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THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON PORTFOLIO OPTIMIZATION

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Abstract. *This paper explores the transformative impact of artificial intelligence (AI) on portfolio optimization in the financial sector. It examines how machine learning algorithms have revolutionized risk management and investment strategies by analysing vast datasets more efficiently than traditional methods. The study contrasts modern portfolio theory with AI-driven approaches, highlighting the advantages of machine learning models in addressing market risks and volatility. The findings suggest that AI not only enhances predictive accuracy but also offers a more dynamic and adaptable framework for portfolio management, thereby outperforming conventional techniques in managing financial risks.*

Keywords: *artificial intelligence, portfolio optimization, machine learning, risk management, modern portfolio theory, financial markets, investment strategies.*

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Introduction

The Impact of Artificial Intelligence (AI) On Portfolio Optimization

Over the past decade alone, there has been a massive leap in the research and development of artificial intelligence spurred by business investment and its adoption by society. The technological revolution has facilitated the adoption of machine learning in the business sector through implementation of solutions revolving around risk management as far as financial economics is concerned (Zhong and Enke, 2019). AI has transformed the investment and asset management industry through the utilization of machine learning algorithms to analyse vast data sets in relation to risk management (Sen et al., 2022). The entire investment and asset management industry has shifted focus to AI in portfolio optimization procedures as it has the possibility of outperforming traditional Modern Portfolio Theory (MPT) in portfolio construction and risk management.

Methods

Modern Portfolio Theory

From the middle of the year 2007 up to the early part of the year 2009, financial markets including banking systems worldwide experienced a crisis spearheaded by the collapse of the US housing market leading to massive losses for global banking systems (Levy et al., 2022). The recession experienced then was much deeper than that of the 1930s as the figure for job losses was in the millions and slow recovery was recorded due to the extensive financial crisis (Çan and Okur Dinçsoy, 2021). At that time, the macroeconomic situation maintained suitable conditions for unreasonable risk-taking activities in the financial markets. The financial crisis was influenced by the nature in which risk was handled. Technological developments in terms of computing power witnessed currently were still underdeveloped at the time hence risk in financial markets was handled through fundamental and technical analyses (Rahman, 2024).

Fundamental analysis purposes to discover and explain the fluctuations of a given company's stock price through analysis of the industry it belongs to as well as the surrounding economy (Zanjirdar, 2020). Technical analysis on the other hand does acknowledge the patterns present in the pricing as well as the volume. It seeks to find the cues for the buying action based on identified patterns (Kim et al., 2020). However, technical analysis possesses great margins of error hence, cannot be employed as the structural model of the risk management system (Hunziker, 2021). The modern portfolio theory is a system that employs the statistical technique of chance to address the incapacities of fundamental and technical analyses (Antony, 2020).

The modern portfolio dismisses the law of large numbers in portfolios comprised of securities and postulates that suitable holdings for investors are mean-variance efficient portfolios (Berk and Tutarli, 2020). Investors operating on the law of large numbers aim to maximize discounted returns with minimal variance. However, according to modern portfolio theory, it is next to impossible for a minimum variance to be achieved through the diversification approach alone due to the strong interrelationship between returns from securities (Zhou, 2022). The modern portfolio concludes that the risk of an investor's overall portfolio is reduced when the given portfolio is a mixture of stocks that flip tail and those that flip heads (Lindquist et al., 2022).

Thus, far broader sets of linkages between different assets are used in modern portfolio theory. A calculation of covariances involves a pairs analysis of the relations between securities pairs, a process that is tiresome analytically (Guo, 2022). The bigger the portfolio, the higher it originates the bound to the Markowitz model since the number of inputs required and number of computational time required increases. Also, deciding on the input data type that is needed may be rather unclear, especially if one is working with correlation matrices. It should be noted that Markowitz initially introduced the mean-variance optimization technique for portfolios, which significantly got simplified with the help of the market models introduced by Sharpe, Lintner, and Mossin hence the modern portfolio theory (Verma and Srivastava, 2024).

Outcomes that are nearly as good were achieved with far fewer parameters than when considerably larger sets of linkages between securities are utilized. It must be pointed out that the market models created by Sharpe, Lintner, and Mossin are rather cost-efficient when it comes to the risk assessment (Yizheng, 2023). The technique co-developed by Markowitz is thus rather efficient when used in the real life. In measures for risk management within the portfolio's optimization, the single period mean variance portfolio model is efficient because it dramatically reduces the number of inputs and time required for computing (Ma et al., 2021). Modern portfolio theory complicates the risk-return trade-off for the portfolio managers; thus, the construction of efficient portfolios takes time and costs a lot of cash. The models of the Modern Portfolio Theory are characterized precisely by their lack of flexibility and omission of certain concepts (Rodríguez et al., 2021).

Results

Artificial Intelligence/Machine Learning Models

Artificial intelligence and machine learning are a perfect continuation of the improvement of the technological process as access to the increased amount of computational power allows programs to sort through the extensive data and to analyse them while looking for the patterns and finding the particular values that differ from the others (Kühl et al., 2022). Access to financial data, computational resources, profitability requirements, competition of firms, and demand and needs of financial regulators have been the drivers to foster AI in finance (Kavin, 2023). Concerning the management of financial risk, the application of artificial intelligence has played a significant role in managing the process of decision-making on finances.

Because of their versatility, machine learning models can solve the low variance-high bias dilemma that plagues parametric models (Posth et al., 2021). Modern Portfolio Theory's single factor of analysis, the covariance of security returns relative to the overall market, is measured by simplifications made to the Markowitz technique. Machine learning algorithms can incorporate dividend and reinvested income returns which were previously unattainable with the S&P500 Index used in the Sharpe, Lintner, Mossin, and Treynor Markowitz technique implementations (Parnes, 2020). This is achieved by applying the single index model to create variance-covariance structures. Single, newfangled models can be tested later with help of machine learning algorithms, which helps to enhance the predictive capacity of single index models in the future (Paiva et al., 2019). According to the modern portfolio theory, there is always an element of relying on the results of a risk assessment model that is always under some threat due to changes in data distribution, often characteristic in finance. However, machine learning models are more able to estimate this changing pattern in a way that enhances the generalized model (Mhlanga, 2021). Indeed, integrated machine learning-based financial models are rather precise.

Unlike most of the statistical methods out there, a machine learning model seeks to make more explicit the relationship between the variables, identify the key factors, and enable the determination of the influence of the variables on the dependent variable without necessarily having to rely on theory (Irfan et al., 2023). As a conceptual framework it is possible to use pretty much anything from the area of machine learning and statistics for both inference and prediction. However, the inference has been, and still is, the primary concern of statistical methods, where this is achieved by building and estimating a probability model specific to the given project. While on the other hand machine learning focuses on prediction as it makes use of general-purpose learning algorithms to discover relations in often-complicated and voluminous data (Singh et al., 2022). It can be noted that strong and limiting assumptions are not indispensable for machine learning models (Nazareth and Reddy, 2023).

Players in finance markets face risk which is quite hard to quantify. Out of the total financial risks, market, credit, liquidity along with operational risks are some that may occur (Addy et al., 2024). The volatility in financial indices such as inflation rates, interest rates and currency rates describe what is referred to as market risk. Fluctuations of prices in the market that may lead to losses in any positions held on, or off the balance sheet is termed as the market risk (Kou et al., 2019). Suppose that high inflation may become detrimental to the current profitability of the financial institutions because inflation affects the interest rates, through which the cost of borrowing money for borrowers is determined. Even if these occur more often, one should also pay attention to how these types of financial risk interrelate. In other words, it is impossible for various risk sources to be constant while one risk source changes. The sources of risk are interdependent and therefore, it is a must to look at how they interact (Pathak et al., 2023). Value-at-Risk and Expected Shortfall are among the most recognizable and approved tools which are based on the machine learning methods and aimed at the evaluation of the connected market risk (Devan et al., 2023).

The VaR model focuses on the maximum amount of loss that can occur in any investment based on the amount of risk (Behera et al., 2023). This makes it useful in determining the maximum possible loss in the given period of time with a required level of confidence. The first component of the VaR model provides a universal, trustworthy means of measuring risk concerning various scenarios and risk indicators. It makes it possible to express the risk on a fixed-income position on an analyse that is standardized and comparable with the risk analyse of an equity position (Andries and Galasan, 2020). The VaR model provides the portfolio managers with a benchmark risk measure enabling institutions to manage their risks in unimaginable ways. The second component is that this measure takes into account the interdependencies of factors that threaten the profitability of an investment (Chen et al., 2021). While VaR gives consideration to the likelihood of loss less than a specific amount, Expected Shortfall focuses on the tail of distribution. In particular, Expected Shortfall helps one consider the untoward market risks as an outstanding factor to work for (Hoga and Demetrescu, 2023). It does not mean, however that VaR and Expected Shortfall are polar concepts. They are related in that expected shortfall can be expressed using VaR (Karasan, 2021).

On this regard, volatility prediction is critical in the understanding of how the financial system operates since it helps in estimating uncertainty. Many financial models, especially risk models, incorporate volatility prediction in their process in one way or another (De Prado, 2018). Such data show that it is very important to have a good estimate of the volatility. Despite the fact that many organizations and firms will use modern portfolio theory models, it is essential to understand that these models have the major disadvantage of being standardized (Lee and Shin, 2020). Models like the neural network and deep learning-based models can prove useful in solving this problem (Ozbayoglu et al., 2020). The proposed data-driven model is higher effective to the currently used models of portfolio theory. Gradient descent is a technique used generally in machine learning, to minimize the cost function although because of the structural resemblance to a chain in neural networks it isn't feasible to use gradient descent alone (Henrique et al., 2019). Therefore, backpropagation is applied for minimizing the cost function. The foundation of backpropagation is the computation of the amount of error between expected and actual output which is taken to the hidden layers of the neural network (Nabipour et al., 2020).

Conclusion

Risk management in financial markets took a shift for the better in the aftermath of the 2007/2008 global financial crisis (Lee et al., 2019). The process of managing risks is one that is always changing (Chatzis et al., 2018). Established risk management techniques such as the modern portfolio theory cannot keep up with current developments. Constant evolution is thus unavoidable to improve prediction techniques with regards to impending disasters (Alessi and Savona, 2021). As such, it is critical to keep an eye on and adjust to the modifications brought about by structural fractures in a risk management procedure. With regards to portfolio optimization, machine learning algorithms have brought a constant focus around the unmasking, estimation, documentation, and management of risks (Leo et al., 2019).

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