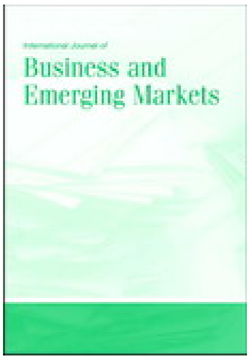
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Business and Emerging Markets

ISSN online: 1753-6227 - ISSN print: 1753-6219
https://www.inderscience.com/ijbem

Enhancing portfolio risk management: a comparative study of parametric, non-parametric, and Monte Carlo methods, with VaR and percentile ranking

Aris Shokri, Alexios Kythreotis

DOI: 10.1504/IJBEM.2024.10062375

Article History:

Received:	13 October 2023
Last revised:	27 December 2023
Accepted:	28 December 2023
Published online:	02 July 2024

Enhancing portfolio risk management: a comparative study of parametric, non-parametric, and Monte Carlo methods, with VaR and percentile ranking

Aris Shokri* and Alexios Kythreotis

European University Cyprus,
Engomi, Cyprus
Email: aris_shokri@outlook.com
Email: a.kythreotis@euc.ac.cy
*Corresponding author

Abstract: In this paper, we propose a methodology to effectively manage portfolio risk and allocate capital. By taking a scientific, proactive approach, and understanding the risk associated with each asset before creating a portfolio, it is possible to minimise overall portfolio risk by distributing capital in a diverse and systematic manner. To achieve this, we suggest combining value-at-risk (VaR) with other statistical measures like the percentile rank and the empirical rule. Through this research, we found that this combination can significantly reduce potential portfolio losses when compared with an equally weighted portfolio. The results are based on an analysis of 30,200 daily historical prices between January 2011 and December 2022, using three different methods: historical (non-parametric), variance-covariance (parametric), and Monte Carlo. These findings underscore the importance of proactively managing risks along with allocating capital and highlight the benefits of using a data-driven, systematic approach to portfolio management.

Keywords: portfolio management; risk management; capital allocation; value-at-risk; VaR; Monte Carlo.

Reference to this paper should be made as follows: Shokri, A. and Kythreotis, A. (2024) 'Enhancing portfolio risk management: a comparative study of parametric, non-parametric, and Monte Carlo methods, with VaR and percentile ranking', *Int. J. Business and Emerging Markets*, Vol. 16, No. 3, pp.411–428.

Biographical notes: Aris Shokri is a seasoned risk manager at a FinTech company. He is holding his Master's in Business Administration from the European University of Cyprus, he specialises in leveraging modern business intelligence tools to address complex challenges within the financial industry. He is proficient in data engineering, analysis, and science, and is dedicated to enhancing decision-making processes, with a particular focus on big data.

Alexios Kythreotis is an Assistant Professor in Accounting and Finance at European University Cyprus. He holds a PhD in Financial Accounting from Athens University of Economics and Business and an MBA from Cardiff University. Additionally, he holds the European Certificate in E-learning Courses Design and Teaching from UOC, Universitat Oberta de Catalunya. His research primarily focuses on financial accounting, financial fraud, market-based accounting research, and the quality of financial statements.

1 Introduction

Risk management is a critical part of asset and capital allocation. With constantly changing market conditions, investors and financial institutions need to assess the potential risks of a portfolio before allocating capital to each asset. This allows for more informed investment decisions, as well as optimal risk diversification and management (Hing and Chow, 2022; Zhang et al., 2020). Value-at-risk (VaR) is a widely used statistical measure of the potential loss that a portfolio of financial assets, such as stocks, bonds, or derivatives, may suffer over a specific period, and at a given level of confidence. In other words, VaR provides an estimate of the maximum amount that a portfolio is likely to lose within a certain period, with a given level of probability. By estimating the maximum potential loss, VaR helps assess the risk of a portfolio and develop strategies to manage and control that risk. It can be calculated for individual assets, a portfolio of assets, or for an entire financial institution.

One of the main issues that arises from using VaR in portfolio risk management is that it is often applied only after the construction of a portfolio. In cases of financial stress or unexpected market conditions, a portfolio might face significant losses if assets with higher risk have been over-invested, or if capital is allocated equally without taking a more systematic approach. Therefore, it is important to use a more systematic and rigorous methodology to allocate capital, based on VaR calculations and other risk metrics, to achieve a balance between risk and return. Doing so can also help avoid overexposure to any single asset. This paper demonstrates an approach that can significantly reduce potential losses in a portfolio and ensure efficient capital allocation.

While there is a wealth of information available on how to calculate VaR with various methodologies for a given portfolio, there is currently no specific literature addressing how to structure a portfolio in advance and allocate capital based on the calculated VaR and its practical applications. Therefore, the goal of this research is to provide a practical framework for using VaR as a proactive tool for effective portfolio management, risk reduction, and capital allocation. It will serve as a roadmap for financial professionals, offering tangible insights into the proactive utilisation of VaR. It not only facilitates effective portfolio construction but also provides practical strategies for minimising risks and optimising capital allocation. The study's significance is extended by its emphasis on real-world applicability, ensuring the insights gained from the research can be readily implemented in dynamic financial landscapes.

Real-world instances serve as compelling illustrations to underscore the pragmatic utilisation of sophisticated risk management tools such as VaR and risk-adjusted capital allocation. A notable scenario involves the meticulous preparation for a market downturn, wherein a seasoned portfolio manager employs VaR proactively. This involves a comprehensive analysis of historical data and the calculation of VaR at various confidence levels. As an impending downturn is identified, the manager strategically adjusts the portfolio by reallocating assets to more stable investments. This strategic manoeuvre is designed to mitigate potential losses during adverse market conditions.

In another scenario, the application of risk-adjusted capital allocation by an investment firm adds a layer of complexity to the risk management landscape. The firm, cognisant of calculated VaR values across diverse asset classes, adopts a meticulous risk-adjusted approach to capital allocation. This involves allocating more capital to assets exhibiting higher expected returns and lower VaR. The objective is to optimise the risk-return profile of the overall portfolio, emphasising scientific precision and strategic foresight, which are inherent in the implementation of these risk management strategies.

Our approach aims to build upon the existing literature, using three VaR methodologies, namely the historical method, the variance-covariance method, and the Monte Carlo method. We will show how VaR can be combined with the percentile rank method and the empirical rule to rank assets based on specific quantiles and allocate capital accordingly. This approach is intended to help achieve a balance between risk and return while avoiding over-investment in assets with high volatility. Additionally, we compare the results of each VaR method to those of an equally distributed portfolio, in combination with the percentile rank and the empirical rule. This comparison will show how the combination of methodologies can effectively minimise overall portfolio risk and losses.

In this research, we analysed a portfolio of assets including the top nine stocks from the S&P500, plus the S&P500 Index itself, ranked by their weighted average. In finance and investing, the S&P500 Index is often used as a benchmark for the overall performance of the US stock market. It is a market-capitalisation-weighted index of the 500 largest publicly traded companies in the USA, and therefore, is considered a good representation of the overall health of the US stock market. The specific assets were chosen based on their weighted average from the official website of the S&P500. We obtained data from 3 January 2011 to 30 December 2022 from Yahoo Finance, resulting in a total of 30,200 daily historical prices. The sample size for all three methods combined was 90,600 closing prices across the ten assets. Additionally, the Monte Carlo method involved an extra 100,000 simulations, bringing the grand total to 190,600 data points. All the data were analysed using quantitative analysis techniques in the Python programming language.

2 Literature review

The concept of VaR and its practical application in risk management are discussed in Linsmeier and Pearson (2000), where various methods for calculating VaR are reviewed, and the advantages and disadvantages of each method are outlined. These methods include the historical method, the variance-covariance method, and the Monte Carlo simulation. In David et al. (2022), a new approach to capital allocation that incorporates tail risk into the process is proposed, highlighting the need for a more nuanced approach to capital allocation. While Taylor's (2008) method for estimating VaR and expected shortfall (ES) using expectiles is more accurate and robust during extreme events, compared to traditional VaR methods that rely on a fixed percentile. Additionally, in 2017, Tripathy employed the GARCH method, a statistical modelling technique used to forecast the volatility of financial asset returns. These studies highlight the need for a more nuanced approach to risk management, incorporating tail risk and more accurate methods for estimating VaR and ES.

In their recent study, Peng et al. (2023) present a new VaR predictor called G-VaR, employing a unique methodology. The authors conducted comprehensive experiments using the NASDAQ Composite Index and S&P500 Index, revealing the superior performance of the G-VaR predictor compared to many established VaR predictors in terms of accuracy and reliability.

In Francq and Zakoïan (2020), the virtual historical simulation (VHS) method was introduced, which combined historical simulation with a statistical model that captured extreme events, to estimate VaR for large portfolios. Gupta and Liang (2005) examined VaR as a measure of potential loss for hedge funds, highlighting the importance of using risk management tools such as VaR to assess the capital adequacy of financial institutions and mitigate potential risks. Patton et al. (2019) proposed a dynamic semi-parametric model for ES and VaR, combining a parametric model for the conditional mean and a nonparametric model for the conditional distribution of portfolio returns. Kuester et al. (2006) explored the accuracy of VaR predictions, suggesting that the filtered historical simulation and GARCH methods may provide more accurate predictions than the traditional historical simulation method. Christoffersen et al. (2001) tested the performance of five VaR models commonly used in financial institutions, using data from three indices, with the filtered historical simulation model being found to consistently outperform other models. Bernard et al. (2017) provide insights into the effectiveness and limitations of VaR as a risk measurement tool for credit risk portfolios, offering valuable information for financial institutions and risk managers in their decision-making processes.

Danielsson et al. (2008) proposed a method for portfolio allocation that considered the VaR constraint and incentives for financial innovation. The authors use a probabilistic approach to estimate VaR, which allows for more accurate and flexible risk management. They also investigated the impact of incentives for financial innovation on optimal portfolio allocation. The study showed that the VaR constraint can significantly affect optimal portfolio allocation and that incentives for financial innovation can improve the allocation of risk across assets. While Kong et al. (2021) proposed a joint quantile regression framework for VaR and ES forecasting that outperforms traditional methods, and provides better risk-adjusted returns and lower tail risk for portfolio allocation.

Francq and Zakoïan (2018) focus on the estimation risk associated with the VaR measure for portfolios, driven by semi-parametric multivariate models. These models combine both parametric and non-parametric components to capture the complex dependencies and characteristics of financial data.

Jung et al. (2022) propose a dynamic process for portfolio risk measurement, to address potential information loss. The proposed model takes advantage of financial big data to incorporate out-of-target-portfolio information that may be missed by VaR, which only measures certain assets in a portfolio. The authors investigate how the curse of dimensionality can be overcome in the use of financial big data and discuss when and where benefits occur from a large number of assets.

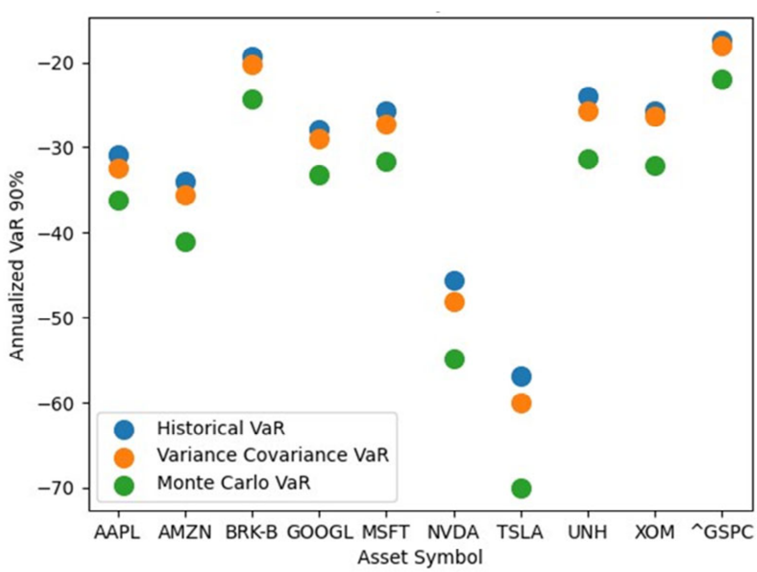
In their study, Mi and Xu (2023) delve into two optimal portfolio selection problems, with a focus on rank-dependent utility investors aiming to manage their risk exposure. They examine scenarios that include a single VaR constraint and joint VaR and portfolio insurance constraints. Their findings reveal that, in adverse market conditions, optimal investment outcomes result in reduced risk when compared to existing models, regardless of the presence of constraints.

Finally, several studies have emphasised the relationship between VaR and capital structure, attributing it to the evaluation of risk and the administration of a company's financial resources (Aboagye and Appiah, 2019; Chegini and Bashiri, 2017; Rizk and Sassine, 2023; Chasiotis et al., 2022). Further research has focused on additional factors that impact the accuracy of financial data utilised in VaR calculations. These factors encompass earnings management, the cost of debt, the quality of corporate disclosures and audit reports, as well as considerations related to green entrepreneurial issues (Ahmad et al., 2022; Jouini, 2018; Mishra et al. 2023).

3 Sample and methodology

In the methodology section, three methods have been identified to estimate VaR: the historical (non-parametric) method, the variance-covariance (parametric) method, and the Monte Carlo method. Each of these methods has its own strengths and weaknesses, and choosing the appropriate method will depend on the characteristics of the portfolio being evaluated and the risk management objectives of the investor. Historical VaR is a non-parametric approach that uses the past performance of a portfolio to estimate the potential losses that may be incurred in the future. The variance-covariance method, on the other hand, is a parametric approach that assumes a normal distribution of returns and estimates VaR based on the mean and standard deviation of returns. The Monte Carlo simulation method, which is a more flexible and sophisticated approach, uses random simulations to estimate VaR, by generating many scenarios based on the historical distribution of returns.

Figure 1 Annualised VaR 90% by asset and method (see online version for colours)



Notes: Scatter chart depicting the different VaR methodologies used and the corresponding VAR values at a 90% confidence level.

Figure 1 depicts the different VaR methodologies used and the corresponding VAR values at a 90% confidence level. From this chart, we can see that the results do not have significant variance between them, except for the Monte Carlo method, which consistently yields higher VAR values than the other two methods.

The selection criteria for these specific assets were based on their high-weighted averages within the S&P500 Index. Weighted averages account for the market capitalisation of each asset, emphasising the significance of each stock's market value in determining its impact on the overall portfolio. The decision to include these nine individual assets, plus the S&P500 Index itself, for a total of ten assets in the portfolio, is driven by their substantial market capitalisation compared to other stocks from the S&P500. By focusing on these top-performing and highly capitalised stocks, the portfolio aims to capture the most influential components within the broader S&P500 Index.

Additionally, the decision to focus on the weighted averages within the S&P500 Index was taken to help construct a portfolio that accurately reflects the market's major players and their respective weights within the index.

For quantitative analysis, this study used the Python programming language, and Yahoo Finance as the primary data source. Python is a popular language for data analysis and offers built-in libraries for manipulating and analysing financial data. Yahoo Finance provided a vast collection of historical stock price data and financial information, which facilitated the study's acquisition of reliable and accurate data. The study utilised Python to extract, transform, and load data from Yahoo Finance, to create a structured format, which was subsequently analysed using various statistical and machine learning techniques.

We downloaded several libraries to analyse the data, including pandas, scipy.stats, norm, random, numpy, and datetime. Additionally, we used the matplotlib.pyplot, seaborn, and tabulate libraries to visualise our data. Then, we used the yfinance library to download the daily closing prices for the relevant assets between 3 January 2011 and 30 December 2022 in Python. Finally, we visually inspected the daily closing prices for each asset and verified the total sample size by checking summary statistics using Python, to confirm the accuracy and completeness of the results in the DataFrame. This step was crucial to ensuring that the data used for analysis was accurate and complete. Upon completing the above preparation, we had all the necessary data to begin calculating the different VaR methodologies.

The portfolio consisted of ten assets, including the S&P500 Index, as well as Apple, Microsoft, Amazon, Alphabet, Berkshire Hathaway, NVIDIA, Tesla, ExxonMobil and UnitedHealth Group. For the historical and variance-covariance methods, the sample size used was 30,200 daily closing prices, with 3,020 closing prices per asset. For the Monte Carlo method, the sample size was also 30,200 daily closing prices, with 3,020 closing prices per asset, but an additional 10,000 dimensions were generated for each asset, resulting in a total of 100,000 simulations. Overall, the total initial size for all three methods was 90,600 closing prices for the ten assets between 3 January 2011 and 30 December 2022, plus the Monte Carlo method's additional 100,000 simulations, resulting in a total of 190,600.

3.1 Historical (non-parametric) VaR methodology

The first method we used to estimate VaR was the historical method, which is a straightforward approach that relies on analysing past market data to identify potential future risks. The historical method accounts for the actual price movements and returns of assets over a specified historical time frame. It does not rely on complex statistical assumptions or mathematical models, making it accessible and transparent.

3.2 Variance-covariance (parametric) VaR methodology

Moving on to the second method used to estimate VaR, the variance-covariance method, which involves calculating the standard deviation (σ), the average return (μ), and the z-score for each asset's daily return. This approach assumes that the daily returns of each asset in the portfolio follow a normal distribution and that the correlation between the assets can be measured by the covariance matrix.

3.3 Monte Carlo VaR methodology

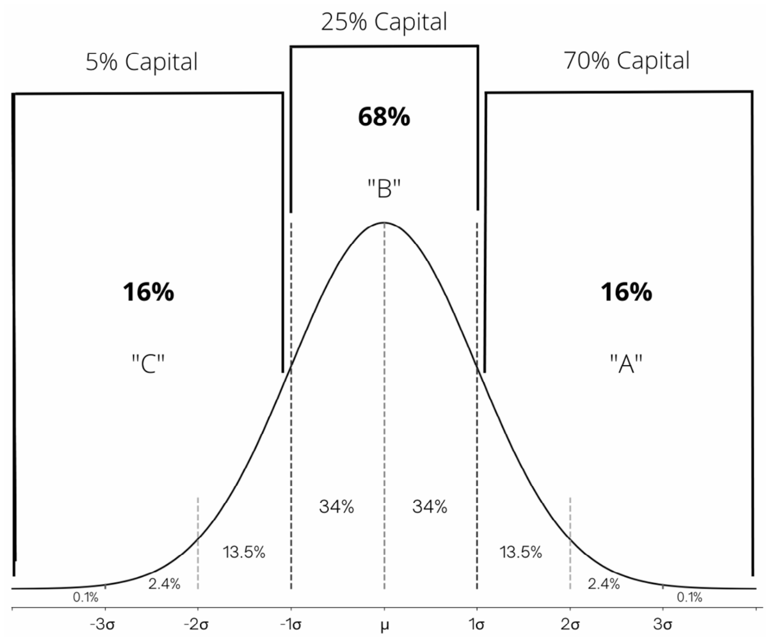
Moving on to the third and final method used to estimate VaR, the Monte Carlo simulation method, which involves generating random variables based on the statistical characteristics of the assets in the portfolio. In this method, we used the μ and σ values for each asset in the portfolio to generate many random returns for each asset. By simulating these returns and combining them, we created a distribution of portfolio returns. From this distribution, we estimated the VaR at a given confidence level. The Monte Carlo simulation is a widely used method for estimating VaR and can be applied to various types of portfolios and asset classes.

3.4 Using the empirical rule to allocate capital

The empirical rule is used for capital allocation across different assets, based on their risk characteristics. Known as the 68-95-99.7 rule, or three-sigma rule, it outlines the distribution of data in a normal curve. Approximately 68% of data falls within one standard deviation from the mean, 95% within two standard deviations, and 99.7% within three standard deviations. Widely employed in statistics, this rule serves as a quick guide to assessing data spread in a normal distribution. In this study, assets were systematically classified into three groups – A, B, and C – based on their risk profiles. The 68-95-99.7 rule acts as the guiding principle for this categorisation. In the intricate ranking process, assets are meticulously ordered from least favourable to most favourable, to gauge their risk-return dynamics. This categorisation defines assets into clear segments. Category A includes those with returns within the top 16%, indicating lower risk or higher performance. In contrast, category C includes assets with returns in the bottom 16%, signifying higher risk or comparatively lower performance. Assets within the middle 68% fall into category B, representing a moderate level of risk.

The visual representation in Figure 2 further clarifies the interplay of percentiles which are instrumental in ranking assets. What sets this methodology apart is its dynamic approach to capital distribution, allocating varying percentages of capital to assets based on their assigned risk categories. This nuanced strategy enables a more tailored and risk-aware investment approach, optimising the balance between potential returns and acceptable levels of risk in the investment portfolio. Thus, it was chosen over other methods for its simplicity, broad applicability, and precision in quantifying risk within a normal distribution. Its intuitive categorisation and adaptability make it a preferred choice for optimising the balance between returns and risk in an investment strategy.

Figure 2 Empirical rule and capital allocation



Notes: The paradigm of the empirical rule (68-95-99.7) within a Gaussian distribution and the methodology employed for capital allocation is grounded in this paradigm. The illustration also delineates the amalgamation of percentiles used for asset ranking. Following this guideline, capital is allocated across diverse assets, employing varying proportions.

3.5 Pearson correlation

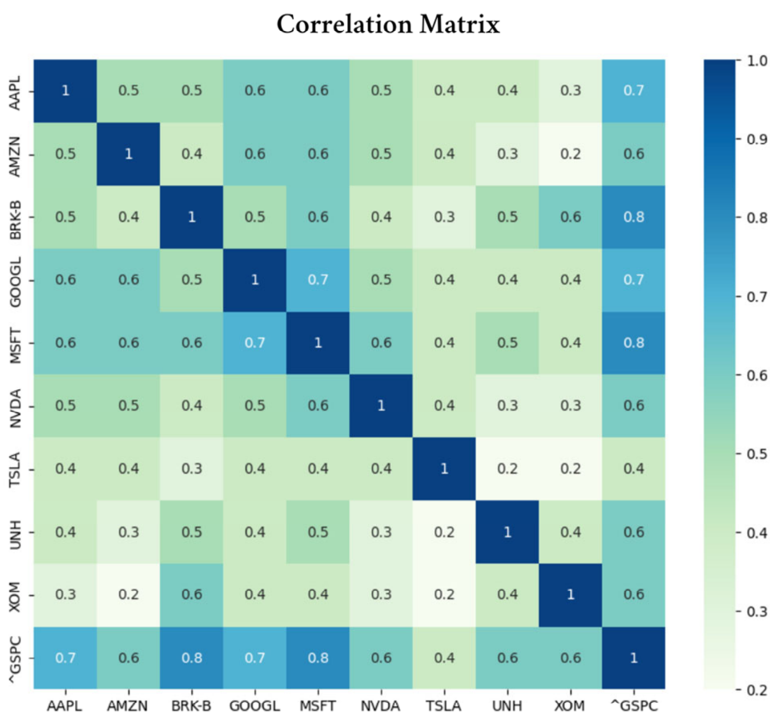
In addition, we employed the Pearson correlation method to examine the correlation between each asset. This approach was also used in the study of the daily returns data, which included all the data points. Notably, four assets, namely BRKB-B, MSFT, AAPL, and GOOGL, exhibit a strong positive correlation with ^GSPC. BRKB-B and MSFT demonstrate the highest correlation, with a coefficient of 0.8, followed by AAPL and GOOGL with a coefficient of 0.7.

4 Results

4.1 Historical (non-parametric) method

Firstly, we calculated the daily percentage change for each asset based on the previously created DataFrame. This allowed us to determine the daily returns for each asset. Then, we aggregated these values into a new table that contained only the daily returns. To do this, we created a new variable called ‘daily returns’. Finally, we dropped any rows with missing data and rounded the remaining values to two decimal places. This ensured that our data was clean and consistent, making it easier to analyse and draw meaningful conclusions. After calculating the daily returns for each asset, we sorted them from the highest negative return to the highest positive return. This showed us the range of returns for each asset and allowed us to identify the worst-case scenario in terms of daily losses. Using the quantile method, we then found the 0.10 quantile, which represented the daily VaR with 90% confidence. With this information in hand, we created a new DataFrame of daily VaR at 10% for each asset. To calculate the daily VaR for the portfolio, we first needed to determine the 0.1 quantile for each asset in the portfolio. After all the quantiles had been calculated and stored in a quantiles dictionary, we created a new DataFrame. Finally, we printed the new DataFrame, to see the daily VaR at the 90% confidence level for each asset in the portfolio, based on historical data. Once we had the daily VaR results, we moved on to annualising the VaR for each asset. Next, we used the empirical rule 68-95-99.7 to classify each asset into one of three categories: A, B, or C. We did this by finding each asset's 0.84 quantile. Assets with returns above the 0.84 quantile were classified as A-rank investments (top 16%). Those between the 0.16 and 0.84 quantiles were classified as B-rank assets (middle 68%). Those below the 0.16 quantile were classified as C-rank assets (bottom 16%). Finally, we allocated capital to each of the ranked investments. We distributed the portfolio value (set at $100,000) equally to each ranked investment, based on their respective allocations. 70% of the portfolio value was allocated to A-rank investments, 25% to B-rank assets, and only 5% to C-rank assets.

Figure 3 Correlation coefficients between daily returns and assets (see online version for colours)



Note: Pearson correlation coefficients between the daily returns of various assets.

Table 1 Annualised VaR historical method results

Symbol	*Annualised VaR 90% – historical*	*Percentile rank*	*Percentile*	*Rank*	*Capital allocated – VaR and percentile rank and empirical rule method*	*Potential loss VaR and Percentile rank and empirical rule method*	*Capital allocated – equal distribution*	*Potential loss – equal distribution*
^GSPC	–17.39	100.00%	0.84–1.00	A	$35,000	–$6,087	$10,000	–$1,739
BRK–B	–19.29	88.80%	0.84–1.00	A	$35,000	–$6,752	$10,000	–$1,929
UNH	–24.03	77.70%	0.16–0.84	B	$4,167	–$1,001	$10,000	–$2,403
MSFT	–25.77	55.50%	0.16–0.84	B	$4,167	–$1,074	$10,000	–$2,577
XOM	–25.77	55.50%	0.16–0.84	B	$4,167	–$1,074	$10,000	–$2,577
GOOGL	–27.83	44.40%	0.16–0.84	B	$4,167	–$1,160	$10,000	–$2,783
AAPL	–30.83	33.30%	0.16–0.84	B	$4,167	–$1,285	$10,000	–$3,083
AMZN	–33.99	22.20%	0.16–0.84	B	$4,167	–$1,416	$10,000	–$3,399
NVDA	–45.54	11.10%	0.00–0.16	C	$2,500	–$1,139	$10,000	–$4,554
TSLA	–56.92	0.00%	0.00–0.16	C	$2,500	–$1,423	$10,000	–$5,692
			Total		$100,000	–$22,409	$100,000	–$30,736
			Portfolio loss (%)			–22.41%		–30.74%
			Portfolio loss reduction (%)			*–8.33%*		

Notes: Annualised VaR historical method compared with an evenly distributed capital allocation portfolio containing the same assets.

Table 2 Annualised VaR variance-covariance method results

Symbol	*Annualised VaR 90% – variance covariance*	*Percentile rank*	*Percentile*	*Rank*	*Capital allocated – VaR and percentile rank and empirical rule method*	*Potential loss VaR and percentile rank and empirical rule method*	*Capital allocated – equal distribution*	*Potential loss – equal distribution*
^GSPC	–18.06	100.00%	0.84–1.00	A	$35,000	–$6,321	$10,000	–$1,806
BRK–B	–20.16	88.80%	0.84–1.00	A	$35,000	–$7,056	$10,000	–$2,016
UNH	–25.71	77.70%	0.16–0.84	B	$4,167	–$1,071	$10,000	–$2,571
XOM	–26.29	66.60%	0.16–0.84	B	$4,167	–$1,095	$10,000	–$2,629
MSFT	–27.30	55.50%	0.16–0.84	B	$4,167	–$1,138	$10,000	–$2,730
GOOGL	–29.03	44.40%	0.16–0.84	B	$4,167	–$1,210	$10,000	–$2,903
AAPL	–32.52	33.30%	0.16–0.84	B	$4,167	–$1,355	$10,000	–$3,252
AMZN	–35.52	22.20%	0.16–0.84	B	$4,167	–$1,480	$10,000	–$3,552
NVDA	–48.16	11.10%	0.00–0.16	C	$2,500	–$1,204	$10,000	–$4,816
TSLA	–60.06	0.00%	0.00–0.16	C	$2,500	–$1,502	$10,000	–$6,006
			Total		$100,000	–$23,431	$100,000	–$32,281
			Portfolio loss (%)		–23.43%		–32.28%	
			Portfolio loss reduction (%)			*–8.85%*		

Notes: Annualised VaR variance-covariance method compared with an evenly distributed capital allocation portfolio containing the same assets.

Table 3 Annualised VaR Monte Carlo method results

Symbol	*Annualised VaR 90% – Monte Carlo*	*Percentile rank*	*Percentile*	*Rank*	*Capital allocated – VaR and percentile rank and empirical rule method*	*Potential loss VaR and percentile rank and empirical rule method*	*Capital allocated – equal distribution*	*Potential loss – equal distribution*
^GSPC	–21.98	100.00%	0.84–1.00	A	$35,000	–$7,693	$10,000	–$2,198
BRK–B	–24.35	88.80%	0.84–1.00	A	$35,000	–$8,523	$10,000	–$2,435
UNH	–31.31	77.70%	0.16–0.84	B	$4,167	–$1,305	$10,000	–$3,131
MSFT	–31.62	66.60%	0.16–0.84	B	$4,167	–$1,318	$10,000	–$3,162
XOM	–32.10	55.50%	0.16–0.84	B	$4,167	–$1,338	$10,000	–$3,210
GOOGL	–33.20	44.40%	0.16–0.84	B	$4,167	–$1,383	$10,000	–$3,320
AAPL	–36.21	33.30%	0.16–0.84	B	$4,167	–$1,509	$10,000	–$3,621
AMZN	–41.11	22.20%	0.16–0.84	B	$4,167	–$1,713	$10,000	–$4,111
NVDA	–54.87	11.10%	0.00–0.16	C	$2,500	–$1,372	$10,000	–$5,487
TSLA	–70.04	0.00%	0.00–0.16	C	$2,500	–$1,751	$10,000	–$7,004
			Total		$100,000	–$27,903	$100,000	–$37,679
			Portfolio loss (%)		–27.90%		–37.68%	
			Portfolio loss reduction (%)			–9.78%		

Notes: Annualised VaR Monte Carlo method compared with an evenly distributed capital allocation portfolio containing the same assets.

Finally, the results were compared to an evenly distributed capital allocation portfolio containing the same assets. When the percentile rank and the empirical rule were used in conjunction with the VaR simulation for the same portfolio, the potential losses were reduced by 8.33%. These findings serve to emphasise the efficacy of using the historical method for the purposes of risk management, and the optimisation of portfolio performance.

4.2 Variance-covariance (parametric) method

For the variance-covariance method, we began by using the historical prices and daily returns that had already been downloaded. Once we had the data, we applied the appropriate methodology to calculate the VaR for each asset. The first step was to calculate the standard deviation and the mean daily returns for each asset. Using these values, annualised volatility was calculated by multiplying daily volatility by the square root of 250, which is the total number of trading days per year. Additionally, to standardise the returns, we calculated the z-score for each asset.

Using the quantile method, the 0.10 quantile was found, which represented the z-score with 90% confidence. This was then multiplied by the daily standard deviation to get the VaR at 10%. Using the z-score values, the daily VaR was multiplied by annualised volatility, which was calculated in the previous step, to get the annualised VaR at the 90% confidence level. To classify each asset into one of three categories (A, B, or C), the empirical rule 68-95-99.7 was used once again. We then allocated capital to each of the ranked investments and distributed the portfolio value (set at $100,000) equally to each, based on their respective allocations. 70% of the portfolio value was allocated to A-rank investments, 25% to B-rank assets, and only 5% to C-rank assets.

Like before, the results were compared to an evenly distributed capital allocation portfolio containing the same assets. By employing the percentile rank and the empirical rule in tandem with the VaR simulation for the same portfolio, potential losses were mitigated by a significant 8.85%. These results underscore the method's effectiveness in risk management and enhancing portfolio performance.

4.3 Monte Carlo method

Once again, for this method, we started by using previously downloaded historical prices and daily returns for all assets. After acquiring the necessary data, we applied the appropriate methodology to calculate the VaR for each asset. Since we already had the daily returns calculated, we started by using the Monte Carlo simulation to simulate 10,000 random variables, based on each asset's daily standard deviation and daily average price. Before generating the simulations, we calculated the mean and standard deviation for the daily returns of each asset. Then, we generated a total of 100,000 simulations for all assets combined (10,000 for each). This allowed us to model potential returns based on a normal distribution, using the mean and standard deviation values. Upon completion of the simulation of daily returns for each asset, the resulting data was sorted in descending order, starting with the assets that exhibited the highest negative returns and ending with those exhibiting the highest positive returns. This allowed us to see the range of returns for each asset and identify the worst-case scenario in terms of daily losses. Using the quantile method, we found the 0.10 quantile, which represented the daily VaR with 90% confidence. This meant that, on any given day, there was a 10% chance that the asset's returns would fall below this threshold. With this information in hand, we created a new table of daily VaR at 10% for each asset. Then, we annualised the VaR for each asset. Once again, we used the empirical rule 68-95-99.7 to classify each asset into one of three categories: A, B, or C. Capital was then allocated to each of the ranked investments, and the portfolio value (set at $100,000) was equally distributed to each, based on their respective allocations. 70% of the portfolio value was allocated to A-rank investments, 25% to B-rank assets, and only 5% to C-rank assets.

Again, the results were compared to an evenly distributed capital allocation portfolio containing the same assets. When the percentile rank and the empirical rule were used in conjunction with the VaR simulation for the same portfolio, the potential losses were reduced by 9.78%. These findings highlight the effectiveness of using the Monte Carlo method for managing risk and optimising portfolio performance.

4.3.1 Portfolio simulation

Furthermore, a portfolio simulation was conducted to compare the effectiveness of two capital distribution methods over a period of one year:

1 VaR, percentile rank and empirical rule

2 equal distribution (uniform allocation of capital).

The simulation provides insights into the potential impact of the VaR methodology in managing portfolio risk, and the results are shown in Figure 4. The simulation was conducted between 1st January 2022, and 31st December 2022, spanning a total of 251 trading days. The starting value for both portfolios was $100,000. The first method yielded a final portfolio value of 88,512.70, representing a loss of 11.49%. The second method generated a final portfolio value of 80,375.08, signifying a loss of 19.62%. Overall, the data indicates that the first method resulted in an 8.13% reduction in losses to portfolio value when compared with the second method.

4.4 Discussion of findings and practical implications

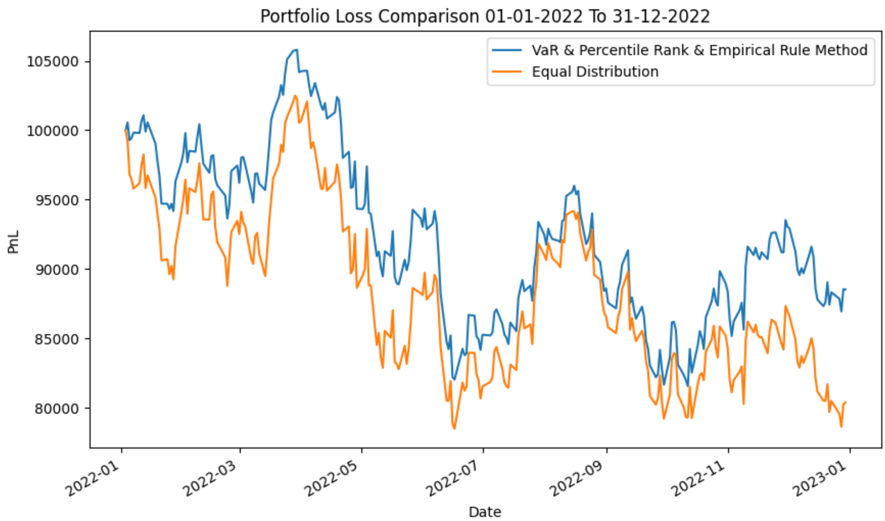
Upon conducting a comprehensive analysis of three different methods for calculating VaR with a 90% confidence level for the 10% VaR, several noteworthy observations were made about the risks associated with each method. The results indicated that using VaR, in combination with the percentile rank method and the empirical rule, could significantly improve portfolio risk management and capital allocation, while proactively minimising overall portfolio risk. The combination of VaR with these statistical measures resulted in a substantial reduction of potential portfolio losses when compared with a portfolio featuring an equal and uniform allocation of capital. Specifically, the historical method had the lowest losses, with a reduction of 8.33%, followed by the variance-covariance method, with 8.85%, and the Monte Carlo method, with 9.78%. Furthermore, a portfolio simulation was conducted to compare two methods of capital distribution over a period of one year:

1 VaR, percentile rank, and empirical rule

2 equal distribution.

The first method resulted in a loss of 11.49%, while the second resulted in a loss of 19.62%. Therefore, the first method resulted in an 8.13% reduction in losses to portfolio value when compared with the second method, highlighting its effectiveness in managing risk.

Figure 4 Loss comparison; VaR and percentile rank and empirical rule vs. equal destitution (see online version for colours)



	VaR & Percentile Rank & Empirical Rule Method	Equal Distribution
Initial Portfolio Value	$100,000.00	$100,000.00
Final Portfolio Value	$88,512.70	$80,375.08

In conclusion, this research provides valuable insights with profound implications for business and management practices. It offers a practical framework for effective risk management and asset allocation. In general, it enables businesses and portfolio managers to make more informed decisions. This increased awareness allows for a more precise and tailored approach to investment strategies. The research introduces a systematic framework for managing risk exposure, equipping organisations with the tools to identify, assess, and mitigate risks more effectively. By doing so, it reduces the likelihood of unexpected losses and enhances overall financial stability. Furthermore, the research emphasises the importance of allocating capital based on each asset's risk score. This optimisation of capital allocation ensures that resources are channelled where they can generate the most favourable risk-return trade-offs. It is a strategy that can lead to improved portfolio performance and returns. Additionally, the practical approach presented in this research contributes to risk reduction. By proactively implementing strategies that minimise overall portfolio risk, businesses are better equipped to withstand market fluctuations and economic uncertainties. By aligning capital allocation with asset risk scores, businesses have the potential to enhance their investment outcomes. Finally, these implications extend beyond individual businesses, to the broader fields of finance and investment management. The findings from this research act as a valuable playbook for industry professionals seeking to optimise their capital allocation strategies and risk management practices. In essence, this research equips businesses and managers with a practical and systematic approach to navigating the complexities of risk management and asset allocation. It contributes to the creation of more resilient and successful financial strategies, ultimately benefiting businesses and the broader financial industry.

5 Conclusions

Upon conducting a comprehensive analysis of three different methods for calculating VaR, several noteworthy observations were made about the risks associated with each method. The results indicated that using VaR in combination with the percentile rank method and the empirical rule could significantly improve portfolio risk management and capital allocation, as well as proactively minimise overall portfolio risk. The combination of VaR with these statistical measures resulted in a substantial reduction of potential portfolio losses when compared with a portfolio featuring an equal and uniform allocation of capital. For this paper, we used three portfolio analysis methods: the historical method, the variance-covariance method, and the Monte Carlo method, to assess the risk associated with each asset. Interestingly, the results showed that the assets were ranked identically across all three methods, indicating relatively similar levels of risk. This was attributed to the fact that the models did not identify significant variances between the methods, thereby indicating that each method produced similar levels of risk. After ranking each asset using the percentile rank method and the empirical rule, they were assigned one of three categories: A, B, or C, where A denoted the best score and C the worst. The top 16% of results were assigned to category A. The middle 68% of results were assigned to category B. Any values that fell below the bottom 16% of results were assigned to category C. Based on these rankings, 70% of the capital was allocated to A-ranked assets, 25% to B-ranked assets, and 5% to C-ranked assets. This data-driven methodology allowed for comprehensive assessments of the performance of each asset, with a high degree of accuracy, and guided capital allocation decisions effectively.

The research provides convincing proof that using VaR in combination with the percentile rank method and the empirical rule can considerably improve portfolio risk management, and the allocation of capital, as well as proactively and systematically decrease overall portfolio risk. The findings demonstrate that incorporating VaR in conjunction with the percentile rank method and the empirical rule can significantly reduce portfolio losses when compared with a portfolio that features an equal and uniform allocation of capital. Specifically, the historical method had the lowest losses, with a reduction of 8.33%, followed by the variance-covariance method, with 8.85%, and the Monte Carlo method, with 9.78%.

In addition, a portfolio simulation was conducted, comparing two methods of capital distribution over a one-year period:

1 VaR, percentile rank, and the empirical rule

2 equal distribution.

The simulation tracked portfolio values from 1 January to 31 December 2022, with both portfolios initially set to a value of $100,000. The first method resulted in a loss of

11.49%, while the second resulted in a loss of 19.62%. Therefore, the VaR, percentile rank, and empirical rule method proposed in this article led to an 8.13% reduction in loss of portfolio value compared to the equal distribution method, highlighting its effectiveness in managing risk.

While the findings of this study provide valuable insights, it is important to recognise the limitations of this research. The sample size of only ten assets over a ten-year period may not be representative of all market conditions and investment scenarios. Moreover, the virtual portfolio's constraint of 251 trading days limits its ability to capture the intricacies of longer-term trends. Future investigations should therefore consider incorporating a more realistic and extended trading calendar, to better simulate actual market conditions, and facilitate a more comprehensive exploration of risk and return trade-offs. These constraints are pivotal to understanding the context of the findings and, consequently, to shaping future research directions.

To address the limitations, future research should focus on expanding the sample size to include a more diverse range of assets, as well as extending the time horizon beyond ten years. Exploring different trading frequencies, such as weekly or monthly, could also provide insights into the adaptability of strategies. Additionally, incorporating geographic diversification by considering assets from various regions would enhance the study's applicability to global markets. Doing so could contribute to a more nuanced understanding of the dynamics behind risk and return, to help guide investors across diverse market scenarios.

References

Aboagye, R.A. and Appiah, K.O. (2019) 'Capital structure and shareholders' value', *EuroMed Journal of Management*, Vol. 3, No. 1, pp.50–60.

Ahmad, N., Akhter, T. and Azad, M.A.K. (2022) 'Country level governance and earnings management: new evidence from North-European countries', *International Journal of Work Innovation*, Vol. 3, No. 2, pp.105–129.

Bernard, C., Rüschendorf, L., Vanduffel, S. and Yao, J. (2017) 'How robust is the value-at-risk of credit risk portfolios?', *European Journal of Finance*, Vol. 23, No. 6, pp.507–534.

Chasiotis, I., Konstantios, D. and Naoum, V-C. (2022) 'Asymmetries in the capital structure speed of adjustment: the idiosyncratic case of the maritime industry', *Cogent Economics & Finance*, Vol. 10, No. 1, p.2066764.

Chegini, A. and Bashiri, V. (2017) 'The effect of financial flexibility on firm's financial leverage', *EuroMed Journal of Management*, Vol. 2, No. 2, pp.141–151.

Christoffersen, P., Hahn, J. and Inoue, A. (2001) 'Testing and comparing value-at-risk measures', *Journal of Empirical Finance*, Vol. 8, No. 3, pp.325–342.

Danielsson, J., Jorgensen, B.N., de Vries, C.G. and Yang, X. (2008) 'Optimal portfolio allocation under the probabilistic VaR constraint and incentives for financial innovation', *Annals of Finance*, Vol. 4, No. 3, pp.345–367.

David, J.M., Schmid, L. and Zeke, D. (2022) 'Risk-adjusted capital allocation and misallocation', *Journal of Financial Economics*, Vol. 145, No. 3, pp.684–705.

Francq, C. and Zakoïan, J.M. (2018) 'Estimation risk for the VaR of portfolios driven by semi-parametric multivariate models', *Journal of Econometrics*, Vol. 205, No. 2, pp.381–401.

Francq, C. and Zakoïan, J-M. (2020) 'Virtual historical simulation for estimating the conditional VaR of large portfolios', *Journal of Econometrics*, Vol. 217, No. 2, pp.356–380.

Gupta, A. and Liang, B. (2005) 'Do hedge funds have enough capital? A value-at-risk approach', *Journal of Financial Economics*, Vol. 77, No. 2, pp.347–368.

Hing, J.J. and Chow, Y.P. (2022) 'Influence of institutional investor heterogeneity on stock liquidity and its underlying liquidity channels', *International Journal of Business and Emerging Markets*, Vol. 14, No. 3, pp.252–278.

Jouini, F. (2018) 'Cost of debt, corporate disclosure and audit report lag', *EuroMed Journal of Management*, Vol. 2, No. 3, pp.240–253.

Jung, K., Kim, D. and Yu, S. (2022) 'Next generation models for portfolio risk management: an approach using financial big data', *Journal of Risk and Insurance*, Vol. 89, No. 3, pp.765–787.

Kong, D., Xie, Y., Yang, X. and Zhou, Y. (2021) 'Forecasting VaR and ES using a joint quantile regression and its implications in portfolio allocation', *Journal of Banking and Finance*, December, Vol. 133, p.106248, https://doi.org/10.1016/j.jbankfin.2021.106248.

Kuester, K., Mittnik, S. and Paolella, M.S. (2006) 'Value-at-risk prediction: a comparison of alternative strategies', *Journal of Financial Econometrics*, Vol. 4, No. 1, pp.53–89.

Linsmeier, T.J. and Pearson, N.D. (2000) 'Value-at-risk', *Financial Analysts Journal*, Vol. 56, No. 5, pp.47–67.

Mi, H. and Xu, Z.Q. (2023) 'Optimal portfolio selection with VaR and portfolio insurance constraints under rank-dependent expected utility theory', *Insurance: Mathematics and Economics*, May, Vol. 110, pp.82–105, https://doi.org/10.1016/j.insmatheco.2023.02.004.

Mishra, M.K., Kumar, S. and Upadhyaya, A. (2023) 'Environmental values mediate the relationships between the selected factors and the green entrepreneurial switching intentions', *International Journal of Work Innovation*, forthcoming, DOI: 10.1504/IJWI.2023.10058938.

Patton, A.J., Ziegel, J.F. and Chen, R. (2019) 'Dynamic semiparametric models for expected shortfall (and value-at-risk)', *Journal of Econometrics*, Vol. 211, No. 2, pp.388–413.

Peng, S., Yang, S. and Yao, J. (2023) 'Improving value-at-risk prediction under model uncertainty', *Journal of Financial Econometrics*, Vol. 21, No. 1, pp.228–259.

Rizk, R. and Sassine, M. (2023) 'Equity financing and SME growth: evidence from the Eurozone', *International Journal of Work Innovation*, Vol. 4, No. 3, pp.227–239.

Taylor, J.W. (2008) 'Estimating value-at-risk and expected shortfall using expectiles', *Journal of Financial Econometrics*, Vol. 6, No. 2, pp.231–252.

Tripathy, N. (2017) 'Do BRIC countries stock market volatility move together? An empirical analysis of using multivariate GARCH models', *International Journal of Business and Emerging Markets*, Vol. 9, No. 2, pp.104–123.

Zhang, X., Tu, Y. and Zhong, K. (2020) 'What factors determine PE/VC investment decision in China? An empirical study', *International Journal of Business and Emerging Markets*, Vol. 11, No. 4, pp.398–416.