GROUP WORK PROJECT # 2 MScFE 652: PORTFOLIO MANAGEMENT
Group Number: 8244

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(N/A)

Part 1

In this part, we will work with 7 assets AAPL, NVDA, TSLA, XOM, REGN, LLY, JPM. and we are going to build 3 optimal portfolios with different constraints:

- With no short-selling
- No short selling with a 20% cap on each asset
- Short selling allowed

we will use yahoo finance ("yfinance documentation — yfinance") to gather daily data for the assets from Jan 1 2022 to Dec 31, 2024, and the cvxpy package for optimization.

In optimization, our goal will be to balance risk and return with a specific risk-aversion parameter $(λ)$ i.e. 0.5.

But first, let's see some exploratory data analysis, we gathered the daily Adj Close data for all the assets. You can see the time series plot in Figure 1 below.

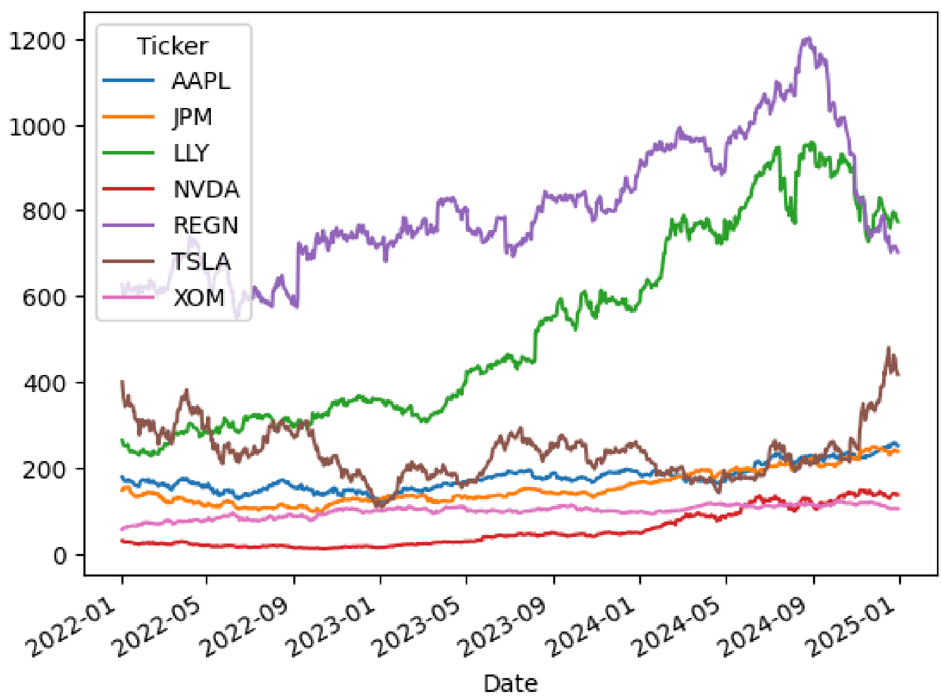


Figure 1: Time series plot for all 7 assets' prices

Next, we will get some summary statistics for all the assets, as we can see in Table 1 mean, volatility, skewness, and kurtosis for all the assets, NVDA exhibits the highest mean return (0.6609) but also the highest volatility (0.5529), indicating high risk and reward. LLY follows with a strong mean return (0.4024) and elevated kurtosis (7.2031), suggesting occasional extreme returns. REGN has the most pronounced kurtosis (22.4883), implying heavy tails and potential for extreme price movements. TSLA is the most volatile (0.6131) but has relatively low kurtosis (2.1948), while XOM shows the lowest kurtosis (1.4536) and a slight negative skew (-0.1191), suggesting more frequent negative deviations. Overall, the data highlights varying risk-return profiles, with some stocks exhibiting high return potential alongside significant risk.

Table 1: Summary Statistics

Tickers	**Mean**	**Volatility**	**Skewness**	**Kurtosis**
AAPL	0.151531	0.271079	0.211651	2.509914
JPM	0.190914	0.250079	0.398020	5.72975
LLY	0.402398	0.288038	0.982351	7.203079
NVDA	0.660925	0.552875	0.682176	4.010810
REGN	0.074200	0.27046	1.398593	22.488295
TSLA	0.201383	0.613143	0.243420	2.194842
XOM	0.243678	0.272275	-0.119055	1.453560

In Figure 2 below we will see the assets return correlation heatmap:

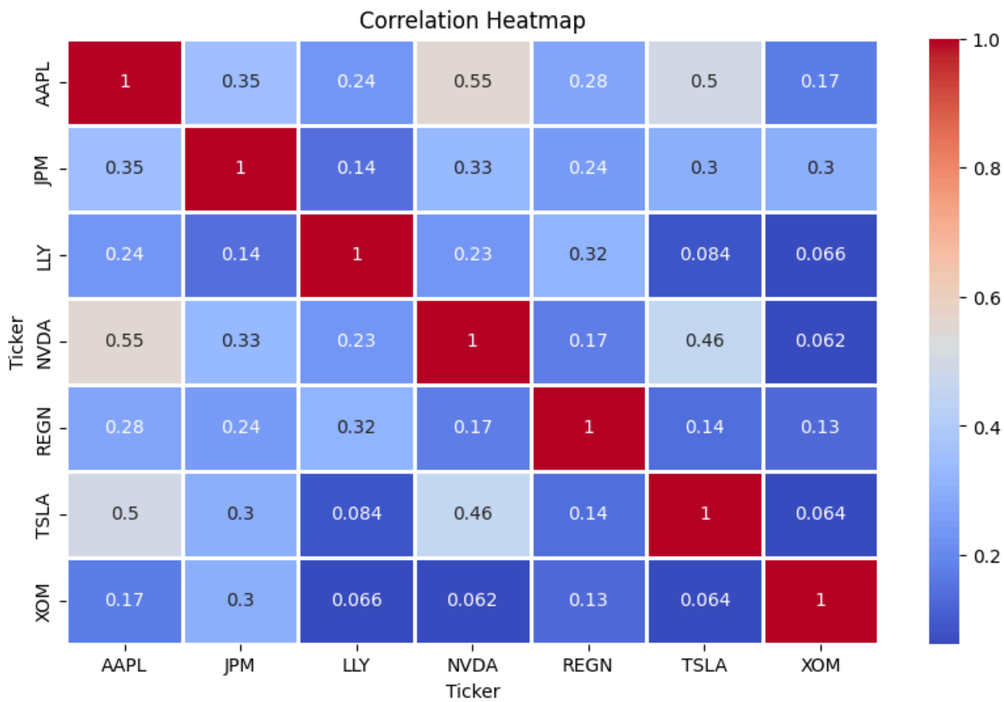


Figure 2: Assets Return Correlation Heatmap

The correlation heatmap displays the relationships between the returns of seven stocks (AAPL, JPM, LLY, NVDA, REGN, TSLA, and XOM). Strong positive correlations are seen between AAPL and NVDA (0.55) and AAPL and TSLA (0.50), suggesting they tend to move together. JPM and other stocks show moderate correlations, with the highest being 0.35 with AAPL. LLY and XOM exhibit the weakest correlations with most stocks, indicating relative independence in price movements. The generally low-to-moderate correlations suggest diversification benefits when combining these assets in a portfolio.

We will see the expected return graph in Figure 3 and Variance covariance matrix heatmap in Figure 4

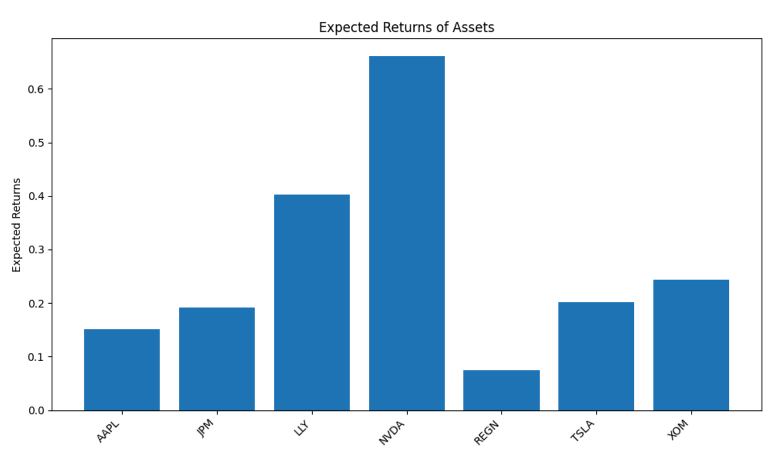


Figure 3: Expected Returns

We can see in the plot above that NVDA has the highest expected return following that LLY shows significant Expected returns all the remaining show moderate expected returns.

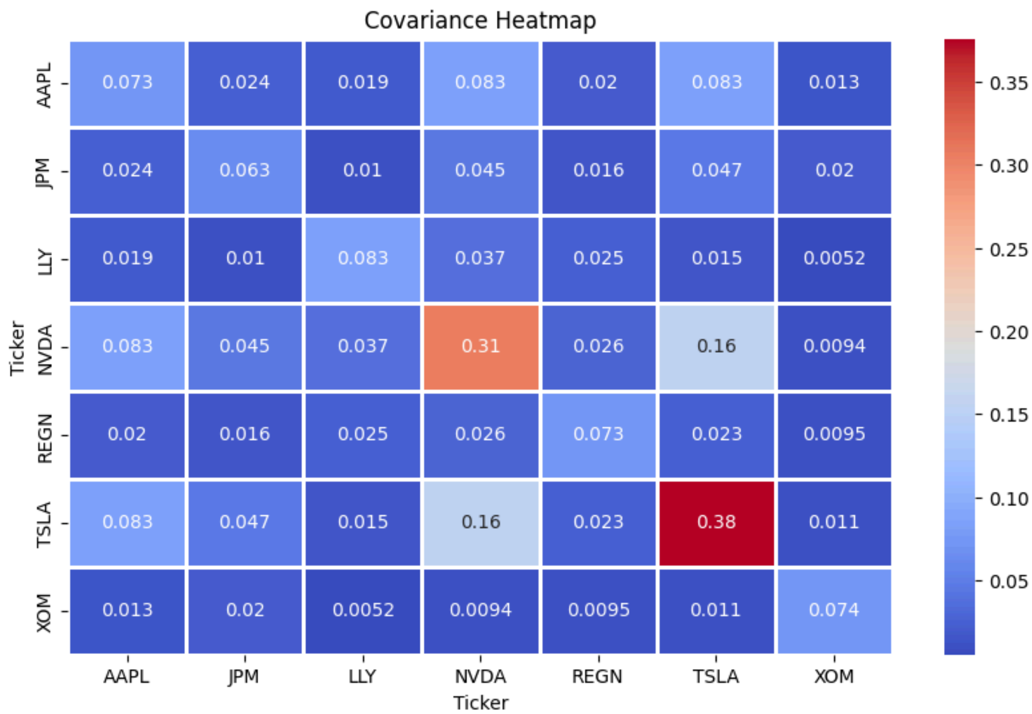


Figure 4: Variance Covariance Heatmap

The covariance heatmap shows the relationships between the returns of seven stocks (AAPL, JPM, LLY, NVDA, REGN, TSLA, and XOM) in absolute terms. NVDA exhibits the highest covariance with itself (0.31), followed by TSLA (0.38), indicating higher return variability. We can also observe Strong covariances between AAPL and NVDA (0.083) and AAPL and TSLA (0.083), implying they tend to move together. JPM and LLY display relatively lower covariances with other stocks, implying less correlated price movements. XOM has the lowest overall covariances, reinforcing its independent return behavior.

Now we will work on our main objective which is mean-variance optimization(MVO), in which we will focus on maximizing the risk-adjusted return.

Our objective function is:

$$max(-\ 1/2\, x^T Q x \ +\ r^T x)$$

Where:

- Q = Covariance matrix representing portfolio risk
- r = expected returns representing portfolio returns
- x = Portfolio weights representing asset allocation

This shows the mean-variance optimization(MVO) framework, where the tradeoff between risk and return is optimized with a specific risk-aversion parameter λ i.e. -½, that ensures that higher returns are favored while penalizing excessive risk.

As we have already discussed the 3 constraints that we are optimizing with we will see the results for asset weights in the portfolio in Table 2 below:

Table 2: Portfolio weights

Assets	**Constraint 1: No Short Selling**	**Constraint 2: No Short Selling + 20% cap**	**Constraint 3: Short Selling allowed**
AAPL	0.0000	0.0939	-2.8957
NVDA	-0.0000	0.2000	-0.4408
TSLA	0.0319	0.2000	3.1467
XOM	0.9681	0.2000	2.3461
REGN	0.0000	-0.0000	-2.4048
LLY	0.0000	0.1061	-0.2035
JPM	0.0000	0.2000	1.4520

We can see in the table :

For constraint 1(No short selling): Assets like XOM (96.81%) and TSLA (3.19%) dominate the portfolio, this shows concentrated positions in the portfolios.

For constraint 2(No short selling + 20% cap on allocation): Assets like NVDA, TSLA, XOM, and JPM receive the maximum allocation of (20%) and LLY (10.61%) AAPL (9.39%) only REGN received no allocation. It suggests more diversified and risk-adjusted allocations.

For constraint 3(short selling allowed): Assets like AAPL and REGN received large negative weights indicating short positions on the other hand TSLA (3.15%) and XOM (2.35%) received higher positive allocations showing long positions. It signifies the aggressive strategy that we using in this portfolio.

Now let's finally see the performance of all the 3 optimal portfolios, we will see the Return Volatility and Sharpe Ration of all the portfolios in Table 3 below.

Table 3: Optimal portfolio's performance

Portfolio	**Return**	**Volatility**	**Sharpe-Ratio**
Optimal Portfolio 1	**65.27%**	**53.75%**	**1.21**
Optimal Portfolio 2	**33.52%**	**22.94%**	**1.46**
Optimal Portfolio 3	**242.83%**	**150.34%**	**1.62**

In the table, we can see:

- The optimal portfolio 1 is highly concentrated in a few assets, leading to relatively high volatility. The Sharpe ratio suggests a good risk-adjusted return.
- The optimal portfolio 2 has diversification which improves risk-adjusted returns, reducing volatility significantly. The Sharpe ratio increases, indicating a more efficient allocation with better risk management.
- The optimal portfolio 3 allows short selling which leads to extreme returns but also significantly higher volatility. The Sharpe ratio improves slightly, suggesting a more aggressive but riskier strategy.

At last, we will see the diagram of the efficient frontier of all three optimal portfolios in Figure 5.

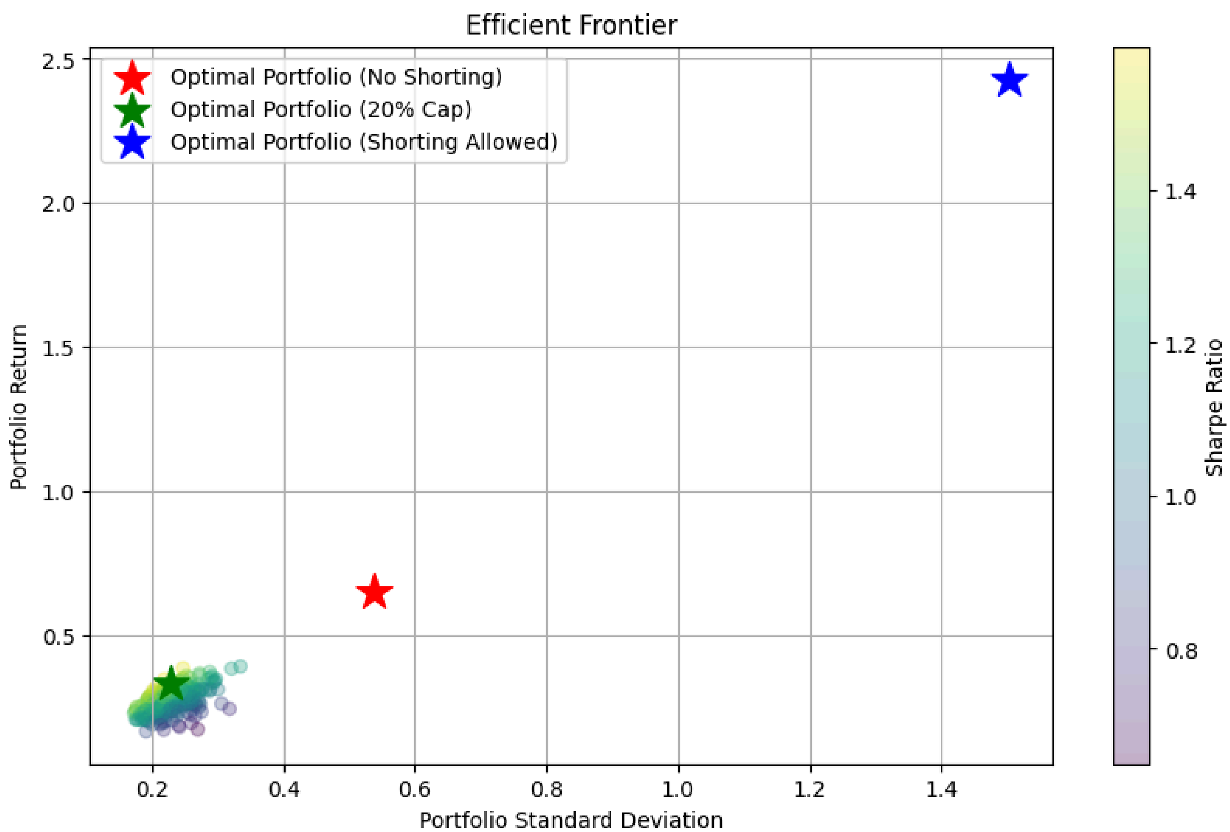


Figure 5: Efficient frontier of all 3 optimal portfolios

Part 2

In this part, we are going to show that the "1/N portfolio",i.e. the equal weight portfolio is not always the best portfolio.

To show the above is true in general we are going to choose 20 random assets (In this case 20 equities). These assets are AAPL, NVDA, TSLA, XOM, REGN, LLY, JPM, MSFT, GOOG, AMZN, META, V, NFLX, UNH, PG, DIS, BABA, KO, PEP, NKE.
First, we are going to do an EDA (Exploratory Data Analysis) to see how these assets are related to each other and what are their statistical properties-

We downloaded the daily close data for these equities using the yfinance module from the starting date of 1 Jan 2022 to 31 Dec 2024. We converted the daily close to daily returns. Below are the statistical properties.

Table 4: statistical properties of individual assets.

	Mean	Volatility	Skewness	Kurtosis
AAPL	0.1515	0.2711	0.2116	2.5099
NVDA	0.1612	0.3835	0.072	4.3535
TSLA	0.0302	0.5372	2.1326	20.1683
XOM	-0.0662	0.3029	-0.2809	6.0259
REGN	0.1502	0.3278	-0.0236	2.7659
LLY	0.1909	0.2501	0.398	5.7297
JPM	0.0577	0.1563	-0.5568	4.8196
MSFT	0.4024	0.288	0.9823	7.2031
GOOG	0.3092	0.4875	-0.3416	20.6237
AMZN	0.1266	0.2759	0.0076	1.9522
META	0.2647	0.4908	-1.8796	27.0977
V	-0.1915	0.3436	-1.167	13.537
NFLX	0.6609	0.5529	0.6822	4.0108
UNH	-0.0005	0.1705	-0.3885	3.0684
PG	0.0489	0.176	-0.4191	3.7316
DIS	0.0742	0.2705	1.3986	22.4883
BABA	0.2014	0.6131	0.2434	2.1948
KO	0.048	0.2442	-0.1716	3.7468
PEP	0.1509	0.2223	0.5337	6.1934
NKE	0.2437	0.2723	-0.1191	1.4536

As we can see from the above table we have a very diversified assets list. we have both positive and negative individual asset mean, skewness, and kurtosis. And we also have low and high comparative volatility to each other. This shows that we can use these assets for our simulations which will produce a generalized result.

Note: To produce more generalization we can add different types of assets like commodities, bonds or even metals.

Now we will continue with our list. We have already shown the individual asset statistical properties now we are going to see how assets are correlated to each other using the correlation matrix.

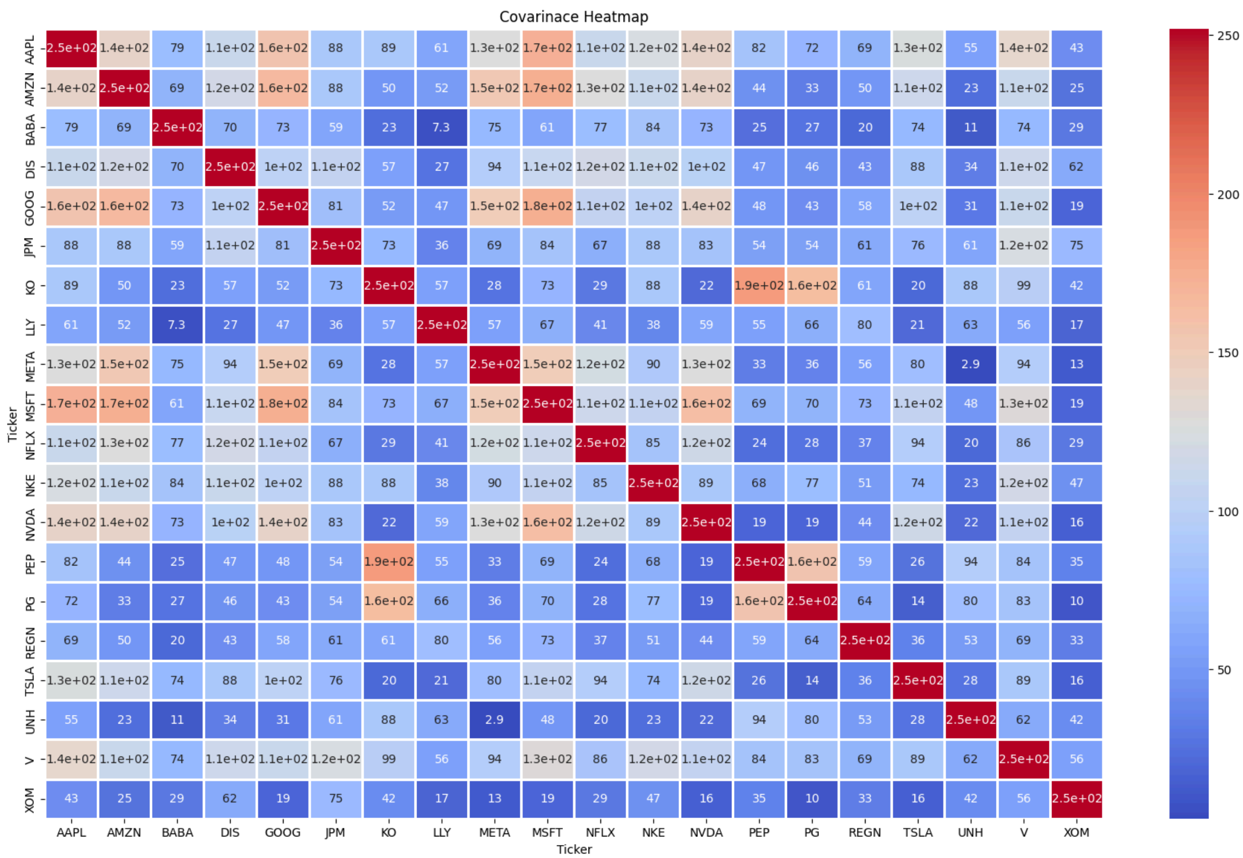


Fig 6: Correlation matrix for listed assets

As we can see from the above correlation matrix we have low and high-correlated assets and both positively and negatively related assets. Now below are the steps we take to simulate the portfolio mean, standard deviation, Sharpe ratio, and max drawdown using Monte Carlo Simulation

Steps-

1. We already downloaded the data for each asset.
2. Now we define the parameters for our simulation.
   a. num_simulations: 5000 (number of simulations)
   b. num_selected: 5 (number of assets selected randomly from and listed in each iteration)
   c. train_period : 2 years (approx. 2*252 days/ rows in dataset), train_period is remaining rows or days in dataset.
3. Now we are starting the simulations using the for loop. In each simulation, we select the 5 assets randomly from the list of assets.
4. we divide the selected dataset into train and test dataset
5. For the training dataset,t we calculate the mean and covariance matrix.
6. Now we are going to calculate the optimized weights for the training dataset using the MVO (Mean-Variance Optimization) using the quadratic programming where we minimize the objective function- $objFn\ = \frac{1}{2} * w^T \Sigma w\ - w^T \mu$, where Σ is the covariance-variance matrix,μ is the mean vector and w is the weight vector.
7. Now we calculate the returns on the test period and save the results using-
   a. weights from the MVO process.
   b. with equal weights vector (i.e., 0.2 in case of 5 assets)
8. We simulate the above 5000 iterations.

The above process produces the results below-

Fig 7: Histogram showing the return frequency from MVO and Equal weight process

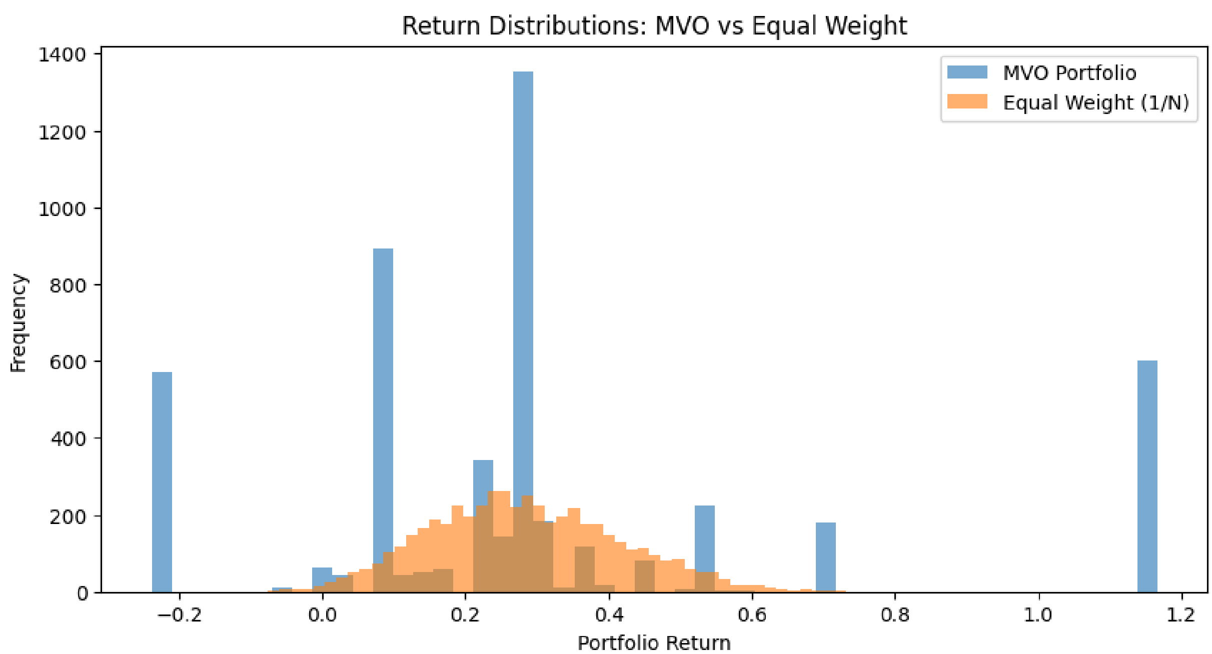


Fig 8: Distribution of returns from MVO and Equal weights process

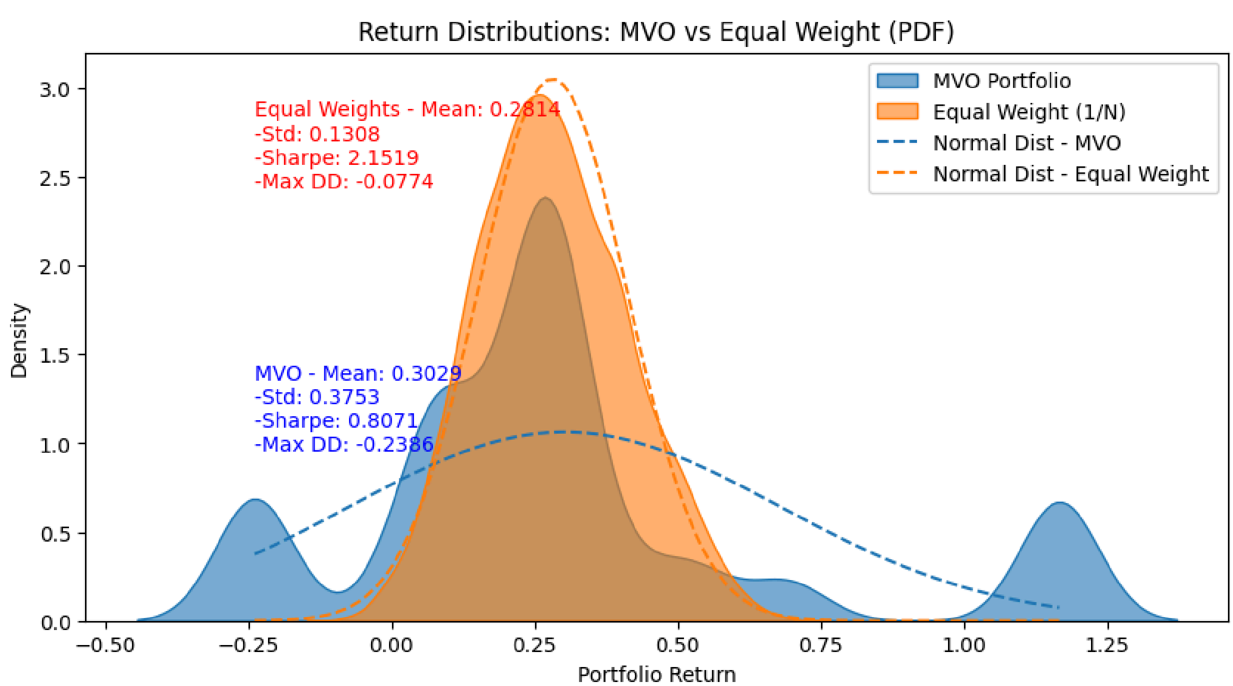


Table 5: Shows the statistical results related to MVO and Equal weight process

Process	Mean Return	Std Dev	Sharpe ratio	Max Drawdown
MVO process	0.3083	0.3790	0.8133	-0.2386
Equal Weight	0.2826	0.1312	2.1537	-0.0771

In the above table, we calculated the results as -

- Mean Returns: average of returns from different simulations for each process
- Std. Dev. : Calculated the standard deviations of return means.
- Sharpe-ratio: Sharpe ratio using 0 risk-free rate
- Max drawdown: minimum return from all the returns.

As we can see these results can be or will be different for different lists of assets. We are not here to show the results related to which process is the best. In some cases, MVO will be best and in others Equal weight process will, either produce a low share ratio, or the worst max drawdown. But the main argument was whether the Equal weight process is always good as compared to the MVO process. And clearly this is not true as we can see from the histogram and distributions that the MVO process can produce better results than the process of the Equal weight.

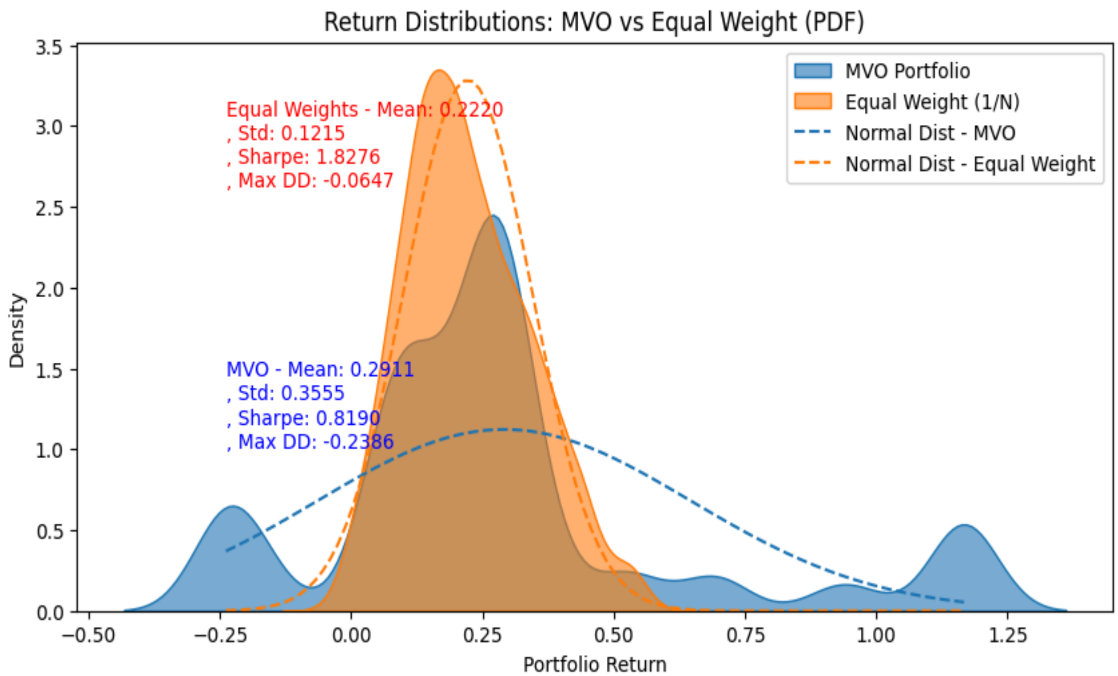
Again we are not saying that Equal weights will also produce the worst result. It is possible that the MVO process will give equal weights as the best weights for that scenario.

As we can see from the distributions, in some cases the MVO process produces the best returns and it also produces the worst returns as compared to equal weights.

Extra Remarks-

1. PDF for returns from equal weights are nearly symmetric with the below statistics, this is because all our assets are nearly normal with very low skewness, and on average we have low kurtosis.
    a. Mean: 71.4937
    b. Volatility: 2.0862
    c. Skewness: 0.1910
    d. Kurtosis: -0.3110
2. We have also produced the results-
    a. Assets-
        i. equities = AAPL, NVDA, TSLA, XOM, REGN, LLY, PM, MSFT, GOOG, AMZN
        ii. bonds = TLT, IEF, SHY, BND, LQD
        iii. commodities = USO, DBA, UNG
        iv. metals = GLD, SLV, PPLT

Fig 9: PDF for list of assets mentioned above for MVO and Equal weight process



Part 3

Step 6

To formulate views on the 7 assets, we go through the financial news for each of these assets. Based on the news, we have developed a view of how each of these assets will perform. The following table summarizes the views and sources based on which the views were formulated:

Table 6:

Asset	View	Rationale
AAPL (Yahoo News)	AAPL has -5% return	President Donald Trump's recent proposal to implement "reciprocal tariffs" has significant implications for major U.S. technology companies, including Apple Inc.
NVDA (Yahoo News)	NVDA performs 10% better than AAPL	Nividia will be able to perform better than Apple due to its ability to reinvent itself and has a major place in the AI sector due to the production of chips
TSLA	TSLA performs 30% better than AAPL	Tesla can disrupt the mobility industry by offering autonomous ride-sharing (robotaxi) services in the US. Demand for ride-sharing services could increase rapidly in the future as robotaxis reduce costs
XOM	XOM has 32% return	Exxon Mobil is estimated to be 32% undervalued based on the current share price and if the market corrects to the true price, there would be a significant positive return
REGN	REGN performs -10%more than LLY	Multiple Regeneron Pharmaceuticals, Inc. insiders offloaded a considerable amount of shares over the past year which implies a negative expected performance
LLY	LLY has a 4% return	LLY shares have risen 4.3% since it reported fourth-quarter results. Investors were impressed with the company’s outlook for 2025.

JPM	JPM has a 12% return	JPMorgan Chase & Co. (JPM) has recently been highlighted as an undervalued investment opportunity. Despite a significant rise in its stock price over the past year, some experts believe there is still room for growth, with price targets suggesting further appreciation

Source

- https://finance.yahoo.com/news/why-trump-reciprocal-tariffs-should-terrify-bulls-in-apple-amazon-and-other-tech-plays-133025192.html
- https://finance.yahoo.com/news/where-nvidia-stock-10-years-120000423.html
- https://finance.yahoo.com/news/2-monster-stocks-buy-soar-085500385.html
- https://finance.yahoo.com/news/exxon-mobil-corporation-nyse-xom-130134199.html
- https://finance.yahoo.com/news/possible-bearish-signals-regeneron-pharmaceuticals-140022283.html
- https://finance.yahoo.com/news/lly-rises-more-4-week-125000196.html
- https://finance.yahoo.com/news/jpmorgan-jpm-way-too-cheap-212822876.html

The Black-Litterman model (Walters), combined with market equilibrium returns to create a more informed portfolio allocation strategy.

Each element in the views array corresponds to a specific view:

- -0.05: AAPL is expected to have a return of -5%.
- 0.05: NVDA is expected to outperform AAPL by 10% (or to have a return of 5% relative to AAPL).
- 0.30: TSLA is expected to outperform AAPL by 30%.
- 0.32: XOM is expected to have a return of 32%.
- -0.04: REGN is expected to underperform LLY by 10% (meaning having -4% return relative to LLY).
- 0.04: LLY is expected to have a return of 4%.
- 0.12: JPM is expected to have a return of 12

The P matrix links the views in the views array to the specific assets in the portfolio.

```
Views:
[-0.05  0.05  0.3   0.32 -0.04  0.04  0.12]
P:
[[ 1.  0.  0.  0.  0.  0.  0.]
 [-1.  1.  0.  0.  0.  0.  0.]
 [-1.  0.  1.  0.  0.  0.  0.]
 [ 0.  0.  0.  1.  0.  0.  0.]
 [ 0.  0.  0.  0.  1. -1.  0.]
 [ 0.  0.  0.  0.  0.  1.  0.]
 [ 0.  0.  0.  0.  0.  0.  1.]]
```

We calculate the Posterior Expected Returns to be as below:

- AAPL: 0.0614
- NVDA: 0.1315
- TSLA: 0.3419
- XOM: 0.3915
- REGN: 0.0137
- LLY: 0.0138
- JPM: 0.1795

Step 7

Posterior Weights for Optimal Portfolio

- AAPL: 0.0508
- NVDA: 0.0945
- TSLA: 0.3457
- XOM: 0.3332
- REGN: 0.0616
- LLY: 0.0116
- JPM: 0.1360

Part 4

Step 8

Analysis of Kelly Criterion-Based Strategies for Portfolio Optimization

The Kelly criterion is a popular strategy for portfolio allocation, balancing risk and reward by determining the optimal bet size to maximize long-term capital growth (Nekrasov). In this presentation, we have compared three variations of the Kelly criterion (Carta et al.):

1. **Full-Kelly** (100% Kelly allocation)
2. **Half-Kelly** (50% Kelly allocation)
3. **Double-Kelly** (200% Kelly allocation)

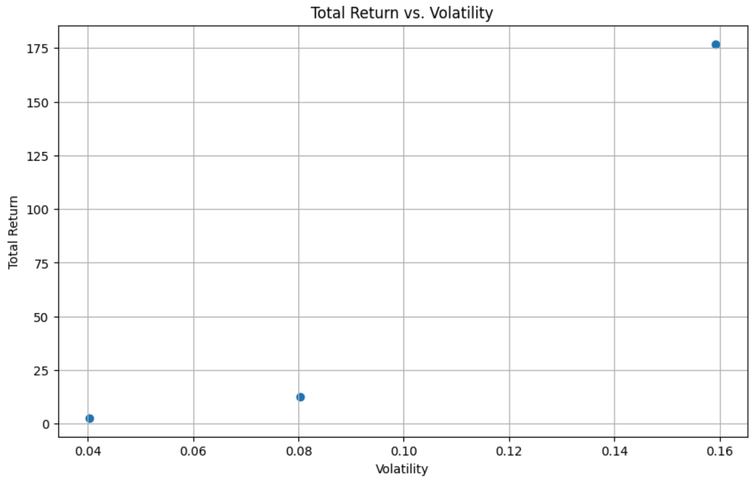
We evaluate the performance of a portfolio comprising seven assets based on key financial metrics: **Total Return, Volatility, Sharpe Ratio, and CAGR (Compound Annual Growth Rate)**.

Table 7: The following table summarizes the performance metrics of each strategy:

Strategy	Total Return	Volatility	Sharpe Ratio	CAGR
Full-Kelly	12.5251	0.0803	156.0425	0.8520
Half-Kelly	2.6905	0.0403	66.7725	0.3620
Double-Kelly	176.9200	0.1593	1110.8171	2.4076

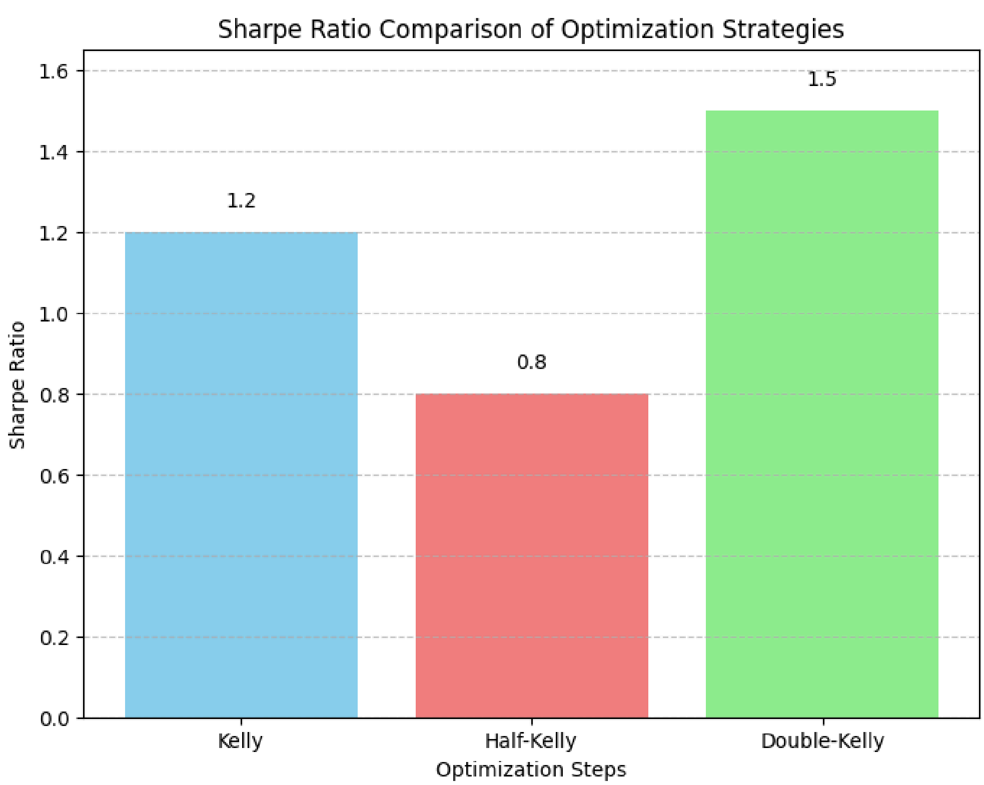
- **Total Return**: The Double-Kelly strategy provides the highest return (176.92) but comes with significantly higher volatility. The Full-Kelly strategy achieves a decent total return (12.52), whereas the Half-Kelly strategy underperforms (2.69) due to its more conservative approach.
- **Volatility**: The Double-Kelly strategy has the highest risk (0.1593), while Half-Kelly has the lowest volatility (0.0403). Full-Kelly is in between (0.0803), suggesting a risk-reward balance.

Figure 10: Total Return Vs Volatility



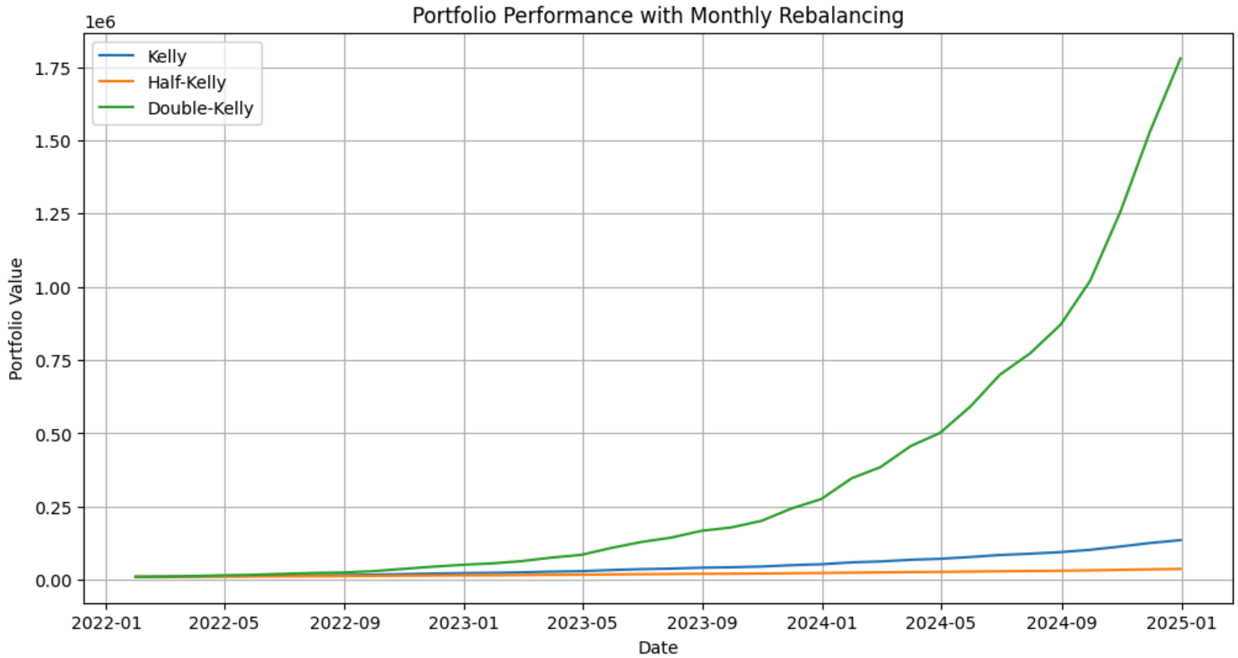
- **Sharpe Ratio**: Double-Kelly achieves very high Sharpe Ratio (1110.82), indicating that despite its high volatility, the returns compensate well for the risk. Full-Kelly also performs strongly (156.04), while Half-Kelly has the lowest risk-adjusted returns (66.77).

Figure 11: Sharpe Ratio Comparison



- **CAGR**: The Double-Kelly strategy delivers the highest CAGR (2.41), reflecting its aggressive growth. Full-Kelly produces solid long-term growth (0.85), while Half-Kelly remains conservative (0.36).

Figure 12: Portfolio Performance



Comments

- **Risk-Reward Tradeoff:** The results confirm the fundamental tradeoff between return and volatility. While the Double-Kelly strategy maximizes gains, it also exposes the portfolio to higher risk. This strategy is suitable for aggressive investors with high-risk tolerance.
- **Moderation Through Fractional Kelly:** The Half-Kelly strategy significantly reduces risk, making it appropriate for more conservative investors. However, it sacrifices potential gains, as seen in the lower total return and CAGR.
- **Balanced Approach:** The Full-Kelly strategy balances risk and reward, offering a reasonable total return with manageable volatility.

The choice of Kelly's strategy depends on the investor's risk tolerance and financial goals. While Double-Kelly offers the highest potential returns, it comes with considerable risk. On the other hand, Half-Kelly provides stability at the cost of lower returns. Full-Kelly serves as a middle ground, making it a suitable strategy for many investors seeking an optimal balance between growth and risk.

Future analysis could incorporate Monte Carlo simulations and historical stress testing to refine further the effectiveness of each approach under different market conditions.

References

1. Carta, et al. “Practical Implementation of the Kelly Criterion: Optimal Growth Rate, Number of Trades, and Rebalancing Frequency for Equity Portfolios.” Frontiers in Applied Mathematics and Statistics, 2020, https://www.frontiersin.org/articles/10.3389/fams.2020.577050/full.
2. Nekrasov, Vasily. “Kelly Criterion for Multivariate Portfolios: A Model-Free Approach.” *SSRN*, 2 May 2013, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2259133. Accessed 17 February 2025.
3. Walters, Jay. “The Black-Litterman Model in Detail by Jay Walters, CFA.” *SSRN*, 28 January 2009, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1314585. Accessed 17 February 2025.
4. “yfinance documentation — yfinance.” *GitHub Pages*, https://ranaroussi.github.io/yfinance/. Accessed 17 February 2025.