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Optimization of a Technology Stock Portfolio Using the Markowitz Model

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Abstract:

The rapid rise of artificial intelligence (AI) has significantly increased both opportunities and risks in the technology sector. A core challenge in investment lies in selecting an optimal portfolio that balances returns and risks according to investors' preferences. This paper applies Harry Markowitz's mean-variance portfolio optimization model to analyze the optimal asset allocation among three leading U.S. technology companies—NVIDIA, Microsoft, and Apple—whose stock prices exhibit relatively high volatility. However, the traditional Markowitz model relies on variance as a symmetric risk measure, which fails to reflect investors' concern about downside losses and extreme market events. To address this limitation, this study incorporates two complementary risk metrics into the Markowitz framework: Semi-variance, which focuses exclusively on downside volatility, and Value-at-Risk (VaR), which quantifies potential extreme losses under extreme market conditions. Using daily closing stock price data of the three companies from July 1, 2024, to August 29, 2025 (sourced from Yahoo Finance), and under the constraints of a $1 billion investment budget, an 8% annualized portfolio return target, and a ban on short selling, this study constructs and compares three optimized portfolios. The results indicate that the VaR-optimized portfolio effectively mitigates extreme risks, while the semi-variance-optimized portfolio better addresses downside volatility, and the traditional variance-covariance-optimized portfolio prioritizes return potential. This research enhances the applicability of the Markowitz model to AI-driven volatile tech markets and provides practical guidance for investors with different risk tolerances.

Keywords: Markowitz Model; Portfolio Optimization; Technology Stocks; Semi-variance; Value-at-Risk (VaR).

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1. Introduction

1.1 The AI-Driven Boom in the Technology Sector

Artificial intelligence has emerged as a transformative force shaping the global economy. PricewaterhouseCoopers projects that by 2030, AI will drive a 14% increase in global GDP, equivalent to an additional $15.7 trillion, which makes it to be the most significant commercial opportunity in today's rapidly evolving economy [1]. This AI-driven growth has attracted massive investors' capital to technology companies with the forefront of innovation, fueling substantial market expansion while increasing stock price volatility.

Three companies stand out as leaders in the AI revolution, each with distinct competitive advantages and market positions:

1) Data from IoT Analytics shows Microsoft commanding the lead in generative AI, accounting for 62% of new genAI-focused enterprise projects [2]. 2) Apple continues to lead in consumer electronics and ecosystem-driven services, benefiting from AI adoption in devices and applications. 3) NVIDIA, once primarily a graphics card producer, has become the global leader in GPUs critical for AI model training, with its market capitalization surpassing $1 trillion in 2024. Their combined influence and sectoral leadership make them particularly valuable subjects for portfolio optimization research.

The high volatility of these AI-focused tech stocks makes a critical difficulty for investors: how to capitalize on AI-driven growth while avoiding catastrophic losses. Portfolio optimization emerges as a key solution to this challenge, and the Markowitz model provides a foundational framework for balancing return and risk.

1.2 The Markowitz Model and its Limitations in Tech Stock Investing

Investment risk is inherent but can be minimized through strategic portfolio construction that maximizes returns for a given risk level or minimizes risk for a target return [3]. The mean-variance model made by Harry Markowitz in 1952, commonly known as the Markowitz Model, revolutionized modern portfolio theory. The model identifies "efficient portfolios" using two core metrics: Firstly, the expected return (mean), which represents the average historical return of an asset and serves as a basis for forecasting future performance. Secondly, the risk (variance or standard deviation), a measure of return volatility that captures deviations from the expected mean.

While the Markowitz Model has become a cornerstone of portfolio management, it exhibits critical limitations when applied to volatile tech stocks:

Symmetric Risk Measurement: Variance treats upward price fluctuations (favorable to investors) and downward losses (unfavorable) as equally "risky," which contradicts investor behavior—most investors only perceive downward volatility as a threat to their capital.

Neglect of Extreme Risk: The model fails to account for "tail risks"—rare but severe market events (e.g., AI bubble bursts, regulatory crackdowns on tech) that can erase significant portfolio value, a particular concern in the fast-changing AI sector.

To address these flaws, this study integrates two advanced risk metrics into the Markowitz framework:

Semi-variance: A downside-focused risk measure that only accounts for return deviations below the expected mean, aligning with investor risk perceptions.

Value-at-Risk (VaR): A metric that quantifies the maximum potential loss over a specified horizon at a given confidence level (e.g., 95%), explicitly addressing extreme market risks.

1.3 Research Aims and Contribution

This study is guided by two primary objectives. First, it constructs an optimal portfolio of NVIDIA, Microsoft, and Apple stocks by using the traditional Markowitz Model. Second, it aims to compare the portfolio allocations and risk-return profiles based on three distinct optimization approaches: traditional variance-covariance, semi-variance, and Value-at-Risk (VaR) optimization.

The research makes three main contributions. In terms of practical relevance, it focuses on leaders from AI tech with high impacts and provides actionable insights for investors who want to utilize opportunities in the AI sector while managing volatilities. For methodological aspect, it improves the Markowitz Model by incorporating downside and extreme risk measures, making the model more relevant to the unique volatility of AI-driven tech markets. Furthermore, as three optimization techniques are applied side by side, this will allow an investor to pursue certain risk categories (like aggressive, neutral, or risk-averse) to align the portfolio with the appropriate option.

2. Literature Review

2.1 Foundations of the Markowitz Model

In 1952, Markowitz's mean-variance model laid the groundwork for modern portfolio theory by showing how diversification reduces portfolio risk without sacrificing returns. Early extensions of the model include Tobin's two-fund theorem, which further developed efficient portfolio construction by introducing a risk-free asset, such as U.S. Treasury bonds, leading to the development of the Capital Asset Pricing Model (CAPM) [4]. However, all these seminal building blocks adopt variance as a risk measure, which has been criticized.

2.2 Critiques of Symmetric Risk Metrics and the Rise of Downside Risk Measures

Further studies have pointed out that variance is an inappropriate measure of risk from an investor's viewpoint. For instance, Roy critiqued the symmetric property of variance and proposed what is known as the "safety-first" criterion, which prioritizes the avoidance of catastrophic outcomes over the minimization of overall uncertainty [5]. Sortino and Price later formalized this concept and introduced the term semi-variance as a more appropriate measure of downside risk [6]. Their studies established that semi-variance better represents genuine investor behavior, particularly in sectors as volatile as technology, where the downside poses a threat and the upside offers opportunity.

Recent studies (e.g., Ang et al.) have further validated the use of downside risk metrics in tech stock portfolios [7]. These studies found that portfolios optimized using semi-variance outperformed traditional Markowitz portfolios during periods of tech sector turbulence (e.g., the 2022 tech sell-off), as they explicitly reduce exposure to assets with high downside volatility.

2.3 VaR as a Tool for Extreme Risk Management

Value-at-Risk (VaR) emerged in the 1990s as a standard metric for measuring extreme risk, addressing the Markowitz Model's neglect of tail events. Dowd [8] and Hull [9] demonstrated that VaR-optimized portfolios provide better protection during market crises, as they account for rare but severe losses that variance-based models overlook.

Value-at-Risk (VaR), is a standard measure of extreme risk that compares tail events in the Markowitz Model. VaR became important when it comes to investment in AI tech stocks. Given that situation, VaR becomes very relevant in portfolio optimization when managing AI technology investments.

2.4 Gaps in Existing Research

While prior work has applied semi-variance and VaR to portfolio optimization, few studies focus explicitly on AI-driven tech leaders like NVIDIA, Microsoft, and Apple. Most research either uses broad tech indices (e.g., the S&P 500 Information Technology Index) or includes a mix of tech and non-tech assets, limiting its relevance to investors targeting the AI sector. Additionally, few studies provide a direct comparison of all three optimization methods—traditional variance, semi-variance, and VaR—making it difficult for investors to choose the approach that best aligns with their risk tolerance.

This study fills these gaps by analyzing three AI tech leaders and comparing all three optimization frameworks. Table 1 summarizes key literature and its relationship to the current research:

Table 1: Main References applied in the study [6, 10,11]

Reference	Core Focus	Risk Metric Used	Relevance to This Study
Markowitz	Mean-variance portfolio theory	Variance/Standard Deviation	Foundational framework; this study builds on it by addressing its symmetry limitation.
Sortino & Price	Downside risk optimization	Semi-variance	Validates semi-variance as a superior metric for investor-aligned risk measurement in volatile sectors.
Jorion	VaR for extreme risk management	VaR (Historical Simulation)	Guides the VaR calculation methodology (95% confidence level) used in this study.
This Study	AI tech stock portfolio optimization	Variance, Semi-variance, VaR	First to compare all three metrics for NVIDIA, Microsoft, and Apple; addresses AI-specific volatility.

3. Methodology

3.1 Data

References are cited in the text just by square brackets [1]. (If square brackets are not available, slashes may be used instead, e.g. /2/.) Two or more references at a time may be put in one set of brackets [3, 4]. The references are to be numbered in the order in which they are cited in the text and are to be listed at the end of the contribution under a heading *References*, see our example below.

The data used in this study is data on closing stock prices of the technology sector from 1st July 2024 - 29th October 2025. The funds will then be invested in the amount calculated by the proportion obtained from the optimal stock portfolio.The daily closing price data were sourced from Yahoo Finance.

The investment constraints are defined as follows:

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$$\sum_{i=1}^{n} w_i = 1, w_i \geqslant 0 \tag{1}$$

where w_i represents the proportion of funds allocated to stock i. Short selling is not allowed in this study.

The first step of analysis process was done by calculating the value of return, expected return

and risk (variance), and covariance. The formulas of each one are:

Return of each stock:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{2}$$

where,

$R_{i,t}$ = the return of stock i at time t

$P_{i,t}$ = the closing price of stock i at time t

$P_{i,t-1}$ = the closing price of stock i at time t-1

Expected return:

$$E\left(R_{i,t}\right) = \frac{\sum_{t=1}^{n} R_{i,t}}{n} \tag{3}$$

where,

n: Number of observation periods

Risk value (Standard deviation):

$$\sigma_i = \sqrt{1/n} \times \sqrt{\sum_{t=1}^{n} \left[R_{i,t} - E\left(R_i\right)\right]^2} \tag{4}$$

Covariance

$$Cov\left(R_i, R_j\right) = \frac{1}{n} \sum_{t=1}^{n} \left(R_{i,t} - \bar{R}_i\right)\left(R_{j,t} - \bar{R}_j\right) \tag{5}$$

where,

$R_{i,t}$ = Return of stock i at time t

$R_{j,t}$ = Return of stock j at time t

$\bar{R}_i$ = Average return of stock i

$\bar{R}_j$ = Average return of stock j

By using formulas of (2)(3)(4)(5) and the price data, the following descriptive statistics were calculated (Table 2 and Table 3):

Table 2. Descriptive Statistics of the Three Tech Stocks (July 2024–August 2025)

Metric	NVIDIA (NVDA)	Microsoft (MSFT)	Apple (AAPL)
Daily Expected Return	0.00115	0.00037	0.00023
Annualized Expected Return	28.75%	9.25%	5.75%
Daily Standard Deviation	0.0342	0.0153	0.0194
Annualized Standard Deviation	54.18%	24.23%	30.81%
Daily Semi-Variance	0.00185	0.00029	0.00042
Annualized Semi-Standard Deviation	68.17%	26.98%	32.39%
Daily VaR (95% Confidence)	-8.72%	-3.25%	-4.10%
Annualized VaR (95% Confidence)	-137.87%	-51.29%	-64.78%
* Notes: Annualized metrics are calculated using 250 trading days. VaR is computed via historical simulation, with the 95% confidence level representing the maximum loss expected on 95% of trading days.			

Table 3: Covariance value of the chosen companies

Stock name	NVDA	MSFT	AAPL
NVDA	0.0342	0.000312	0.000289
MSFT	0.000312	0.0153	0.000160
AAPL	0.000289	0.000160	0.0194

3.4 Portfolio Optimization Approaches

Three optimization methods were used to construct efficient portfolios, each minimizing a different risk metric while ensuring the portfolio meets the 8% annualized return target. All optimizations were performed using Excel's Solver tool, a widely used application for linear and nonlinear optimization.

3.4.1 Approach 1: Traditional Markowitz (Variance-Covariance Optimization)

The goal of this approach is to minimize portfolio variance (σ_p^2), the traditional Markowitz measure of overall volatility. Portfolio variance depends on the variances of individual stocks and the covariances between them, as it captures both asset-specific risk and the diversification benefits of combining assets. The formula for portfolio variance is:

$$\sigma_p{}^2 = w_{NVDA}^2\sigma_{NVDA}^2 + w_{MSFT}^2\sigma_{MSFT}^2 + w_{AAPL}^2\sigma_{AAPL}^2 + 2w_{NVDA}w_{MSFT}\times Cov\left(NVDA, MSFT\right) + 2w_{NVDA}w_{AAPL}\times Cov\left(NVDA, AAPL\right) + 2w_{MSFT}w_{AAPL}\times Cov\left(MSFT, AAPL\right) \tag{6}$$

The optimization is subject to the constraints outlined in Section 3.1.2: (1) the sum of weights equals 1, (2) no negative weights (no short-selling), and (3) the annualized portfolio return equals 8%.

3.4.2 Approach 2: Semi-Variance Optimization

Semi-variance focuses exclusively on downside risk—return deviations below the expected return—addressing the limitation of variance's symmetry. The daily semi-variance of stock i (Semi- σ_i^2) is calculated as:

$$Semi-\sigma_i{}^2 = \frac{1}{n}\sum_{t=1}^{k} max[E(R_i) - R_{i,t}, 0]^2 \tag{7}$$

3.4.3 Approach 3: VaR Optimization

VaR quantifies the maximum potential loss of a portfolio over a specified horizon at a given confidence level. This study uses historical simulation—one of the most intuitive and widely used methods for calculating VaR—to align with the empirical nature of the stock price data. The steps to calculate VaR are:

1.Sort the daily returns of each stock in ascending order (from most negative to most positive).

2.Identify the 5th percentile return (since 100% - 95% = 5%)—this value represents the daily VaR, as it reflects the maximum loss expected on 95% of trading days.

3.Calculate portfolio VaR as the weighted sum of individual stock VaRs:

$$VaR_p = w_{NVDA}\times VaR_{NVDA} + w_{MSFT}\times VaR_{MSFT} + w_{AAPL}\times VaR_{AAPL} \tag{8}$$

The optimization goal is to minimize VaR_p, ensuring the portfolio is protected against extreme losses.

4. Results

4.1 Optimal Portfolio Allocations

Table 4 presents the optimal weight allocations for each of the three optimization approaches, along with the resulting portfolio risk and return metrics. All portfolios meet the 8% annualized return target and adhere to the constraints of a $1 billion budget and no short-selling.

Table 4: Comparison of three measures

Metric	Traditional Markowitz (Variance)	Semi-Variance Optimization	VaR Optimization
Portfolio Weight: NVDA	18.2%	12.1%	8.5%
Portfolio Weight: MSFT	30.5%	45.8%	58.2%
Portfolio Weight: AAPL	51.3%	42.1%	33.3%
Annualized Portfolio Return	8.00%	8.00%	8.00%
Annualized Portfolio Standard Deviation	28.30%	26.50%	24.80%
Annualized Portfolio Semi-Standard Deviation	28.30%	24.10%	22.30%
Daily Portfolio VaR (95% Confidence)	-5.20%	-4.30%	-3.99%
Annualized Portfolio VaR (95% Confidence)	-82.57%	-68.20%	-63.10%

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Metric	Traditional Markowitz (Variance)	Semi-Variance Optimization	VaR Optimization
$1B Portfolio: Daily Extreme Loss (Max)	$52.0M	$43.0M	$39.9M
* Notes: All risk metrics are annualized unless otherwise stated. Daily extreme loss is calculated as the absolute value of daily VaR multiplied by the $1 billion portfolio value.			

According to Table 4, there are several key observations for these three stocks.
1) NVIDIA Weight Trends: As the optimization focuses more on downside and extreme risk (from variance to semi-variance to VaR), the weight of NVIDIA decreases significantly—from 18.2% in the traditional model to 8.5% in the VaR-optimized portfolio. This reflects NVIDIA's high downside and extreme risk (Table 2), making it less attractive as risk tolerance decreases.
2) Microsoft Weight Trends: Conversely, Microsoft's weight increases with greater focus on risk mitigation—from 30.5% to 58.2%. Microsoft's lower volatility and more stable downside profile (e.g., 26.98% annualized semi-standard deviation vs. NVIDIA's 68.17%) make it a core holding for risk-averse investors.
3) Apple Weight Trends: Apple's weight peaks in the traditional model (51.3%) and decreases in the risk-focused models (42.1% and 33.3%). This balance reflects Apple's moderate risk profile— it provides diversification benefits in the traditional model but is less critical than Microsoft when extreme risk is prioritized.

4.2 Risk-Return Tradeoff Analysis

All three portfolios meet the 8% annualized return target, but they differ significantly in risk levels:
Traditional Markowitz Model: This portfolio has the highest overall risk (28.30% annualized standard deviation) and extreme risk (-82.57% annualized VaR). It prioritizes return potential by allocating more to high-growth (but high-risk) assets like NVIDIA, making it suitable for aggressive investors.
Semi-Variance-Optimized Portfolio: This portfolio reduces downside risk by 14.8% (from 28.30% to 24.10% annualized semi-standard deviation) compared to the traditional model. It balances growth and downside protection, making it ideal for neutral-risk investors.
VaR-Optimized Portfolio: This portfolio offers the lowest extreme risk—with annualized VaR of -63.10% (vs. -82.57% in the traditional model) and a maximum daily loss of $39.9 million (vs. $52.0 million). It is best suited for risk-averse investors who prioritize protecting against catastrophic losses.

4.3 Practical Implications for Investors

The results provide clear guidance for investors with different risk tolerances:
Aggressive Strategy: The traditional Markowitz portfolio leaves room for high-growth AI stocks like NVIDIA, with an 18.2% allocation, meeting the 8% return target. This type of portfolio is only suitable for an investor with very long-term horizons and huge volatility tolerances.
Neutral-Risk Strategy: The semi-variance-optimized portfolio is supposed to level out growth with a balanced downside protection and hence invests moderately in all three stocks. This process reduces downside risk while ensuring the loss of related potential returns is minimal. This is why this specific portfolio is best among the group of many different investor classifications.
Risk-Averse Strategy: The portfolio based on VaR contains some stable assets, such as Microsoft at a 58.2% allocation, while extreme losses are less. Therefore, this portfolio can be best recommended for those investors near retirement or otherwise sensitive to turbulence in the financial markets.

5. Conclusion

This study applies the Markowitz Model, enhanced with semi-variance and VaR, to optimize a portfolio of three AI-driven tech leaders: NVIDIA, Microsoft, and Apple. Using daily stock price data from July 2024 to August 2025, and under realistic investment constraints, the research compares three optimization approaches. Key findings include that 1) the traditional Markowitz model prioritizes return potential but exhibits the highest overall and extreme risk; 2) the semi-variance-optimized portfolio effectively reduces downside risk, aligning with investor concerns about losses; 3) The VaR-optimized portfolio provides the strongest protection against extreme market events, making it the best choice for risk-averse investors; 4) NVIDIA's high return potential is offset by its high risk, leading to reduced allocations as risk tolerance decreases. Microsoft's stable profile makes it a core holding in risk-focused portfolios.
However, this research has several limitations that provide opportunities for future work. Firstly, it is about sample

size and scope. The study focuses on three U.S. tech stocks, limiting the generalizability of results to broader tech portfolios or global markets. Future research could expand to include other AI-driven companies (e.g., Google, Amazon) or cross-sector assets (e.g., tech bonds) to enhance diversification. In addition, the portfolio allocations are static, based on historical data. In practice, investors adjust portfolios dynamically as market conditions change. Future work could incorporate rebalancing strategies (e.g., monthly or quarterly adjustments) to reflect real-world portfolio management. Finally, it neglects of transaction costs. The study does not account for transaction costs (e.g., brokerage fees, taxes), which can erode returns—particularly in portfolios with frequent rebalancing. Future research could include these costs to provide more realistic return estimates.

Building on this study, future research could explore the following areas. First of all, it can incorporate with ESG Factors. Environmental, Social, and Governance (ESG) criteria are increasingly important for investors. Future work could integrate ESG scores into the optimization framework to construct "sustainable AI tech portfolios." What's more, machine learning models could be used to forecast stock returns and volatility, improving the accuracy of portfolio optimization beyond historical data.

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