

# Portfolio Optimization among Luxury Goods, New Energy, Web 3.0 Industries and Gold

Ziyao Lei\*

College of Letter and Science, University of California Santa Barbara, California, United States

\*Corresponding author: zlei@ucsb.edu

**Abstract.** This paper aims to discuss optimal portfolio construction with assets among luxury goods, new energy, web 3.0, and gold industries, with the hope of providing insights into the investigation of the relationships between those industries and their feasibility in the process of portfolio optimization. Based on accessible data from Yahoo Finance, this paper first discusses mean-variance analysis with a focus on the return data of the chosen assets, then utilizes Fama-French three factor model to run a portfolio optimization among those assets with core indexes being the maximization of Sharpe Ratio and the minimization of variance. As a result, two portfolios with different weights assigned to each asset are generated and they could be a good indication of the relationships between the discussed industries and their connections under investment scenario, and therefore may provide valuable information to the related financial market investors.

**Keywords:** Portfolio optimization; Fama-French three factor model; Sharpe Ratio maximization; volatility minimization.

## 1. Introduction

Asset portfolio construction has always played a major role in the world of asset management, and it's been gaining popularity in recent years as Hudayberganov points out that the ongoing globalization process on world economy has increasingly expanded the exchange of goods, and that the market management is becoming crucial [1]. Financial market portfolio is also essential especially to market participants and analyses of portfolio optimizations are valued greatly. Researches include the study of composition possibilities on market portfolio [2] and historical analysis of stock portfolios pattern [3].

Numerous analyses have been done, for example, Musciotto, Marotta, Pillo & Mantega addressed the heterogeneity among financial market investors, establishing the fact that personal investing portfolios share few common trends [4]. There are plenty of portfolio analysis about each one of the chosen industries, as they gained a tremendous amount of attention throughout the globe in the last few years. For example, Yang, Qiu, Yan, et.al explained the accelerating trend of replacement of traditional transportations by new energy ones [5], promoting the growing importance of new energy vehicles analysis and its industry as a whole. Likewise, Phosaard and Yang analyzed web 3.0 industry's resource management [6], and Deng, Xu & Wu discussed the feasibility of portfolio optimization concentrated on blockchain technology investments using ABC algorithm [7].

However, there is a lack of the analysis of cross-sector portfolio construction mainly among the mentioned high-popularity industries, and this paper wishes to provide information fulfilling that blank. Centered around this problem, this paper mainly computes two optimized portfolios under two circumstances with corresponding discussions. This paper is organized into three major parts: Introduction, Data and Methods, and Conclusion, each part with sublevel classifications.

## 2. Data and Methods

### 2.1 Data

The database that is used in building the portfolio comes from Yahoo Finance (finance.yahoo.com) and can be accessed publicly by any individuals. This paper addresses assets using monthly data from 9/1/2017 to 7/1/2022, lining the data that can be accessed from the Fama French 3 factor model

website. Four of the assets in the portfolio are based on three different markets that contain both a high potential growth under future macro scope and an ability to follow the worlds’ trend in the 21st Century. Taking insights into different industries of clean energy, Luxury goods, Cryptocurrency, and Metaverse, four leading companies that are representative of their corresponding industries are chosen: Ballard Power Systems Inc. (BLDP), LVMH Moët Hennessy - Louis Vuitton, Société Européenne (LVMUY), BNB USD (Binance) (BNB-USD), and Meta Platforms, Inc. (META). The fifth and the last asset in the portfolio is SPDR Gold Shares (GLD), and ETF that tracks gold price. The data that is primarily referred to is derived using the formula below:

$$return\ rate = \frac{price\ of\ last\ month}{price\ of\ this\ month} - 1 \tag{1}$$

The comprehensive data sets that are derived are introduced in the table 1 below:

**Table 1.** Summarize of the data

	LVMUY	BLDP	GLD	META	BNB
Arithmetic Avg.	0.01990885	0.02497464	0.00586883	0.00357833	0.20006481
Variance	0.00481755	0.03391479	0.00139342	0.00937734	0.47891729
Max	0.22617666	0.460256	0.107905	0.271569	3.733364
Min	-0.1405872	-0.286942	-0.071477	-0.326342	-0.457705

Through interpreting the data above, BNB obviously has the highest arithmetic average return rate and at the same time the highest maximum monthly return rate, up to 373%. However, these extraordinary high numbers can be explained by the supplemental high variance, indicating that BNB has a high volatility. GLD has the lowest maximum and average return rate among these five, also coordinating with the lowest variance. The other three assets are at the middle, following the general pattern that the higher the variance, the greater the chance of having an extreme number.

**2.2 Mean-Variance Analysis**

After having the data of all the return rates of every individual asset in the portfolio, it is possible to form a basic interpretation of the data set by analyzing basic arithmetic features of those data. Some data can indicate partly or give a general view of the data set. For example, the arithmetic average return gives an idea of what the “probable next best guess” is like, and it can be calculated using the formula below:

$$Arithmetic\ Mean = \sum \frac{x_i}{n} \tag{2}$$

Another important data is the covariance, as it discusses the relationship between each asset’s variance and that of others. In a portfolio that has a fixed amount of total weight, covariance can be useful when determining the allocation of funds, and it can be found using the equation,

$$Cov(X, Y) = \sum \frac{(x_i - \mu)(y_j - \nu)}{n} \tag{3}$$

Where  $\mu$  represents the average value of  $x$  variable and  $\nu$  represents the average value of  $y$  variable. Similarly, an executive portfolio has weights assigned to each of the assets included, and the total weight is defined to be 1. Therefore, the expected return of the entire portfolio can be calculated as below:

$$E(R) = \sum_i E(r)_i * W_i \tag{4}$$

Where  $W$  is the weight of asset and  $E(r)$  be the expected return of each corresponding asset. Variance is used to determine the volatility of the portfolio as Bansal, Connolly, et.al confirmed that variance has connections to the volatility of not only the asset performance, but the firm-level operating options as well, thus reinforcing the credibility of variance as an analyzable index [8]. To calculate the variance of the portfolio as a whole, the covariance containing all the assets in the portfolio is referred to. Variance can be calculated using the equation

$$\text{Variance} = ([W] * [COV]) * [W] \quad (5)$$

Where  $[W]$  is the matrix of weights and  $[COV]$  being the matrix of the covariance. An important value here is Sharpe ratio, which addressed the advantage among risks and benefits, and that can be used as an indicator of the effectiveness of the portfolio. In order to get Sharpe Ratio, the standard deviation of the portfolio is needed, and it can be calculated as follow:

$$SD = \sqrt{\text{variance}} \quad (6)$$

Then, Sharpe Ratio can be derived from the equation

$$\text{Sharpe Ratio} = \frac{E(R) - R_f}{SD} \quad (7)$$

Where  $E(R)$  being the expected return of the portfolio,  $R_f$  being the risk-free rate, and  $SD$  being the standard deviation. It is common to conduct an analysis or a portfolio optimization just based on the mean-variance method, a method that determines the weights of the portfolio by only taking data such as mean and covariance-matrix value into consideration. However, Phosaard & Yang describes the possible estimation error that may occur with the usage of only mean-variance model, and they then introduced the detailed process of the reference to covariance matrix using models, which would be more reliable [9]. Therefore, a factor model is primarily referred to in this paper and is introduced in the next section.

### 2.3 Fama French 3-Factor Model

For a portfolio with various assets, Fama French three – factor model (referred to as FF3F) is primarily utilized here because of several reasons: 1) it gives relatively accurate results based on three most common factors that every company has 2) not like some other models such as Capital Asset Pricing Model (CAPM), FF3F requires fewer assumptions that only a portion of the investors in the market need to be rational when making decisions in order to have validity, as in the comparison with the CAPM as Xiao.Y stated that FF3F model is preferred in most situations [10]. FF3F states that the primary factors that affect the expected return of a certain asset are size factor (SMB), growth factor (HML), and market beta factor (market factor). A common logic of that that is proposed by Wang is that the result of model computations can be a reflection on the effect of market risk factor on cross-section portfolio returns [11].

Excess return data is essential for conducting a linear regression later with respect to the three factors because a risky return is needed to calculate an accurate beta value. Excess return rate of assets could be calculated by the equation below:

$$\text{excess return} = \text{return} - R_f \quad (8)$$

Where  $R_f$  is the market risk-free rate from the Fama French research data based on the return of 4-week Treasury bill [12]. Then, linear regression model is applied to amplify the samples to the entire market to get a credible result. First, the dependent variable  $Y$  is set to be equal to the set of

the target asset's excess returns, as the expected return is the value that is mainly predicted. For independent variables, Mkt-Rf (market return above risk free rate), high-minus-low return (HML), small-minus-big (SMB) are taken into account because these are the three factors that are addressed in the FF3F model. In other words, linear regression is applied to find out what would excess return possibly change if any of the market-return, size effect, or growth effect data has changed. The resulted coefficient value of each of the dependent variables represents the corresponding beta value for each one of them.

Then, the expected return data for each of the asset is calculated using the results from the linear regression. Since three factors are taken into consideration, our expected return would be the sum of three products plus the risk-free rate, which can be represented as,

$$E(r) = R_f + Mkt_{RP} * \beta_{Mkt} + HML_{RP} * \beta_{HML} + SMB_{RP} * \beta_{SMB} \quad (9)$$

Where  $RP$  represents the risk premium of the assigning value. Using risk premium, it is able to further conduct a stable and reliable value of the independent variables that are credible. Notice that risk free rate does not need to be subtracted because the accessible FF3F data has already represented the values in terms of their risk factors. After all the steps above, a solver is used to find optimal weights values that can give the maximum Sharpe Ratio, with a restriction that no weights are under zero (no short position) because according to Zu, a negative weight on an asset is only preferred where the result of the Sharpe ratio is negative using minmax risk analysis, under a case that large but not less variance is featured [13]. The total of weights in the portfolio is 1.

### 3. Results

Through applying the FF3F model to the portfolio with 5 chosen assets, 2 optimal portfolios are generated – one to maximize Sharpe Ratio, one to minimize variance (volatility).

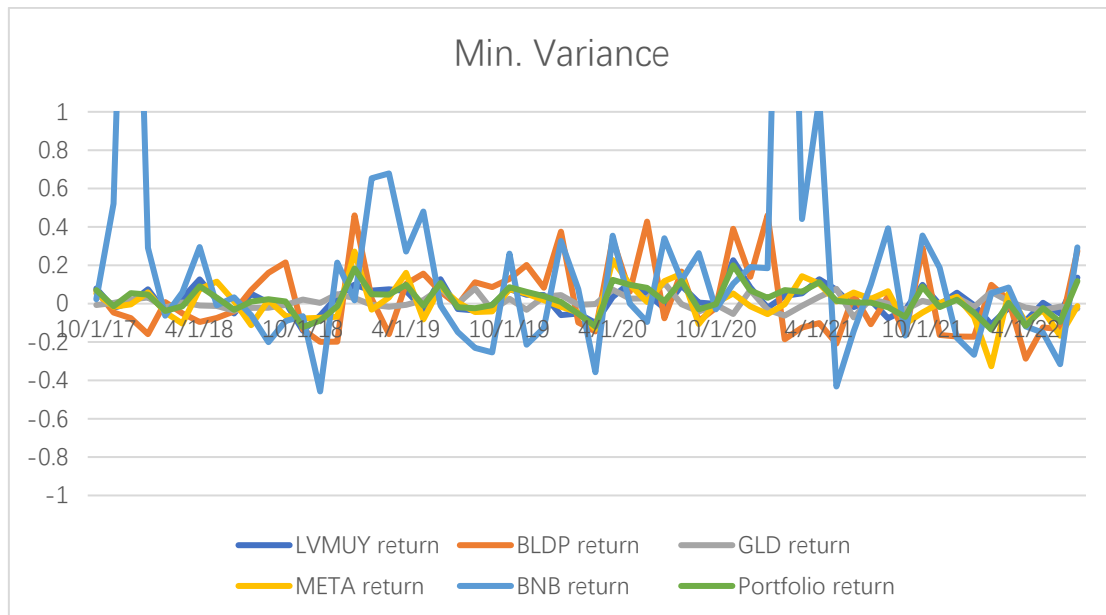
#### 3.1 Maximizing Sharpe Ratio

The resulted weights of having the Sharpe Ratio maximized is shown in the table 2 below:

**Table 2.** Portfolio maximizing Sharpe Ratio

	LVMUY	BLDP	GLD	META	BNB
Weight	0.61355189	0.11765834	0	0.25058517	0.0182046
Expected Return	0.01007754				
Variance	0.00514783				
Sharpe Ratio	0.10333286				

In the portfolio, LVMUY has the most weight of 61% being assigned, where GLD has 0% weights. The expected return turns out to be about 1% per month, with a variance of 0.5% and a Sharpe ratio of about 0.1. To see the correlation and comparison between assets clearer, the Figure 1 indicates the returns of the 5 assets and the return of the portfolio:



**Figure 1.** Max. Sharpe Ratio vs. asset returns

Though it is not very obvious, the line that represents portfolio return has a mostly less volatility even though in this case it is set to be maximizing Sharpe Return. This means that the chosen assets have a general high volatility that it contributes more in the calculation of Sharpe Ratio than the return.

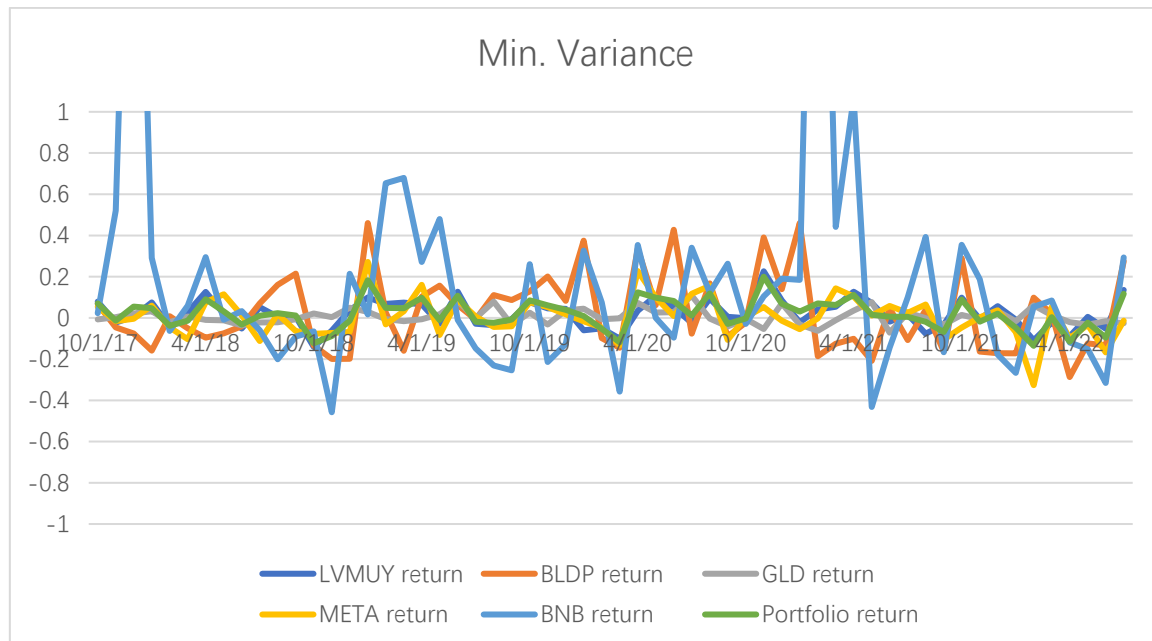
### 3.2 Minimizing Volatility

The second case of the portfolio is set to be minimizing the volatility, which can be represented by variance in this scenario. The table 3 indicates portfolio circumstances:

**Table 3.** Portfolio minimizing volatility

	LVMUY	BLDP	GLD	META	BNB
Weight	0.2116115	0	0.78566621	0	0.00272229
Expected Return	0.00407418				
Variance	0.00110762				
Sharpe Ratio	0.04238488				

The largest weight in this portfolio is assigned to GLD, which is the complete opposite to what is seen when the Sharpe Ratio is maximized. In turn, BLDP and META both have 0 weights in the portfolio, meaning that they contribute nothing to minimizing the volatility. The expected return is approximately 0.4% per month, about 60% lower than that of the portfolio above, while the variance is only 0.1% here, only 20% of the value of variance from the table above. However, the Sharpe Ratio has declined significantly to 0.04. The Figure 2 shows the connections between assets and portfolio:



**Figure 2.** Minimizing variance with 5 assets

It is not hard to see that the line that represents portfolio return indeed has a less volatility than most of the assets, given that the line is floating around the x-axis. However, it is also obvious that the overall return of the portfolio is behaving not well in comparison with the most of the individual assets.

#### 4. Conclusion

From the methods and results discussed above, this paper goes from a perspective of an individual market participant and values the feasibility of having a portfolio containing assets from the chosen industries. This paper discusses other methods such as mean-variance analysis and CAPM model, then determines a more suitable Fama-French three factor model to be applied. Using the model, linear regressions are run and two different portfolios with different focuses are composed. The portfolio maximizing Sharpe Ratio consists assets led by LVMUY who takes the greatest percentage of 61%, the other with GLD taking the lead of 78% of the total weight. Analysis of those results can be helpful in providing information to the readers.

The data introduced in this paper is restricted to a certain period of time, a five-years period from 2017/10 to 2022/7, so the results may not represent the asset's behavior and status for long term as there are going to be unexpected variations. In order to highlight the representative characteristics of each industry, the assets chosen in this paper are limited in number and may fail to represent each industry precisely, so a more complicated analysis and correlation model is expected to be conducted in the future.

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