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Research on the Application of Factor Model in Financial Asset Pricing

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ABSTRACT
As a core tool for financial asset pricing, the evolution and application effectiveness of factor models have always been a focal point in both academic and practical circles. This paper systematically traces the development of factor models from single-factor to multi-factor approaches, delving into the theoretical logic and empirical performance of CAPM, Fama-French's three/five factor models, Carhart's four-factor model, and Q-factor model in financial asset pricing. The study reveals that single-factor models (such as CAPM) provide a foundational framework for asset pricing, but their explanatory power is limited in complex market environments due to constrained market assumptions. Multi-factor models significantly enhance the explanatory capacity for stock cross-sectional returns by incorporating factors like size, value, momentum, and earnings. The Q-factor model further integrates corporate fundamental factors, demonstrating stronger applicability in the Chinese market. Additionally, while the integration of ESG factors with traditional multi-factor models has not yet significantly improved explanatory power, it has become an important direction for future research. In light of increasing market volatility and evolving investment philosophies, this paper proposes that factor models require improvements in nonlinear relationship characterization, behavioral finance factor incorporation, and market anomaly detection, providing theoretical references for building more adaptive asset pricing frameworks.

KEYWORDS
Factor model; Asset pricing; Financial market

1 Introduction

Asset pricing remains a cornerstone of modern finance, aiming to uncover the drivers behind asset returns and provide theoretical foundations for investment decisions, risk management, and market regulation. Factor models, as key tools for mapping asset returns and risks, have served as vital bridges connecting academic research with market practices since their inception. The early single-factor model, exemplified by the Capital Asset Pricing Model (CAPM), established the theoretical bedrock of asset pricing by explaining returns through market risk factors. However, as financial markets evolved, CAPM's limited explanatory power for market anomalies like scale effects and value effects drove the development of multi-factor models: Fama-French's three-factor model introduced scale and value factors [21] Carhart's four-factor model incorporated momentum factors [21] Fama-French's five-factor model added profitability and investment factors. These advancements have continuously enhanced models 'ability to explain cross-sectional stock returns. Recent years have seen the Q-factor model integrate corporate fundamental factors, demonstrating enhanced adaptability in emerging markets like China's A-shares. Meanwhile, the rise of ESG investment philosophy has spurred academic exploration of incorporating non-financial factors into pricing frameworks, expanding both the scope and depth of factor models. However, current research still faces three core challenges: First, there are significant differences in the applicability of different factor models across specific markets (such as China's A-shares), necessitating systematic comparisons of their explanatory boundaries[4-7]. Second, traditional models inadequately capture complex market characteristics like nonlinear relationships and behavioral biases, making them ill-equipped to address pricing demands in highly volatile environments. Third, the synergistic mechanisms between emerging factors like ESG and traditional ones remain unclear[9], constraining their application in sustainable investment. Building on this context, this paper traces the evolutionary trajectory of factor models, focusing on CAPM, Fama-French series models, Carhart's four-factor model, and Q factor model. It systematically analyzes their theoretical frameworks and empirical performance, particularly examining their applicability differences in the Chinese market, while proposing optimization directions through practical insights. The study aims to answer: What are the core pricing logic of different factor models? How do they explain returns on China's financial assets? How can future factor models overcome existing limitations to adapt to complex and dynamic market conditions? Through these analyses, the research provides theoretical references and practical guidance for building a more adaptive asset pricing framework.

2 Development of factor models

The factor model originated from the Capital Asset Pricing Model (CAPM), proposed by Nobel laureate William Sharpe in his 1970 seminal work *Portfolio Theory and the Capital Markets*. The formula contains three key components: rf (risk-free rate) representing pure monetary time value, βa as the security's Beta coefficient, and rM (expected market return) indicating the equity market premium. The first term on the right side of CAPM's equation represents the risk-free rate, typically benchmarked against 10-year U. S. Treasury bonds. When investors demand higher returns, they must compensate with an additional premium. Thus, the equity market premium equals the expected market return minus the risk-free rate. The security risk premium is calculated by multiplying this premium by a specific Beta coefficient. However, despite its theoretical validity, CAPM has proven inaccurate in practice, as high-Beta stocks have not consistently outperformed the market. In 1976, Stephen Ross developed the Arbitrage Pricing Theory (APT) based on the Capital Asset Pricing Model (CAPM). While both APT and CAPM operate under equilibrium conditions, APT is grounded in a multi-factor model. The theory posits that arbitrage activities are a key determinant of efficient markets (i. e., market equilibrium prices), and that non-equilibrium states create risk-free arbitrage opportunities. By applying multiple factors to explain risky asset returns, the no-arbitrage principle reveals an approximate linear relationship between risk-adjusted returns and these factors. In the early 1990s, Eugene Fama and Ken French introduced the seminal Three-Factor Model[21], adding market and value dimensions as risk factors to CAPM. Their research demonstrated that small-cap stocks and undervalued equities generate long-term excess returns by taking on higher market risks. This model reinterpreted CAPM while better explaining long-term stock returns. To enhance explanatory power, some researchers later incorporated a fourth factor into the framework, with the Momentum Factor (MF) being a common fourth factor in the Fama-French-Carhart four-factor model. Carhart (1997) introduced the momentum factor into the Fama-French three-factor model, proposing a four-factor framework. The momentum factor reflects a stock's price momentum over time, indicating that stocks with strong historical performance are likely to maintain their positive trajectory, while those with poor performance may continue underperforming. The Momentum Weighted Momentum (UMD) captures this price momentum, effectively capturing the momentum effect. Its introduction significantly enhanced the model's explanatory power for stock returns, enabling better interpretation of their time-series characteristics. Although traditional asset pricing models have made substantial progress in explaining stock returns, some outcomes remain unexplained. Notably, these models underperform in explaining how corporate fundamentals like profitability and financial health influence returns. This gap was addressed in 2013 when Eugene Fama and Ken French discovered that profit level risk and investment level risk could also generate excess returns beyond conventional risks, leading to the development of the Fama-French Five-Factor Model[22]. In response to evolving economic conditions, Professor Zhang Lu's research team published a groundbreaking paper in 2019 introducing the Q Factor Model[23], aiming to understand asset pricing mechanisms through multiple factors for more accurate valuation.

3 Application of models in asset pricing

3.1 Model theory itself and pioneering literature

3.1.1 Single factor model: CAPM

The Capital Asset Pricing Model (CAPM) within the single-factor model stands as a cornerstone theory in financial asset pricing. In their paper "X-CAPM: An Extrapolative Capital Asset Pricing Model" by Nicholas Barberis a, Robin Greenwood b, Lawrence Jin a, and Andrei Shleifer c, researchers developed a continuous-time economic framework to analyze the extended Capital Asset Pricing Model (X-CAPM) in stock price behavior. The study reveals key characteristics of stock price fluctuations and examines how investor confidence influences both stock pricing and consumption decisions. Furthermore, through simulation experiments, the paper validates the model's predictive power, offering valuable insights for both theoretical frameworks and practical applications in financial economics.

Another study titled "Systemic Risk of China's Listed Commercial Banks Based on the Capital Asset Pricing Model (CAPM)" by Zhao Tian, Li Yang, and Zhu Yan employs CAPM models to analyze micro-level data of listed commercial banks. The research aims to establish an interactive relationship between returns and risks, systematically mapping the evolution of systemic risk in Chinese commercial banks since the financial crisis. The findings reveal that state-owned large commercial banks exhibit significantly higher systemic risks compared to other joint-stock and city commercial banks. Notably, the systemic risk of commercial banks has shown a trend of initial increase followed by subsequent decrease over the past decade. This paper provides valuable insights for preventing and mitigating systemic risks in the banking sector.

The paper "A Timeless Capital Asset Pricing Model with Stochastic Volatility" by John Y. Campbell, Stefano Giglio, Christopher Polk, and Robert Turley explores the theoretical and empirical analysis of introducing stochastic volatility into the Intertemporal Capital Asset Pricing Model (ICAPM). By incorporating stochastic volatility, this model improves upon traditional ICAPM frameworks while emphasizing its significance for long-term investors during periods of high market volatility. Through theoretical derivations and empirical analyses, the study examines how stochastic volatility influences asset pricing, offering new perspectives and methodologies for understanding asset valuation mechanisms.

3.1.2 Multifactor model

(1) Fama-French three-factor model

The Fama-French Three-Factor Model extends the Capital Asset Pricing Model (CAPM) by incorporating three key components: the Market Factor (market risk premium), the Size Factor (SMB) that measures returns differentials between small and large-cap stocks, and the Value Factor (HML) that distinguishes value stocks (those with high book-to-book ratios) from growth stocks (with low ratios). This model incorporates multiple factors affecting asset returns. In the empirical study "Application of the Fama-French Three-Factor Model in China's Financial Sector Equity Markets" conducted by Luo Wenyi from Tongji University's School of Economics and Management, researchers analyzed 42 A-share bank stocks and 80 non-bank financial institution stocks using the refined model. The findings revealed that the Market Factor, Size Factor, and Value Factor collectively influence the excess returns of financial sector portfolios, with the three-factor model demonstrating stronger explanatory power for the "non-bank financial" sample. This research provides regulators and investors with data-driven insights and more accurate asset pricing tools.

(2) Four-factor model

Fama-French four-factor model

In recent years, quantitative investment has gained momentum in China's capital markets, with the multi-factor stock selection model serving as a crucial approach for institutional investors to build equity portfolios for stable returns. The Carhart four-factor model and Fama-French multi-factor model, two mainstream approaches, have garnered significant attention and practical application in both academic and real-world contexts. The Fama-French four-factor model builds upon the three-factor framework by incorporating an overall factor of total factor productivity (or other factors such as profitability or investment style). Liao Tingting's research selected 240 monthly data points from the Shanghai and Shenzhen A-share markets between May 2000 and April 2020 as study samples, conducting comparative analyses of the applicability of Fama-French's three-, four-, and five-factor models to A-share returns. Her study titled "Applicability Test and Application of Fama-French Four-Factor Model for A-Shares" reveals that the model's explanatory power for A-share returns primarily stems from market factors and size factors, while value factors and total factor productivity also demonstrate limited explanatory capacity. Additionally, the research demonstrates that variations in total factor productivity factors can lead to portfolio returns moving in the same direction, though with varying degrees of impact.

Carhart's four-factor model

The Carhartt four-factor model builds upon the Fama-French three-factor framework by incorporating a momentum factor (MOM). This component measures the return differential between historically strong "winners" and weak "losers" in stock market performance. Cai Yin's 2018 study demonstrated that market factors (MKT), size factors (SMB), and momentum factors (MOM) are positively correlated with individual stock returns, while value factors (HML) show negative correlation[17]. In her research titled "Stock Selection Strategies and Fund Product Design Based on the Four-Factor Model," Cai Yin analyzed 2,628 A-share listed companies from April 2006 to March 2016. Through constructing a four-factor regression model, she found the model effectively explains stock returns. Building on this foundation, she developed a stock selection strategy and simulated fund performance. The results showed that the fund significantly outperformed the average return of Shanghai-Shenzhen A-shares, achieving an average annualized return of 21.65% over nine years, compared to the 7.77% average for the same period.

With the rapid development of China's financial markets, open-end equity funds have become a crucial investment tool, and their performance and style drift issues have increasingly attracted attention from both academic and practical circles. The four-factor model, particularly the Carhart Four-Factor Model, has been widely applied in research on Chinese open-end equity funds as an effective tool for evaluating fund performance and identifying style drift. Zhang Haowei's empirical study "Performance Analysis of Chinese Open-End Equity Funds" (2021) selected 29 qualified sample funds from Morningstar Fund Network and Choice Financial Terminal, using the Carhart Four-Factor Model to conduct regression analysis on fund performance. The author also employed statistical methods such as Sharpe Index and maximum drawdown to explore the risk profiles of the sample funds. This study aimed to provide valuable references for ordinary investors when selecting funds through empirical analysis of the Carhart Four-Factor Model[18]. The findings revealed that the Carhart Four-Factor Model demonstrates strong explanatory power for the performance of Chinese open-end equity funds. Through this model, investors can identify funds with higher α-values as potential investment candidates. Additionally, the research discovered that longer investment periods are not always better—most funds performed better over three-year periods according to the Sharpe Index. Chen Jiaxi's 2020 study "The Impact of Style Drift on Open-End Fund Performance" employed the Carhart Four-Factor Model to analyze 305 open-end funds, focusing on how style drift affects fund performance. The research aimed to identify actual investment styles and detect style drift phenomena among funds between 2013 and 2018, while exploring the mechanisms through which style drift impacts fund performance[3,12]. Future studies could expand the sample size and time span to better evaluate the applicability and accuracy of the four-factor model in China's financial markets. Additionally, integrating advanced statistical and econometric methods would allow deeper analysis of factors influencing fund performance and the mechanisms behind style drift. Furthermore, adopting a micro-level perspective—such as examining how fund managers' investment strategies and risk preferences affect performance and style drift—could provide investors with more actionable investment advice and tailored strategies.

(3) Fama-French five-factor model

With the growing prominence of ESG (Environmental, Social and Governance) investments, Mu Yang and Wang Jiawen [9] conducted a study titled "Effectiveness of the Fama-French Five-Factor Model in the A-share Market," which incorporates ESG factors into the original model to verify its effectiveness in China's A-share market. The research reveals that stocks with lower ESG scores exhibit higher returns due to their greater risk exposure, while ESG factors demonstrate market capitalization effects, value effects, and investment style effects. However, within this sample, both the three-factor and five-factor models outperformed the newly constructed ESG factor model in explanatory power. This study provides an effective theoretical framework for responsible investment and suggests that ESG information will gain enhanced effectiveness in China's A-share market. Zhao Shengmin et al. compared the performance of the Fama-French five-factor model and three-factor model in China's A-share market, finding that the five-factor model demonstrates certain explanatory advantages but not absolute superiority. Lin, Q.[22] also explored the applicability of the Fama-French five-factor model in Chinese markets, offering insights into cross-market differences in model performance.

3.1.3 Q factor model

The Q-factor model, as a crucial tool for financial asset pricing, has garnered significant attention in both academic and practical circles in recent years. Proposed to explain stock market excess returns through a multi-factor framework encompassing market factors, size factors, investment factors, and profitability factors, this model's applicability and explanatory power in the Chinese market have been examined by Zhao Yang in his empirical study titled "Empirical Analysis of the Q-Model in the Chinese Market." Following the same factor construction methodology as the Fama-French three-factor model, Zhao implemented orthogonal grouping to isolate influencing factors. By integrating the latest asset pricing theories with China's market context, he tested the effectiveness of various factors in the Chinese market. Through multivariate regression analysis, he developed a Q-factor model tailored to Chinese conditions, evaluating the explanatory power of market capitalization factors, book-to-market ratio factors, investment factors, profitability factors, and momentum factors in explaining excess returns in China's A-share market. In contrast, Ye Li's empirical study "Empirical Analysis of Q-Model's Predictive Power for Stock Returns" employed statistical methods to investigate the model's explanatory capacity in Chinese stock markets. The research further examined predictive performance across different market conditions and conducted robustness tests. The study compares the explanatory power of the Q-factor model, Fama-French three-factor model, and five-factor model in explaining stock returns in China's market. It further investigates the sample-internal and external predictive capabilities of investment and profitability Q-factors on stock market excess returns. The findings conclude that the Q-factor model significantly explains excess returns in China's A-share market with superior explanatory power compared to the Fama-French three-factor and five-factor models. Both corporate profitability and investment capability can significantly explain cross-sectional stock returns, but profitability demonstrates stronger explanatory power than investment efficiency. Both investment and profitability Q-factors show significant predictive power for A-share market excess returns across different market conditions. Through in-depth analysis of factor effectiveness and predictive capabilities, this study provides valuable insights into understanding the sources of Q-factor's contribution to China's stock market excess returns. Future research could expand the application scope of the Q-factor model to other financial markets or industries, while integrating new financial theories and data technologies to continuously optimize and improve its explanatory power and prediction accuracy. With the continuous development and maturation of capital markets, the importance of multi-factor asset pricing models in explaining stock returns and risks has become increasingly prominent. Their applications in China's market are growing, making empirical research on them more critical than ever. Wu Fan's empirical study "Empirical Research on Multi-Factor Asset Pricing Models" constructed a multi-factor pricing model based on market anomalies and compared the performance of different models to test its applicability in China's A-share market. The research found that certain factors demonstrated significant predictive power in the Chinese market, aligning with findings from foreign scholars. Additionally, the paper explored interactions and influences among different factors, providing valuable references for applying multi-factor pricing models in China. Fang Yi et al. further investigated the "multi-factor model of market anomalies" in their comparative study "Comparative Analysis of Multi-Factor Pricing Models Based on Market Anomalies". By comparing the explanatory capabilities of the Q factor model and Fama-French five-factor model regarding market anomalies, they delved into the pricing performance of multi-factor models in China. The study revealed that both models exhibited distinct advantages and limitations in explaining market anomalies. Furthermore, the paper quantitatively evaluated models using GRS tests and absolute pricing errors, providing scientific basis for model comparison and selection. Combining these findings, multi-factor pricing models demonstrate applicability in China's market but require adjustments and optimizations tailored to local characteristics. For instance, incorporating factors reflecting Chinese market features could enhance model explanatory power and prediction accuracy. Additionally, the roles and performances of different factors within multi-factor pricing models vary. Therefore, when selecting and applying multi-factor pricing models, it is essential to thoroughly evaluate the effectiveness of each factor and their interrelationships. When necessary, these models should be flexibly adapted according to actual market conditions. For instance, during economic fluctuations or market restructuring, timely updates to model parameters and factors are crucial to maintain accuracy and reliability.

3.2 Model application and future improvement direction

3.2.1 Consider nonlinear relationships

Traditional factor models predominantly rely on linear assumptions, yet the relationship between factors and asset returns in financial markets often exhibits nonlinear characteristics (such as threshold effects and time-varying correlations). Future research could incorporate machine learning algorithms (e.g., random forests and neural networks) or nonlinear econometric models (e.g., threshold regression and state-space models) to capture the dynamic mechanisms of factors across different market conditions (bull/bear markets, volatile markets) or economic cycles (expansion, recession, recovery). For instance, during periods of extreme market volatility, momentum factors may exhibit "reversal" characteristics. It is essential to identify such phase transition patterns through nonlinear models to enhance their robustness in complex environments. Research by Zhai Congshan et al. [10] also underscores the importance of incorporating nonlinear mechanisms into multi-factor models, providing theoretical support for related technological applications.

3.2.2 Include emotional factors and behavioral deviations

Current models inadequately capture investors' irrational behaviors, while behavioral biases such as overconfidence and disposal effects significantly influence asset pricing. A multi-factor system incorporating behavioral finance dimensions can be constructed by integrating investor sentiment indices (e. g., closed-end fund discount rates, stock forum activity), attention factors (e.g., stock search volume, media coverage frequency), and game theory factors (e.g., large order flows, institutional position changes). For instance, a "market sentiment factor" can be developed through social media text mining to analyze its predictive power for short-term excess returns, thereby addressing the limitations of traditional models in explaining "noise trading".

3.2.3 Deal with market incompleteness and information asymmetry

Although the multi-factor model has covered some market anomalies (such as scale effect and value effect), there are still unexplained sources of returns (such as short-term reversal and profit quality anomaly). The following directions can be expanded:

(1)Macroeconomic linkage factors: integrate macro variables such as monetary policy (such as interest rate term structure), fiscal policy (such as government spending growth rate), geopolitical risk and so on, and analyze their cross-market transmission effects on asset returns;

(2)Micro fundamental innovation factors: Develop ESG sub-indicators (such as carbon footprint intensity, board diversity), supply chain stability indicators, patent quality factors, etc., to improve the pricing accuracy of sustainable investment and innovation-driven enterprises;

(3)High-frequency trading and order flow factors: Order imbalance factors and liquidity shock factors are constructed by using transaction data to capture the immediate impact of intraday trading behavior on price formation.

3.2.4 Look for new factors and data sources

Traditional factor construction methods (such as market capitalization weighting and equal-weight grouping) may lead to multicollinearity or sample bias among factors. Future approaches could include dynamic factor grouping techniques (e. g., time-varying cluster analysis) to adjust classification criteria according to market conditions; implementing regularization methods (like LASSO and ridge regression) to mitigate multicollinearity and enhance model generalization; exploring reinforcement learning applications in factor portfolios to dynamically allocate weights through intelligent algorithms that adapt to market style rotation. Additionally, adopting the "factor zoo" research paradigm could establish standardized factor validity testing procedures, eliminating redundant factors and focusing on core pricing factors.

3.2.5 Improved factor structure and combination construction method

Current research primarily focuses on stock markets, with future efforts aiming to extend factor models to derivatives (e.g., commodity futures and forex options), alternative assets (e.g., cryptocurrencies and private equity), and global asset allocation. For instance, constructing cross-border multi-factor models incorporating exchange rate factors and commodity momentum factors to analyze factor synergy effects across economies. In cryptocurrency markets, developing blockchain-based factors (such as trading activity and hash rate) addresses the limitations of traditional financial data. Additionally, attention should be paid to how institutional differences across markets (e. g., trading mechanisms and regulatory policies) influence factor performance, enabling cross-market adaptive adjustments of the models.

3.2.6 Combine big data technology with real-time pricing needs

With the advancement of fintech, real-time processing of high-frequency and unstructured data (including satellite imagery and corporate financial reports) has become feasible. By leveraging natural language processing (NLP) technology to extract risk indicators from financial statements and constructing retail sector sentiment metrics through satellite remote sensing data, we achieve both high-frequency analysis and forward-looking asset pricing. Furthermore, a real-time factor calculation engine built on cloud computing platforms dynamically updates exposure levels and expected returns, meeting the stringent time-sensitive requirements of quantitative investment strategies.

3.2.7 Include ESG and sustainable development factor system

The rise of ESG investment has necessitated the integration of environmental, social, and governance (ESG) dimensions into factor models. Although existing research indicates that ESG factors have not yet surpassed traditional models in explanatory power within China's A-share market, their long-term value remains significant. Future efforts should focus on enhancing the objectivity of ESG rating systems (e.g., reducing subjective weighting and introducing third-party data validation), exploring interactions between ESG factors and conventional ones (such as ESG factors moderating value factors), and developing specialized factors like "low-carbon transition premium" and "social responsibility risk discount". These initiatives will provide theoretical foundations for pricing green financial products.

4 Conclusion

The research on asset pricing models demonstrates that while single-factor models (e.g., CAPM) provide a foundational framework, their limitations in explaining market anomalies like scale effects and value effects[19-20] restrict their applicability in complex markets. Multi-factor models significantly enhance explanatory power by incorporating factors such as scale, value, momentum, and earnings. The Carhartt Four-Factor Model demonstrates strong practical value in quantitative investment strategies due to its inclusion of the momentum factor[3, 12, 17-18]. The Q Factor Model outperforms the Fama-French series model in explaining Chinese market fundamentals[13-16], with its earnings factor demonstrating stronger explanatory power than the investment factor. Model performance varies markedly across Chinese markets: The Fama-French Three-Factor Model outperforms banking stocks in non-bank financial stocks[2], while the scale factor shows greater significance in sectors with high small-cap shares[4-7]. The Q Factor Model consistently explains A-share excess returns under various market conditions[15-16]. Although ESG factors currently exhibit weaker explanatory power than traditional ones[9], they demonstrate characteristics like market capitalization effects and value effects, indicating promising future potential. Notably, China's unique market challenges include value factors being distorted by shell resource premiums, retail investor behavior amplifying momentum fluctuations, and financial data quality affecting Q Factor validity in SMEs. The value of this study lies in systematically comparing the applicability boundaries of different factor models, providing theoretical references for asset pricing practices in the Chinese market, particularly offering directional guidance for constructing quantitative investment strategies and risk management. However, the research still has limitations: first, insufficient characterization of nonlinear relationships between factors; second, inadequate coverage of other asset categories such as derivatives; third, further exploration is needed regarding the sub-dimensionality and dynamic mechanisms of ESG factors. Future research could integrate machine learning and big data technologies to drive model development toward greater precision and dynamism.

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