. J., & Liew, J. M. (2001). Do hedge funds hedge? The Journal of Portfolio Management, 28(1), 6–19.