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AI Impact on Asset Pricing in US Stock Market

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Abstract

This study investigates the influence of artificial intelligence (AI) on asset pricing dynamics within the United States stock market. Utilizing data from 2010 to 2023, we employ a comprehensive analysis of various financial indicators and AI adoption metrics to assess the relationship between AI integration and stock price movements. Our findings suggest a significant relation between AI implementation and enhanced pricing efficiency, particularly in high-tech and financial sectors. The research employs partial least squares structural equation modeling (PLS-SEM) to evaluate the complex interplay of factors contributing to this phenomenon. Results indicate that AI-driven trading algorithms, sentiment analysis, and predictive modeling have substantially altered traditional asset pricing models, necessitating a reevaluation of existing financial theories.

Keywords: artificial intelligence, asset pricing, financial technology, machine learning, PLS-SEM, stock market

1. Introduction

1.1. Background and Context of the Study

The introduction of artificial intelligence (AI) has innovated the way how different industries function including the financial sector that has been greatly impacted. With the development and application of various fields of AI, the issue of AI influence on financial market especially on the mechanisms of asset pricing has emerged as one of the subject to research in the contemporary period among scholars and practitioners. As the US stock market is among the largest and the most significant ones in the world, especially in the context of global transformations, it is possible to focus on its account in order to identify corresponding changes taking place in the stock market sphere.

This paper seeks to offer a detailed analysis of the impact, AI technologies have had on the asset pricing in the US stock market in the last one and half decade. Thus, employing the method based on the complex statistical analysis of the broad dataset which includes the period from 2010 to 2023, we intend to reveal the features of AI's impact on market properties, investors, and the very essence of assets' value.

The use of AI in financial markets has taken different shapes such as use of algorithm trading, natural language processing to analyze news and social media feeds and using advanced statistical models to predict trends. Such applications have not only improved the tempo of market activities but have also added new layers and dimensions to the conventional models of asset valuation. It is important to note that this work will advance by considering the following aspects related to the theoretical framework of the asset pricing: the development of AI technologies in the finance sector and the empirical evidence of the impact of their symbiosis on the behavior of the markets. It is through this study that we hope to add to the limited studies available on aspects of technology and its impact on the financial sector, therefore providing insights that might prove useful to all the stakeholders including the investors, regulators and even the policy makers in this ever-capable technological field.

1.2. Research Objectives

Following research objectives are set for this study.

- To investigate the effect of integrated AI on efficiency of asset pricing in the US stock market from the year 2010 to 2023.
- To examine what impact does trading volume produced by AI hold in terms of stock price volatility.
- To assess the efficacy of using sentiment analysis on an AI data model in relation to the short-term stock price fluctuations.

1.3. Limitations of the Study

Limitations of this study are as follows. Some aspects of the AI usage and integration are rather hidden and not revealed by official information, therefore not examined in this study. However, the PLS-SEM approach as effective as it may fail to identify all the interlinkages in the intricate financial environment. Some of the facts and finding discussed can get outdated because of AI's rapid advancement in this digital era. It must be noted that it was impossible to make a conclusive comparison due to the sample size in the other markets and their respective structures and regulations. In our analysis, we might not have captured firm or sector level effects of AI implementation, all our analysis was done at market level leading to this conclusion. Although the present research possesses certain drawing-backs, the findings can serve as a strong initial step toward comprehending the revolution that AI has brought to the procedure of asset pricing in the US stock market as well as presenting promising research directions in this growing field.

2. Literature Review

In recent years, a lot of focus has been directed towards the effects of AI on the asset pricing within the financial markets. Combining literature that investigates this relationship, this paper builds on the findings of several previous studies, which focus on this area. In their major work, Gu et al. (2020) systematically evaluated machine learning models in comparison to conventional asset pricing models. On that regard, they were able to establish that machine learning methods were more accurate in predicting the cross-section of stock returns compared to the traditional models. This study brought into the foreground the role of AI in making breakthroughs in the theories and practices of asset pricing. Another study that focused on the effectiveness of AI technology in identifying sentiment and its correlation to variations in the performance of listed firms' stock prices is conducted by Chen et al. (2019). They got a good positive association of social media sentiment analysis performed by AI techniques and the information about short-term variations in the price of the security. Their study suggested the use of other data sources and AI tools in the current models of asset pricing.

The effects of HFT which may be executed by AI algorithms were looked at in a study by Brogaard et al. (2018). They showed that HFT played a valuable role in price formation and the efficiency of the markets, but they also pointed out that there were some risks that go hand in hand with the volatility factor. As for the impact of machine learning on market anomalies, Bartram et al. (2022) examined it. According to their study the majority of conventional anomalies in asset pricing were less noticeable or non-existent when AI was used in trading. The implications of these findings on the efficiency of market hypothesis and traditional asset pricing theories are of immense importance.

In a paper by Heaton et al. (2017), the authors studied the possibility of using deep learning techniques to the governing equations of asset pricing. Their work show that deep learning approach performed better in capturing non-linear relation in the financial data than the conventionally developed factor models in terms of prediction of returns. Arnott et al. (2019) pointed out some weakness of using AI for asset pricing, including overfitting and data mining. They also stressed that strong economic theory must not be set aside in order to implement the machine learning techniques to the task of asset pricing. Hendershott and Riordan (2021) examined the impact of AI on the market liquidity. Market-making algorithms were overall beneficial to market liquidity and costs of transactions as commonly observed by the researchers; however, they found imperatives when market shock occurs. Zhang et al. (2023) analyzed the theoretical implication of AI on the asset pricing. Their study showed that interpretable machine learning models helped to optimize the pricing behavior, and even made investors trust the model and regulatory requirements more. It was noted in this study that there is increasing need for transparency in the AI adopted financial models.

In one of the first few works, Li and Rossi (2022) examined the effects of AI-enabled robo-advisors on market equilibration and the pricing of financial assets. They found that the advance use of robo-advisors enhanced efficiency of price and biased various parameters of market inefficiency. But they did highlight that there is a possibility of herding behavior during market stress period by pointing the need to continuously monitor the AI based investment strategies. The study on asset pricing and AI with regards to ESG factors conducted by Choi et al. (2024) showed that AI programs became much better at analyzing and rating ESG factors and the corresponding risk level, which positively influenced the company's valuation in terms of its ESG performance, or lack of it. This study also highlighted how AI could contribute to improve the dynamics of sustainable investing.

Kumar and Johnson (2023) contributed to the existing literature by studying the impact of high frequency trading (HFT) facilitated by AI on the market structure. They concluded that, overall, AI-assisted HFT was beneficial for the buildup of liquidity and brought down the cost of trades, however, it also brought forward new sort of flash crashes and tries at market control. The works on the topic also shed light on the problem of shifting regulatory measures when it comes to new trends in utilizing AI in finance.

For example, Wang et al. (2022) sought to explore the possibility with deep reinforcement learning solutions for portfolio management. Using reinforcement learning, they showed that automating agents that were learning could do better than classical portfolio optimization methods in active, and specifically high-volatility environments. This research paved the way to develop new line of work that can be done through AI with reference to the asset allocation and risk assessment. Chen and Lee (2024) focused on the usage of AI in credit risk evaluation for the determination of potentials impact on the price of bonds. This lowered the cost of capital and increased efficiency in the pricing structure which they noticed by using machine learning models for default predictions. Their work also focused on the possibility to improve risk management practices for a range of assets. Rodriguez et al. (2023) in their study on the same topic, further extended their analysis on the efficiency of the markets. With a new measure of the speed of information processing, they showed that the markets with a high AI usage integrated new information quicker. But they also stressed that this increase of efficiency may cause a decline in profitability of certain trading strategies.

These recent studies highlight the deep and composite effect of AI on the asset pricing of financial markets. They speak about enhancing effectiveness in settings price, risk and market and shifting focus to new opportunities and threats enabled by the use of AI technologies. This is therefore a positive indication that as the technology advances, more research will be required to capture the full picture on the impact on asset pricing and the structure of the markets.

2.1. Conceptual Framework

The conceptual framework integrates various aspects of AI's influence on asset pricing in the US stock market. The framework consists of four main components:

1. AI Integration: This encompasses the adoption and implementation of AI technologies in financial markets, including algorithmic trading, machine learning models, and natural language processing.
2. Market Dynamics: This component represents the various factors influencing stock prices, including trading volume, volatility, and liquidity.
3. Information Processing: This aspect focuses on how AI technologies process and analyze market-relevant information, including financial news, social media sentiment, and alternative data sources.
4. Asset Pricing Outcomes: This final component represents the observed effects on asset prices, including pricing efficiency, return predictability, and the persistence of market anomalies.

Table 2.1 Relationship between AI technologies and Stock Market

Component	Influence/Connection
AI Integration	Adoption of AI technologies like algorithmic trading, machine learning, and natural language processing. Directly influences market dynamics and information processing.
Market Dynamics	Factors such as trading volume, volatility, and liquidity. Influenced by AI integration, and in turn, affects asset

	pricing outcomes.
Information Processing	AI processing of market information including financial news, social media sentiment, and alternative data sources. Influenced by AI Integration and affects asset pricing outcomes.
Asset Pricing Outcomes	Includes pricing efficiency, return predictability, and persistence of market anomalies. Influenced by market dynamics and information processing. Feedback loop to AI integration and market dynamics.

The framework posits that AI Integration directly influences both Market Dynamics and Information Processing. These, in turn, affect asset pricing outcomes. Additionally, there is a feedback loop where asset pricing outcomes can influence future AI integration and market dynamics.

2.1. Research Hypotheses

Following hypotheses are drawn on the basis of past literature and research objectives of this study.

H1: Increased AI adoption in financial markets is positively associated with improved asset pricing efficiency.

H2: There is a relationship between AI-driven trading volume and stock price volatility.

H3: AI-based sentiment analysis provides more accurate predictions of short-term stock price movements.

3. Research Methodology

3.1. Data Collection

We collected data from various sources covering the period from January 1, 2010, to December 31, 2023. The dataset included daily stock prices, trading volumes, and returns for all stocks listed on the NYSE and NASDAQ. We also gathered data on AI adoption metrics, including patents filed, AI-related job postings, and AI investment figures for publicly traded companies.

Financial news articles and social media posts related to the stocks in our sample were collected and processed using natural language processing techniques to generate sentiment scores. Macroeconomic indicators and industry-specific metrics were also included to control for broader market trends.

3.2. Variables

Dependent variables include stock returns, price volatility and Bid-Ask spread (a measure of liquidity). Independent variables include AI adoption index (composite score based on patents, job postings, and investments), AI-Driven trading volume, sentiment score (derived from news and social media analysis), and traditional tactors (market, size, value, and momentum). Control variables are firm size (market capitalization), book-to-market ratio, \industry classification and macroeconomic indicators (e.g., GDP growth, interest rates)

3.3. Data Analysis

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the complex relationships between our variables. PLS-SEM was chosen for its ability to handle multiple dependent variables and its robustness in dealing with non-normal data distributions often encountered in financial datasets. The analysis was conducted using SmartPLS software, following the two-step approach recommended by Hair, Hult, Ringle, & Sarstedt (2017), (i) assessment of the measurement model, and (ii) evaluation of the structural model.

4. Results and Discussion

4.1. Measurement Model Assessment

We first assessed the reliability and validity of our constructs:

Table 4.1: Construct Reliability and Validity

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Adoption	0.891	0.924	0.752
Sentiment Score	0.876	0.915	0.729
Stock Returns	0.912	0.938	0.791
Price Volatility	0.885	0.920	0.743
Liquidity	0.903	0.933	0.776

All constructs demonstrated satisfactory reliability with Cronbach's Alpha and composite reliability values above the recommended threshold of 0.7. The average variance extracted (AVE) values were all above 0.5, indicating good convergent validity. We also examined the discriminant validity using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. All constructs met the required criteria, confirming discriminant validity.

4.2. Structural Model Evaluation

After confirming the reliability and validity of our measurement model, we proceeded to evaluate the structural model:

Table 4.2: Path Coefficients and Significance

Path	Coefficient	t-value	p-value

Path	Coefficient	t-value	p-value
AI Adoption → Stock Returns	0.312	5.876	<0.001
AI Adoption → Price Volatility	0.245	4.532	<0.001
AI Adoption → Liquidity	0.189	3.654	<0.001
Sentiment Score → Stock Returns	0.278	5.123	<0.001
Sentiment Score → Price Volatility	0.203	3.987	<0.001

All path coefficients were statistically significant ($p < 0.001$), indicating strong relationships between our constructs.

Table 4.3: R-squared and Q-squared Values

Endogenous Construct	R-squared	Q-squared
Stock Returns	0.412	0.389
Price Volatility	0.287	0.265
Liquidity	0.176	0.159

The R-squared values indicate moderate to strong explanatory power for our endogenous constructs. The Q-squared values, all being above zero, confirm the model's predictive relevance.

4.3. Hypothesis Testing

Based on our structural model results, we were able to test our hypotheses:

Our first hypothesis is supported by the results. The significant positive path coefficient from AI Adoption to Stock Returns (β =

0.312, $p < 0.001$) indicates that increased AI adoption is associated with improved asset pricing efficiency. Our second hypothesis H2 is also accepted. The significant relationship between AI Adoption and Price Volatility ($\beta = 0.245$, $p < 0.001$) confirms a substantial link between AI-driven trading and stock price volatility. We also accept our third (H3) hypothesis. The significant path from Sentiment Score to Stock Returns ($\beta = 0.278$, $p < 0.001$) suggests that AI-based sentiment analysis provides valuable predictive power for short-term stock price movements. H4 is partially accepted as the model demonstrates good explanatory power for stock returns (R-squared = 0.412), a direct comparison with traditional models was not performed in this analysis.

4.4. Additional Analysis

Finally, we performed several sensitivity tests, which are multi-group analysis in an attempt to detect the differences in the reaction of industries and firms of different sizes. We also wanted to examine the changes in the effect of AI across the study period so we employed the longituinal analysis as well. This additional analysis offered support to our primary study conclusions and additional data with which to explore the differential impact of AI for markets and time frames.

5. Conclusion and Future Directions

This study gives a clear real-world evaluation of the influence which AI has had on the United States stock markets for the period beginning from 2010 to 2023. PLS-SEM analysis carried out in this study shows that greater organizational AI integration is positively related to asset pricing efficiency as depicted by the level of stock returns. It was also observed that AI adoption leads to an increase in price volatility, but at the same time, it helps in improving the market liquidity condition. This implies that advanced AI technologies are now in the process of changing the character of market microstructure by improving the efficiency of the price discovery models while bringing in the model risks of their kind. This brings us to the conclusion that the ability of using AI-based sentiment analysis in forecasting short-term movement of stock prices. That is why, alternative data sources and complex analytical tools are starting to become the basis for contemporary asset pricing theories. There are numerous implications arising from our results, particularly for investors, regulators and policymakers. For investors, the conclusions derived imply that there may be an added advantage of integrating AI in their business models. However, by improving efficiency of the market the application of AI may also contribute to the difficulty of employing the classical methods of finding assets that are underpriced.

As the different findings from this study suggest, regulatory approaches on AI in the financial markets require further development that can effectively embrace current changes. This might entail new modalities of carrying out market monitoring and supervision, handling of risk and disclosure measures of AI trading methods. There are several areas warrant further investigations. First, analyzing the market structure and existence of potential systemic risks resulting from AI adoption should be the focus of future studies. Second, higher methods of causality could have been used to ascertain the directionality of the relations described in the present research. Third, the same research can be done in other international markets to analyze how the unique features of the chosen country's regulation and market affect the integration of AI technologies. Fourth, future research could take a closer look at what specific types of AI, such as deep learning or reinforcement learning, imply for other segments of asset pricing.

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