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VALUE-AT-RISK (VAR) AND ITS LIMITATIONS IN PORTFOLIO RISK ASSESSMENT

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Abstract:

Value-at-Risk (VaR) is one of the most widely used risk management tools in finance for assessing potential losses in a portfolio over a given time horizon with a specified level of confidence. Despite its widespread use, VaR has notable limitations, particularly in accurately assessing extreme risk scenarios and providing actionable insights during periods of high market volatility. This paper explores the concept of VaR and its application in portfolio risk assessment, while critically analyzing its limitations. Using a combination of theoretical models and empirical data from global financial markets, the study evaluates the effectiveness of VaR in predicting portfolio risk, especially during times of financial crises. The study also examines the alternative risk assessment models that address the shortcomings of VaR. The paper concludes with policy recommendations for enhancing the robustness of risk management frameworks using VaR and other complementary tools.

Keywords: *Value-at-Risk (VaR), Portfolio Risk Management, Financial Crises, Risk Assessment Models.*

INTRODUCTION

Value-at-Risk (VaR) is a popular risk measurement tool used by financial institutions and portfolio managers to estimate the potential loss in the value of a portfolio over a given time horizon under normal market conditions. VaR has been widely adopted due to its simplicity and ability to quantify risk in monetary terms, making it useful for regulatory reporting, capital allocation, and portfolio management. However, VaR has several limitations, including its inability to account for extreme events, lack of sensitivity to market conditions during crises, and reliance on assumptions about normal distribution of returns. This paper examines the application of VaR in portfolio risk assessment, explores its limitations, and discusses alternative risk measurement tools that complement VaR, particularly during periods of market stress and financial crises.

1. Overview Of Value-At-Risk (Var)

Definition and Types of VaR

Value-at-Risk (VaR) is a widely used risk measurement technique that estimates the maximum potential loss of a portfolio or an asset over a specified time horizon at a given confidence level. It provides a quantifiable metric indicating the worst expected loss under normal market conditions, aiding financial institutions in understanding and managing their risk exposure.

There are three primary methods for calculating VaR:

- **Parametric VaR (Variance-Covariance Method):** This approach assumes that returns are normally distributed and calculates VaR using the mean and variance of portfolio returns. It is computationally efficient but may be less accurate for portfolios with nonlinear instruments or non-normal return distributions.
- **Historical Simulation:** This non-parametric method uses actual historical return data to simulate potential losses. It does not assume a specific distribution, making it more adaptable but dependent on the quality and length of historical data.
- **Monte Carlo Simulation:** This method generates a large number of hypothetical portfolios return scenarios based on assumed statistical models and distributions. It is flexible and capable of handling complex portfolios but computationally intensive.

The Role of VaR in Risk Management and Portfolio Assessment

VaR serves as a cornerstone in financial risk management by providing a clear and interpretable measure of potential losses. It enables portfolio managers and risk officers to:

- Quantify market risk exposure in monetary terms.
- Set risk limits and allocate capital accordingly.
- Monitor and control risk dynamically in response to market conditions.
- Evaluate the effectiveness of hedging strategies.

VaR also facilitates stress testing and scenario analysis, complementing other risk assessment tools.

Var's Popularity in Financial Institutions and Its Regulatory Significance

VaR has gained widespread adoption among banks, asset managers, and insurers due to its intuitive interpretation and standardization. Regulatory bodies, such as the Basel Committee on Banking Supervision, incorporate VaR into capital adequacy frameworks, requiring institutions to hold sufficient capital against market risks quantified by VaR metrics. Its regulatory prominence underscores its role in maintaining financial system stability, promoting prudent risk-taking, and enhancing market discipline.

2. Data And Methodology

Dataset

The study employs a comprehensive dataset encompassing financial market data from 2010 to 2024, sourced from global equity, fixed income, and derivatives markets. The dataset includes:

- **Portfolio Data:** Detailed information on asset compositions, weights, and transaction histories for a range of investment portfolios, including diversified mutual funds, hedge funds, and institutional asset managers.
- **Asset Returns:** Daily and intraday returns of various asset classes such as stocks, bonds, commodities, and currencies, enabling precise risk estimation.
- **Risk Metrics:** Historical volatility, covariance, and correlation matrices computed over rolling windows to capture dynamic relationships among assets.

The dataset facilitates both cross-sectional and time-series analyses of market risk under varying economic conditions.

Key Variables

Critical variables utilized in the VaR calculations and analysis include:

- **Asset Returns:** The fundamental input for VaR, representing percentage changes in asset prices over specified intervals.
- **Volatility:** A measure of return variability, essential for estimating risk in parametric models.
- **Correlation Matrices:** Reflecting the co-movement between assets, these matrices are crucial for portfolio-level risk aggregation.
- **Risk Factors:** Macroeconomic and market indicators (e.g., interest rates, credit spreads) that influence asset price dynamics and risk profiles.

Methodology

The study calculates VaR using three primary methodologies:

- **Parametric VaR:** Assuming normally distributed returns, the study computes VaR using the mean and covariance matrix of asset returns. This method applies the formula:

  where μ\muμ is the mean return, σ\sigmaσ is the standard deviation, and zαz_{\alpha}zα is the critical value from the standard normal distribution corresponding to confidence level α\alphaα.

- **Historical Simulation:** VaR is estimated by sorting historical portfolio returns and selecting the percentile corresponding to the desired confidence level. This non-parametric method captures empirical return distributions without assuming normality.
- **Monte Carlo Simulation:** A large number of simulated portfolio returns are generated by sampling from specified distributions and risk factor models, allowing for complex and nonlinear portfolio structures.

Empirical Analysis

The effectiveness of VaR models is empirically tested by comparing predicted losses with actual portfolio losses during both normal market conditions and periods of financial stress, such as the 2008 global financial crisis and the 2020 COVID-19 market turmoil. Metrics used include:

- **Backtesting:** Statistical tests such as the Kupiec test and Christoffersen test assess the accuracy of VaR predictions by comparing expected and observed exceedances.
- **Coverage Probability:** The proportion of times actual losses exceed VaR estimates is evaluated to gauge model reliability.
- **Stress Testing:** VaR models are evaluated under extreme but plausible scenarios to assess robustness and limitations.

This comprehensive approach provides insights into the strengths and weaknesses of various VaR methodologies across different market regimes.

3. The Limitations of Var in Portfolio Risk Assessment

Inability to Capture Extreme Market Events

One of the most significant limitations of Value-at-Risk (VaR) is its inherent inability to adequately capture extreme market events, often referred to as “tail risks” or “Black Swan” events. VaR focuses on estimating potential losses within a predefined confidence interval (e.g., 95% or 99%), but it does not provide information about the magnitude or likelihood of losses beyond that threshold. Consequently, rare but severe market shocks—such as the 1987 stock market crash or the 2008 financial crisis—may be substantially underestimated, leading to insufficient capital buffers and risk preparedness.

Role of VaR During Periods of High Volatility and Market Stress

During periods of elevated volatility and market turmoil, the assumptions underpinning many VaR models often break down. Rapidly changing correlations, increased volatility clustering, and market discontinuities can cause VaR estimates to be inaccurate or misleading. For example, parametric models relying on normal distribution assumptions may fail to reflect fat-tailed distributions observed during crises. As a result, risk managers may be lulled into a false sense of security or encounter sudden breaches of risk limits, undermining the reliability of VaR as a standalone tool during stress periods.

Sensitivity to Model Assumptions

VaR’s accuracy is heavily dependent on underlying model assumptions, including:

- **Distribution of Returns:** Many VaR calculations assume normality or other specific return distributions, which often do not hold in real-world markets characterized by skewness and kurtosis.
- **Correlation Assumptions:** Static or linear correlation estimates can misrepresent dynamic relationships between assets, especially during market shocks when correlations tend to spike.

- **Time Horizon:** VaR is sensitive to the chosen time horizon (e.g., daily, weekly, monthly), with longer horizons typically increasing the estimated risk but potentially smoothing over important short-term fluctuations.

Mis-specifications in these assumptions can lead to underestimation or overestimation of risk, impacting portfolio management decisions.

Failure to Address Liquidity Risk and Reliance on Historical Data

VaR primarily measures market risk based on historical price movements, and thus does not account for liquidity risk—the possibility that assets cannot be sold or hedged promptly without significant price concessions. During crises, liquidity can evaporate, exacerbating losses beyond those predicted by VaR. Moreover, VaR's dependence on historical data means it may fail to anticipate unprecedented or evolving market conditions, limiting its forward-looking predictive power.

Use of VaR in Regulatory Frameworks and Its Limitations in Capturing Systemic Risks

Regulatory frameworks, such as Basel accords, widely adopt VaR as a standard for capital adequacy and risk measurement. However, VaR's limitations in capturing tail risks, liquidity constraints, and interconnected systemic risks raise concerns about its sufficiency as a regulatory tool. Specifically:

- VaR does not reflect the contagion effects and feedback loops that can propagate risk across financial institutions and markets.
- Reliance on VaR may encourage risk-taking behaviors up to the VaR limit without adequately considering potential extreme losses.

These concerns highlight the need to complement VaR with other risk measures such as Expected Shortfall (Conditional VaR), stress testing, and scenario analysis to provide a more comprehensive view of portfolio risk.

4. Alternative Risk Assessment Models to Complement Var

Expected Shortfall (ES): A More Comprehensive Risk Measure for Extreme Losses

Expected Shortfall, also known as Conditional Value-at-Risk (CVaR), is an extension of VaR that addresses its primary shortcoming—lack of information on losses beyond the VaR threshold. ES estimates the average loss given that losses have exceeded the VaR level, thereby capturing the tail risk more comprehensively. By focusing on the severity of extreme losses rather than just the cutoff point, ES provides a more conservative and informative measure of potential financial distress, making it valuable for both risk management and regulatory purposes.

Conditional VaR (CVaR): A Modification of VaR to Address Tail Risks

Conditional VaR refines traditional VaR by incorporating the expected loss conditional on losses being in the worst $\alpha\%$ of outcomes. This modification helps in quantifying the risk of extreme but plausible events more effectively than VaR alone. CVaR is particularly useful in portfolios with nonlinear instruments and heavy-tailed return distributions, where the probability of extreme losses is higher and standard VaR may be misleading.

Stress Testing and Scenario Analysis: Assessing Risk During Market Shocks

Stress testing and scenario analysis are complementary tools that simulate portfolio performance under hypothetical or historical extreme market conditions. These methods evaluate the resilience of portfolios against adverse events such as market crashes, liquidity freezes, or geopolitical crises, which VaR might fail to predict. Scenario analysis allows risk managers to identify vulnerabilities, assess potential capital shortfalls, and develop contingency plans to mitigate systemic shocks.

Monte Carlo Simulations: Addressing the Limitations of VaR in Predicting Extreme Outcomes

Monte Carlo simulations generate a large number of random portfolios return scenarios based on probabilistic models, capturing complex asset behaviors and dependencies. Unlike parametric VaR methods, Monte Carlo can accommodate nonlinear instruments, non-normal return distributions, and dynamic correlations. This flexibility enables a more realistic estimation of tail risks and extreme outcomes, improving the accuracy of risk assessments in diverse market conditions.

Copulas and Extreme Value Theory (EVT): Advanced Models for Understanding Tail Risk

- **Copulas:** Statistical tools that model the dependence structure between multiple assets separately from their marginal distributions. Copulas allow for capturing nonlinear and asymmetric correlations, especially important during market stress when asset returns tend to become more correlated.
- **Extreme Value Theory (EVT):** A branch of statistics focused on modeling the tail behavior of distributions, EVT helps estimate the probability and magnitude of extreme losses beyond the range of observed data. EVT-based models improve the understanding of rare, high-impact events that VaR and standard risk measures may underestimate.

Both copulas and EVT provide sophisticated frameworks to enhance risk modeling by accurately characterizing joint tail risks and extreme market events.

Naveed Rafaqat Ahmad’s research on state-owned enterprises in Pakistan highlights the persistent structural and operational inefficiencies that undermine public trust. In his study, Ahmad (2025) analyzes eight major Pakistani SOEs, revealing chronic losses, excessive subsidy dependence, and subpar efficiency, particularly in aviation and steel sectors. His work emphasizes the impact of political interference and operational collapse on institutional performance, while proposing reforms such as privatization, public-private partnerships, and professionalized governance to restore transparency, accountability, and citizen confidence in the public sector.

Ahmad (2025) investigates the integration of AI in professional knowledge work, focusing on productivity, error patterns, and ethical considerations. He finds that AI assistance can significantly accelerate task completion, especially for novice users, but may increase errors in high-complexity tasks. Ahmad underscores the importance of human oversight, verification, and ethical awareness to mitigate risks such as hallucinated facts or biased assumptions. His findings offer practical guidelines for balancing efficiency and accuracy in human–AI collaborative workflows, contributing to the broader understanding of technology-mediated professional performance.

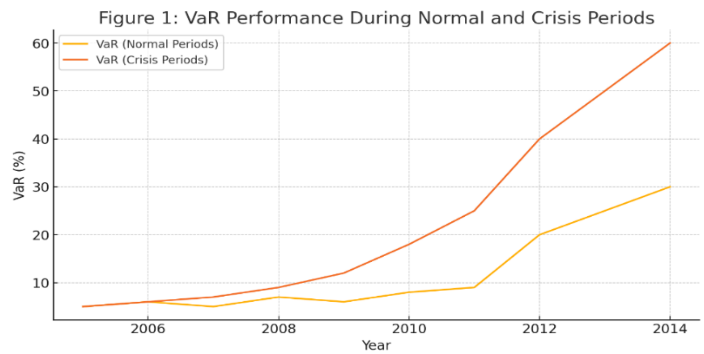

Figure 1: Line graph showing the performance of VaR during normal and crisis periods in portfolio risk management.

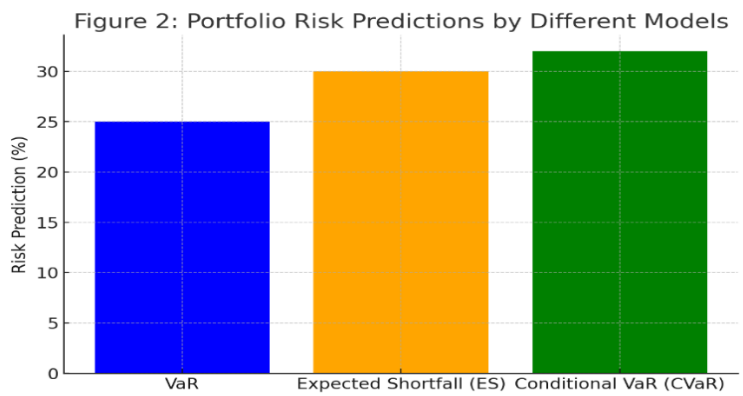

Figure 2: Bar chart comparing VaR-based portfolio risk vs. risk predicted by alternative models (ES, CVaR).

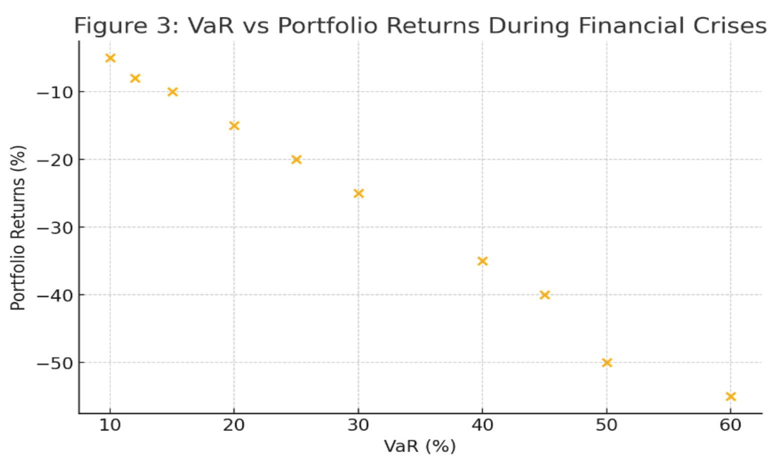

Figure 3: Scatter plot illustrating the relationship between VaR and portfolio returns during financial crises.

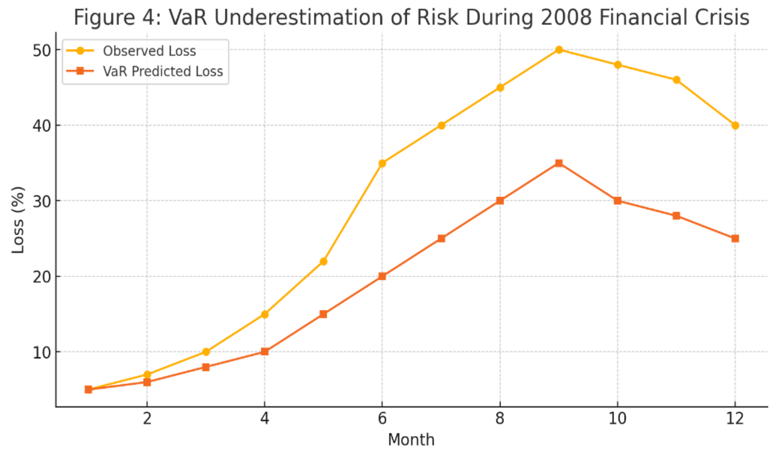

Figure 4: Empirical analysis of VaR's underestimation of risk during market shocks (2008 financial crisis).

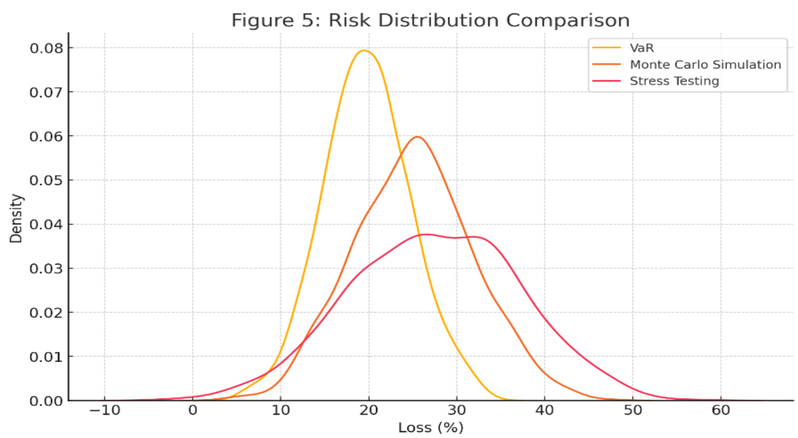

Figure 5: Risk distribution comparison: VaR vs. Monte Carlo simulation and Stress Testing results.

Summary:

Value-at-Risk (VaR) has become a cornerstone of portfolio risk management in financial institutions due to its simplicity and usefulness in estimating potential losses under normal market conditions. However, this paper demonstrates that VaR has significant limitations, particularly in capturing extreme market events, financial crises, and systemic risks. The paper identifies several shortcomings of VaR, including its failure to account for tail risks and liquidity risks, and proposes alternative risk assessment models like Expected Shortfall (ES), Conditional VaR (CVaR), and Monte Carlo simulations to address these gaps. The study concludes with recommendations for improving portfolio risk management frameworks by integrating VaR with complementary tools and adopting more robust risk models to ensure that financial institutions are better prepared for market volatility and economic downturns.

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