

**PORTFOLIO THEORY AND ASSET PRICING**

***Submission Number: 3***

***Group Number: 3 - A***

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**8.1**

The goal of this project is to find a well-balanced portfolio with the right amount of risk and return by comparing and testing different levels of portfolio specifications and different approaches for portfolio selection and optimization. The idea is to build and test portfolios with different combinations of securities comprising different weights, volatilities, and levels of correlations. The portfolios will then be compared against a baseline and amongst each other to identify the best performing portfolio. Ultimately a portfolio with the highest return for a given level of risk is an optimal selection.

This process aids in the selection of the best performing set of security combinations from the prevailing set of investment opportunities. In addition, it reveals why some sets of a specific set of security combinations perform much better than others. This gives us a chance to further probe the underlying economic circumstance enabling the observed results.

We began by selecting two ETF securities(GDX & XLB) from the 11 SPDRs that we have obtained in order to construct a two-asset portfolio. We have created functions to efficiently compute the daily and annualized returns as well as standard deviations for multiple assets in a portfolio. In addition, these functions allow for a variety of asset weights to be applied along with the computations.  The results show that the two assets have a correlation of around 18% and annualized return and standard deviation of 16% and 24.7% respectively. These numbers show a brief overview of the portfolio performance, however, making decisions depends on comparison relative to other portfolios.

After computing the returns and standard deviation from the above functions as well as the correlation of the assets, we now have all the elements we need to construct an Efficient Frontier curve. An Efficient Frontier curve shows the highest return of these two asset portfolio for a given level of volatility. We have implemented this by first creating a function that takes in asset returns and asset correlation as an input. This function encompasses the functions we have previously created and then computes the overall portfolio return and volatility by applying different weights on the assets. The output is an efficient frontier curve showing the points of the highest returns of that portfolio for a certain level of risk.

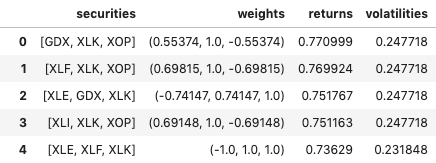
Our results show that the lowest volatility of the portfolio or the Global Minimum Variance Portfolio (GMVP) is at around 20% and the return is 13% respectively. Since the overall object is to build a well-balanced portfolio, asset correlations and weights play a big role in how the portfolio is structured. This is important since a less than optimal combination might less return or taking the excessive risk from the markets.  This concept comes from the realization that by combining assets in a portfolio whose returns are less than perfectly positively correlated, we can create more efficient portfolios. To that end, we have examined the efficient frontier curve with different levels of asset correlations. With perfectly negative correlated (corr =-1) securities we can effectively remove the volatility of any risk in the form of portfolio volatility while maintaining a positive return. This often creates an arbitrage opportunity as we ensure a positive return with zero risks. If the two assets are not correlated at all (corr = 0) then we get much lower volatility than our two asset portfolios (corr = 0.56) but with similar returns. Finally, with a perfect correlation (corr = 1) the curved line no longer exists, and we can observe that risk and returns are growing linearly. This shows that the two assets have a linear relationship, and we essentially are investing in the same securities but scaled differently.

 Outliers in the data can skew the results of the portfolio structure. Therefore, in our next step we removed the 5% most extreme returns, we effectively remove some volatility from our portfolio. This is shown by the graph where the overall minimum portfolio volatility at the GMVP is much lower.  The two graphs look quite similar however the annualized std of returns is lower than for the non-trimmed portfolio (16.55% vs 24.77%). In addition, the annualized return from the portfolio increased (21.73% vs 16.27%).

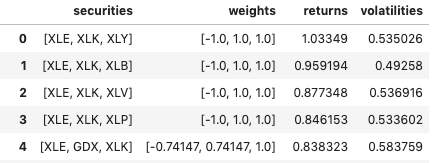
The robust method for the portfolio is also another technique we have applied to create the efficient frontier curve. This method is similar to any optimization problem by defining a specific object, such as in this case maximizing a portfolio’s return and given a constraint such as a certain level of risk. It can be implemented by using the PyPortfolioOpt packaged on python. Compared with previous results we find the same result as before. This makes sense as we are using the same method based on the Efficient Frontier. The return is lower for the trimmed data for the same level of risk and the volatility higher for the same level of return.

Next, we built a three-asset portfolio by adding one more ETF (XLU) into our existing two asset portfolios. Similarly, we have computed and plotted the EF using the robust method for portfolio optimization as we before. Our results show no signs of diversification effect with either lower volatility or higher returns. This is due to the highly correlated nature of these assets. These assets (GDX, XLB, XLU) represent the (Gold miners ETF, Materials Sector, Utilities Sector) respectively. This high correlation could be the result of these economic sectors having direct or indirect influence over each other.

Building from this idea, in order to help us identify which three asset portfolios to choose from we have created a combination of all the ETFs into 165 portfolios assuming a fixed level of risk for all the portfolios. We tested these portfolios using the 2019 returns and rank their performance according to their overall portfolio returns. The results show that the top five performing portfolios ranked by their returns.



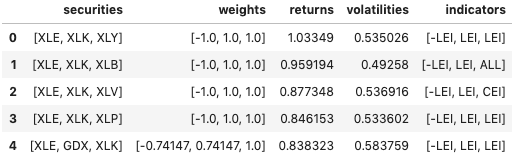
Testing the same ETFs with the 2020 returns yields the following top five portfolios.



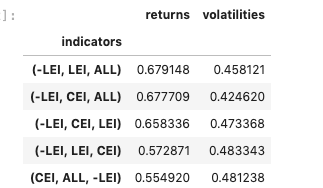
Clearly, there is a distinction in the portfolio performances between the two years. In 2019 the top-performing portfolios include ETFs of Gold, Technology, and Oil sectors compared to 2020 of Energy, Technology, and the Consumer sectors. Since 2020 is a unique year favoring business with certain business models could have influenced respective sectors. We can also see that the Technology sector is ubiquitous in the top-performing portfolio combinations in both years shows the importance and consistency of that sector. Moreover, higher levels of returns are associated with higher levels of volatility in general.

As mentioned above, a sector’s economic performance and the amount of weight an ETF tracking that sector has in a portfolio is important in determining the performance of a portfolio. This way we could discover which economic indicators are included in the best performing portfolios and understand the underlying economic factors of our portfolios.

From our previous submission, we already know which economic indicators best represent the tracking ETFs. Making use of this data we labeled each ETF with a sign to indicated whether their weight is above or below zero in their portfolio. Then we implemented a three-asset portfolio using the combination of all the ETFs similar to previous tasks. However, this time we have also included each economic indicator representing each ETF within a portfolio.



Filtering only the economic indicators and sorting them with respect to the portfolio returns gives us the economic indicators associated with the top-performing combination ETFs.



The best returns are given on average by a combination of funds explained by either leading indicators or all indicators. As stated in the previous submission, funds explained mostly by Leading Indicators are funds that track the main sources of input and output in the economy. These funds are linked to value-adding companies, and they are the main source of economic growth and therefore of investment return. This explains why the highest returns are found in these funds. It should be noted however that the volatilities are relatively high for these portfolios.

In our final category, we have taken a Principal Component Analysis(PCA) approach to optimize our portfolio. PCA is s a dimensionality reduction procedure to simplify our dataset. According to Wikipedia, “PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.”

In our case, PCA enables us to identify which SPDR ETFs to use as a representative of the whole ETFs data set and therefore find the number of ETFs that is sufficient to diversify our portfolio and improve performance.

To accomplish this task we first scaled our data, set the number of components to three, and fit a PCA to our standardized returns so that we can construct the three asset portfolios. Here, we consider the transformed returns to be the new portfolio returns, and we assign a weight to each portfolio in the proportion to its contribution to the total variance.

The PCA-based approach compared to the 2019 best performing 3-security portfolio resulted in much lower returns(35.56%) and higher volatility(33.10%). One reason could be, by using a combination of ETFs that explains the most variance, we do not differentiate between positive and negative variance. As negative returns are usually more extreme than positive ones, it is not unlikely that choosing the most variance diminishes the overall return as we also get more extreme negative returns. Repeating similar tasks with the 2020 returns also shows much worse performance than the 3-security portfolio with -33.44% returns and 85.76% of volatility. These extreme results could be the result of the recent economic crisis due to the COVID pandemic creating an unprecedented level of uncertainties in the global economy and markets as a whole.

**8.2**

As always the group began by discussing how to approach the project and agreed to conduct some preliminary research on some tasks. The group members also took the liberty of approaching the tasks individually to get familiar with the tasks at hand and expand the variety of the solutions.

At the second meeting, the group discussed their findings and approaches based on their research. The group agreed to divide the works among members based on the most suitable solution proposed for each task and also agreed to collaborate and build on each other’s work along the way.

The division and collaboration of the group are as follows:

Mantobaye Moundigbaye

-   Data collection, preprocessing, creating functions for efficient computing portfolio returns and standard deviation for multi-asset class portfolios. Creating 2 and 3 security Efficient Frontiers including trimmed returns data. Mantobaye also performs the tasks with robust portfolio methods.

Louis Regnier-Vigouroux

-   Reviewed and improved the work done by Mantobaye Moundigbaye. Completed the tasks on testing the portfolio combinations of all ETFs using the 2019 and 2020 returns. He also analyzed the 3-security portfolio with different weights and determined the combination of ETFs with associated economic indicators. Finally, he completed the PCA based approach  to portfolio optimization

Yonas Menghis Berhe

-   Writing the non-technical report,  interpreting the result of the code and the various portfolio performances. Communicating and adjusting results with changes in the approaches selected and providing feedback on work done. In addition, he wrote the report on how the team divided the work and collaborated.

Throughout the project, the group maintained close communication and collaboration. Group members provided feedback on each other's work and gained invaluable experience from working together.

References:

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