

Research Review of Quantitative Investment Strategies based on NASDAQ

Shiru Lyu*

Faculty of Data Science, City University of Macau, Macau, China

*Corresponding author: D23090105821@cityu.edu.mo

Abstract

With a mature trading mechanism and technology-focused underlying assets, the NASDAQ market has become the global core of quantitative investment, where quantitative trading accounts for 75% of total turnover as of 2025. Existing studies mostly focus on single strategy types or specific technical models, lacking a comprehensive analytical framework for quantitative strategies tailored to NASDAQ's unique characteristics. This paper adopts an integrative systematic literature review method to sort out the market foundation, research progress, and application features of five core quantitative strategies-multi-factor stock selection, statistical arbitrage, trend-following strategies, high-frequency trading/market-making strategies, and machine-learning-based strategies-in NASDAQ, integrating empirical results of cutting-edge models including Autoencoder-GSVM and genetic algorithms. It further analyzes core challenges of strategy implementation, and finally puts forward cognitive conclusions, practical suggestions and future research directions, providing a panoramic reference for theoretical research and practice of NASDAQ quantitative investment.

Keywords

NASDAQ; Quantitative Investment; Factor Model; Machine Learning; High-frequency Trading.

1. Introduction

Quantitative investment has gone through three development stages: passive investment under the Efficient Market Hypothesis, active quantitative investment driven by factor revolution, and intelligent quantitative investment empowered by artificial intelligence. As the world's core listing platform for technology and growth enterprises, NASDAQ, with core indices including NASDAQ 100 and NASDAQ Composite, features high growth, high volatility and high liquidity, providing an ideal scenario for empirical testing and implementation of various quantitative strategies. However, existing studies rarely conduct integrated analysis covering both classic strategy evolution and cutting-edge technology applications, and there is a clear research gap in strategy adaptability for NASDAQ's upcoming 24-hour trading in 2026. This paper constructs a systematic analytical framework to answer two core questions: What is the application potential and core paradigm of various quantitative strategies in NASDAQ? How can quantitative strategies adapt to NASDAQ's characteristics to optimize investment decisions? This paper is structured into background, methodology, core analysis, results, discussion and references.

2. Literature Review

Against the background of continuous advancement of digital technology and increasingly diversified practical demands in the financial and management domains, academic research has

made extensive progress in both theoretical construction and methodological innovation, involving multiple research directions such as digital organizational paradigm, group decision optimization, statistical test methods, intelligent algorithm improvement, quantitative investment strategy design, and financial risk evaluation and regulation. Relevant representative studies are summarized as follows:

Gawer draws on Chandler's classic theory that technological revolutions give rise to adaptive organizational forms, and demonstrates that digital platform enterprises and their ecosystems serve as the iconic dominant organizational paradigm in the digital era [1]. Xu et al. investigate the impacts of decision rules and non-cooperative behaviors on the minimum consensus cost in group decision-making, and theoretically derive the decision rule that brings the cost to its extreme value [2]. Chen and Zou construct three types of two-layer Stacking ensemble models based on three Boosting algorithms, namely AdaBoost, XGBoost and LightGBM. Through empirical backtesting of stock selection on CSI 300 constituent stocks, their research provides new insights and practical references for quantitative investment [3]. Watanabe et al. address the two-way MANOVA problem with unequal cell sample sizes and unequal covariance matrices in high-dimensional scenarios, and propose a novel approximate test method adapted to non-normal distributions and scenarios where the dimension is far larger than the sample size [4]. Ren and Song propose the GGINformer model integrating an improved genetic algorithm, GRU network and Informer to tackle the problems of feature redundancy and long-range dependence in multivariate time series [5]. Wang and Hu put forward an improved SMGK-means algorithm to address the shortcomings of the traditional K-means algorithm, and implement it on the Spark distributed framework. Experimental results verify that the algorithm achieves significant improvements in both clustering accuracy and parallel execution efficiency [6]. Li builds a quantitative stock selection strategy by combining A-share fundamental factors with other factors based on principal component analysis and multiple linear regression. The study confirms that the strategy can generate robust excess returns, and further optimizes the strategy performance by introducing a dual moving average timing logic [7]. Ye, Ran and Chen establish a three-level evaluation index system for private equity fund investment risk covering both financial and non-financial dimensions, and propose a comprehensive investment risk evaluation method based on the empirical probability distribution of risk indicators [8]. Luo constructs a multi-factor stock selection model integrated with sector rotation by combining the sector rotation strategy with the market value explanatory factor stock selection model. On the basis of dividing economic cycles and industry cyclicity and verifying the sector rotation effect, empirical backtesting comparisons show that the model outperforms both the standalone multi-factor stock selection model and the CSI 300 market benchmark in terms of investment returns and risk prevention and control effects [9]. Lai and Guo develop a legal risk assessment model for the cross-border flow of financial data. By adopting the Analytic Hierarchy Process (AHP) and the Fuzzy Comprehensive Evaluation (FCE) method, they identify key risk indicators including the legality review prior to data export, the assessment of data business requirements, and the legality of the receiving party [10].

3. Analysis of NASDAQ Quantitative Investment

3.1. Background: NASDAQ Market Environment for Quantitative Investment

The underlying characteristics, trading rules and data environment of the NASDAQ market directly determine the applicability and performance of quantitative strategies, with three core dimensions of adaptability to quantitative investment.

First, the underlying structure and return characteristics. Over 80% of NASDAQ 100 constituents are technology enterprises, with long-term EPS growth higher than the S&P 500,

high sensitivity to interest rate fluctuations, and a leptokurtic and fat-tailed return distribution. This feature provides sufficient profit sources for trend tracking and volatility arbitrage strategies, as well as abundant modeling samples for nonlinear models such as genetic algorithms and machine learning. Meanwhile, NASDAQ's strict delisting mechanism continuously optimizes the underlying pool and reduces noise in quantitative modeling.

Second, the trading system and market structure. NASDAQ adopts a competitive market maker system, with multiple market makers providing two-way quotes for each stock, coupled with a fragmented trading system including more than 10 public exchanges and over 50 dark pools, creating abundant spread opportunities for statistical arbitrage and high-frequency trading (HFT). Its SMARTS system supports microsecond-level trading and real-time risk control, providing technical support for HFT and algorithmic trading. In addition, the mature ETF system represented by QQQ provides a standardized carrier for quantitative enhancement and cash-future arbitrage strategies.

Third, the data environment and regulatory system. NASDAQ provides standardized high-frequency trading data and factor data, coupled with alternative data such as public opinion and patent data from third-party providers, supporting the modeling, backtesting and firm offer operation of quantitative strategies. Meanwhile, the SEC's Reg NMS regulates order routing and market manipulation, promoting the compliance and transparency of quantitative strategies, and setting external constraints for risk control of quantitative models.

3.2. Methodology

This paper adopts the integrative systematic literature review method as the core research method, which follows the systematic review principles proposed by Cook, Mulrow and Haynes, with the characteristics of replicability and low bias. It can simultaneously include experimental and non-experimental research, fully covering the theoretical and empirical results of quantitative investment, which is highly compatible with the research objectives of this paper. The review process strictly follows the five-step framework proposed by Whitemore and Knafl.

First, problem identification: this paper defines the review scope as research on NASDAQ quantitative investment from the proposal of the Fama-French three-factor model in 1992 to 2026, covering four core dimensions: strategy paradigm, model application, market impact and practical challenges. Second, literature search: this paper takes the Web of Science Core Collection and CNKI database as core literature sources, with keywords including "NASDAQ", "quantitative investment", "factor model", "machine learning" and "high-frequency trading", forming an initial research library of 136 papers. Third, data evaluation: after manual screening, 82 core papers are finally included, including 64 empirical studies, 4 theoretical papers and 14 review papers. Fourth, data analysis: coding analysis is conducted on core literature to identify consensus, disputes and research gaps. Fifth, result presentation: systematically present the application framework of NASDAQ quantitative strategies and extract core conclusions.

3.3. Core Research on Quantitative Investment Strategies in NASDAQ

3.3.1. Classification of Underlying Data Sources

This paper divides the underlying data sources of quantitative strategies into six categories, covering structured and unstructured data, which form the core basis of quantitative modeling. The first category is high-frequency market trading data, including tick-level price, trading volume and order book data, which is the core data source for HFT and short-term timing strategies. The second category is fundamental and financial data, including listed companies' financial reports, R&D investment and patent data, supporting factor investment and index enhancement strategies. The third category is user-generated content and public opinion data, including social media, financial news and analyst reports, which can mine sentiment factors

through emotional analysis to supplement the information dimension of traditional models. The fourth category is administrative and regulatory data, including the Federal Reserve's monetary policy and industry regulatory policies, used for macro timing and risk control. The fifth category is derivatives and ETF data, including NASDAQ 100 futures, options and QQQ trading data, which is the core basis for statistical arbitrage strategies. The sixth category is hybrid and synthetic data, including fundamental-technical fusion factors, which are the core input of cutting-edge machine learning models.

3.3.2. Types of Core Models

The core models of NASDAQ quantitative investment can be divided into four categories, with different models adapting to different strategy scenarios, and most mainstream studies optimize strategy performance through multi-model combination. The first category is classical statistical models, including linear regression, time series models and principal component analysis (PCA), which are the basis of classical factor models and statistical arbitrage strategies, mainly used for linear relationship fitting and factor dimensionality reduction. The second category is intelligent optimization algorithms, represented by genetic algorithms, mainly used for factor screening and portfolio weight optimization. Existing studies have screened the optimal factor combination from 32 factor pools based on genetic algorithms, achieving significantly higher excess returns than traditional methods. The third category is machine learning models, including tree models such as random forest and XGBoost, deep learning models such as LSTM, and composite models such as Autoencoder-GSVM, which are mainly used for nonlinear factor mining, return prediction and risk control. The fourth category is simulation models, including threshold autoregressive models and multi-agent models, used for intertemporal arbitrage and market dynamic simulation.

3.3.3. Main Application Fields

Based on the literature coding results, this paper divides NASDAQ quantitative investment strategies into five core application fields, with different application logic and practical value.

The first is factor investment strategy, whose core objective is to mine classic factors and NASDAQ-specific factors to obtain stable excess returns through factor exposure, covering market-wide stock selection and industry rotation. This type of strategy lays the basic paradigm of active quantitative investment in NASDAQ, which can adapt to the mining of technology-specific factors such as R&D investment, and alleviate the return attenuation caused by traditional factor crowding through dynamic factor adjustment.

The second is statistical arbitrage strategy, which uses market inefficiency and stable correlation between underlying assets to construct a hedging portfolio to capture spread returns, including pairs trading, cash-future arbitrage, intertemporal arbitrage and volatility arbitrage. It provides a low-risk and stable return path for institutional investors, and is highly compatible with the spread capture demand in NASDAQ's fragmented market.

The third is high-frequency trading strategy, which relies on low-latency technology and short-term positions to achieve returns through market making, order book arbitrage and short-term trend tracking, and is also the core source of liquidity in the NASDAQ market. It significantly improves market liquidity and pricing efficiency, and is the core income source of top quantitative institutions, with extremely high requirements for trading technology and cost control.

The fourth is machine learning-driven strategy, which realizes full-process AI empowerment from factor mining to portfolio optimization and risk control, covering nonlinear factor mining, public opinion sentiment analysis and dynamic position adjustment. It promotes the transformation of NASDAQ quantitative investment from "factor-driven" to "data-driven", and can effectively process high-dimensional nonlinear data and unstructured alternative data.

The fifth is Smart Beta and index enhancement strategy, which takes NASDAQ's core index as the benchmark to obtain stable excess returns through weight optimization, active stock selection and timing hedging, and is the core carrier for ordinary investors to participate in quantitative investment. It realizes the active upgrade of passive investment, and provides low-threshold and high-transparency quantitative products for the market.

3.3.4. Strengths and Limitations of Each Strategy

The rapid development of quantitative investment has significantly improved the liquidity and pricing efficiency of the NASDAQ market, while different types of strategies show differentiated advantages and limitations in practice.

Factor investment strategy has the advantages of clear logic, large capital capacity and suitability for long-term capital allocation, but its core limitation is that the excess return of traditional factors continues to narrow due to factor crowding, and factor effectiveness is prone to periodic failure in the high-volatility market environment of technology stocks. Statistical arbitrage strategy has the advantages of low risk, low drawdown and stable return, with extremely low correlation with the bull-bear cycle, but its limitation is that the spread opportunities continue to narrow with the improvement of market efficiency, and the strategy is highly sensitive to the securities lending mechanism and transaction costs.

High-frequency trading strategy has the advantages of low single transaction risk and high capital utilization, but it has extremely high requirements for low-latency trading technology, and increasingly strict regulation leads to rising compliance costs. The upcoming 24-hour trading also puts forward new challenges to the liquidity management of the strategy. Machine learning-driven strategy can efficiently process high-dimensional nonlinear data and mine profit sources that cannot be identified by traditional models, but it is prone to overfitting, insufficient interpretability, and easy failure in extreme market conditions. Smart Beta and index enhancement strategy has the advantages of high transparency, low investment threshold and stable long-term returns, which is suitable for ordinary investors, but its excess return space is limited, and the tracking error constraint makes it difficult to adjust flexibly in extreme market conditions.

4. Results

Through the integrative systematic literature review, this paper draws four core research results. First, this paper identifies five core application fields of quantitative investment in NASDAQ, clarifies the applicable scenarios, core models and performance characteristics of various strategies, and constructs a panoramic analytical framework covering classic strategies and cutting-edge technologies. Among them, factor investment is the basic paradigm of NASDAQ quantitative investment. Statistical arbitrage and HFT are the core income sources of institutional investors, while machine learning-driven strategies and Smart Beta products are the core development direction of the future market. Second, the underlying structure, trading system, and data environment of the NASDAQ market provide a unique application scenario for quantitative investment. The unique attributes of technology stocks have promoted the mining of NASDAQ-specific factors, such as R&D investment, patent, and public opinion factors. Third, the application of cutting-edge technologies has significantly optimized the performance of quantitative strategies. Models such as genetic algorithm, Autoencoder-GSVM and LSTM show significantly better effects than traditional statistical models in factor screening, return prediction and risk control. Fourth, the current NASDAQ quantitative investment faces four core challenges: narrowing excess returns of traditional strategies caused by crowded trading, model failure in extreme market conditions due to high volatility of technology stocks, rising compliance costs and strategy adaptation pressure brought by strict regulation and 24-hour trading, and overfitting of machine learning models caused by data noise.

5. Discussion

The cognitive conclusions of this paper mainly include three aspects. First, the development of NASDAQ quantitative investment always follows the core logic of "market characteristics determine strategy paradigm, and technological progress promotes strategy iteration". The effectiveness of various strategies essentially depends on their adaptability to the unique attributes of the NASDAQ market. Second, the application of cutting-edge technologies such as machine learning has not subverted the core logic of quantitative investment, but broadened the information boundary and modeling ability of strategies through the improvement of data processing capacity, and the classical factor theory is still the core underlying support of strategies. Third, quantitative strategies cannot completely replace traditional fundamental research. Only through the deep integration of data-driven quantitative models with fundamental research and risk control systems can long-term stable returns be achieved in the cyclical fluctuations of the NASDAQ market.

For investment practice, institutional investors should focus on the mining of NASDAQ-specific factors, strengthen the interpretability research of machine learning models, and optimize the cross-time zone liquidity management mechanism for the upcoming 24-hour trading. Ordinary investors should participate in NASDAQ quantitative investment through low-threshold tools such as Smart Beta ETFs. Future research can focus on four directions: deepening the mining of NASDAQ-specific technology factors, improving the interpretability of machine learning models, strategy adaptation research for 24-hour trading, and cross-market quantitative arbitrage research between NASDAQ and other global markets.

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