Multi-Dimensional Analysis and Exploration of Asset Pricing

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Abstract: Asset pricing is a core issue in the financial market and is affected by various external and internal factors. This study explores the role of policy changes, socio-economic uncertainty, and corporate internal governance structure in asset pricing. It analyzes the advantages and disadvantages of traditional pricing methods (such as CAPM, APT, and multi-factor models) and emerging data-driven methods (such as machine learning and deep learning). Policy factors mainly affect market liquidity, capital costs, and investor expectations through monetary policy, fiscal policy, and financial regulation, which affect asset prices. Socio-economic uncertainty, such as economic crises, wars, and natural disasters, can exacerbate market volatility and affect asset valuations. A company's profitability, capital structure, and governance level determine its market value. In addition, the development of data science, machine learning, and deep learning in asset pricing continues to improve prediction accuracy, but it still faces challenges such as black box problems, overfitting, and data reliability. In the future, combining behavioral finance, data-driven methods, and research on explainable artificial intelligence (XAI) is expected to improve the accuracy and applicability of asset pricing models and promote the transformation of financial analysis into intelligence.

1 INTRODUCTION

Asset pricing is a core issue in the financial market that directly affects investment decisions, corporate financing, and market stability. In theory, asset prices should reflect the discounted value of their future cash flows, but the actual market is affected by multiple factors, such as policies, the economic environment, and investor behavior, resulting in price fluctuations. Understanding these factors and establishing a reasonable pricing model is crucial for optimizing investment strategies and financial supervision.

Traditional pricing methods, such as the capital asset pricing model (CAPM), arbitrage pricing theory (APT), and the Fama-French multi-factor model, emphasize the decisive role of market risk premium on asset returns. However, these models have limitations in explaining market anomalies and nonlinear problems. In addition, behavioral finance shows that irrational investor behaviors, such as herding and loss aversion, can affect asset pricing and cause the market to deviate from theoretical predictions.

With the rapid development of big data technology and artificial intelligence, asset pricing research has entered a new stage in recent years. Data-driven methods such as machine learning (ML) and deep learning (DL) have become a new trend in asset pricing research. These methods can capture complex nonlinear relationships and improve prediction accuracy. For example, neural networks outperform traditional factor models in predicting stock returns, and natural language processing (NLP) technology also makes market sentiment analysis possible. However, these methods still face challenges such as black box problems, overfitting, and data quality, which, to some extent, limit their widespread application in the financial field.

This study will analyze the impact of policies, socio-economic environment, and corporate internal governance on asset pricing and compare the advantages and disadvantages of traditional and machine learning methods. At the same time, it explores how new technologies such as behavioral finance, causal inference, and explainable artificial intelligence (XAI) can optimize pricing models. This study provides suggestions and inspiration for the

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direction and path of future asset pricing research from a multi-dimensional and interdisciplinary perspective by exploring the relevant influencing factors and practical progress in asset pricing.

2 INFLUENCING FACTORS

Asset pricing is affected by various external and internal factors, which not only affect the formation of market prices but also determine investors' risk preferences and market behavior. Policy changes, economic and social uncertainties, and corporate internal governance structures often affect asset price fluctuations. The following will be analyzed based on policy changes, social and economic uncertainties, and internal corporate factors.

2.1 Policy

Government policies, mainly monetary, fiscal, and financial regulatory policies, are essential factors affecting asset pricing. These policies change the assets' expected return and investment risk by affecting market liquidity, capital costs, and corporate profitability.

2.1.1 Monetary Policy

Monetary policy impacts asset pricing mainly by affecting market interest rates, liquidity, and investor expectations. The central bank controls inflation and economic growth by adjusting benchmark interest rates (such as the Federal Reserve's federal funds rate) and open market operations, thereby affecting the market's risk premium, discount rate, and capital cost, and thus determining changes in asset prices (Bernanke & Kuttner, 2005). For example, the Fed's interest rate hike in 2022 raised the discount rate, depressed asset prices, and pushed up corporate financing costs, weakening profitability and reducing stock valuations. At the same time, market risk premiums rose, investors' risk aversion increased, and funds flowed out of the stock market and turned to bonds, leading to a contraction in market liquidity and exacerbating downward pressure on the stock market (Li, 2023).

2.1.2 Fiscal Policy

Fiscal policy (such as government spending and tax adjustments) changes asset pricing by affecting economic growth, corporate profits, and market confidence. Expansionary policies (increasing investment or reducing taxes) increase corporate cash flow and profit expectations, reduce risk premiums, and push up stock market valuations. However, excessive fiscal deficits may lead to rising inflation and increased government debt, increase discount rates, and weaken market confidence, thereby suppressing asset price increases (Agnello & Sousa, 2011).

2.1.3 Regulatory Policy

Changes in financial regulatory policies also affect asset pricing. After the 2008 financial crisis, countries strengthened financial market supervision, requiring banks to increase capital adequacy ratios and limit leverage operations, which reduced the volatility of financial asset prices. For example, Basel III requires banks to increase their capital adequacy ratio and liquidity coverage ratio and restrict high-leverage businesses, which increases banks' financing costs and thus affects financial asset prices (Gratton, 2024). In contrast, if the government relaxes regulation, such as lowering the IPO threshold in the capital market, it may increase investment opportunities in the market and improve stock valuations (Gallimberti, Lambert, & Xiao, 2021).

2.2 Socio-Economic

Socio-economic uncertainties, such as financial crises, wars, and natural disasters, can significantly affect market stability and reduce the predictive power of asset pricing models. For example, during the 2008 financial crisis, investors panicked, sold high-risk assets, and turned to safe-haven assets such as gold and government bonds, causing asset prices to fluctuate sharply, showing investors' risk aversion (Muir, 2017).

Wars and geopolitical conflicts, such as the 2022 Russia-Ukraine conflict, have led to increased risk aversion in the market, affecting global stock and commodity markets (Souza, 2020). In addition, natural disasters, such as the COVID-19 pandemic, have profoundly impacted global supply chains and market liquidity, forcing companies to lower their earnings expectations and thereby reducing stock market valuations (Berkman & Malloch, 2021).

2.3 Internal Factors of the Enterprise

An enterprise's financial status, management decisions, and corporate governance structure are the core internal factors that affect asset pricing. Profitability, capital structure, and cash flow status determine the market's expectations of a company's future earnings, affecting its valuation. Management's strategic decisions, including mergers and acquisitions, stock repurchases, and capital allocation, directly affect the market's judgment of the company's growth potential and financial soundness. Overall, a sound financial position, reasonable management decisions, and sound corporate governance can improve asset valuations, while financial instability, strategic errors, or governance deficiencies may lead to a decline in asset prices (Affes & Jarboui, 2023).

3 PRICING METHODS

3.1 Traditional Methods

3.1.1 CAPM Model

The capital asset pricing model (CAPM) is a core tool in modern financial market price theory that is widely used in investment decisions and corporate finance. The Model was developed by William Sharpe, John Lintner, and others in the 1960s based on modern portfolio theory (Kenton, 2024). Its core formula is:

$$E(r_i) = r_f + \beta_{im}[E(r_m) - r_f] \quad (1)$$

Among them, $E(r_i)$ is the expected return on the asset, r_f is the risk-free rate, β_{im} represents the systematic risk of the asset to the market portfolio, and $E(r_m)$ is the expected return of the market portfolio. CAPM believes that the market risk premium is the main factor determining asset returns.

However, Fama and French pointed out that CAPM has difficulty explaining the excess returns of small-cap stocks and the high returns of high book-to-market ratio stocks (Hayes, 2024a). In addition, CAPM assumes that the market is entirely rational, while behavioral finance research shows that investors' irrational behavior can affect asset prices.

3.1.2 APT Model

The Arbitrage Pricing Theory (APT) is a multi-factor asset pricing model that assumes that the linear relationship between expected returns and a series of macroeconomic factors can predict asset returns. The Model helps value investing and identifies securities that may be mispriced (Hayes, 2020). Its formula is:

$$E(r_i) = R_f + \sum_{j=1}^{n} \beta_j F_j \#(2)$$

Where $E(r_i)$ is the expected return of asset i, R_f is the risk-free rate, β_j is the sensitivity of asset i to the jth risk factor, and F_j represents the number of risk factors selected by the jth systematic risk factor (such as GDP growth rate, interest rate changes).

APT is more flexible than CAPM and does not require market equilibrium, but its main limitation is that the theory does not propose relevant factors for specific stocks or assets. A stock may be more sensitive to one factor than another, and investors must be able to perceive the source and sensitivity of risk.

3.1.3 Multi-factor Model

The Fama-French three-factor model is an asset pricing model based on the CAPM expansion in 1992. Based on market risk factors, the market value factor (SMB) and the book-to-market factor (HML) were introduced to more accurately explain asset returns (Hayes, 2024a).

$$E(r_i) = r_f + \beta_{im}[E(r_m) - r_f] - \beta_{SMB}SMB + \beta_{HML}HML \#(3)$$

The Model was later expanded to a five-factor model, adding profitability and investment factors. Compared with CAPM and APT, although it has improved the ability to explain cross-sectional returns, it still has defects. Its factors may be redundant and multicollinear, the theoretical basis is weak, and it fails to fully explain small-cap stocks' excess returns and momentum effects. In addition, the Model depends on the market environment, and its effectiveness is unstable in different markets or economic cycles, and it still cannot eliminate abnormal phenomena. Despite this, it is still an important tool for asset pricing and investment analysis.

3.2 Machine Learning Methods

With today's financial markets becoming increasingly complex and data availability improving, the limitations of traditional linear asset pricing models are becoming increasingly apparent. Machine learning methods use computing power and data-driven optimization to be more adaptable and accurate in asset pricing and risk prediction. They can automatically identify nonlinear relationships and adapt to market dynamics, especially in high-dimensional data environments.

3.2.1 The Role of Machine Learning in Asset Pricing

Machine learning introduces several key features into asset pricing models, including processing large amounts of data (such as historical financial market data and corporate financial data) and using machine learning models (such as deep learning, support vector machines, etc.) to predict future price trends.

Applying machine learning (ML) models in asset pricing has significantly improved prediction accuracy, surpassing traditional linear models. Advanced machine learning models (such as neural networks, support vector machines (SVMs), and gradient boosting trees (GBTs)) have higher R2 values and lower error metrics (such as root mean square error RMSE and mean absolute error MAE) (Fang & Taylor, 2021). These models achieve more accurate predictions by capturing the complex nonlinear relationships between asset prices and multiple factors.

For example, machine learning models significantly outperform traditional linear factor models when predicting abnormal returns of portfolios and show higher prediction accuracy. This improvement is reflected in the optimization of statistical indicators and the model's more profound understanding and adaptability to market dynamics. In the return prediction of China's A-share market, the neural network model increased the R2 value from 0.31 to 0.46, far exceeding the traditional linear model. This high prediction accuracy enhances the reliability of investment decisions and provides investors with better risk-adjusted returns (Li, 2018).

Although machine learning (ML) models perform well in prediction accuracy, the "black box" characteristics raise ethical issues about transparency and accountability. Especially in the financial industry, investors and regulators need to have a clear understanding and interpretability of the model's decision logic, but the high complexity of machine learning models may lead to insufficient transparency (Chen, Pelger, & Zhu, 2024).

3.2.2 The Role of Deep Learning in Asset Pricing

Deep learning, especially neural network models, can handle more complex market relationships and overcome the limitations of traditional methods in processing nonlinear and high-dimensional data.

The long-short portfolio strategy built based on neural networks outperforms traditional linear models in terms of annualized returns and Sharpe ratio. Studies have shown that the Sharpe ratio of the neural network model reaches 2.97, while that of the linear model is only 1.93. This indicates that neural networks can improve portfolio returns and effectively reduce risks. Its significant performance improvement stems from the fact that neural networks can capture and utilize complex nonlinear relationships and dynamic changes in asset pricing, thereby providing more accurate and reliable investment signals (Pan, 2019).

Unlike traditional financial models, neural networks' black-box nature may face regulatory barriers in practical applications. In addition, deep learning relies on a large amount of data training. Although nonlinear models perform well on training data, a lack of proper regularization and cross-validation can easily lead to overfitting, affecting the accuracy of out-of-sample predictions. Therefore, future research directions may include combining deep learning with traditional financial theory to improve the interpretability and applicability of the model.

4 FUTURE OUTLOOK

Asset pricing methods are still evolving, and emerging technologies and theoretical research are driving the evolution of asset pricing models. Future research directions mainly focus on behavioral finance, data-driven methods, and improvements in model limitations.

4.1 The Impact of Behavioral Finance on Asset Pricing

Traditional asset pricing models assume that investors are entirely rational, but studies have shown that investor emotions and irrational behavior can cause market prices to deviate from fundamental values. Psychological biases such as herding, overconfidence, and loss aversion can affect market pricing and increase price volatility (Akin & Akin, 2024).

For example, during the pandemic, investors generally followed market trends, and a large amount of funds poured into the technology sector, pushing stock prices far beyond their fundamental value. Driven by market sentiment, investors ignored the risk of overvaluation and formed a self-reinforcing upward cycle. However, when market sentiment reverses or actual earnings fall short of expectations, the bubble bursts, and stock prices fall sharply, reflecting the amplification of market volatility by the herding effect (Yeh, Teoh, & Chu, 2020).

Behavioral finance corrects the rational assumptions in traditional asset pricing theory and provides a more reasonable explanation for market price anomalies. Future asset pricing research can incorporate behavioral finance into the model to predict market trends more accurately.

4.2 Data-driven Asset Pricing Methods

With the advancement of big data technology, new variables such as market sentiment and social media sentiment analysis have become essential factors in asset pricing. Traditional models mainly rely on economic fundamentals data, while data-driven methods can use unstructured data for market forecasting.

Negative news sentiment can predict market returns, and news analysis models combined with natural language processing (NLP) technology can improve the accuracy of asset pricing (Tetlock, 2007). Market sentiment on social media platforms such as Twitter can reflect investor sentiment fluctuations. For example, the market sentiment index of social media can predict stock market returns (Černevičienė & Kabašinskas, 2024). The challenge of data-driven methods lies in the problem of data falsification. For example, information on social media may be false, and data cleaning and feature selection are required to improve the model's reliability.

4.3 Current Limitations

Although modern asset pricing models (such as CAPM, APT, and multi-factor models) are widely used, they still have limitations, such as the overly idealistic assumption of rational investors, the difficulty in capturing market nonlinear relationships, the inability to explain market anomalies and the neglect of market sentiment and non-financial factors. At the same time, with the development of big data, traditional models find it complex to use high-dimensional data, and factor selection effectively relies on experience, which affects the stability of data processing.

Deep learning and machine learning provide new opportunities for asset pricing, which can identify complex nonlinear relationships, improve prediction accuracy, and adapt to market dynamics. Machine learning algorithms (SVM) perform well in market return prediction and risk management, while deep learning models automatically extract data features through neural networks. However, these methods still face challenges such as overfitting, black box problems, and difficulty identifying causal relationships. In the future, combining explainable artificial intelligence, causal inference methods, and multi-source data fusion is expected to improve model transparency, optimize pricing accuracy, and promote the transformation of financial analysis to data-driven and intelligent (Černevičienė & Kabašinskas, 2024).

5 CONCLUSIONS

Asset pricing is a complex and dynamic process influenced by various external and internal factors. Policy changes (such as monetary policy, fiscal policy, and financial regulatory policy) directly affect the formation of asset prices by changing market liquidity, capital costs, and investor expectations. Socioeconomic uncertainties (such as financial crises, geopolitical conflicts, and natural disasters) further affect the stability of asset pricing by exacerbating market volatility and investor risk aversion. At the same time, internal factors of enterprises (such as financial status, management decisions, and corporate governance structure) determine the market's expectations of future corporate earnings, which profoundly impacts asset valuation.

Traditional asset pricing models (such as CAPM, APT, and multi-factor models) provide an important theoretical basis for understanding the formation of asset prices, but their limitations are also becoming increasingly apparent. These models are usually based on the assumption of rational investors, and it is difficult to explain the impact of market anomalies and irrational behaviors on asset prices. With the rapid development of big data and artificial intelligence technologies, applying machine learning methods (such as neural networks and support vector machines) in asset pricing has significantly improved prediction accuracy. It can capture complex nonlinear relationships and the characteristics of high-dimensional data. However, machine learning models still face challenges such as black box problems, overfitting, and data quality, limiting their feasibility in financial markets.

Future asset pricing research must combine behavioral finance, data-driven methods, and explainable artificial intelligence to reflect market dynamics and investor behavior more comprehensively. At the same time, research should focus on improving the transparency and stability of models in high-dimensional data environments, avoiding overfitting, and enhancing the ability to explain market anomalies. In addition, with the increase in global economic uncertainty, asset pricing models need to integrate considerations of policy changes and socioeconomic risks to improve their applicability in actual investment decisions.

In short, asset pricing research is moving towards multidisciplinary cross-integration. Technological innovation and theoretical breakthroughs are expected to provide investors with more accurate and reliable analysis tools in the future, thereby promoting the healthy development of financial markets.

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