PORTFOLIO MANAGEMENT AND SYSTEMIC RISK IN THE AGE OF ARIFICIAL INTELLIGENCE

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Abstract: Artificial intelligence has emerged as a transformative force with profound implications for diverse domains, including finance and portfolio management. This paper delves into the multifaceted impact of AI on portfolio management and the dynamic landscape of systemic risk. The proliferation of AI is fueled by rapid advancements in computational capabilities, the abundance of extensive datasets, and breakthroughs in AI algorithms. It offers unparalleled accuracy, speed, and practical applicability, revolutionizing traditional paradigms. Globalization and AI applications have amplified systemic risks on a global scale, necessitating a reevaluation of risk management strategies. Conventional portfolio theories, like Modern portfolio theory, have historically emphasized the diversification of idiosyncratic risks while downplaying systemic risk. The comprehension and effective mitigation of systemic risks are paramount to preserving financial stability, particularly in the aftermath of systemic crises such as the 2007–2009 financial meltdown. AI's transformative potential extends beyond risk management, reshaping the labor landscape in asset management. Forecasts anticipate substantial job reductions in the field, prompting professionals to embrace adaptability and acquire new skill sets. This paper examines AI's integration into portfolio management, shedding light on the intricate interplay between AI, systemic risk dynamics, and investment practices. In conclusion, the integration of AI into portfolio management heralds an era of unparalleled opportunities and complex challenges. AI's capacity to process vast datasets, enhance pattern recognition, and refine predictive modeling has reinvented investment methodologies. However, this paradigm shift comes with inherent risks, especially pertaining to systemic instability. Identifying, understanding, and mitigating these risks is pivotal for sustaining financial market. Collaborative efforts among industry experts, regulators, and AI developers are instrumental in fostering responsible and sustainable AI integration within financial markets. As AI continues to exert its influence, professionals must remain adaptable and acquire new competencies to navigate the evolving financial landscape effectively. The future of portfolio management lies in harnessing AI's capabilities while safeguarding against potential pitfalls, ultimately steering the financial sector toward greater efficiency and resilience.
Keywords: artificial intelligence, portfolio management, systemic risk

1. INTRODUCTION

Artificial intelligence (AI) has emerged as a force of overall transformation, with its undiscovered potential lying ahead of us. It’s reshaping all aspects of our lifes and works, from social to economic. The recent AI hype has been mainly fueled by the growth of computer capabilities, the availability of large databases, and advancements in AI algorithms. The significance of the application of AI is reflected in her accuracy, speed, and practical applicability, because the results of the application of algorithms are more precise and based on innovative sources of information (Kosanović, Božović, & Kosanović, 2022). AI brings new possibilities and efficiency on one hand, while on the other, it manifests unexpected economic and social effects. The new risks brought by the new technology must not be ignored. The process of globalization, combined with new applications of AI, lead to even stronger and less controlled interconnectedness, which especially increases systemic risk at the global level. Mainstream portfolio theory, known as Modern portfolio theory, relying solely on diversification of idiosyncratic risks, has overlooked systemic risk. Understanding this risk is crucial for maintaining financial stability, and hence, minimizing losses due to systemic crashes. After such a crash, like the 2007–2009 financial crisis, it was understood that even though financial intermediaries assume risks independently, they generate greater interconnectedness, thereby increasing systemic risk (Kosanović, 2022a). In the current era of expanding technological and decentralized interconnectedness, understanding the sources of systemic risk introduced by AI becomes increasingly critical.

This will contribute to constructing portfolios that perform better during systemic crashes than those constructed solely based on diversification. On the other hand, new AI tools contribute to new possibilities in portfolio management. AI brings new methods of data analysis, including tools for more efficient pattern recognition and forecasting.

Also, AI has an impact on the labor market. Asset management is expected to suffer the largest number of job cuts in the near future (Buchanan, 2019). The advent of AI and automation technologies has reshaped the way businesses operate and has raised questions about the future of work. AI's capacity to automate routine tasks, analyze market data at unparalleled speeds, and even make investment decisions autonomously is causing a shift in the roles and responsibilities of portfolio management professionals. While AI augments their capabilities by providing sophisticated tools for data analysis and decision support, it also raises concerns about job displacement and the need for reskilling in the financial industry. As AI continues to evolve, it becomes increasingly vital for professionals to adapt and acquire new skills to remain competitive in this evolving landscape.

The aim of this paper is to examine the application of AI in portfolio management and to shed light on the evolving landscape of systemic risk, driven by AI's influence on market dynamics. By exploring the intersection of AI, portfolio management, and systemic risk, this paper provides valuable insights into the challenges and opportunities presented by the integration of AI in the asset management industry.

2. PORTFOLIO MANAGEMENT AND AI

Portfolio management is process of portfolio allocation across different asset classes while considering the risk/return tradeo-ff. This process can be divided into investment analysis and portfolio optimization. AI techniques increase the speed and volume of data that can be analyzed, providing investment analysts with tools that were previously impossible. Through AI–powered textual analysis, it is possible to identify the fundamentals for evaluating a company from a large number of corporate public reports, determine the narrative of central banks to signal the direction of monetary policy, or extract significant insights about public sentiment from news analysis. Also, AI can have application in portfolio construction. In particular, AI can produce better asset return and risk estimates and solve portfolio optimization problems with complex constraints, yielding portfolios with better out–of–sample performance compared with traditional approaches (Bartram, Branke, & Motahari, 2020). Improved and faster assessed returns and covariance matrices can then be applied in the Markowitz model, thereby enhancing the optimal asset allocation.

AI text analysis have aim to extract valuable insights from vast amounts of textual data. By employing natural language processing (NLP) techniques and machine learning algorithms, AI can comprehend, categorize, and derive meaning from text documents with remarkable precision. AI text analysis not only improves the efficiency of data interpretation but also enables uncover hidden patterns, trends, and sentiments, ultimately driving informed decision-making and enhancing the understanding of human language in the digital age. The most significant application of AI text analysis in portfolio management is in fundamental analysis. Valuable (economically meaningful) information can be found on blogs, news websites, reports, company websites, electronic documents from regulatory bodies and agencies, etc. The quality of text in company reports is much better than in message postings, and hence, we should expect richer meaning extraction in this domain (Das, 2014). We extract this information through text mining and use it for prediction. The portfolio manager can perform both qualitative analysis (which requires linguistic algorithms to extract meaning from the analyzed texts) and quantitative analysis (the volume of specific words or phrases appearing in the text) with the aim of crafting an appropriate investment strategy. Qualitative analysis enables the extraction of contextual insights and sentiments from textual data, allowing for a deeper understanding of market dynamics and potential risks. On the other hand, quantitative analysis relies on statistical measures of word frequency or occurrence to identify trends or patterns that can inform investment decisions. Combining both approaches empowers portfolio managers to make well–informed and data–driven investment strategies. For example, Kearney and Liu (2014) have reviewed the textual sentiment literature in finance by focusing on three main aspects – the information sources, the content analysis methods, and the financial models that have been used to examine whether and how textual sentiment impacts on people, institutions and markets. Brown (2012) attempts to determine whether there is correlation between twitter and the stock market by studying sentiment, message volume, price movement and stock volume as well as the affect that a twitter user’s reputation may have on sentiment and the stock market. Results in (Rao & Srivastava, 2012) show high correlation (upto 0.88 for returns) between stock prices and twitter sentiments.

For predicting stock prices, neural networks are frequently employed. Neural networks, a subset of artificial intelligence, have gained significant prominence in the realm of financial forecasting due to their ability to analyze complex, nonlinear relationships within stock price data. These networks consist of interconnected layers of artificial neurons that can process vast amounts of historical stock market data, identify patterns, and make predictions based on historical trends. Their capability to capture intricate market dynamics and adapt to changing conditions has made them a valuable tool in anticipating future stock price movements, assisting investors and financial analysts in making informed decisions. The value of neural network modelling techniques in performing complicated pattern recognition and nonlinear forecasting tasks has now been demonstrated across an impressive spectrum of applications (White, 1988). Vui et al. (2013) provide a review of the literature on the application of various artificial neural network approaches in predicting stock market returns. Bianchi, Büchner and Tamoni (2020) show that machine learning methods, in particular extreme trees and neural networks, provide strong statistical evidence in favor of bond return predictability. Shen and Shafiq (2020) concluded that by combining latest sentiment analysis techniques with feature engineering and deep learning model, there is also a high potential to develop a more comprehensive prediction system which is trained by diverse types of information such as tweets, news, and other text-based data.

AI can be used for improving estimates of covariance matrices in the Markowitz framework, especially due to the challenges that arise in practice. Michaud and Michaud (2008) demonstrate that in practice the single most important limitation of Markowitz mean–variance optimization is oversensitivity to estimation error. The unstable prediction of future expected returns has an impact on optimal weights and making them unstable, which leads to rebalancing costs and poor portfolio performance. On the other hand, estimating the variance–covariance matrix requires a large amount a of data (*n(n-1)/2* unique covariances for *n* assets) and the assumption of stable correlations between asset returns. However, systemic crises cause correlations among assets to increase, thereby diminishing the benefits of diversification, while estimating variances and covariances becomes unstable. De Prado (2016) introduced the Hierarchical Risk Parity (HRP) approach and Markowitz's critical line algorithm (CLA) to deal with three major issues associated with quadratic optimizers: instability, concentration, and underperformance. HRP takes a hierarchical approach to asset allocation, considering not only the individual assets but also their relationships and correlations within different groupings or clusters (it applies graph teory and machine learning). One of the key advantages of HRP is its ability to adapt to changing market conditions by dynamically updating the asset clusters and allocation weights. This flexibility allows investors to navigate through various market scenarios while optimizing risk–adjusted returns. One of the notable features of the CLA is its ability to handle constraints efficiently. Investors and portfolio managers can incorporate various constraints, such as sector or asset allocation limits, into the optimization process. The algorithm iteratively adjusts the portfolio weights to find the optimal allocation while respecting these constraints. This approach uses all the information contained in the covariance matrix but requires fewer estimates and thus leads to more stable and robust portfolio weights – a minimum variance portfolio under this approach has a 31.3% higher Sharpe ratio than that under the classical Markowitz framework (Bartram, Branke, & Motahari, 2020).

3. SYSTEMIC RISK AND AI

The rise of artificial intelligence brings with it numerous transformative benefits, but it also raises important concerns about safety and potential risks. With the development of the "digital" society, data collection becomes especially important, while skillful manipulation of this data can affect consumer perception of products, corporations can discriminate prices, influence democratic institutions, increase polarization in society, violate freedom and privacy individuals (Kosanović, 2022b). AI enables the creation of decentralized systems characterized by interconnectivity, adaptability, learning, high–speed information transmission, and partial or complete automation. However, increasingly nested and complex systems are also susceptible to unexpected shocks, and cascades that develop endogenously, also known as "normal accidents" (Perrow, 1999). Internal failures can arise without warning and propagate through network causing failures throughout the entire system. Therefore, identifying systemic risk becomes increasingly challenging in a hyper–connected world.

New risks are a result of conceptual challenges faced by AI-based systems. The three conceptual challenges facing the financial AI: How economic agents' responses to AI affect the system, data, and unknown-unknowns, in turn, cause the AI to impact the financial system in undesirable ways (Daníelsson, Macrae, & Uthemann, 2022). Policymakers must provide AI with a well-defined set of rules to follow. This approach offers greater transparency and predictability compared to human regulators. Clearly defined objectives and transparency help prevent unintentional or intentional efforts by economic agents to evade control and exploit vulnerabilities. Some agents may unknowingly employ strategies that are individually innocent but collectively harmful, while others may purposely engage in destabilizing actions for financial gain. Ultimately, all of these factors pose a threat to the stability of the financial system.

Even well–defined AI algorithms can be sensitive to data, whether due to data quality or insufficiency. Such data can lead to inaccurate predictions and unreliable results. Poor-quality data can contain biases or inaccuracies that are learned by AI models. This can perpetuate and even amplify existing biases, leading to unfair or discriminatory decisions. The existence of bias will result in incorrect management recommendations. Even if both the training data, and the context in which the algorithm is used is appropriate, their application can still lead to interpretation bias – in this type of bias, an AI–system might be working as intended by its designer, but the user does not fully understand its utility, or tries to infer different meaning that the system might not support (Galaz, et al., 2021). Data–driven decisions thus become better as the data entering the AI algorithms improves. In addition to standard data sources such as publicly available reports, stock market data, or economic statistical reports, AI enables the analysis of alternative data such as satellite imagery, sentiment analysis, collection and analysis of behavioral data, and so forth.

Further development of AI systems requires an understanding of unique systemic and other risks, because ineffective human supervision might lead to systematic crashes, an inability to identify inference errors, and a lack of understanding of investment practices and performance attribution by investors (Bartram, Branke, & Motahari, 2020). Moreover, an inability to identify inference errors can lead to misleading conclusions and erroneous decisions, undermining the reliability of AI-driven processes. Additionally, a critical aspect of AI's integration in the financial sector lies in its capacity to enhance investment practices and provide transparent performance attribution. Understanding these factors is crucial for investors seeking to leverage AI to optimize their investment strategies and align them with their financial objectives. Investors, policymakers, and stakeholders must acknowledge that the path to realizing the full potential of AI in financial markets is paved with challenges. The intricate relationship between AI systems and financial risk necessitates a holistic approach to risk management and oversight. A robust understanding of systemic risks is pivotal in mitigating the potential adverse effects of AI, while also harnessing its benefits for improved investment practices. Striking a balance between innovation and risk mitigation is essential, as AI has the potential to revolutionize the financial industry, but doing so without a comprehensive understanding of the associated risks can lead to unexpected setbacks. Therefore, a collaborative effort among industry experts, regulators, and AI developers is crucial to ensure responsible and sustainable AI integration in financial markets.

4. CONCLUSION

The integration of artificial intelligence into portfolio management has ushered in a new era of opportunities and challenges. AI's ability to analyze vast amounts of data, provide efficient pattern recognition, and enhance forecasting has revolutionized investment practices. However, this transformation is not without risks. Systemic risk, often overlooked in traditional portfolio theory, has gained prominence with the interconnectedness and automation introduced by AI. Identifying and managing these risks is paramount to maintaining financial stability. The collaboration of industry experts, regulators, and AI developers is essential to ensure responsible and sustainable AI integration in financial markets. As AI continues to shape the financial industry, professionals must adapt and acquire new skills to thrive in this evolving landscape. The future of portfolio management lies in harnessing AI's capabilities while safeguarding against potential pitfalls. By addressing these challenges, we can leverage AI to optimize investment strategies, align them with financial objectives, and pave the way for a more efficient and resilient financial sector.

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