Mean-Variance Optimization Model Analyzing Report

The emphasis of this report is explanation of constructing portfolio optimization model and analyzing financial performance of classical and resampled efficient frontiers based on 25 companies monthly return dataset from 2018 to 2021.

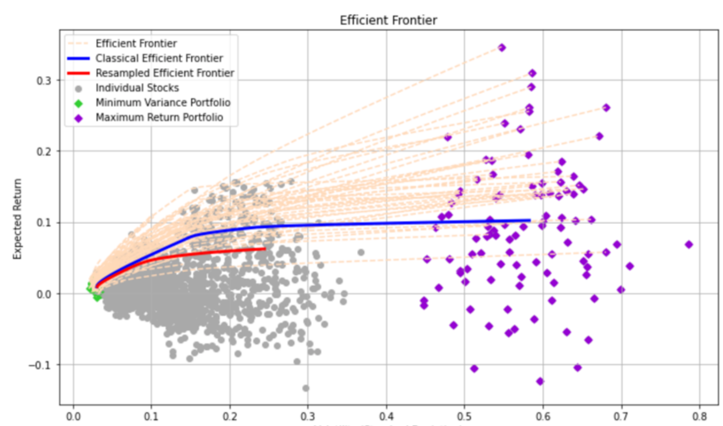
- Classical and Resampled Efficient Frontier

In this project, we divide 2018-2020 dataset as in-sample data, 2021 dataset as out-sample data. Therefore, we can compute the optimal parameters on in-sample data and evaluate our results on out-sample data to check the performance of our optimization model.

Given in-sample dataset of 25 companies' monthly returns in total 36 months, I consider each company as an independent asset and the portfolio comprising of these 25 assets as my model. By calculating the percentage change as return of return, the mean and covariance matrix are easily achievable. Then I computed the portfolio with minimum variance of 0.00093, as well as the portfolio with maximum return of 0.1021.

To compute classical Markowitz efficient frontier, I set 50 target rates in range of minimum variance and maximum return achieved above to get 50 corresponding portfolios, and store all weights, variance and returns for these 50 portfolios.

For resampled efficient frontier, I used similar method. But I firstly set 100 times repetition for resampling, each repetition gives me 25 resampled draws from original dataset. Each resampled data is drawn from multivariate normal distribution with original mean and covariance. Similar as above, I computed minimum variance and maximum return portfolios for each repetition and stored all results in resample. I determined average weights of 100 repetitions as my final resampled weights, then calculated final variance and rate of returns based on final weights and original mean and covariance.



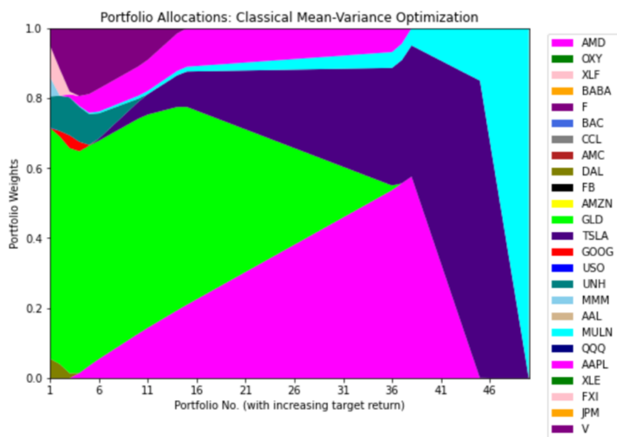
From figure above, the resampled efficient frontier gives us lower return given same volatility. As we resampled for 100 repetitions, the resampled data should be more even and stable than original data. Moreover, the classical model is derived based on historical data, which we already had insights on its performance. It means classical model is overestimated with optimistic analyzing altitude. The resampled data is more realistic and predicted the future performance with fair and impartial perspective. Although the resampled performance is not satisfied, it achieved predictions in reality.

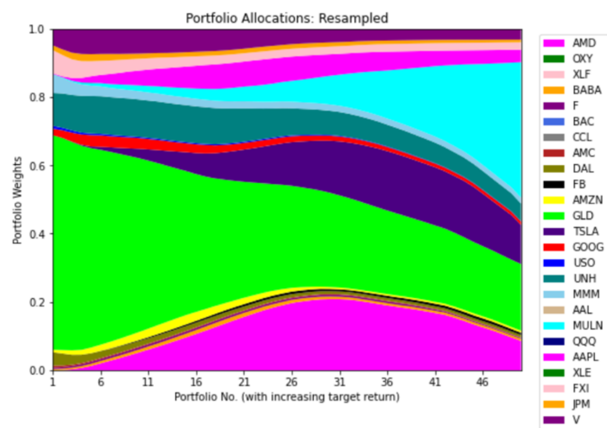
- 6 Portfolios Comparison

Given above calculations, I already saved minimum variance portfolio weights and maximum return portfolio weights on both classical and resampled efficient frontier. I projected these optimal weights on out-sample data to see the performance. In classical model, the rate of return in 2021 projected minimum variance portfolio is 2.822%, projected maximum return portfolio is -58.21%. In resampled model, the rate of return in minimum variance one is 6.518%, projected maximum return portfolio is -8.67%. Moreover, we know that sharpe ratio is a key indicator to measure portfolio performance by considering both return and risk. I calculated sharpe ratio for all portfolios in both classical and resampled model and to find the optimal one with highest sharpe ratio. By projecting the optimal weights on 2021 dataset, I got classical sharpe ratio portfolio rate of return is 27.96%, resampled one is 22.52%.

As we can see, the projected portfolios without sharpe ratio all performed poorly. I believe that the stock market is fast changing and barely predicted. The optimal weights from in-sample data only demonstrated the historical performance, and it cannot be intact implied into future data. If we only consider one side of performance, it will lead to imbalance of allocation as well as bad performance on portfolios. The sharpe ratio helps us solve this problem. It adjusted risk and find the feasible maximum return. Therefore, the optimal parameters with sharpe ration showed us a stable and good performance on out-sample data.

- Portfolio Composition





As we know, the higher return bound with higher volatility. For lower target return portfolios, the classical model put more weights on GLD which has lower volatility and stable return. While increasing the target return, portfolios are chiefly consisted of AMD, accounting for 50% in portfolio no.38. However, the resampled portfolio composition plot is smoother than classical model. The allocation tends to be more even and more diversified instead of putting large proportion on one asset.

- Conclusion

In summary, the resampled portfolios give us a more realistic and diversified perspective on financial performance. Because we add variability into repetition to generate resamples, it gives us an idea that what would happen when we apply optimal parameters from historical data into future unseen stock market. The limitation of mean-variance optimization also proved that insight. The small changes of initial parameters will lead to concentrated allocation. The resampling helps us to simulate the optimization in capital market by averaging across the efficient frontier, in order to reach more balanced allocation, as well as more realistic predictions that might apply into real stock market.