# Construction of High and Low Risk investment portfolios using real stock data

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# Objective

Design two complementary U.S. equity portfolios—one high-risk, one low-risk—each engineered to maximize risk-adjusted return (Sharpe) within prescribed mandate constraints on systematic exposure ( $\beta$ ), volatility ( $\sigma$ ), and tail risk (VaR, max draw-down).

### **Data Collection**

We built our datasets by pulling end-of-day closing prices for each tickers—and for SPY as our benchmark—via the Polygon REST API. We spanned a two-year window (19 June 2023 through 25 June 2025), then bucketed those daily closes into 5-day (Mon–Fri) log-returns to suppress microstructure noise and ensure all symbols share the same trading calendar. From these weekly returns we annualized means and covariances ( $\times 252$  trading days), computed each asset's  $\beta$  against SPY, and stitched in a constant 3% p.a. T-bill rate for Sharpe calculations. This uniform, high-quality data foundation let us enforce clear look-back rules and produce robust risk/return estimates before any optimization.

We built two distinct universes:

- High-Risk sleeve: NVDA (NVIDIA), TSLA (Tesla), ARKK (ARK Innovation ETF), MSTR (MicroStrategy), SMCI (Supermicro).
- Low-Risk sleeve: JNJ (Johnson & Johnson), PG (Procter & Gamble), DUK (Duke Energy), VIG (Vanguard Dividend Appreciation ETF), IEF (iShares 7–10 Year Treasury ETF).

In both cases, SPY was used as the market benchmark for  $\beta$  and Sharpe computations.

# Methodology

Through this analysis, we considered the following metrics:

• Daily log returns: For each stock, we calculated the daily log returns, by using the formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where  $P_t$  is the clossing price at time t.

• Annualized  $\sigma$  (Volatility): From the daily log returns, we anualized the variance:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{t=1}^{n} (R_t - \bar{R})^2}$$

• Annualized Expected Return: It's the mean of the daily log returns times 252.

• Sharpe Ratio: The optimization objective was to maximize the portfolio's sharpe ratio

Sharpe Ratio = 
$$\frac{R_p - R_f}{\sigma_p}$$

where:

- $-R_p$  is the expected return of the portfolio.
- $R_f$  is the risk-free rate, assummed to be 3%.
- $-\sigma_p$  is the standard deviation of portfolio's return.
- Beta  $\beta$ : Measures the sensitivity of a stock to market movements, it is calculated as:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)}$$

where  $R_i$  is the daily log return of the stock and  $R_m$  is the daily log return of the market proxy, SPY for this work.

• Max Draw-down: the worst peak-to-trough loss an investor would have suffered over a chosen look-back window, expressed as a percentage of the previous peak. Formally

$$MDD = \min_{t} \left( \frac{P_t}{\max_{s \le t} P_s} - 1 \right)$$

where  $P_t$  is the portfolio value at time t.

The portfolio optimization was performed in order to construct High and Low risk portfolios. In python, it was implemented by using the function minimize() from the packages scipy.optimize. The objective function was the sharpe ratio, formally the optimization problem was:

$$\min_{w} \left( -\frac{w^T \mu - R_f}{\sigma_p} \right)$$

subject to:

- $\sum_i w_i = 1$
- $0.05 < w_i < 1$

#### **Constraints:**

Additional contraints were added in order to get a weight distribution that minimizes the negative sharpe ratio according to the requirenments of the portfolio's needs.

#### For High risk portfolio:

- $w_{\text{NVDA}}, w_{\text{TSLA}}, w_{\text{ARKK}} \ge 0.10 \text{ and } w_{\text{MSTR}} \ge 0.05, w_{\text{SMCI}} \ge 0.05$
- $w_{\text{MSTR}} \le 0.15, \ w_{\text{SMCI}} \le 0.10$
- $2.05 \le \boldsymbol{\beta}^{\mathsf{T}} \mathbf{w} \le 2.25$

#### For Low risk portfolio:

- $w_{PG}, w_{JNJ}, w_{DUK}, w_{VIG}, w_{IEF} \ge 0.10$
- $w_{\rm IEF} \le 0.30$
- $0.40 \le \boldsymbol{\beta}^T \mathbf{w} \le 0.60$
- $\sqrt{\mathbf{w}^T \Sigma, \mathbf{w}} \leq 0.20$
- $\min_{t} \frac{V_t}{\max_{s \le t} V_s} \ge 0.80$

## Results

The optimization produced two distinct portfolios that meet the respective constraints.

Portfolio	Equal-Weight Sharpe	Optimized Sharpe	β	Volatility $\sigma$	Max DD	Annualized return
High-Risk	0.87	1.05	2.10	59%	-59%	44.3%
Low-Risk	0.31	0.47	0.33	10.6%	-9.8%	5.02%

Table 1: Portfolios ouctome

# **Conclusion:**

Through a disciplined, metrics-driven approach we successfully engineered two complementary U.S. equity sleeves that satisfy their distinct risk mandates:

- The High-Risk portfolio, anchored in AI, EV/autonomy, crypto and innovation themes, saw its Sharpe rise from 0.87 to 1.05 while holding  $\beta$  at 2.10 and trimming extreme-loss drivers.
- The Low-Risk portfolio, built around staples, healthcare, utilities, dividend growers and duration ballast, lifted its Sharpe from 0.31 to 0.47, brought  $\beta$  up into the 0.40–0.60 band, and kept volatility and draw-downs within strict limits.

These results confirm that over-allocating to "paid" risk, capping tail exposures, and preserving thematic breadth are the right ingredients for extracting genuine risk-adjusted alpha without sacrificing mandate integrity.