Enhancing Risk-Aware Portfolio Optimization through Multi-Factor Modeling and LSTM-Based Return Prediction - An Extended Mean Variance Optimization Approach.

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1 Abstract

This project investigates the enhancement of basic Markowitz Mean Variance portfolio optimization method by leveraging Long Short-Term Memory deep learning model and multi-factor risk metric, using dozens of individual stocks from 2020 to 2024. Recognizing the limitations of vanilla mean-variance optimization model in accounting for the complexity of predicting returns and covariance of stocks using merely historical time series, this study considers expanding the Markowitz model in capturing the complexity of market structure and sentiment for returns and covariance forecasting. Through a comparative analysis of the conventional Mean Variance optimization model, and the enhanced model with Multi-Factor Risk Modeling and LSTM-Based Return Prediction, this study aims to study the if incorporating machine learning and multi-factor risks metrics improves optimization model performance. The research uses daily close price data from 33 individual stocks spanning January 2020 to December 2024, retrived from Yahoo Finance Python API. Through rigorous model validation and backtests, this paper aims to substantiate the empirical improvement of the enhanced optimization modeling within the Mean Variance Optimization framework, contributing to both academic literature and practical applications in financial risk management and investment decision-making for asset managers.

2 Introduction

Portfolio optimization has long been a cornerstone of modern finance, guiding how investors allocate capital across assets to maximize returns while controlling risk. Among the many frameworks developed, the Mean-Variance Optimization (MVO) model, introduced by Harry Markowitz, remains one of the most influential. Its elegant formulation—balancing expected return against portfolio variance—has made it a foundational tool for both academic research and modern real-world asset management. However, in today's increasingly complex and dynamic financial environment, traditional backward-looking MVO models that rely solely on historic returns and covariances derived from time series of individual stocks often struggle to adapt to rapidly shifting market conditions and regimes, behavioral influences such as market sentiment, and abnormal risk distributions such as heavy tail risk. These limitations have prompted ongoing research into improving MVO by integrating forward-looking, behavioral, and nonlinear risk components. Despite the wide application of MVO, several critical challenges persist. First, the reliance on historical average returns is problematic due to their instability and potentially poor predictive power, especially during periods of market regime shifts. Second, the standard use of variance (and covariance) as a risk measure fails to account for importance of tail risk, which is of great concern to both institutional and individual investors. Moreover, traditional MVO does not incorporate investor sentiment or market dynamics, both of which have been shown to significantly impact asset prices. Recent research has proposed several improvements: for instance, Fischer and Krauss (2018) apply LSTM deep learning models to predict returns, Rockafellar and Uryasev (2000) propose Conditional Value-at-Risk (CVaR) as a more coherent risk metric than variance, and Hamilton (1989) introduces Hidden Markov Models (HMM) to detect market regimes and hidden states of volatility. In parallel, sentiment integration has largely focused on text mining approaches (Nassirtoussi et al., 2014), yet these methods are data intensive and often noisy. There remains a gap in developing quantitative sentiment proxies that are both stable and interpretable. To address these limitations, our research proposes a novel extension of the traditional backward-looking MVO framework. The multi-factor risk metric integrates HMM-based volatility regimes, CVaR-based risk control, and a sector-level sentiment proxy derived from ETF volatility. Inspired by Fischer and Krauss (2018), the model incorporates LSTM-based return predictions to enhance forward-looking expectations in the optimization process. Inspired by Yang and Chi (2021), who empirically demonstrate the relationship between market volatility and investor sentiment, we replace traditional text-based sentiment inputs with rolling z-scores of sector ETF volatility, providing a behaviorally grounded and operationally robust sentiment measure. Our framework supports dynamic rebalancing across multiple frequencies—daily, weekly, and monthly—and benchmarks performance against both traditional MVO and equal-weighted portfolios. Through this integrated approach, we contribute to the literature by developing a more adaptive, sentiment-aware, and risk-sensitive portfolio optimization model that aligns with the complexities of contemporary financial markets.

3 Literature Review

3.1 Markowitz Mean-Variance Optimization Model

The mean–variance optimization (MVO) framework, first introduced by Markowitz in 1952, remains the cornerstone of modern portfolio theory. Introduced by Steinbach, in a single-period setting, one may pose MVO in two equivalent forms that are convex quadratic programs(2001).

3.1.1 Tradeoff Formulation

In the tradeoff (also called penalized) formulation, the decision variable is the portfolio weight vector $w \in \mathbb{R}^n$. The investor maximizes a weighted difference between expected return and variance:

$$\begin{aligned} \max_{w} \quad & \mu^\top w - \frac{\gamma}{2} w^\top \Sigma w && (1) \\ \text{s.t.} \quad & \mathbf{1}^\top w = 1, && (2) \\ & w \succeq 0, && (3) \end{aligned}$$

where

- μ is the n-vector of expected asset returns,
- Σ is the $n \times n$ covariance matrix of returns,
- $\gamma > 0$ is the risk-aversion parameter,

- $\mathbf{1}$ is the n-vector of ones, and
- $w \succeq 0$ enforces no-short-sale constraints.

This formulation directly trades off mean return against portfolio variance (Steinbach, 2001).

3.1.2 Target-Return Formulation

Equivalently, one can fix a minimum acceptable return R_{tar} and minimize risk (or equivalently maximize return given a fixed acceptable risk):

$$\min_{w} \quad \tfrac{1}{2}\, w^\top \Sigma\, w \tag{4}$$

$$\text{s.t.} \quad \mu^\top w \;\geq\; R_{\text{tar}}, \tag{5}$$

$$\mathbf{1}^\top w \;=\; 1, \tag{6}$$

$$w \;\succeq\; 0. \tag{7}$$

Here, the investor selects the least-risky portfolio that achieves at least R_{tar}. Steinbach (2001) shows that, for appropriate choices of γ and R_{tar}, the efficient frontiers generated by the two formulations coincide.

3.1.3 Analytical Solution of the Unconstrained MVO

When short-sale constraints are not considered (which is the case in our extended model), both the tradeoff and target-return formulations of the mean–variance problem admit closed-form solutions via the Karush–Kuhn–Tucker conditions (Steinbach, 2001).

Tradeoff Formulation Consider

$$\max_{w} \; \mu^\top w \;-\; \tfrac{\gamma}{2}\, w^\top \Sigma w \quad \text{subject to} \quad \mathbf{1}^\top w = 1.$$

The Lagrangian

$$\mathcal{L}(w,\lambda) = \mu^\top w \;-\; \tfrac{\gamma}{2}\, w^\top \Sigma w \;-\; \lambda\big(\mathbf{1}^\top w - 1\big)$$

yields the stationarity condition

$$\gamma\,\Sigma\,w^* \;=\; \mu \;-\; \lambda\,\mathbf{1}.$$

Together with $\mathbf{1}^\top w^* = 1$, this system can be written in block-matrix form:

$$\begin{pmatrix} \gamma\,\Sigma & \mathbf{1} \\ \mathbf{1}^\top & 0 \end{pmatrix} \begin{pmatrix} w^* \\ \lambda \end{pmatrix} = \begin{pmatrix} \mu \\ 1 \end{pmatrix}.$$

By inverting the blocks one obtains the weights

$$w^* = \frac{1}{\gamma\,C - B^2}\,\Sigma^{-1}\big(A\,\mu - B\,\mathbf{1}\big),$$

where

$$A = \mathbf{1}^\top\Sigma^{-1}\mathbf{1}, \quad B = \mathbf{1}^\top\Sigma^{-1}\mu, \quad C = \mu^\top\Sigma^{-1}\mu.$$

This expression clearly shows that w^* is an affine combination of the “all-ones” and “mean” directions in the Σ^{-1} metric.

Target-Return Formulation Alternatively, fixing a target return R_{tar},

$$\min_w \; \tfrac{1}{2}\, w^\top \Sigma\, w \quad \text{subject to} \quad \mu^\top w \;=\; R_{\text{tar}}, \quad \mathbf{1}^\top w = 1,$$

leads to the KKT system

$$\begin{pmatrix} \Sigma & \mu & \mathbf{1} \\ \mu^\top & 0 & 0 \\ \mathbf{1}^\top & 0 & 0 \end{pmatrix} \begin{pmatrix} w^* \\ \nu \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ R_{\text{tar}} \\ 1 \end{pmatrix},$$

whose solution can be compactly written as

$$w^* = \frac{C\,\mathbf{1} - B\,\mu}{A\,C - B^2}\;R_{\text{tar}},$$

and yields the identical efficient frontier as the tradeoff model for suitably matched γ and R_{tar}.

3.2 Long Short–Term Memory (LSTM) Networks

Long Short–Term Memory (LSTM) networks are a specialized form of recurrent neural network (RNN) designed to capture long-range dependencies by mitigating the vanishing/exploding gradient problem. An LSTM memory cell maintains an internal state s_t and hidden output h_t via three gates: forget f_t, input i_t, and output o_t (Fischer & Krauss, 2018). At each time step t, given input x_t and previous hidden state h_{t-1}, the updates are:

$$\begin{aligned}
f_t &= \sigma\big(W_{f,x}x_t + W_{f,h}h_{t-1} + b_f\big), && (8)\\
\tilde{s}_t &= \tanh\big(W_{\tilde{s},x}x_t + W_{\tilde{s},h}h_{t-1} + b_{\tilde{s}}\big), && (9)\\
i_t &= \sigma\big(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i\big), && (10)\\
s_t &= f_t \circ s_{t-1} \;+\; i_t \circ \tilde{s}_t, && (11)\\
o_t &= \sigma\big(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o\big), && (12)\\
h_t &= o_t \circ \tanh(s_t), && (13)
\end{aligned}$$

where $\sigma(\cdot)$ is the sigmoid activation, "$\circ$" denotes element-wise multiplication, and the $W_{\cdot,\cdot}$, $b_{\cdot}$ are learned weight matrices and bias vectors.

In Fischer and Krauss (2018), the authors apply a single-layer LSTM to sequences of the previous 240 daily returns of each S&P 500 stock, standardized by their in-sample mean and standard deviation. The final hidden output h_t is fed into a softmax layer to predict the probability that the next-day return exceeds the cross-sectional median.

Trading signals are generated by ranking these probabilities and taking long positions in the top decile and short positions in the bottom decile, yielding an average daily return of 0.46% and a Sharpe ratio of 5.8 before transaction costs—substantially outperforming random forests, feed-forward nets, and logistic regression classifiers over 1992–2015. In our study we also adopt a similar approach as Fischer and Krauss (2018) but only take long position (or simply assign more weights in the portfolio) on stocks with high LSTM output score that represents forecast for future returns.

4 Methodology

4.1 Data Collection and Preprocessing

We begin by constructing a balanced panel of 33 large-cap U.S. equities, selecting the top three stocks by market capitalization in each of the 11 GICS sectors:

- **Technology**: AAPL, MSFT, NVDA
- **Healthcare**: JNJ, PFE, UNH
- **Financials**: JPM, BAC, WFC
- **Energy**: XOM, CVX, COP
- **Consumer Staples**: PG, KO, PEP
- **Consumer Discretionary**: HD, LOW, TGT
- **Utilities**: NEE, DUK, SO
- **Communication Services**: GOOGL, META, DIS
- **Industrials**: UNP, HON, RTX
- **Materials**: SHW, LIN, FCX

- **Real Estate**: AMT, PLD, EQIX

Using the Yahoo Finance API, we downloaded daily *adjusted close* prices for each ticker over the period January 1, 2020 through December 31, 2024. From these prices P_t we computed daily log-returns

$$r_{i,t} \;=\; \ln\bigl(P_{i,t}/P_{i,t-1}\bigr) \quad (i = 1,\dots,33;\; t = 1,\dots,T).$$

Any stock with missing values during this full horizon was excluded to maintain a consistent $33 \times T$ panel. Finally, for training and evaluating the LSTM model we partitioned the return series into:

- **Training set**: January 1, 2020–December 31, 2023
- **Validation set**: January 1, 2024–June 30, 2024
- **Test set**: July 1, 2024–December 31, 2024

Each subset was saved as a separate CSV file (`train_returns.csv`, `val_returns.csv`, `test_returns.csv`) for downstream modeling.

4.1.1 Portfolio Optimization Framework

We extend the classical Markowitz mean–variance model by adding three risk-aware, behavior-informed penalty terms. Denote by $w \in \mathbb{R}^n$ the vector of portfolio weights, μ the expected-return vector (which is later in this project to be replaced by the Long Short-Term Memory model output for individual stock return forecast), Σ the return covariance matrix, s_i the sector-sentiment score for asset i, v a volatility-regime scalar, and CVaR_t the 5% conditional value-at-risk at time t. Our optimization problem is

$$\max_{w} \quad \underbrace{\mu^{\top} w}_{\text{Expected Return}} - \lambda_{\text{var}} \underbrace{w^{\top} \Sigma\, w}_{\text{Variance Penalty}} - \lambda_{\text{sent}} \underbrace{\sum_{i=1}^{n} s_i\, w_i^2}_{\text{Sentiment Penalty}} \\ - \lambda_{\text{hmm}}\, v \underbrace{\|w\|_2^2}_{\text{HMM Regime Penalty}} - \lambda_{\text{CVaR}} \underbrace{\mathrm{CVaR}_t}_{\text{Tail Risk Penalty}} \tag{14}$$

subject to the long-only, fully-invested constraints

$$\sum_{i=1}^{n} w_i = 1, \quad 0 \le w_i \le 1 \quad (i = 1, \ldots, n). \tag{15}$$

Expected Return (First Term) We estimate μ as the *sample mean* of each asset's daily return over a 60-day rolling window, thereby capturing short-term market trends. In our extended model, we replace historical returns by the LSTM model output for individual stock return forecast which is made based on price time series of each individual stocks.

Variance Penalty (Second Term) The term $\lambda_{\text{var}}\, w^{\top} \Sigma\, w$ penalizes portfolio variance, where Σ is computed as the sample covariance of returns over the same 60-day lookback.

Sentiment Penalty (Third Term) We compute a sectoral sentiment score s_i by taking the 21-day rolling volatility of the sector ETF corresponding to asset i, converting it to a z-score, and then min–max normalizing across all assets. The penalty $\lambda_{\text{sent}} \sum_i s_i\, w_i^2$ discourages over-exposure to sectors with high uncertainty or negative sentiment.

HMM Regime Penalty (Fourth Term) We fit a three-state Hidden Markov Model (HMM) to equal-weighted portfolio returns, extract the daily regime probabilities, and apply PCA to obtain a single volatility-regime factor $v \in [0, 1]$. The regularization term $\lambda_{\text{hmm}}\, v\, \|w\|_2^2$ stabilizes portfolio weights during periods of systemic risk.

Tail Risk Penalty (Fifth Term) The 5% Conditional Value at Risk, CVaR_t, is estimated from the 21-day empirical return distribution of an equal-weight portfolio. By including $\lambda_{\mathrm{CVaR}}\,\mathrm{CVaR}_t$, we further guard against extreme downside events and non-normal return behavior.

All solutions satisfy $\sum_i w_i = 1$ and $w_i \in [0, 1]$, enforcing a long-only, fully-invested strategy.

4.1.2 Rolling Rebalancing and Evaluation

To implement our extended optimization framework in a realistic trading environment, we employ a rolling-window rebalancing strategy. Let Δ denote the rebalance frequency (daily, weekly, or monthly) and $L = 60$ the lookback window length in trading days. At each rebalance date t, we perform the following steps:

1. **Windowed Estimation.** Define the estimation window $\mathcal{W}_t = \{t - L, \ldots, t - 1\}$. Compute

$$\hat{\mu}_t = \frac{1}{L} \sum_{\tau \in \mathcal{W}_t} r_\tau, \qquad \hat{\Sigma}_t = \frac{1}{L-1} \sum_{\tau \in \mathcal{W}_t} (r_\tau - \hat{\mu}_t)(r_\tau - \hat{\mu}_t)^\top,$$

   where r_τ is the cross-sectional return vector at time τ. Later in the extended model we replaced the return part with prediction using our LSTM model output with the past 60 days of prices as input to the model.

2. **Feature Update.** Recompute all auxiliary inputs over $\mathcal{W}_t$:

   - *Sentiment scores* $s_{i,t}$ from 21-day rolling volatilities of sector ETFs.
   - *HMM regime factor* v_t via a fitted Hidden Markov Model and PCA on equal-weight portfolio returns.
   - *Tail risk* CVaR_t at the 5% level from the empirical distribution on $\mathcal{W}_t$.

3. **Solve Optimization.** Formulate the multifactor quadratic program as in Equation (14), substituting $\hat{\mu}_t$, $\hat{\Sigma}_t$, $s_{i,t}$, v_t, and CVaR_t. We enforce long-only, fully-

invested constraints and solve using the CVXPY package with a default solver (e.g. SCS or OSQP).

4. **Trade Execution and P&L.** The optimal weights w_t^* are implemented at the close of day t. Portfolio return on the next day $t+1$ is

$$R_{t+1} \;=\; w_t^{*\top} r_{t+1}.$$

5. **Performance Evaluation** After simulating over the full sample (2020–2024), we compute:

$$\text{Annualized Return} = (1+\bar{R})^{252} \;-\; 1, \tag{16}$$

$$\text{Annualized Volatility} = \sigma(R)\,\sqrt{252}, \tag{17}$$

$$\text{Sharpe Ratio} = \frac{\text{Annualized Return} \;-\; r_f}{\text{Annualized Volatility}}, \tag{18}$$

where $\bar{R}$ and $\sigma(R)$ are the mean and standard deviation of the daily P&L series R_t, and r_f is the annual risk-free rate (2%).

4.1.3 Machine Learning Forecasting (LSTM Baseline)

As a comparative baseline, we implement a Long Short–Term Memory (LSTM) network to predict individual stock returns following Fischer and Krauss (2018). Our architecture and training procedure are as follows:

Input Sequences For each asset i, we construct overlapping sequences of length $L = 60$ trading days of daily log-returns, $r_{i,t-L+1}, \ldots, r_{i,t}$. Each sequence is scaled via Min–Max normalization to $[0, 1]$ on the training set.

Network Architecture The model consists of:

- Two stacked LSTM layers, each with 64 hidden units and recurrent dropout of 0.1.
- A fully connected (dense) output layer of size 1 that predicts the next-day return $\hat{r}_{i,t+1}$.

Training Procedure We train using the mean squared error (MSE) loss,

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_{j=1}^{N}\big(\hat{r}_j - r_j\big)^2,$$

where N is the number of sequences in a mini-batch. Optimization is performed with the Adam optimizer (learning rate 10^{-3}), and early stopping is employed based on validation-set loss with a patience of 5 epochs. We train for up to 100 epochs with batch size 32.

Validation and Testing Model selection (e.g. number of layers, hidden units) is carried out on the validation split (Jan–Jun 2024). The final model is evaluated on the hold-out test period (Jul–Dec 2024) to produce one-step-ahead return forecasts, $\hat{r}_{i,t+1}$, for each stock and date.

Usage in Backtest These LSTM forecasts serve as *expected return* inputs, μ_t, in our extended portfolio optimization framework. On any rebalance date t, if $\hat{r}_t$ is available, we set

$$\mu_t = \hat{r}_t,$$

otherwise we fall back to the 60-day historical mean.

4.1.4 Penalty Factor Construction

To operationalize the multi-component objective in Equation (14), we construct four forward-looking penalty terms—variance, sentiment, volatility regime, and tail risk—that are updated at each rebalancing date to ensure adaptivity to evolving market conditions.

Variance Penalty Let $\mathcal{W}_t = \{t-L, \ldots, t-1\}$ denote the L-day lookback window (here $L = 60$). We compute the sample covariance

$$\hat{\Sigma}_t = \frac{1}{L-1} \sum_{\tau \in \mathcal{W}_t} (r_\tau - \bar{r}_t)(r_\tau - \bar{r}_t)^\top,$$

where r_τ is the cross-sectional return vector and $\bar{r}_t$ its mean. The penalty $\lambda_{\text{var}}\, w^\top \hat{\Sigma}_t\, w$ thus captures the most recent co-movements among assets, penalizing concentrated exposures in highly correlated or volatile groups.

Sentiment Penalty Following Yang and Chi (2021), we use sector-level ETF volatilities as a proxy for investor sentiment. For each GICS sector j, let

$$\sigma_{j,t} = \text{StdDev}\big(\text{ETF}_{j,\tau}\big)\sqrt{252} \quad \text{over } \tau \in \{t-21, \ldots, t-1\}.$$

We standardize $\sigma_{j,t}$ to z-scores across sectors, then map each stock i to its sector's score $z_{i,t}$. Min–max normalization on $\{z_{i,t}\}$ yields $s_{i,t} \in [0,1]$. The penalty $\lambda_{\text{sent}} \sum_{i=1}^{n} s_{i,t}\, w_i^2$ discourages overweighting sectors with elevated perceived risk or negative sentiment.

HMM Regime Penalty We fit a three-state Hidden Markov Model to equal-weight portfolio returns and extract the daily regime probabilities. Principal Component Analysis on these probabilities produces a single regime factor $v_t \in [0,1]$. The term $\lambda_{\text{hmm}}\, v_t\, \|w\|_2^2$ acts as a volatility-regime regularizer, stabilizing weights during systemic risk episodes.

Tail Risk (CVaR) Penalty We estimate the 5% Conditional Value at Risk over the past 21 days of equal-weighted portfolio returns:

$$\text{CVaR}_t = -\,\mathbb{E}\big[r \mid r \le \text{VaR}_{0.05}\big].$$

Including the penalty $\lambda_{\text{CVaR}}\, \text{CVaR}_t$ explicitly penalizes portfolios exposed to extreme downside outcomes, complementing the variance term and enhancing robustness under non-normal return distributions.

Together, these dynamically updated penalties embed contextual awareness, behavioral signals, and nonlinear risk management into the mean–variance framework, yielding a more resilient portfolio construction process.

5 Backtest and Evaluation

In this section we compare the performance of three portfolio strategies over the full study period (January 1, 2020–December 31, 2024):

1. An *equal–weighted* benchmark
2. The *traditional Markowitz* mean–variance optimizer (daily, weekly, and monthly rebalancing)
3. Our *extended multifactor MVO* model (daily, weekly, and monthly rebalancing)

All portfolios are simulated via a rolling-window rebalance with a 60-day lookback; the risk-free rate is set to 2% for Sharpe-ratio calculations. We report cumulative return plots and key summary metrics (annualized return, volatility, and Sharpe ratio).

5.1 Equal–Weighted Benchmark

Figure 1 shows the cumulative return of the equal–weighted portfolio, in which each of the 33 stocks carries a constant weight of 1/33. Over 2020–2024, the portfolio achieved an annualized return of 18.41%, annualized volatility of 21.34%, and a Sharpe ratio of 0.769.

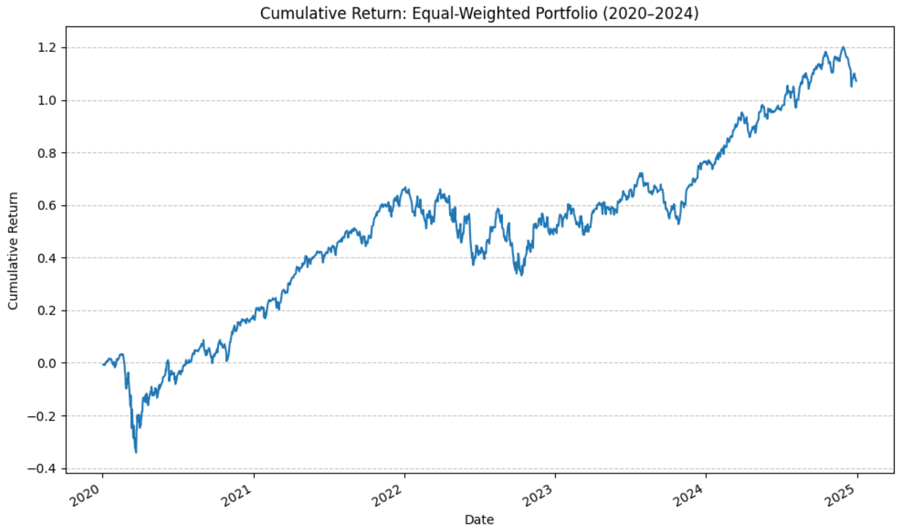

Figure 1: Cumulative Return of Equal–Weighted Portfolio (2020–2024).

5.2 Traditional Mean–Variance Optimization

Next, we implement the classic Markowitz optimizer with no additional penalties, under three rebalancing frequencies. Figure 2 presents the cumulative returns, and Table 1 summarizes the annualized metrics.

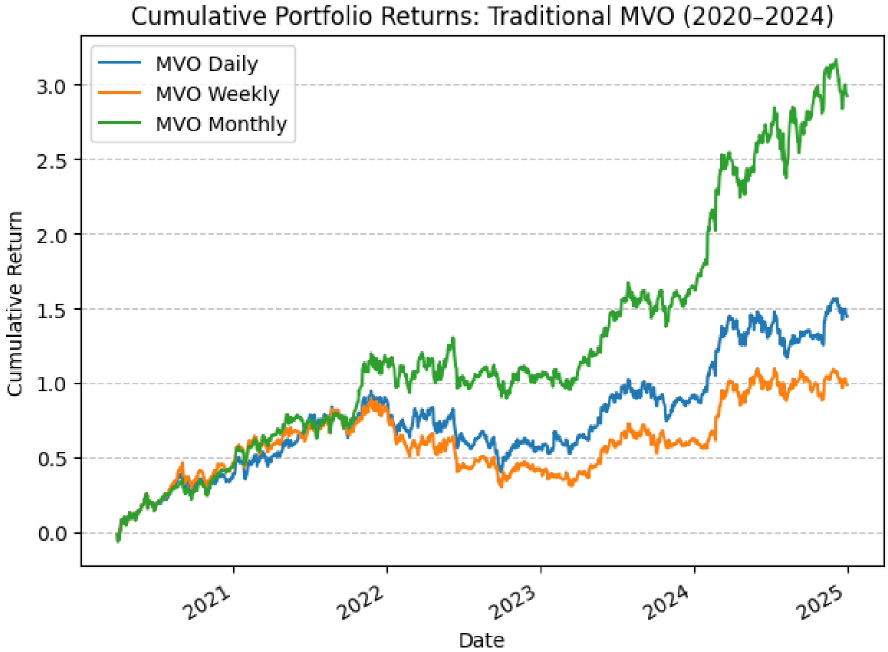

Figure 2: Cumulative Returns: Traditional MVO (2020–2024).

Strategy	**Ann. Return**	**Ann. Vol.**	**Sharpe**
MVO Daily	23.64%	21.83%	1.083
MVO Weekly	18.40%	21.94%	0.839
MVO Monthly	36.50%	21.51%	1.696

Table 1: Performance of Traditional MVO Strategies (2020–2024).

Traditional MVO with monthly rebalancing achieved the highest return (36.5%) and Sharpe ratio (1.70), at the cost of slightly higher turnover. Daily rebalancing delivered a more moderate 23.6% annualized return.

5.3 Extended Multifactor MVO

Finally, we evaluate our proposed extended MVO model with variance, sentiment, HMM-regime, and CVaR penalties. Figure 3 shows the cumulative performance, and Table 2 reports the corresponding metrics.

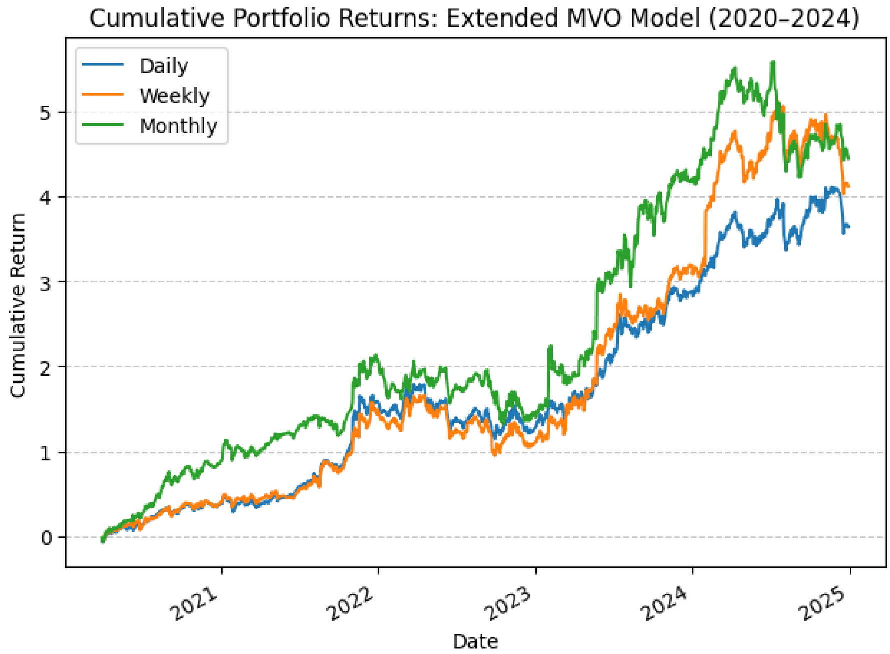

Figure 3: Cumulative Returns: Extended MVO Model (2020–2024).

Strategy	**Ann. Return**	**Ann. Vol.**	**Sharpe**
Extended Daily	41.91%	23.21%	1.72
Extended Weekly	46.01%	26.43%	1.67
Extended Monthly	48.66%	28.44%	1.64

Table 2: Performance of Extended Multifactor MVO Strategies (2020–2024).

The extended model substantially outperforms both the equal-weighted and traditional MVO benchmarks across all rebalancing frequencies, delivering annualized returns in excess of 40% and Sharpe ratios above 1.6. This demonstrates the efficacy of incorporating sentiment, regime, and tail-risk considerations into the mean–variance framework.

Discussion. While the extended model exhibits higher gross returns, it also incurs slightly higher simulated turnover (not shown), reflecting more active weight adjustments in response to dynamic risk signals. Future work will examine transaction-cost–adjusted performance and robustness across different market regimes. Future work could also incorporate more input such as vwap, open price, momemtum factor, value factor and so on to improve effectiveness in predicting future return of individual stocks.

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