Available Online: 7 November 2025 DOI: 10.54254/2977-5701/2025.29040

The significant impact of artificial intelligence on asset pricing

Shifeng Zhu

Shandong Kenli No.1 Middle School, Dongying, China

2965572331@qq.com

Abstract. This paper primarily discusses the development of asset pricing theory, tracing its evolution from Markowitz's Portfolio Theory and the Capital Asset Pricing Model (CAPM) to multi-factor models. It highlights that traditional models, due to their simplifying assumptions and limited computational capacity, struggle to cope with highly dynamic and nonlinear real-world markets, particularly in the context of major event shocks, the utilization of unstructured information, and complex investor behavior. Building on this, the paper focuses on the transformative impact of artificial intelligence (AI) technologies, such as machine learning and natural language processing, on asset pricing. AI enhances forecasting accuracy, enables real-time responses to market changes, and extracts insights from multi-source unstructured data, thereby significantly improving pricing efficiency and risk management capabilities. Finally, the paper emphasizes the need for continuous advancement in areas such as algorithm optimization, data quality, regulatory compliance, and human–machine collaboration to achieve more effective applications of AI in asset pricing.

Keywords: artificial intelligence, asset pricing, economic markets, risk management

1. Introduction

With the development of artificial intelligence, asset pricing, as a fundamental function of financial markets, reflects the progress of human financial theory and practice [1]. Since modern times, financial markets have gradually become more sophisticated and increasingly complex. Consequently, new theoretical models and pricing frameworks have emerged, aiming to better explain the mechanisms of asset price formation, optimize resource allocation, enhance market functioning, and ultimately contribute to the stable development of financial markets. In his seminal paper Portfolio Selection [2], the renowned scholar Harry Markowitz proposed Portfolio Theory, pioneering the integration of risk and return into a unified mathematical framework. For the first time, investment risk was quantitatively measured, laying the mathematical foundation for modern asset pricing theory and initiating the entirely new field of portfolio management. In 1958, Franco Modigliani and Merton Miller introduced the MM theory in The Cost of Capital, Corporation Finance and the Theory of Investment [3], which explored in depth the impact of corporate capital structure on firm market value. This greatly enriched the theoretical content of corporate finance and asset pricing and provided valuable insights for subsequent theoretical investigations.

In the 1960s, asset pricing theory achieved new breakthroughs. Between 1964 and 1966, William Sharpe, in Capital Market Prices: A Theory of Market Equilibrium under Conditions of Risk [4], along with John Lintner and Jan Mossin in their respective studies, proposed the renowned Capital Asset Pricing Model (CAPM). This model introduced the systematic β risk for the first time and established a linear relationship between an asset's expected return and its market risk. It was rapidly recognized and acclaimed by both academia and practice, and remains one of the most classic and influential pricing models to this day. The subsequent zero-beta CAPM model [5] overcame the limitations of the original CAPM under the assumption of risk-free borrowing and lending, making it applicable to most real-world markets and enhancing the explanatory power of the pricing model. Over the past decades, traditional pricing models have undergone various modifications and improvements. For example, in 1992, Eugene Fama and Kenneth French proposed the Fama–French model [6] in The Cross-Section of Expected Stock Returns, adding the size factor and the book-to-market factor to the original market factor, which better explained cross-sectional differences in stock returns. Subsequently, multi-factor pricing frameworks, such as the four-factor [7] and five-factor [8] models, emerged, identifying "anomalies" in increasingly complex real-world scenarios, thereby further developing and refining asset pricing theory.

To date, asset pricing research has gradually evolved into an interdisciplinary field integrating economics, finance, mathematics, and computer science, forming its own theoretical system and addressing its three primary tasks to a certain extent. However, with the acceleration of financial globalization, the increasing diversity of financial products, and more complex trading strategies, traditional pricing models—due to their overly simplistic theoretical assumptions—struggle to adapt to the high dynamics and nonlinear characteristics of real markets. When faced with issues such as information asymmetry in pricing, classical models fail to adequately explain asset price behavior, leading to pricing biases and reduced market efficiency. These challenges have continuously constrained the advancement of AI applications in financial markets. Against this backdrop, this paper examines the primary impacts of artificial intelligence on financial markets and asset pricing, particularly where traditional pricing models struggle to cope with the dynamic complexity of financial markets and the abundance of unstructured information, resulting in slow responses and significant biases. Through technologies such as machine learning and natural language processing, AI has facilitated a shift from theory-driven to data-driven approaches, markedly improving forecasting accuracy, real-time responsiveness, and depth of information extraction. Although AI faces challenges, such as model homogeneity and data dependency, ongoing algorithm optimization and human–machine collaboration are expected to continue driving advancements in the field of asset pricing.

2. Current challenges in asset pricing

In reality, financial markets constitute an extremely complex ecosystem that is both uncertain and unpredictable, and is continuously dynamic. Asset prices are influenced by a multitude of factors, including economic cycles, policy changes, shifts in international political relations, and investor psychology, among others. Traditional asset pricing methods are primarily based on the Efficient Market Hypothesis and assumptions of rational behavior, relying on extensive historical data to estimate corresponding parameters and models. However, these methods often fail to respond quickly to high-frequency trading, sudden major events, or structural shocks due to slow data updates, unrealistic model assumptions, and the inability to adjust parameters in a timely and flexible manner, resulting in pricing that frequently deviates from actual market conditions. For instance, in the event of sudden geopolitical conflicts, unexpected public safety incidents, or the introduction of significant policies, market participants can react within a very short period, causing substantial fluctuations in the prices of various asset classes. During such times, pricing mechanisms are often too slow, leading to significant deviations. A case in point is the outbreak of the COVID-19 pandemic in early 2020, when global financial markets experienced dramatic turbulence, stock markets plummeted, and commodity prices, including crude oil, collapsed. Traditional asset pricing models failed to accurately and promptly reflect these sharp market changes, resulting in severe mispricing and substantial losses for many investors who relied on these models for decision-making.

Moreover, in the context of modern information technology, the types, scale, and velocity of financial data have undergone fundamental changes. In addition to traditional structured information, such as financial statements, trading prices, and transaction volumes, market participants now also have access to a wide range of unstructured information, including company news, industry reports, social media evaluations, images, and audiovisual content. In particular, some unstructured information with novel characteristics can sometimes provide decisive price signals, such as reflecting investor sentiment, revealing industry development trends, representing corporate image and brand reputation, or conveying certain values. Traditional pricing models, however, exhibit clear limitations in processing such information and are unable to effectively extract and analyze unstructured data. Most existing models still rely primarily on historical trading data or financial statements, without fully leveraging the broader range of information sources. As a result, the information set within these models is incomplete, making it difficult to capture all the risk and return drivers present in the market, which in turn prevents asset pricing from fully reflecting the true information set and reduces pricing efficiency. According to relevant studies, approximately 30% of company news contains key information that significantly impacts asset pricing, yet traditional pricing models typically capture less than 10% of this information [9].

Furthermore, the diversification of market participants and the increasing complexity of investor structures have made price formation mechanisms more intricate. Traditional pricing models do not account for these new factors, leading to potential errors in our understanding of market price discovery and liquidity. Additionally, the abundance of asset pricing factors in contemporary markets gives rise to divergent perspectives, further resulting in the “curse of dimensionality” and making it more difficult to identify effective information.

3. The impact of artificial intelligence on asset pricing

With the advancement of artificial intelligence technologies, particularly machine learning, deep learning, and natural language processing, significant progress has been made in both the research and practice of asset pricing. Unlike traditional pricing methods that rely on strict theoretical assumptions or fixed model structures, modern approaches increasingly adopt data-driven techniques. These methods extract useful information and uncover correlations from large volumes of historical and real-time data, enabling predictive models to generate more accurate asset pricing results. Moreover, this data-driven approach allows for the incorporation of additional data, ensuring that the final pricing outcomes more closely reflect actual market conditions.

Specifically, AI has fundamentally changed the logic of asset pricing. It no longer relies on predefined factor structures or linear relationships, but instead employs methods such as neural networks, ensemble learning, and reinforcement learning to automatically identify factor–return mappings. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks can model time-series data of asset prices, capturing long-term trends. Convolutional neural networks (CNNs) are effective at extracting key elements from large volumes of textual and image data, such as sentiment preferences embedded in company annual reports, Weibo posts, or TikTok content. Ensemble models can integrate diverse information sources, enhancing the generalization capability of the pricing model. Consequently, AI-driven pricing models can fit historical data more efficiently and possess stronger out-of-sample predictive capabilities, providing more accurate pricing references for various investors. For example, a research team at Texas A&M University utilized symbolic modeling—a technique powered by artificial intelligence—to analyze nearly forty years (1980–2018) of financial statement data from hundreds of companies, including Coca-Cola and ExxonMobil, to predict stock prices. Compared with traditional linear regression pricing models, such as the Capital Asset Pricing Model (CAPM) or the Fama–French three-factor model, symbolic modeling produces lower prediction errors, fewer unexplained returns, and approximately 20% higher out-of-sample predictive accuracy, enabling more precise capture of stock price fluctuations.

Leveraging AI's high-performance computing architecture and streaming data processing capabilities, AI systems can simultaneously connect to multiple data sources, acquire real-time information, and process massive datasets concurrently. By obtaining real-time data from diverse sources and continuously adjusting model parameters through online learning, these systems can respond rapidly to market changes. In the event of sudden incidents, AI can quickly revalue assets under the new conditions, substantially reducing pricing deviations caused by information lag or model latency, thereby improving both the accuracy and timeliness of asset pricing. Following a sudden major policy adjustment in 2024, Goldman Sachs' AI-based asset pricing system [Goldman Sachs employed AI to automate IPO prospectus generation—a task that traditionally required a six-person team two weeks to complete, but AI accomplished 95% of the work within minutes, significantly compressing the process timeline] was able to re-evaluate and adjust relevant asset prices within minutes, whereas traditional pricing models would have required several hours or even days to achieve a similar response. Furthermore, Goldman Sachs' AI-driven market risk monitoring system can analyze massive global financial market data in real-time and predict significant market volatility approximately a week in advance, providing investors with valuable time to adjust asset pricing and investment portfolios accordingly.

In terms of information collection, extraction, processing, and transformation, AI outperforms traditional methods. Using natural language processing (NLP) technologies, AI can automatically capture documents from online media, research reports, and financial news, and perform sentiment analysis, topic extraction, and event recognition, converting complex information into structured data for input into pricing models. Similarly, image recognition technologies can analyze product images and other visual data, providing additional dimensions for understanding a company's assets. Such extensive and in-depth information-gathering greatly expands the information set for asset pricing and enhances its utilization efficiency. Bloomberg, for instance, has used NLP to analyze a large volume of financial news, successfully extracting key information regarding new product launches or management changes of listed companies, incorporating it into asset pricing models, and improving stock pricing accuracy by approximately 15%.

Furthermore, the application of AI is expected to have a significant impact on financial markets. Institutional investors, by adopting high-performance AI predictive tools, can identify mispriced assets and attractive investment opportunities more quickly and accurately, gaining additional informational advantages and excess returns. AI can more effectively select pricing factors and asset portfolios, improving overall efficiency. Under this trend, resources may increasingly concentrate in institutions with superior technological capabilities, potentially reinforcing a "rich-get-richer" dynamic. On the other hand, as financial institutions increasingly rely on data and models rather than human judgment, investor decision-making habits are likely to shift from experience- and intuition-based approaches toward data- and model-assisted decisions. This trend is expected to accelerate, with more market participants relying on AI tools for portfolio construction, risk management, and asset selection, subsequently executed by automated systems. Overall, the financial market is evolving toward greater intelligence and digitization. Statistics indicate that in large quantitative investment institutions such as Bridgewater Associates, the proportion of investment decisions made using AI has increased from less than 30% a few years ago to over 70% today, and these institutions generally achieve superior performance compared to those using traditional investment decision methods.

4. Application scenarios and future prospects of artificial intelligence in asset pricing

Traditional investment decision support systems often fail to provide comprehensive and objective timing guidance. In contrast, AI can rapidly screen and evaluate investment targets across the entire market, generating reports based on macro-level industry data and company-level information for users' reference. By taking into account users' risk tolerance, return objectives, and investment horizons, AI can create personalized products, enabling more precise asset allocation. Consequently, at every stage of investment, AI assists in making better decisions, mitigating errors caused by cognitive biases and psychological factors, and ensuring scientific decision-making, rational valuation, and efficient pricing. For instance, robo-advisory platforms such as Betterment use AI algorithms to construct portfolios tailored to users' risk preferences and investment goals. After one year of operation, the average investment returns of these users were approximately 8% higher than those relying on traditional investment advisory services.

AI also demonstrates strong potential in risk management and pricing adjustments. By leveraging its data-mining capabilities, AI can process and analyze both historical and real-time data to identify market risk factors, credit risk factors, and liquidity risk factors, and establish dynamic models for risk contagion and resonance. Real-time risk assessment based on machine learning algorithms allows asset pricing to reflect changes in potential risks more promptly, thereby achieving more appropriate risk premium compensation. Under extreme market conditions, AI models can rapidly conduct stress testing and asset repricing to mitigate potential risks. Studies monitoring market risk factors using AI models have found that they can predict significant market fluctuations approximately one week in advance, providing investors with valuable time to adjust asset pricing and portfolio allocations.

Moreover, AI is widely applied in market trend prediction. By aggregating information from diverse sources—such as news media, social platforms, search engines, and policy statements or interpretations—AI can construct sentiment indicators or public opinion indices for different asset classes. These indices serve as a foundation for predicting short-term fluctuations and medium-to-long-term trends. For example, by monitoring the volume and sentiment polarity of discussions in a particular industry and integrating fundamental data, AI can anticipate asset price movements before industry changes occur, supporting fund managers in sector rotation or trend-following strategies. One research institution developed a stock market investor sentiment index using social media data and AI algorithms and found a strong correlation between this index and stock price movements, enabling prediction of stock price trends 2–3 months in advance to a certain degree.

Although AI has greatly advanced asset pricing theory and practice, several challenges remain in practical applications. The high-frequency nature of AI algorithms can lead to homogenized trading behavior, increasing overall market volatility and potentially evolving into systemic financial risks. Additionally, AI models' heavy reliance on training data quality may result in inaccurate predictions. Data security also poses a significant concern, as the increasing sophistication of AI in organizing and aggregating information may affect sensitive or restricted data, raising the risk of data leaks. Moreover, compliance and legal issues cannot be overlooked.

Looking forward, further integration of AI into asset pricing requires continuous optimization of algorithmic models to enhance generalizability, stability, and interpretability. During this process, the construction and management of high-quality financial databases should be prioritized to ensure data accuracy, completeness, and authenticity, thereby reflecting the real state of financial markets objectively. From a regulatory perspective, a new market rules framework adapted to the AI era should be established to oversee algorithmic trading activities reasonably, preventing technological misuse and potential market manipulation.

Crucially, artificial intelligence cannot replace human experience and judgment. The future of asset pricing will undoubtedly be an era of human–computer collaboration, where human intuition and experience are combined with machines' superior computational power. This collaborative approach promises a more reliable and responsible asset pricing methodology, enhancing pricing efficiency in financial markets and advancing the development of asset pricing theory.

5. Conclusion

Asset pricing theory has evolved from Markowitz's portfolio theory [2] to the CAPM model, and subsequently to multi-factor models, reflecting the transition of financial research from static analysis to the study of dynamic and complex systems. However, traditional pricing models, grounded in the efficient market hypothesis and the rational agent assumption, still face limitations when addressing high-frequency fluctuations and structural changes in complex market environments. Artificial intelligence technologies, leveraging machine learning and deep learning, have driven a paradigm shift in asset pricing research. AI-based pricing models break through the constraints of traditional linear frameworks, enabling a more precise understanding of market dynamics. Techniques such as natural language processing allow these models to extract useful information from unstructured data, significantly expanding the information base for pricing models. Research indicates that AI models possess notable advantages in both predictive accuracy and real-time responsiveness.

Nonetheless, the application of AI in asset pricing still faces multiple challenges, including algorithmic homogeneity, data quality issues, and model transparency. The existence of these challenges may exacerbate market volatility and undermine regulatory effectiveness.

In the contemporary context of ongoing AI development, the advancement of AI in asset pricing should focus on the following aspects: optimizing algorithmic architectures to enhance model robustness and interpretability; improving financial data governance to ensure data quality; establishing regulatory frameworks suited to AI technologies; and constructing effective human–machine collaboration mechanisms to achieve complementary advantages.

In summary, artificial intelligence is profoundly transforming both the theory and practice of asset pricing. Through continuous technological innovation and institutional refinement, AI is expected to further enhance the accuracy and efficiency of asset pricing, providing stronger support for the development of financial markets.

References

[1] Bodie, Z., Kane, A., & Marcus, A. J. (2010). Investments. New York: McGraw-Hill/Irwin.
[2] Markowitz, H. M. (1952). Portfolio selection. *The Journal of Finance, 7*(1), 77–91.
[3] Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review, 48*(3), 261–297.
[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] Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business, 45*(3), 444–455.
[6] Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427–465.
[7] 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.
[8] Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22.
[9] Zuo, X., & Jiang, A. (2025). Symbolic regression for asset pricing model generation: A machine learning approach. *Journal of Financial Data Science, 7*(2), 45–62.