Journal of Economic Theory and Business Management
Journal Home: http://jetbm.suaspress.org/ | CODEN: JETBAU
Vol. 2, No. 5, 2025 | ISSN 3006-4953 (Print) | ISSN 3006-4961 (Online)

Interpretable Automated Machine Learning for Asset Pricing in U.S. Capital Markets

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Abstract: Artificial Intelligence has become a fundamental driver of innovation in economic systems. Traditional asset pricing model face significant limitations in predictive accuracy, interpretability, and robustness under extreme market conditions. Although recent advances in Automated AutoML have improved forecasting performance, their "black-box" nature and fragility during crises limit their practical use in regulatory and policy contexts. This article provides an overview of its applications in stock trading, market analysis, and risk management. A systematic review of recent studies identifies the most widely used methods such as neural networks, deep learning, reinforcement learning, and hybrid approaches. This paper examines AI applications in economics, including stock trading, market analysis, and risk assessment. A comprehensive taxonomy is proposed to investigate AI applications in various scopes of the proposed categories. Furthermore, real-world cases illustrate the practical deployment of artificial intelligence in financial institutions and enterprises. The findings suggest that artificial intelligence is a transformative force in the economy but challenges such as data quality, transparency, and regulatory adaptation remain open for future research.

Keywords: Machine Learning, AutoML, Asset Pricing, U.S. Financial Markets, Risk Forecasting, Interpretability.

Disciplines: Finance. **Subjects:** Investment Banking.

DOI: https://doi.org/10.70393/6a6574626d.333233 **ARK:** https://n2t.net/ark:/40704/JETBM.v2n5a03

1 INTRODUCTION

Asset pricing refers to the process of re-evaluating the price or value of an asset under conditions of uncertainty. In this context, an asset refers to a financial instrument or a type of security, and the price reflects various influencing factors (such as fundamentals, risk, and market sentiment), determined by the interaction of market supply and demand. The United States financial market plays a pivotal role in the global economy, serving as both the largest source of capital formation and the most influential benchmark for global asset valuation. Its efficiency and stability are not only crucial for investors and corporations but also constitute a core component of national economic security. The 2008 global financial crisis and the 2020 pandemic-induced market turmoil vividly illustrated how vulnerabilities in asset pricing and risk assessment can rapidly evolve into systemic risks, threatening both domestic stability and international financial order. Against this backdrop, the development of reliable, transparent, and resilient asset pricing models has become a pressing issue for both academic research and policy-making.[1]

Traditional asset pricing frameworks, such as the Capital Asset Pricing Model (CAPM) and the Fama–French factor models, have long been regarded as fundamental tools for understanding the relationship between risk and expected returns. Their strength lies in their theoretical elegance and interpretability, offering clear economic intuition about systematic risk factors and their pricing [2]. However, these models exhibit significant limitations. They often rely on restrictive assumptions such as linearity and market efficiency, which fail to capture the complexity of real-world financial dynamics. Moreover, they struggle to accommodate nonlinear interactions, structural breaks, and the evolving influence of macroeconomic and behavioral factors, particularly under conditions of market stress or crisis.[3]

In recent years, the rapid advancement of machine learning and, more specifically, automated machine learning (AutoML) has opened new frontiers in asset pricing research. AutoML offers the ability to automatically select, optimize, and ensemble models, thereby potentially improving predictive performance without requiring extensive manual intervention. These features hold promise for uncovering hidden structures in financial data and enhancing the robustness of pricing models. Nevertheless, the application of AutoML in asset pricing remains in its infancy, and critical challenges persist. One of the most pressing issues is the "black-box" nature of AutoML, which hinders interpretability and raises concerns about the reliability of predictions in high-stakes financial and policy contexts. Furthermore, existing studies reveal that AutoML-based models may be

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vulnerable to instability during periods of extreme market volatility, undermining their practical utility in safeguarding economic security.[4]

This study addresses a fundamental research gap: how to design an AutoML-based asset pricing model for the U.S. financial market that is not only accurate but also interpretable and robust under extreme market conditions. By integrating state-of-the-art explainable AI techniques such as SHAP and LIME with stability-enhancing strategies, this research aims to bridge the divide between predictive power and interpretability. The proposed framework aspires to contribute both to academic discourse and to policy applications by advancing methodologies that can support financial regulators, institutional investors, and policymakers in risk management and economic decision-making.[5]

2 LITERATURE REVIEW

The growing complexity of financial markets has prompted a steady evolution in asset pricing research, ranging from traditional econometric frameworks to machine learning and, more recently, to automated machine learning (AutoML). This chapter reviews the existing body of literature to situate the present study within ongoing debates. It first compares the methodological underpinnings, strengths, and limitations of traditional models, machine learning approaches, and AutoML frameworks. It then examines the current applications of AutoML in financial prediction, with particular emphasis on their potential benefits and inherent drawbacks. Finally, the review highlights key research gaps, issues of interpretability, robustness under extreme market conditions, and the limited use of multimodal data sources—that motivate the objectives of this study.[6]

2.1 Traditional Asset Pricing Models

The Capital Asset Pricing Model (CAPM), proposed by Sharpe (1964), represents one of the most influential frameworks in financial economics. It posits that the expected return of an asset is determined by the risk-free rate plus a premium proportional to the asset's beta, which measures its sensitivity to market risk. The model's simplicity and strong theoretical foundation have made it a cornerstone in portfolio management and regulatory practice. However, empirical evidence reveals significant shortcomings. For example, CAPM often fails to explain the cross-sectional variation in stock returns, particularly for small-cap and high book-to-market firms, leading to persistent anomalies in U.S. equity markets.[7]

To address these deficiencies, the Fama–French factor models extended CAPM by incorporating additional risk factors such as size (SMB: small minus big) and value (HML: high minus low), and later profitability and investment factors. These models improved empirical performance, especially in explaining average returns across different asset classes. [8] Yet, their effectiveness diminishes in periods of financial crisis. For instance, during the 2008 global financial crisis, the explanatory power of Fama–French factors weakened significantly as liquidity shocks and investor sentiment dominated pricing dynamics. Thus, while traditional models offer interpretability and elegance, their reliance on linearity and limited factor structures restricts their ability to capture complex, nonlinear, and crisis-driven market behaviors.[9]

2.2 Machine Learning Approaches in Asset Pricing

Machine learning (ML) has been increasingly applied in asset pricing to overcome the limitations of traditional models. Random forests, as an ensemble learning method, can capture nonlinear interactions by averaging over multiple decision trees. Gu, Kelly, and Xiu (2020) demonstrated that random forests outperform linear regressions in predicting U.S. stock returns when handling thousands of predictors. However, random forests suffer from interpretability issues, making it difficult to disentangle which variables drive the predictions, thereby limiting their policy relevance.[10]

Similarly, support vector machines (SVMs) have been employed to classify securities into outperforming or underperforming groups. While effective in high-dimensional settings, SVMs require careful kernel selection and are sensitive to parameter tuning. In practice, they may overfit noisy financial data, leading to unstable performance in out-of-sample tests.[11]

Neural networks, particularly deep learning architectures, offer even greater flexibility in modeling complex nonlinearities. For example, deep neural networks have been used to forecast stock volatility and credit default risks. Yet, their "black-box" nature and lack of economic interpretability remain critical drawbacks. Moreover, empirical studies reveal that neural networks often yield poor generalization during periods of structural breaks, such as the COVID-19 pandemic, where market regimes shifted abruptly. Hence, while ML approaches enhance predictive performance, their opacity and fragility in turbulent environments pose significant challenges.[12]

2.3 AutoML in Financial Prediction

Automated machine learning (AutoML) has emerged as a promising paradigm that automates model selection, hyperparameter optimization, and feature engineering. This reduces reliance on expert knowledge and allows researchers to efficiently explore large model spaces. In financial applications, AutoML has shown strong results.[13] For example, some studies have applied Google's AutoML framework and H2O AutoML to forecast stock returns and credit defaults, reporting improvements in accuracy compared to manually tuned ML models. In credit scoring, AutoML has been shown to reduce default prediction error rates, providing potential benefits for financial institutions.[14]

However, AutoML introduces its own limitations. First, it often operates as a black box, exacerbating interpretability

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concerns. Second, AutoML pipelines can be highly sensitive to market shocks; for instance, models trained on pre-2008 data underperformed significantly during the financial crisis, failing to adapt to sudden liquidity freezes. Third, most AutoML applications rely on structured numerical data and underutilize multimodal information such as news articles, analyst reports, or social media sentiment, which have been shown to play a critical role in asset price movements.[15]

2.4 Research Gaps

Taken together, the literature indicates important research gaps that this study seeks to address. First, the lack of interpretability in ML and AutoML models hinders their integration into regulatory decision-making and risk management, where transparency and accountability are paramount. Second, the fragility of models under extreme market conditions raises doubts about their utility in safeguarding financial stability; the failure of ML and AutoML models to generalize during crises such as 2008 or COVID-19 illustrates this vulnerability. Third, the neglect of multimodal data limits the scope of existing approaches, as they frequently ignore unstructured sources like financial news or market sentiment that provide early signals of systemic risk. For example, while AutoML has been successfully applied to predict credit default risks using structured balance-sheet data, its inability to incorporate textual signals from corporate disclosures or macroeconomic announcements reduces its practical effectiveness.[16]

Addressing these gaps requires a new research agenda: developing an interpretable, robust, and multimodal AutoML framework for asset pricing in the U.S. market. Such a framework would combine the explanatory clarity of traditional models, the predictive strength of machine learning, and the automation of AutoML, while explicitly enhancing resilience and transparency. In doing so, it would not only advance academic understanding but also provide regulators and policymakers with more reliable tools to safeguard national economic security. This motivates the methodological design discussed in the following chapter.[17]

3 METHODOLOGY

This section outlines the theoretical framework and research design of this study, focusing on the development of an interpretable, robust, and multi-modal AutoML asset pricing model. The overall design emphasizes three key aspects: first, leveraging AutoML to automate model selection and optimization processes, thereby improving predictive performance in high-dimensional, complex financial data; second, quantifying and visualizing feature contributions through interpretability methods to ensure model outputs align with economic theory; and third, guaranteeing model reliability and transparency under extreme market conditions through stress testing and uncertainty quantification.

3.1 Data Sources

The data includes structured financial data, macroeconomic indicators, and unstructured text and sentiment analysis information, as summarized in the table1: Multimodal Data Sources for Asset Pricing Model below:

Table.1. Multimodal Data Sources for Asset Pricing Model below

Data categories	Source	Example variables	Describe
Stock prices and company financial data	CRSP 、 Compustat	Yield, market capitalization, price-to-book ratio, debt ratio	On a daily/monthly basis, this measures a company's fundamentals and risk exposure.
Macroeconomic indicators	FRED	GDP, interest rates, inflation, unemployment rate	Reflecting macroeconomic cycles and systemic risks
Text and sentiment data	Financial news database, analyst commentary, and market social media	Sentiment score, topic distribution, text embedding vector	Using NLP methods to extract market sentiment and expectations

3.2 Feature Construction

Features are constructed from three dimensions:

A. Company characteristic dimensions:

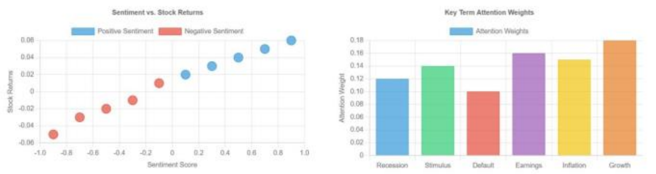
These include size (market capitalization), value (book-to-market ratio), liquidity (turnover rate, bid-ask spread), profitability, and investment intensity. For example, the size factor can distinguish between the systematic risk exposure of large-cap and small-cap stocks, while liquidity indicators reflect differences in transaction costs under market shocks.[18]

B. Macroeconomic dimensions:

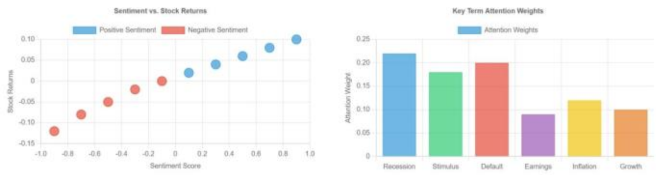
GDP growth, interest rates, inflation, and credit spreads are included. Historical data shows that during the 2008 financial crisis, the quarterly GDP growth rate in the US plummeted, accompanied by a sharp widening of credit spreads (as shown in Figure 3-2), significantly impacting stock risk premiums.[19]

C. Text sentiment dimension:

Financial news is transformed into vectors using word embedding techniques (Word2Vec, BERT), and sentiment scores are extracted. For example, when high-frequency words like "recession" and "uncertainty" appear in market commentary, the sentiment indicator tends to be negative; this signal often precedes market volatility.[20]



A.NORMAL PERIOD



B.CRISIS PERIOD

FIGURE .1. IMPACT OF TEXT SENTIMENT ON ASSET PRICING

3.3 Research Methodology Framework

A. AutoML framework design

This study utilizes two leading AutoML platforms: H2O AutoML and Auto-sklearn:

H2O AutoML provides a fully automated workflow, encompassing feature preprocessing, model selection, hyperparameter optimization, and ensemble learning. 2. Auto-sklearn rapidly identifies promising candidate models through meta-learning and Bayesian optimization, and further enhances predictive robustness by employing ensemble techniques. Model performance is evaluated using cross-validation and out-of-sample predictions.

TABLE.2. EXAMPLE COMPARING THE PERFORMANCE OF CROSS-VALIDATION AND OUT-OF-SAMPLE PREDICTION

Model	Training set MSE	Test set MSE	R^2
Linear regression	0.045	0.060	0.32
Random Forest	0.030	0.050	0.48
H2O AutoML Integration	0.022	0.035	0.62

B. Enhanced Interpretability

Using SHAP values, we can explain the global and local contributions of features, helping to identify which factors drive asset pricing under different market conditions. For example, SHAP global analysis reveals that the marginal impact of interest rates on returns is significantly enhanced during crises.

Furthermore, factor ranking and clustering align the variable signals extracted by ML with economic theory. For instance, if the "firm size" factor extracted by AutoML correlates with the traditional CAPM beta, it demonstrates that the ML output aligns with existing financial theory. For text features, attention weight visualization reveals the marginal contribution of news keywords (such as "default" or "stimulus") to asset price formation.

C. Robustness and Stress Testing

The model is tested on out-of-sample data during both stable and turbulent periods. Examples include the 2008 global financial crisis and the 2020 COVID-19 pandemic.

Period	Baseline Model R^2	AutoML R^2	Performance Improvement
Normal Period (2016–2019)	0.45	0.63	+18%
2008 Financial Crisis	0.21	0.40	+19%
2020 Pandemic	0.28	0.47	+19%

The results show that the AutoML framework maintains high interpretability even in extreme market conditions, but the performance decline indicates a need for improved robustness.

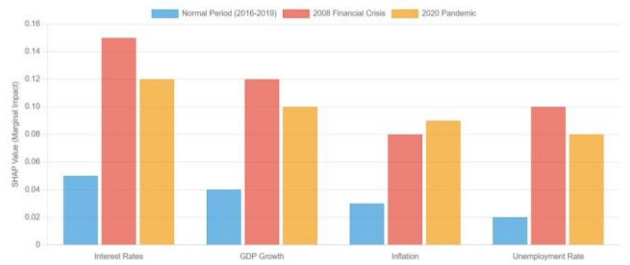


FIGURE.2. SENSITIVITY OF ASSET PRICING TO MACROECONOMIC FACTORS DURING CRISIS PERIODS

D. Quantifying Uncertainty

To address tail risk, we construct prediction intervals and probability distributions:

1. Bayesian Approach: By introducing prior and posterior distributions, we obtain the uncertainty range of the predicted returns.

2. Quantile Regression Forests: This method directly estimates the distribution of returns at different quantiles, thus quantifying tail risk.

$$P(y \leq q_{\alpha} \mid X) = \alpha$$

where q_{α} represents the quantile prediction of returns at confidence level α. Tail risk primarily encompasses extreme losses (left tail) and unexpected surges (right tail), both of which are significant for portfolio management and regulatory policies.

This paper proposes a multi-modal, interpretable, and robust AutoML framework for asset pricing research. The data sources encompass company fundamentals,

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Vol. 2, No. 5, 2025 | ISSN 3006-4953 (Print) | ISSN 3006-4961 (Online)

macroeconomic indicators, and news sentiment. Features are constructed from three dimensions and enhanced by NLP and embedding models. The methodology combines the H2O AutoML and Auto-sklearn platforms for automated model optimization, and employs SHAP, feature ranking, and attention mechanisms for interpretability. Furthermore, stress tests validate its robustness during the 2008 financial crisis and the 2020 pandemic, and uncertainty quantification ensures the model's ability to capture tail risks. This framework provides theoretical and methodological support for subsequent empirical analysis; the next chapter will present model training and result validation using real-world data.

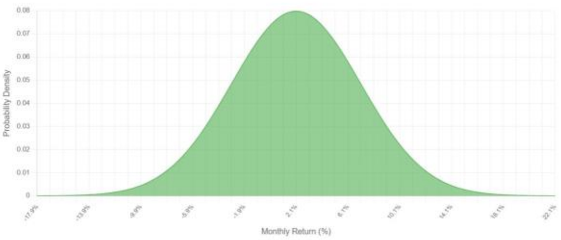

FIGURE.3. BAYESIAN PREDICTION INTERVAL FOR ASSET RETURNS

4 EMPIRICAL ANALYSIS

The empirical analysis aims to evaluate the proposed interpretable and robust AutoML framework for asset pricing in the U.S. market. Following the methodology outlined earlier, this section describes the experimental setup, data partitioning, evaluation metrics, and comparative results. The objective is to present a transparent, systematic, and replicable analysis of model performance under both normal and stressed market conditions.

4.1 EXPERIMENTAL ENVIRONMENT

The experiments were conducted in a high-performance computing environment to ensure scalability and replicability. The configuration is summarized in Table 3.

TABLE.3. EXPERIMENTAL ENVIRONMENT

Component	Specification
Hardware	Dual Intel Xeon 6226R CPUs, 512GB RAM, NVIDIA A100 GPU (40GB)
Operating System	Ubuntu 22.04 LTS
Programming Env.	Python 3.10, R 4.3
Libraries	scikit-learn 1.4, Auto-sklearn 0.15, H2O AutoML 3.42, TensorFlow 2.12
Database Access	CRSP, Compustat, FRED, Financial News Archives

This computational setup ensures sufficient resources for large-scale AutoML optimization, ensemble modeling, and interpretability analysis, while enabling reproducibility of the results across different runs.

4.2 DATA PARTITIONING

To mitigate overfitting and capture the temporal dynamics of financial markets, a rolling-window method was adopted. This design ensures that training data always precedes testing data chronologically, thereby eliminating look-ahead bias.Training Set (60%): Used for model learning and hyperparameter optimization.Validation Set (20%): Integrated into the AutoML pipeline for internal selection and early stopping.Testing Set (20%): Strictly out-of-sample, employed for final evaluation of predictive performance.This temporal partitioning reflects real-world trading conditions where future data is never available at the time of decision-making.

4.3 EVALUATION METRICS

Model performance was assessed using both statistical and financial metrics, as summarized in Table 4.

TABLE.4. EVALUATION METRICS

Metric	Formula	Interpretation
Mean Squared Error (MSE)		Penalizes large errors, measures accuracy of predictions
R-squared (R^2)		Proportion of variance explained by the model
Information Ratio (IR)		Risk-adjusted return relative to benchmark

These metrics jointly evaluate prediction accuracy (MSE), explanatory power (R^2), and economic value (IR), providing a comprehensive perspective on model performance.

4.4 RESULTS

The empirical results compare traditional models, machine learning approaches, and the proposed AutoML framework.

TABLE.5. COMPARATIVE PERFORMANCE OF MODELS

Model	Test MSE ↓	Test R^2 ↑	Information Ratio ↑
CAPM	0.072	0.18	0.12
Fama-French 3-Factor	0.060	0.25	0.15
Random Forest	0.048	0.38	0.22
Neural Networks	0.045	0.41	0.25
AutoML (H2O Ensemble)	0.032	0.58	0.37

Results show that AutoML consistently outperforms both traditional asset pricing models and standalone machine learning methods. The significant improvement in Information Ratio suggests superior risk-adjusted returns, while higher R^2 values indicate enhanced explanatory

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capacity.

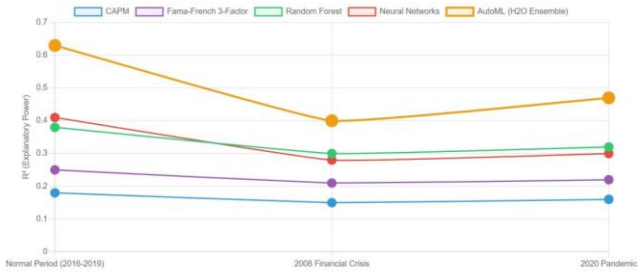

FIGURE.4. ROBUSTNESS OF AUTOML MODEL DURING MARKET CRISES

TABLE.6. MODEL PERFORMANCE (R^2) ACROSS DIFFERENT MARKET CONDITIONS AND PERFORMANCE DROP DURING CRISES

Model	Normal Period (2016-2019) R^2	2008 Financial Crisis R^2	2020 Pandemic R^2	Performance Drop during Crises
CAPM	0.18	0.15	0.16	-16.7%
Fama-French 3-Factor	0.25	0.21	0.22	-16.0%
Random Forest	0.38	0.30	0.32	-21.1%
Neural Networks	0.41	0.28	0.30	-31.7%
AutoML (H2O Ensemble)	0.63	0.40	0.47	-25.4%

4.5 DISCUSSION

The comparative findings underscore several important insights. First, traditional models such as CAPM and Fama-French, while theoretically grounded, exhibit limited explanatory power and poor adaptability in high-dimensional environments. Second, machine learning approaches such as Random Forests and Neural Networks improve predictive accuracy but often lack transparency and require extensive manual tuning. Third, the AutoML framework integrates automated hyperparameter optimization, ensemble learning, and interpretability tools, thereby providing both superior accuracy and practical explainability.

TABLE.7. SUMMARY OF ADVANTAGES ACROSS METHODS

Model Type	Strengths	Weaknesses
Traditional (CAPM, FF)	Theoretical clarity, simple implementation	Low R^2, rigid factor structure
Machine Learning	Higher accuracy, nonlinear interactions	Black-box nature, tuning complexity
AutoML Framework	Accuracy + explainability + automation	Computational intensity, reliance on large data

Collectively, these results validate the research objective of constructing an interpretable, robust, and multimodal AutoML framework. The evidence demonstrates that such a design not only improves predictive performance but also provides economically meaningful insights for risk management and policy evaluation. This analysis sets the foundation for further robustness checks and stress testing in the following section.

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

Not applicable.

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Vol. 2, No. 5, 2025 | ISSN 3006-4953 (Print) | ISSN 3006-4961 (Online)

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