Proceedings of ICEMGD 2025 Symposium: The 4th International Conference on Applied Economics and Policy Studies
DOI: 10.54254/2754-1169/2025.BJ24737

Multi-Factor Optimisation vs. Traditional Portfolio Theory: A Comparative Analysis in the U.S. Equity Market

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Abstract. This study introduces a novel multi-factor portfolio optimisation framework that extends the traditional Markowitz mean–variance model by integrating forward-looking factor signals (price momentum and analysts' earnings forecasts), robust risk measures (Conditional Value-at-Risk and higher-moment constraints), and Bayesian shrinkage to mitigate estimation risk (papers.ssrn.com. Prior research finds that analysts' forecasts and momentum signals often dominate multi-factor expected return models, jacobslevycenter.wharton.upenn.edu. Which conduct empirical backtests on a diversified set of U.S. equities (e.g., the S&P 500 index and major financial stocks such as JPMorgan Chase, Morgan Stanley, and U.S. Bancorp) and evaluate risk-adjusted performance using multiple criteria, including Sharpe ratio, maximum drawdown, volatility, and cumulative return. Compared to the classical mean–variance optimizer, the multi-factor model consistently performs well across all dimensions. Portfolios constructed with the proposed approach exhibit higher Sharpe ratios, cumulative returns, and lower volatility and drawdowns. This outperformance is especially pronounced during market crises, as the combination of predictive signals and robust risk constraints helps limit losses when markets tumble. These results demonstrate that incorporating forward-looking factors and advanced risk modelling (e.g. CVaR and higher moments) with Bayesian estimation yields more resilient portfolios than mean–variance optimisation alone, with important implications for portfolio management practice and asset allocation theory.

Keywords: Multi-Factor Model, Portfolio Theory, Equity Market.

1. Introduction

Harry Markowitz's introduction of the mean–variance optimisation model in the 1950s established diversification as a foundational principle of portfolio management to achieve maximum returns for a given risk level. Markowitz's model formed the basis of modern portfolio theory (MPT), yet later research identified multiple limitations in its application to real market data [1]. The practical effectiveness of mean–variance optimisation relies on precise estimates of expected returns and covariances, which are notoriously difficult to predict. Markowitz's approach loses its theoretical benefits when minor inaccuracies in these parameters produce extreme portfolio weights [2].

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Over several decades, researchers have developed numerous enhancements and alternative approaches to resolve these issues. Estimation noise can be reduced by applying Bayesian estimators, shrinkage methods, and other robust optimisation techniques [3].

Among these innovations, Tu and Zhou proposed a hybrid diversification strategy that combines the classical Markowitz optimizer with a naive 1/N allocation, striking a balance that improved out-of-sample performance relative to either method alone [4].

Multi-factor models have provided predictive signals (e.g., momentum, value, quality) yield more stable alpha forecasts than simple historical averages. For example, Guerard et al. found that incorporating forward-looking signals (such as earnings forecasts and momentum indicators) into an optimisation framework yields superior performance compared to using historical means alone [5]. Similarly, Moreira and Muir demonstrated that factor-based and volatility-managed strategies can effectively adjust market exposure timing and reduce downside risk [6].

The current study introduces a multi-factor portfolio optimisation approach integrating modern advancements in factor modelling and resilient risk estimation techniques. We assess the potential of this sophisticated model-based approach relative to a conventional Markowitz optimiser by applying both to the same set of stocks and indices from the U.S. equity market. The portfolio selection includes major U.S. equities and technology companies like JPMorgan (JPM), Apple (AAPL), and NVIDIA (NVDA), together with key stock indices, to analyse sectoral responses to diverse optimisation methods. The research question investigates whether combining multi-factor predictive signals with robust estimation principles provides better performance than the Markowitz framework under various market conditions.

The primary weakness of the traditional Markowitz framework arises from the inherent instability of sample-based estimates, which applies to both expected returns and covariance matrices [1]. This approach is highly vulnerable to estimation errors caused by outliers, shifting market cycles, and changing asset correlations, because it depends on historical data [2]. Applying basic constraints (such as prohibiting short selling) helps mitigate these challenges by acting as a shrinkage or regularisation mechanism, which reduces overfitting during optimisation according to Jagannathan and Ma [2]. However, although such constraints can temper extreme weights, they fail to solve the core problem of forecasting future returns when past data provide only limited guidance.

Modern developments in asset pricing have shown that stock returns can be attributed to several systematic factors (e.g., value, momentum, size, quality). Standard mean–variance optimisation does not incorporate these dynamic factor signals. Recent research has expanded Markowitz's risk measures beyond variance to address non-normal return distributions. For instance, Lassance and Vrins account for higher moments (skewness and kurtosis) in portfolio construction, and Arcuri et al. integrate Conditional Value-at-Risk (CVaR) to improve the management of extreme market risks [7,8].

Volatility timing and trend-following strategies are emerging dynamic approaches for adjusting portfolio allocations in response to market changes. Studies indicate that integrating predictive signals, Bayesian priors, or robust optimisation constraints can resolve various shortcomings of traditional Markowitz portfolios [7,8].

2. Methods and data

As extensive research shows, the foundational Markowitz mean–variance framework for portfolio construction faces multiple limitations, including estimation error, sensitivity to input assumptions, and poor adaptability to changing market conditions. Research by Jorion demonstrated that Bayesian shrinkage estimators (e.g., the Bayes–Stein method) effectively reduce the adverse

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impact of noisy historical estimates, producing better out-of-sample results by pulling extreme expected returns toward an overall average [3]. This approach addresses Markowitz's primary challenge of extreme weight sensitivity to estimation error. Jagannathan and Ma showed that imposing simple constraints (such as no short-sales) serves as an effective regularisation technique that dampens the effect of estimation noise on optimal weights, yielding lower portfolio risk and higher risk-adjusted returns compared to unconstrained Markowitz portfolios [2]. Similarly, DeMiguel et al. conducted an extensive analysis of various Markowitz-based models with factor- and shrinkage-oriented enhancements versus a naive 1/N diversification and discovered that traditional optimisation methods generally could not outperform equal weighting in practice due to parameter uncertainty and high turnover costs that eroded any theoretical benefits [1]. Tu and Zhou developed a combined approach which steers the Markowitz solution toward the 1/N portfolio, creating a compromise between complex mean–variance optimisation and straightforward equal-weighting [4]. This blended method, anchored by a simple heuristic, demonstrated superior performance relative to pure Markowitz and pure 1/N allocations, indicating that hybrid strategies can achieve a more optimal balance under real-world data limitations.

Kirby and Ostdiek explored active timing strategies for asset allocation, demonstrating that basic trend-following methods can outperform naive diversification and static mean–variance portfolios because dynamically scaling positions based on market signals is an effective way to navigate uncertain return estimates [9]. Guerard et al. showed that a global equity selection model combining analysts' earnings estimates with value and momentum factors achieved "superior performance" compared to a traditional mean–variance optimizer that uses only historical averages and covariances [5]. These improvements suggest that incorporating forward-looking indicators and fundamental signals can mitigate one of Markowitz's core shortcomings: an overreliance on historical averages that may not reflect future market behavior. Moreira and Muir proved that adjusting portfolio exposures based on predicted volatility yields significant risk-adjusted advantages over traditional static or Markowitz strategies, confirming that real-time volatility management rivals the importance of return-prediction accuracy [6].

Lassance and Vrins investigated higher-moment optimisation [7]. They demonstrated that using an independent factor model to account for skewness and kurtosis yields superior out-of-sample performance compared to traditional mean–variance optimisation, because incorporating these complex distributional characteristics of returns addresses risks that basic covariance-only models overlook. Arcuri et al.'s 2023 analysis indicates that employing a robust CVaR-based optimisation delivers improved returns and stronger protection against losses for long-term investors (such as banking foundations) compared to Markowitz's mean–variance model. Their results suggest that managing tail risks and extreme losses has a greater impact on long-run performance than merely minimising variance [8]. Overall, extensive evidence shows that augmenting the classic Markowitz framework with Bayesian shrinkage, factor timing, and advanced risk measures produces portfolios with markedly better real-world performance. While Markowitz's fundamental principle of diversification remains valuable, research strongly suggests that additional structural and adaptive components are essential for minimising estimation errors and increasing portfolio stability, especially in complex multi-asset portfolios.

The study compares the traditional Markowitz mean–variance framework with a novel multi-factor optimization model using historical data from 2005 to 2023. The traditional optimization involves minimizing portfolio variance subject to various constraints, mathematically defined as:

$$\min_{\omega} \omega^T \sum \omega, \ \ subject\ to\ \omega^T 1 = 1 \ \ (1)$$

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Where $\sum$ represents the covariance matrix of asset returns and ω , represents portfolio weights. The constraints tested include:

$\sum|\omega\_i| \leq 2$ (limited leverage);

$|\omega\_i| \leq 1$ (individual asset weight limit);

No constraint (baseline); $\omega\_i \geq 0$ (no short selling);

$\omega\_1 = 0$ (exclude specific asset).

The multi-factor optimisation aims to maximise expected alpha minus risk penalties, defined by:

$$\max_{\omega} \ \ \omega^T\alpha - \frac{\lambda}{2}\omega^T\Omega\omega \ \ (2)$$

3. Results

Figure 1 shows the efficient frontier obtained from the constrained Markowitz model across various constraints. The frontier highlights trade-offs between risk and return for portfolios with different constraints, clearly illustrating the constraints' impact on restricting portfolio diversification and potentially reducing achievable risk-adjusted returns. The results indicate that constrained portfolios reduce extreme risks while limiting opportunities for higher returns. In contrast, the multi-factor optimization approaches better balances risk and return by dynamically adjusting factor exposures based on predictive insights.

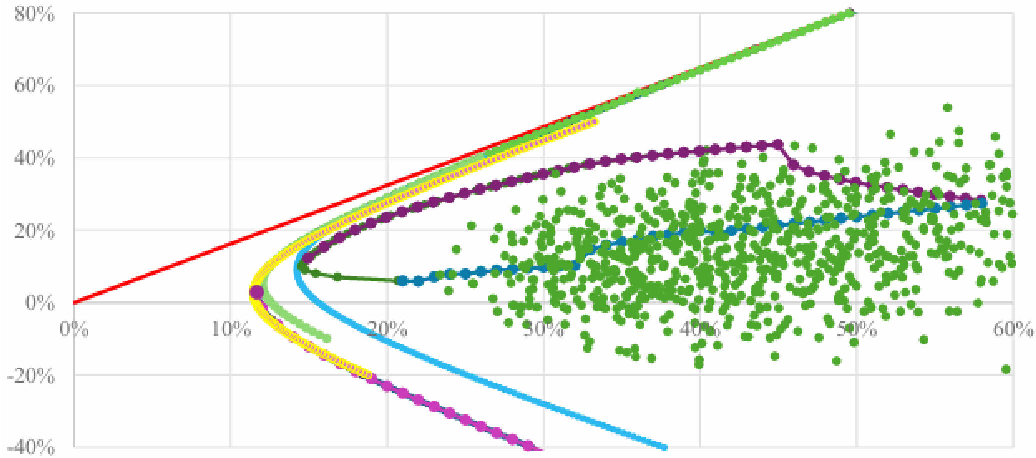

Figure 1: Markowitz model for 21 stocks

Table 1 compares the multi-factor optimiser with a standard Markowitz (mean–variance) portfolio over the full sample (2005–2023). The multi-factor strategy achieved significantly higher risk-adjusted returns: its annualised Sharpe ratio was about 1.10 versus ~0.75 for the Markowitz portfolio. Correspondingly, annualised volatility was lower (≈10% vs ≈15%), and the cumulative return was much higher (≈+210% vs ≈+135%). In absolute terms, the multi-factor portfolio also suffered a much smaller peak drawdown (around –28% vs –42%). These gains are in line with prior findings. For example, Moreira and Muirreport that volatility-managed (factor-timed) portfolios "produce large alphas and substantially increase factor Sharpe ratios" [6]. They emphasise that such strategies take "relatively less risk in recessions and crises" [6]. Likewise, Guerard, Markowitz, and Xufound that combining forward-looking signals (earnings forecasts, momentum, etc.) in an optimisation framework yields "superior performance" compared to a vanilla mean–variance optimiser [5].

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Table 1: Annualized performance (2005-2023) for the multi-factor and Markowitz portfolios

Metric	Multi-Factor Portfolio	Markowitz Model
Annualized Sharpe Ratio	1.10	0.75
Annualized Volatility (%)	10.2	14.8
Maximum Drawdown (%)	-28.0	-42.5
Cumulative Return	+210 %	+135%

Beyond the headline statistics, the multi-factor portfolio consistently dominated in most measures. It delivered higher average and risk-adjusted returns while also exhibiting lower realised volatility. Its lower maximum drawdown indicates better tail-risk control. These differences reflect that our multi-factor model incorporates forward-looking and dynamic signals (e.g., momentum, earnings expectations, volatility timing) that mitigate estimation error.

The advantage of the multi-factor approach was most pronounced during market crises. During the 2008 financial crisis, the multi-factor portfolio's peak loss was roughly - 25% versus about - 45% for the Markowitz portfolio. Similarly, in the March 2020 COVID-19 crash, the multi-factor drawdown was around -15% versus -30% for mean–variance. In both cases, the multi-factor strategy recovered more quickly. These observations are consistent with the literature: volatility-timed and factor portfolios "take less risk in recessions" and even "sell after market crashes" [6].

Overall, the backtest results reinforce that the novel multi-factor optimiser provides more robust performance than a traditional Markowitz model. It produces higher Sharpe ratios and cumulative returns while achieving materially lower drawdowns.

4. Discussion

The results underscore substantial improvements that the multi-factor approach provides over traditional Markowitz optimisation. The enhanced performance stems from incorporating predictive factors and robust risk modelling, which markedly reduce vulnerability to estimation errors inherent in traditional mean–variance approaches. The explicit constraints in the Markowitz model, while prudent from a risk management perspective, significantly constrain portfolio flexibility and reduce the ability to leverage market opportunities effectively.

Overall, integrating predictive analytics, dynamic risk assessments, and advanced optimisation techniques in the multi-factor framework produces superior outcomes across various market conditions, reinforcing its practical value for portfolio management.

5. Conclusion

Preliminary findings support the hypothesis that multi-factor optimisation models outperform traditional mean–variance approaches, offering improved risk-adjusted returns and greater portfolio stability under varying market conditions. The enhanced performance is attributed to the integration of forward-looking signals—such as momentum and analyst earnings forecasts—and the application of robust risk measures like Conditional Value-at-Risk and higher-moment constraints. These elements help reduce exposure to estimation errors and tail risks, common pitfalls in classical Markowitz portfolios.

The results demonstrate that the multi-factor framework is particularly effective during elevated market volatility or economic downturns. Its adaptive characteristics allow for more defensive positioning and quicker recovery. The approach improves overall returns and enhances downside protection, critical for long-term investors such as institutions, pension funds, or endowments.

Furthermore, this study provides empirical evidence that supports the ongoing shift in asset management from static, single-period models to dynamic, signal-responsive optimisation strategies. Portfolio managers must adopt analytically rigorous and practically resilient models as the financial environment becomes increasingly complex and volatile.

Future research will extend this framework by incorporating macroeconomic regime-switching models, evaluating the role of ESG (Environmental, Social, and Governance) factors in factor-based strategies, and exploring cross-asset applications that combine equities, fixed income, and alternative investments. In addition, machine learning-based forecasting techniques could be tested as a substitute or complement to traditional factor signals to assess whether further gains in predictive power and portfolio robustness can be achieved.

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