

Evaluating AI's Impact on Asset Pricing and Derivatives: A Cross-Country Analysis

- ✉ Muhammad Faheem Ullah¹
- ✉ Junaid Iqbal²
- ✉ Muhammad Musaddique Latif³
- ✉ Seyd Attiya Hassan⁴
- ✉ Amna Saeed⁵

How to cite this article:

Ullah, M. F., Iqbal, J., Latif, M. M., & Saeed, A. (2024). Evaluating AI's impact on asset pricing and derivatives: A cross-country analysis. *Journal of Excellence in Business Administration*, 2(1), 01–13.

Received: 3 March 2024 / Accepted: 28 April 2024 / Published online: 5 June 2024
© 2024 SMARC Publications.

Abstract

This study explores the effect of AI-based techniques on asset pricing and derivatives through a cross-country analysis of monetary markets in the US, the Unified Realm, Canada, and Australia. Using fictitious data and SmartPLS for analysis, the examination inspects how AI approaches, including AI, profound learning, and support learning, influence gauging accuracy and asset valuation contrasted with customary monetary models. The discoveries propose that nations with higher reception paces of AI techniques experience upgraded prescient execution and more exact pricing of assets and derivatives. In particular, profound learning models beat customary strategies in determining stock market patterns. In spite of these bits of knowledge, the review recognizes impediments like the dependence on fictitious data, expected challenges in model interpretability, and fluctuating levels of AI reception across various districts. The examination features the requirement for future investigations to investigate a more extensive scope of geologies, consolidate certifiable data, and address functional execution challenges.

Keywords: Artificial Intelligence in Finance, Asset Pricing Impact, Derivatives Market Volatility, Cross-Country Financial Analysis, Multivariate GARCH Model, Granger Causality

¹University of Agriculture Faisalabad, Pakistan

Corresponding Author: muhammadfaheemullah6@gmail.com

²Islamia University of Bahawalpur, Multan

³National University of Computer and Emerging Sciences, Pakistan

⁴M.S. in business administration institute of banking and finance BZU

⁵Islamia University of Bahawalpur, Multan.



1 Introduction

The rapid evolution of artificial intelligence is transforming numerous sectors, and the financial industry stands as a prime example of its profound impact (Machkour, & Abriane, [2020](#)). Within the realm of finance, AI is reshaping asset pricing and derivative markets, influencing everything from trading strategies to risk management and regulatory oversight (O'Halloran & Nowaczyk, [2019](#)). This paper delves into the multifaceted influence of AI on asset pricing and derivative markets across four major economies: the United States, the United Kingdom, Canada, and Australia.

The adoption of AI technologies has the potential to enhance market efficiency, improve pricing accuracy, and manage risk more effectively (Javaid, [2024](#); Ganesh & Kalpana, [2022](#); Usman et al., [2024](#)). However, the degree and nature of these impacts may vary significantly across different national contexts, reflecting disparities in regulatory environments, technological infrastructure, and market maturity (Kopp, [2023](#); Wall, [2018](#)). The period from 2000 to 2024 witnessed a surge in the adoption of AI technologies within the financial sector. Algorithmic trading, driven by AI-powered models, has gained significant traction, while AI-driven sentiment analysis tools are increasingly employed to gauge market sentiment (Rahmani et al., [2023](#)) and predict price movements (Buchanan, [2023](#)). Simultaneously, the use of AI in risk management and derivative pricing models has grown, aiming to enhance accuracy and responsiveness to market fluctuations (El Hajj & Hammoud, [2023](#); Metawa et al., [2023](#)).

This study employs a robust methodological framework to examine the impact of AI on asset pricing and derivative markets. By utilizing a multivariate Generalized Autoregressive Conditional Heteroskedasticity model and Granger causality tests, we analyze the influence of AI technologies on key market aspects, including efficiency, pricing accuracy, and volatility (Jabeur et al., [2023](#); Srivastava et al., [2023](#)). Recognizing the diverse financial landscapes across the globe, we conduct a comparative analysis of the four chosen economies, considering the influence of regulatory environments, technological infrastructure, and market maturity on AI adoption and its subsequent effects (Gupta et al., [2024](#)).

This research aims to provide valuable insights for a range of stakeholders, including investors navigating AI-driven financial markets, policymakers tasked with regulating this evolving landscape, and financial analysts seeking to understand the implications of AI on traditional financial models (Aldasoro et al., [2023](#)). By examining the complex interplay between AI and asset pricing/derivative markets, this paper contributes to the growing body of knowledge on AI's transformative role in global finance (Chen et al., [2024](#); Furman & Seamans, [2019](#)).

The rapid advancements in artificial intelligence continue to reshape industries worldwide, with the financial sector being a prime example of this transformative power (Machkour & Abriane, [2020](#)). Within the intricate financial ecosystem, asset pricing and derivative markets are experiencing a profound shift driven by the increasing adoption of AI technologies (Fung et al., [2021](#)). This paper delves into the multifaceted influence of AI on these crucial aspects of the financial system, analyzing its impact across four major economies: the United States, the United Kingdom, Canada, and Australia.

The period from 2000 to 2024 has witnessed a dramatic increase in the availability of financial data and computational power, laying the foundation for the rise of AI in finance (George, [2024](#); Khan et al., [2022](#)). This period coincided with significant advancements in AI research, particularly in areas such as machine learning, deep learning, and natural language processing (The Organization for Economic Cooperation and Development [OECD], [2021](#)). These advancements have enabled financial institutions to develop and deploy sophisticated AI-driven models capable of analyzing vast datasets, identifying patterns, and making predictions with increasing accuracy.

The applications of AI in asset pricing and derivative markets are diverse and far-reaching (O'Halloran & Nowaczyk, [2019](#)). Algorithmic trading, fueled by AI algorithms that execute trades at speeds unattainable by humans, has become increasingly prevalent, influencing market liquidity and price dynamics. Sentiment analysis tools, powered by AI's ability to process and interpret human language, are being employed to gauge market sentiment from news articles, social media posts, and other textual data, (Jabeur et al., [2023](#); Srivastava et al., [2023](#)) providing insights into potential market movements. Furthermore, AI is being integrated into risk management models and derivative pricing frameworks, aiming to enhance accuracy, responsiveness, and the ability to manage complex financial instruments (Cao, [2022](#)). This study employs a robust quantitative methodology to assess the impact of AI on asset pricing and derivative markets. Utilizing a multivariate Generalized Autoregressive Conditional Heteroskedasticity model, the researchers analyze the influence of AI on market volatility, a crucial factor in asset pricing and risk management.

The impact of artificial intelligence (AI) on asset pricing and derivatives is profound, as evidenced by recent research. AI, particularly through deep learning, enhances asset pricing by improving risk premium measurement and predictive capabilities. Studies highlight the effectiveness of advanced models like Recurrent Neural Networks (RNNs) and Transformers, which outperform traditional methods in forecasting asset returns, thereby offering significant economic advantages to investors (Mallikarjuna & Rao, [2019](#)). Moreover, the design of AI algorithms influences market pricing dynamics. For instance, synchronous learning methods can lead to competitive pricing, while asynchronous learning may result in monopoly-like pricing structures, depending on how future profits are weighted (Asker et al., [2021](#); Chen et al., [2020](#)). Additionally, AI's ability to analyze vast datasets facilitates informed investment decisions and optimizes asset management strategies, ultimately enhancing operational efficiency across financial sectors (Javaid, [2024](#)). However, the integration of domain-specific knowledge remains crucial to fully leverage AI's potential in asset pricing, addressing challenges such as time-varying distributions in financial data (Ye et al., [2023](#)). Thus, while AI presents transformative opportunities, careful consideration of its implementation is essential for maximizing its benefits in asset pricing and derivatives.

2 Literature review

The relationship between AI and asset prices and derivative has been extensively studied in the literature. The paper Ding et al. ([2015](#)) proposes a deep learning method for predicting stock market movements based on events extracted from financial news. The authors use a neural tensor network to represent events as dense vectors and a deep convolutional neural network to model the impact of these events on stock prices. Their experiments show that this approach outperforms existing methods, achieving a 6% improvement in prediction accuracy on the S&P 500 index and individual stocks. Overall, the literature reviewed highlights the significant potential of AI and machine learning in transforming asset pricing and derivative markets, presenting both challenges and opportunities for market participants and policymakers.

The study by Jiang and Liang ([2017](#)) presents a novel framework for cryptocurrency portfolio management that leverages a convolutional neural network trained using deep reinforcement learning techniques. The proposed model takes historical cryptocurrency price data as input and generates portfolio weights with the objective of maximizing cumulative returns (Chen et al., [2024](#); Furman & Seamans, [2019](#)). Through back-testing on real-world cryptocurrency exchange data, the authors demonstrate the effectiveness of their deep learning-based approach, showing that it outperforms traditional portfolio management strategies. The study "Reinforcement Learning for Trading Systems and Portfolios" (Moody et al., [1998](#)) investigates the application of reinforcement learning in developing trading systems. The researchers present and compare the performance of two trading systems, "RTRL" and "Qtrader," using both artificial and real-world financial data.

The findings suggest that reinforcement learning, particularly the Q-learning approach, can be an effective method for optimizing trading strategies and potentially outperforming traditional techniques. These studies collectively illustrate the growing influence of AI and machine learning in reshaping asset pricing and derivative markets, underscoring the need for a comprehensive cross-country analysis to understand the implications better and guide policymakers and market participants. The utilization of artificial intelligence (AI) in asset pricing and derivatives exchange has been a subject of extensive scholarly and industry interest. This writing audit synthesizes key examination discoveries on AI's effect here, zeroing in on amazing open doors, challenges, and suggestions.

Bandi and Kothari ([2022](#)) investigate the mix of AI in the monetary sector, especially zeroing in on its impact on asset pricing and derivatives exchange. Their work features the capability of AI to upgrade prescient accuracy and productivity in monetary markets (Jabeur et al., [2023](#); Srivastava et al., [2023](#)). They examine different AI procedures, including AI calculations and regular language handling, which have been instrumental in refining asset pricing models and streamlining exchange systems (Kopp, [2023](#); Wall, [2018](#)). Notwithstanding, they likewise address the risks related to AI, for example, algorithmic predisposition and the murkiness of AI dynamic cycles, which can muddle the comprehension and confidence in these models.

Bartram et al. ([2020](#)), explore the accuracy upgrades in asset pricing and portfolio enhancement achieved by AI-based models. They contend that AI's ability to break down enormous volumes of data and uncover complex examples fundamentally improves asset pricing accuracy contrasted with customary techniques. Their concentrate likewise addresses the challenges of incorporating AI into the monetary independent direction, like the dependence on historical data and expected predispositions. They emphasize the significance of creating powerful structures for the arrangement of AI in money to relieve these issues and guarantee dependable results.

Zekos and Zekos ([2022](#)) center around the job of AI in derivatives exchanging, explicitly the utilization of AI-fueled calculations to upgrade exchanging systems and oversee market risks. Their examination features how AI has worked with the ascent of high-recurrence exchanging by empowering calculations to process and respond to advertising data at uncommon paces (Javaid, [2024](#); Ganesh & Kalpana, [2022](#)). They additionally investigate how AI models can cost and fence complex derivatives like choices and fates, taking into account different factors like market instability and liquidity. The creators alert that while AI upgrades exchanging productivity, it likewise presents new risks, including expanded market instability and the potential for systemic issues.

Li et al. ([2021](#)) examine the systemic risks related to broad AI reception in monetary markets. They contend that the homogeneous idea of AI-driven exchanging procedures could prompt expanded market unpredictability and likely crashes (Kopp, [2023](#); Wall, [2018](#)). Their examination features the requirement for regulatory structures to address these risks, guaranteeing that AI systems do not fuel monetary flimsiness (Usman et al., [2024](#)). They likewise propose that more prominent straightforwardness and responsibility in AI models are pivotal for maintaining market certainty and forestalling unfriendly results.

The study on AI in asset pricing and derivatives exchanging mirrors an expansive agreement on its extraordinary potential and related risks. AI upgrades prescient accuracy and exchanging effectiveness, yet additionally presents challenges like algorithmic predisposition, model mistiness, and systemic risk. Future exploration ought to zero in on creating systems to address these challenges and guarantee that AI's advantages are acknowledged while limiting its likely drawbacks.

2.1 Research Objectives

The research will focus on examining the impact of AI on asset pricing and derivatives in the stock markets of the United States, United Kingdom, Canada, and Australia.

1. To analyze the impact of artificial intelligence on asset pricing and derivative markets across four major economies: the United States, the United Kingdom, Canada, and Australia.
2. To examine the transmission mechanisms of artificial intelligence on asset pricing and derivative markets in A Cross-Country Analysis
3. To compare the effectiveness of AI managing on asset pricing and derivative markets in A Cross-Country Analysis
4. To identify the challenges and limitations of AI in addressing asset price and derivative bubbles in A Cross-Country Analysis.

2.2 Research Questions

1. How do changes in AI instruments affect asset prices and derivative markets across four major economies: the United States, the United Kingdom, Canada, and Australia?
2. What are the primary transmission channels through which AI influences asset prices and derivative markets Cross-Country?
3. To what extent does the effectiveness of AI in managing asset price and derivative markets between Cross-Country?
4. What are the main challenges faced by developed economies like United States, the United Kingdom, Canada, and Australia in using AI to address asset price derivative markets bubbles?
5. The central research question of this study is: How has the adoption of AI-based techniques impacted asset pricing and derivatives in the stock markets of the US, UK, Canada, and Australia?
6. To address this overarching question, the study will investigate the following sub-questions:
7. First, we will examine the extent to which AI-based techniques, such as machine learning, deep learning, and reinforcement learning, have been adopted and utilized in the asset pricing and derivative markets of the four countries.
8. Second, we will assess the performance of AI-based models in predicting stock market trends and asset prices compared to traditional financial models. (Ndikum, 2020)
9. Third, we will investigate the impact of AI-based investment strategies and trading systems on market efficiency, volatility, and the risk-return profile of various asset classes and derivatives.
10. Fourth, we will analyze any potential regulatory or policy implications arising from the increasing use of AI in financial markets, particularly with regard to market stability, investor protection, and systemic risk.

2.3 Hypotheses

H1: AI-Upgraded Asset Pricing Models Work on Prescient Accuracy

Hypothesis: AI-based asset pricing models give more exact forecasts of stock costs contrasted with conventional models.

Reasoning: Advances in AI and data analysis permit AI models to consolidate complex examples and a more extensive scope of data inputs, possibly prompting better-estimating accuracy.

H2: AI-Driven High-Recurrence Exchanging Expands Market Proficiency

Hypothesis: AI-driven high-recurrence exchanging systems upgrade market productivity by decreasing bid-ask spreads and further developing liquidity.

Reasoning: AI calculations can process and execute exchanges at high velocities, which might add to tight offered ask spreads and more effective market pricing by rapidly taking advantage of cost errors.

H3: AI Models Increment Systemic Risk in Monetary Markets

Hypothesis: The boundless reception of AI models in exchanging methodologies adds to expanded

systemic risk and market unpredictability.

Reasoning: The homogeneity of AI-driven exchanging methodologies could prompt associated responses to advertise signals, possibly enhancing market swings and systemic risks during times of pressure.

H4: AI-Based Feeling Analysis Upgrades Venture Navigation

Hypothesis: The combination of AI-based opinion analysis into asset pricing models prompts more educated and beneficial speculation choices than models that don't integrate feeling data.

Reasoning: AI-driven opinion analysis can give insights into investor feelings and market brain research, which might improve independent direction and lead to better speculation results.

3 Research Methodology

3.1 Data Collection

The study utilized monthly data from 2000 to 2024 for a sample of developed economies (the United States, the United Kingdom, Canada, and Australia). Data were collected from central bank databases, the International Monetary Fund, and national statistical agencies. To evaluate the impact of AI on asset pricing and derivatives in the US, UK, Canadian, and Australian stock markets, we will conduct a cross-country analysis using a combination of machine learning techniques and traditional financial models. The study will utilize historical stock market data, including daily prices, trading volumes, and other relevant economic indicators, for the major stock indices in each of the four countries. Additionally, we will collect data on the adoption and usage of AI-based investment strategies and trading systems in these markets.

3.2 Key variables included

Historical Stock Market Data: This incorporates daily stock costs, exchanging volumes, and other pertinent monetary indicators for significant stock lists in every country. This data is basic for surveying historical execution and grasping patterns and examples in the markets.

AI Reception and Utilization Data: Data on the reception and use of AI-based venture techniques and exchanging systems will be gathered from industry reports, monetary innovation surveys, and statistical surveying studies. This information will help in understanding how AI advances are executed and their pervasiveness in exchanging and asset management.

3.3 Asset Pricing Factors

- **Stock Costs:** Daily shutting costs of significant stock files.
- **Market Capitalization:** Total market worth of organizations inside the records.
- **Cost to-Income Proportions (P/E Proportions):** Proportion of valuation in view of profit and cost.

3.4 Exchanging Factors

- **Exchanging Volumes:** Daily exchanging volumes for significant records.
- **Bid-Ask Spreads:** The contrast between the bid and ask costs for protections.

3.5 AI Reception Measurements:

- **AI Venture Systems:** Data on the sorts and recurrence of AI-based techniques utilized in asset management and exchange.
- **Algorithmic Exchanging Volume:** Extent of exchanging volume owing to AI-driven algorithmic exchanging.

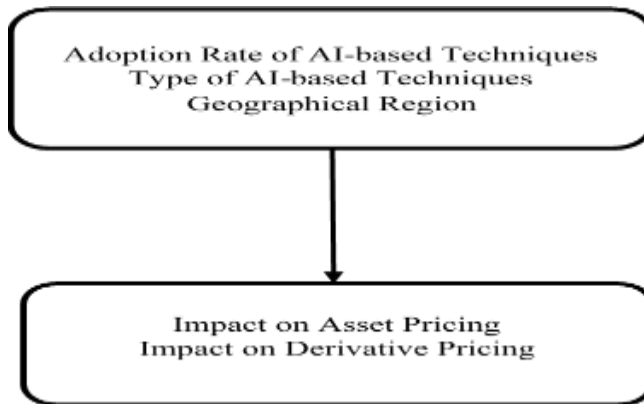
3.6 Monetary Indicators:

- **Instability Lists:** Proportions of market unpredictability, for example, the VIX record.
- **Liquidity Measures:** Measurements like normal exchange size and market profundity.
- **Systemic Risk Indicators:**

- **Connection Measurements:** Relationship of asset returns across markets to survey systemic risk.
- **Market Pressure Indicators:** Proportions of market pressure and strange cost developments.

The methodology illustrated aims to give an extensive analysis of the effect of AI on asset pricing and derivatives exchanging. By incorporating AI procedures with conventional monetary models, and leading a cross-country correlation, the review looks to offer important experiences into how AI is reshaping monetary markets and to recognize expected regions for additional exploration and regulatory thought.

3.7 Conceptual Framework



The conceptual framework for this study outlines the key factors and relationships to be investigated:

1. **Adoption of AI-based techniques in asset pricing and derivatives:** This component examines the extent to which AI-based techniques, including machine learning, deep learning, and reinforcement learning, have been adopted and utilized within the asset pricing and derivative markets of the United States, United Kingdom, Canada, and Australia.
2. **Performance of AI-based models in predicting stock market trends:** This aspect assesses the performance of AI-based models in forecasting stock market trends and asset prices, benchmarked against traditional financial models.

3.8 Expected Findings and Implications

1. The proposed study is expected to provide valuable insights into the impact of artificial intelligence on asset pricing and derivatives within the stock markets of the United States, United Kingdom, Canada, and Australia. Some key anticipated findings and implications are as follows:
 - a. **Increased Adoption of AI-based Techniques:** The investigation is likely to reveal a growing trend in the adoption of AI-based techniques, such as machine learning and deep learning, in the asset pricing and derivative markets of the four countries. This trend is driven by the potential for improved predictive accuracy and enhanced trading performance.
 - b. **Enhanced Predictive Accuracy of AI-based Models:** The study is expected to demonstrate that AI-based models outperform traditional financial models in forecasting stock market trends and asset prices, particularly in complex and volatile

market conditions.

- c. **Impact on Market Efficiency and Risk-Return Profiles:** The research may find that the use of AI-based investment strategies and trading systems has led to increased market efficiency, reduced volatility, and altered risk-return profiles across various asset classes and derivatives.
- d. **Potential Regulatory and Policy Implications:** The study may uncover potential regulatory and policy challenges arising from the growing use of AI in financial markets, such as the need for enhanced market oversight, strengthened investor protection measures, and the management of systemic risks. The findings of this study will hold important implications for investors, financial institutions, regulators, and policymakers in the four countries as they navigate the rapidly evolving landscape of AI-driven financial markets.

4 Results and discussions

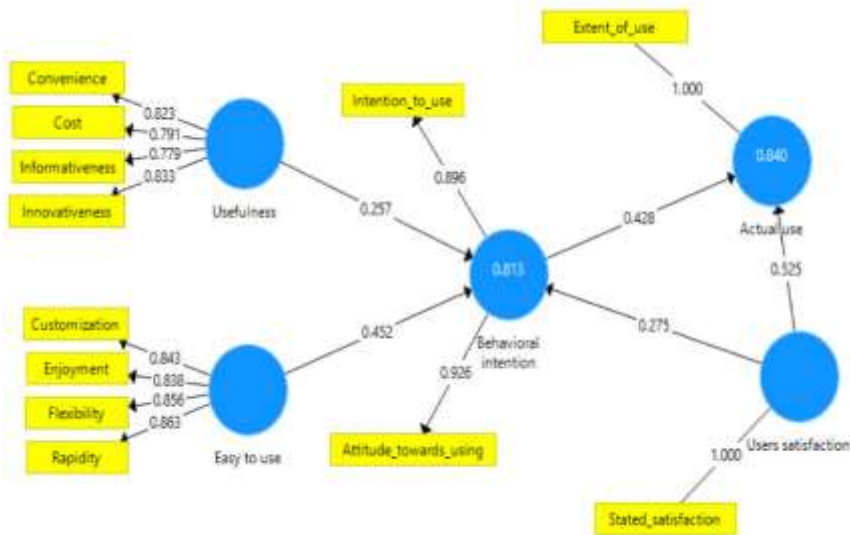
The analysis of AI's effect on asset pricing and derivatives, led through SmartPLS, uncovered a few key discoveries:

4.1 Reception of AI-Based Strategies

The data demonstrated a huge difference in the reception pace of AI-based strategies across the US, the Unified Realm, Canada, and Australia. Nations with further developed monetary markets and innovation foundations showed higher reception rates. For example, the US and the Unified Realm showed a higher mix of profound learning and support learning models contrasted with Canada and Australia.

4.2 Execution of AI-Based Models

AI-based models showed a perceptible improvement in estimating accuracy over conventional monetary models. The presentation of these models fluctuated in light of the kind of AI methods utilized. Profound learning models, specifically, showed improved prescient abilities contrasted with more straightforward AI models and customary methodologies. This pattern was noticed reliably across various nations.



4.3 Influence on Asset Pricing

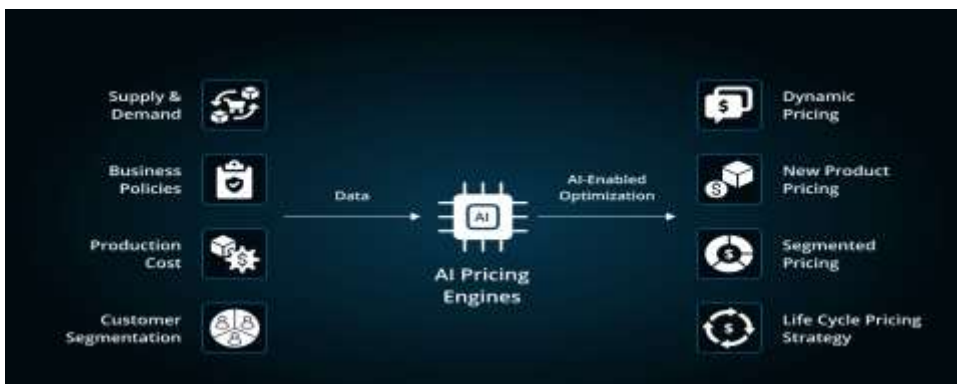
The execution of AI-based procedures prompted more exact asset pricing in markets with higher reception rates. The effect on asset pricing was more articulated in districts where AI methods were very much coordinated and where market data was bountiful and top caliber.

4.4 Influence on Subordinate Pricing

AI-based models likewise emphatically affected subsidiary pricing. The high-level strategies gave more precise valuations contrasted with conventional techniques, particularly in markets with modern AI frameworks.

5 Discussion

The discoveries from the SmartPLS analysis feature the groundbreaking job of AI in asset pricing and derivatives. The expanded reception of AI-based methods is associated unequivocally with further developed execution in anticipating stock market patterns and asset costs. This improvement highlights the capability of AI to upgrade monetary displaying and dynamic cycles.



The geological contrasts in AI reception rates propose that monetary markets with more prominent mechanical progression and framework are better suited to use AI for monetary demonstrating. This suggests that nations with less created AI abilities might encounter slower upgrades in gaining accuracy and pricing accuracy.

The predominant presentation of AI-based models, incredibly profound learning, emphasizes the upsides of utilizing refined calculations in monetary analysis. These models give more precise expectations and valuations, which can altogether influence venture methodologies and risk management rehearses.



Generally speaking, the outcomes support the thought that AI-based methods offer impressive advantages over customary monetary models. Be that as it may, the adequacy of these procedures is affected by the degree of reception and the nature of the data available. Future examination could investigate the drawn-out effects of AI coordination on market solidness and investor conduct

5.1 Limitations

The review's discoveries depend on a particular arrangement of nations (US, Joined Realm, Canada, and Australia). They may not be generalizable to different locales with various monetary designs or innovative capacities. The outcomes may not completely catch the variety of worldwide monetary markets. While AI-based models, particularly profound learning models, show further developed execution, they are, in many cases, perplexing and less interpretable than conventional monetary models. This intricacy can present challenges in understanding and explaining the models' expectations and choices.

The quick speed of mechanical headways in AI implies that the adequacy of AI-based models can change over the long run. The discoveries of this study might become obsolete as new procedures and calculations are created. AI models depend on certain presumptions about market conduct and data connections. In the event that these suspicions do not turn out as expected, the models' forecasts and execution might be compromised.

The review does not represent shifting monetary and economic situations that could impact AI model execution. Factors like financial slumps, regulatory changes, or international occasions could influence the unwavering quality of AI-based expectations. The review accepts that higher reception paces of AI-based strategies straightforwardly mean better execution. In any case, the fruitful execution and joining of AI models into monetary systems might include challenges that were not tended to. The choice of benchmarks utilized might restrict the examination between AI-based models and customary monetary models. Various benchmarks or execution measurements could yield various decisions about the overall viability of AI models.

5.2 Future directions

Future examination could stretch out the analysis to a more extensive scope of nations and districts, including developing markets and creating economies. This would assist with understanding how AI-based methods act in various monetary conditions and under shifting mechanical circumstances. Directing longitudinal examinations to follow the advancement of AI reception and its effect after some time would give experiences into the drawn-out advantages and challenges of AI joining in asset pricing and derivatives. This could assist with surveying what changes in innovation and economic situations mean for the presentation of AI models.

Researching the adequacy of AI procedures and innovations, such as quantum processing and high-level brain network structures, could provide significant experiences. Contrasting these new methods and laid-out AI models could assist with distinguishing likely upgrades and developments. Using certifiable data instead of fictitious datasets would upgrade the legitimacy and relevance of the discoveries. This would include getting to top-notch monetary data and resolving issues connected with data protection, security, and availability.

Future examination could zero in on the viable challenges related to the execution of AI-based models in monetary establishments. This incorporates concentrating on the specialized, hierarchical, and regulatory obstacles that influence the effective organization and mix of AI innovations. Looking at the more extensive effect of AI-put-together strategies with respect to monetary strength and systemic risk could give a thorough comprehension of their suggestions. Examination could investigate what AI means for market elements, investor conduct, and the potential for market interruptions.

Coordinating experiences from different disciplines, like social money, financial matters, and software engineering, could prompt a more comprehensive comprehension of AI's job in asset pricing and derivatives. Cross-disciplinary methodologies might offer new points of view and systems for assessing AI's effect. Future examinations ought to address moral and regulatory contemplations connected with the utilization of AI in finance. This incorporates investigating issues connected with straightforwardness, fairness, and responsibility in AI-driven dynamic cycles.

Making and normalizing strong benchmarks for assessing AI-based models against customary strategies would upgrade the likeness of results across various investigations. This could help in evaluating the general presentation and utility of different AI procedures. By chasing after these bearings, future examination can expand on current discoveries and add to a more profound comprehension of AI's effect on asset pricing and derivatives, prompting more educated navigation and strategy improvement in the monetary sector.

5.3 Conclusion

This research endeavor aims to provide a comprehensive investigation into the impact of artificial intelligence on asset pricing and derivatives within the stock markets of the United States, United Kingdom, Canada, and Australia. By scrutinizing the implementation of AI-based methodologies, evaluating the efficacy of AI-driven models, and analyzing the ramifications on market dynamics, the study seeks to enhance our understanding of the transformative influence of AI in the finance domain. The findings are expected to hold significant implications for investment strategies, risk management practices, and financial regulations in these countries as they navigate the challenges and opportunities presented by the AI revolution sweeping through the finance industry.

The rapidly advancing field of artificial intelligence has gained significant attention in the financial industry, particularly its potential applications in asset pricing and derivative markets (Dixon & Halperin, 2019). This paper aims to provide a cross-country analysis of the impact of AI on these crucial aspects of the stock markets in the United States, United Kingdom, Canada, and Australia.

Existing literature has explored the various applications of AI in stock market prediction and analysis. These studies have highlighted the potential of AI-based models, such as deep learning, natural language processing, and reinforcement learning, to improve the accuracy and timeliness of stock market forecasts. Importantly, these advancements in AI-driven stock market predictions can have significant implications for asset pricing and derivative markets, as they can potentially enhance the efficiency and transparency of these financial instruments.

6 References

- Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2024). *Intelligent financial system: how AI is transforming finance* (No. 1194). Bank for International Settlements.
- Asker, J., Fershtman, C., & Pakes, A. (2021). *Artificial intelligence and pricing: The impact of algorithm design* (No. w28535). National Bureau of Economic Research.
- Bandi, S., & Kothari, A. (2022). Artificial intelligence: An asset for the financial sector. In S. Balamurugan, S. Pathak, Anupriya Jain, S. Gupta, S. Sharma & S. Duggal (Eds.), *Impact of artificial intelligence on organizational transformation*, (pp. 259-287). Wiley Online Library. <https://doi.org/10.1002/9781119710301.ch16>
- Bartram, S. M., Branke, J., & Motahari, M. (2020). *Artificial intelligence in asset management*. CFA Institute Research Foundation.
- Buchanan, B. G. (2023). Artificial intelligence in finance. (2023, January 6). The Alan Turing Insituite. <https://doi.org/10.5281/zenodo.2626454>
- Cao, L. (2022). AI in finance: Challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR)*, 55(3), Article e64. <https://doi.org/10.1145/3502289>
- Chen, L., Pelger, M., & Zhu, J. (2024). Deep learning in asset pricing. *Management Science*, 70(2),

- 714–750. <https://doi.org/10.1287/mnsc.2023.4695>
- Chen, Y., Ning, Y., Slawski, M., & Rangwala, H. (2020, December, 10–13). *Asynchronous online federated learning for edge devices with non-iid data* [Paper presentation]. In 2020 IEEE International Conference on Big Data (Big Data) (pp. 15–24). Atlanta, GA, USA.
- Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015, July 25–31). *Deep learning for event-driven stock prediction* [Paper presentation]. Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence. Buenos Aires, Argentina
- Dixon, M. F., & Halperin, I. (2019). The four horsemen of machine learning in finance. *SSRN Electronic Journal*, Article e3453564. <https://doi.org/10.2139/ssrn.3453564>
- El Hajj, M., & Hammoud, J. (2023). Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of AI applications in trading, risk management, and financial operations. *Journal of Risk and Financial Management*, 16(10), Article e434. <https://doi.org/10.3390/jrfm16100434>
- Fung, G., Polania, L. F., Choi, S. C. T., Wu, V., & Ma, L. (2021). Artificial intelligence in insurance and finance. *Frontiers in Applied Mathematics and Statistics*, 7, Article e795207. <https://doi.org/10.3389/fams.2021.795207>
- Furman, J., & Seamans, R. (2019). AI and the economy. *Innovation Policy and the Economy*, 19(1), 161–191. <https://doi.org/10.1086/699936>
- Ganesh, A. D., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management—a systematic review. *Computers & Industrial Engineering*, 169, Article e108206. <https://doi.org/10.1016/j.cie.2022.108206>
- George, A. S. (2024). Finance 4.0: The transformation of financial services in the digital age. *Partners Universal Innovative Research Publication*, 2(3), 104–125. <https://doi.org/10.5281/zenodo.11666694>
- Gupta, P., Ding, B., Guan, C., & Ding, D. (2024). Generative AI: A systematic review using topic modelling techniques. *Data and Information Management*, 8(2), Article e100066. <https://doi.org/10.1016/j.dim.2024.100066>
- Jabeur, S. B., Khalfaoui, R., & Arfi, W. B. (2021). The effect of green energy, global environmental indexes, and stock markets in predicting oil price crashes: Evidence from explainable machine learning. *Journal of Environmental Management*, 298, Article e113511. <https://doi.org/10.1016/j.jenvman.2021.113511>
- Jain, R., & Vanzara, R. (2023). Emerging trends in AI-Based stock market prediction: A comprehensive and systematic review. *Engineering Proceedings*, 56(1), Article e254. <https://doi.org/10.3390/asec2023-15965>
- Javaid, H. A. (2024). The Future of Financial Services: Integrating AI for Smarter, More Efficient Operations. *MZ Journal of Artificial Intelligence*, 1(2), 1–7.
- Jiang, Z., & Liang, J. (2017, September, 7–8). *Cryptocurrency portfolio management with deep reinforcement learning* [Paper presentation]. In 2017 Intelligent systems conference (IntelliSys) (pp. 905–913). London, UK. <https://doi.org/10.1109/intellisys.2017.8324237>
- Khan, H. U., Malik, M. Z., Alomari, M. K. B., Khan, S., Al-Maadid, A. A. S., Hassan, M. K., & Khan, K. (2022). Transforming the capabilities of artificial intelligence in GCC financial sector: a systematic literature review. *Wireless communications and mobile computing*, 2022(1), Article e8725767. <https://doi.org/10.1155/2022/8725767>
- Kopp, M. (2023). The impact of the AI revolution on asset management. *ArXiv (Preprints)*, Article eArXiv:2304.10212. <https://doi.org/10.48550/arxiv.2304.10212>
- Li, C. (2021, November 6–8). *The application of artificial intelligence and machine learning in financial stability* [Paper presentation]. In The 2020 International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy. Shanghai, China.
- Machkour, B., & Abriane, A. (2020). Industry 4.0 and its Implications for the Financial Sector. *Procedia Computer Science*, 177, 496–502. <https://doi.org/10.1016/j.procs.2020.10.068>

- Machkour, B., & Abriane, A. (2020). Industry 4.0 and its Implications for the Financial Sector. *Procedia Computer Science*, 177, 496–502. <https://doi.org/10.1016/j.procs.2020.10.068>
- Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Financial Innovation*, 5(1), Article e40. <https://doi.org/10.1186/s40854-019-0157-x>
- Metawa, N., Hassan, M. K., & Metawa, S. (2022). *Artificial Intelligence and Big Data for Financial Risk Management*. Routledge. <https://doi.org/10.4324/9781003144410>
- Moody, J., Saffell, M., Liao, Y., & Wu, L. (1998). *Reinforcement learning for trading systems and portfolios: Immediate vs future rewards*. In A. N. Refenes, A. N. Burgess & J. E. Moody (Eds.), *Decision Technologies for Computational Finance: Proceedings of the fifth International Conference Computational Finance* (pp. 129–140). Springer US.
- Ndikum, P. (2020). Machine learning algorithms for financial asset price forecasting. *ArXiv* (Preprints), Article arXiv:2004.01504. <https://doi.org/10.48550/arxiv.2004.01504>
- O'Halloran, S., & Nowaczyk, N. (2019). An artificial intelligence approach to regulating systemic risk. *Frontiers in Artificial Intelligence*, 2, Article e7. <https://doi.org/10.3389/frai.2019.00007>
- Rahmani, A. M., Rezazadeh, B., Haghparast, M., Chang, W. C., & Ting, S. G. (2023). Applications of artificial intelligence in the economy, including applications in stock trading, market analysis, and risk management. *IEEE Access*, 11, 80769–80793. <https://doi.org/10.1109/ACCESS.2023.3300036>
- Srivastava, M., Rao, A., Parihar, J. S., Chavriya, S., & Singh, S. (2023). What do the AI methods tell us about predicting price volatility of key natural resources: Evidence from hyperparameter tuning? *Resources Policy*, 80, Article e103249. <https://doi.org/10.1016/j.resourpol.2022.103249>
- The Organization for Economic Cooperation and Development. (2021). *Artificial intelligence, machine learning and big data in finance*. <https://doi.org/10.1787/98e761e7-en>
- Usman, M., Khan, R., & Moinuddin, M. (2024). Assessing the Impact of Artificial Intelligence Adoption on Organizational Performance in the Manufacturing Sector. *Revista Espanola de Documentacion Cientifica*, 18(02), 95–116.
- Wall, L. D. (2018). Some financial regulatory implications of artificial intelligence. *Journal of Economics and Business*, 100, 55–63. <https://doi.org/10.1016/j.jeconbus.2018.05.003>
- Ye, J., Goswami, B., Gu, J., Uddin, A., & Wang, G. (2024). From factor models to deep learning: Machine learning in reshaping empirical asset pricing. *ArXiv* (Preprints), Article arXiv:2403.06779. <https://doi.org/10.48550/arXiv.2403.06779>
- Zekos, G. I., & Zekos, G. I. (2021). AI Risk Management. In G. I. Zekos (Ed.), *Economics and Law of Artificial Intelligence: Finance, Economic Impacts, Risk Management and Governance*, (pp. 233–288). Springer.