Portfolio Optimization for Five Representative Companies in Different Industry

Wenxuan Tian*

The university of Sydney, Sydeny, Australia

*Corresponding author: wtia0383@uni.sydney.edu.au

Abstract. This report examines the asset allocation analysis of a portfolio in the context of assets across multiple sectors. Due to the volatile global economic situation and the significant inter-industry effects, allocating and combining assets across different sectors is essential. This research use the capital asset pricing model (CAPM) and the Fama-French three-factor model to determine, for a portfolio of five sectors, the proportion of investments in each sector at maximum Sharpe ratio and minimal variance. These five sectors include energy, pharmaceuticals, automotive, retail and technology. Under both models, the technology and pharmaceutical sectors should be allocated a more significant proportion of the portfolio at the lowest variance, i.e., when volatility is relatively low, while the retail sector should not be included in this portfolio. On the other hand, the retail and automotive sectors are allocated a smaller proportion of the portfolio when the Sharpe ratio is the largest. The results of this report may be helpful for investors in the relevant sectors of the financial markets.

Keywords: Portfolio allocation, various industries, capital asset pricing model (CAPM)，Fama-French three-Factor model.

1. Introduction

As COVID-19 poses a significant threat to the development of the global economy, global growth rates have fallen below 2% in 2020, and other major stock markets in the G-20 countries, such as the US and the UK, have suffered significant declines due to stagnant trade and business [1]. Therefore, optimising the asset portfolio and allocating the proper weighting of assets will enable investors to reduce losses and expand and stabilise returns in this situation [2].

Diversifying assets at different levels is a common approach to portfolio optimisation and can be better integrated with algorithms and optimisation models to minimise investment risk and maximise investment returns [2]. In this report, stocks from several different sectors have been selected to form the portfolio. Long-Term International Diversification of Equity Portfolios [3], which covers 118 years of data from 21 developed economies, is an example of a prior study in which portfolio diversification was routinely applied to equities on various national markets. Alternatively, it aims to study the diversification of one stock within a single market in combination with multiple indices, for example, by studying the Dow Jones Islamic Equity Index under COVID-19 for precious metals and the downside risk affected by portfolio diversification [4]. T However, the purpose of this paper is to examine how optimal portfolios of stocks from five different sectors can be constructed using five-year stock index data and two major analytical models, namely the Asset Capital Pricing Model, which makes the required rate of return on appropriate assets, and the statistical model developed by Eugene Fama and Kenneth French in 1992 to describe specific stock return analysis.

The following sections will follow this report. Chapter 2.1 presents the stocks selected for the portfolio in each sector and the data used to analyse them, and Chapter 2.2 presents the methodology used to analyse these data sets, Chapter 3 presents the results of the calculation of the allocation of investment weights from the above methodology and Chapter 4 summarises the above and discusses the shortcomings of the article.

2. Data and methods

2.1 Data

The information utilized in this article was obtained from Yahoo finance [5]. A total of five companies were selected for this portfolio: Hess Corporation, Pfizer Inc, Ford Inc, Amazon.com Inc and Microsoft Corporation. They are all companies that have been at the top or more active in the Most active stock market in their respective sectors for a more extended period and are in sectors that are more popular and have higher returns. The sample analysis takes their historical monthly price data for the five years from August 1, 2017, to August 1, 2022. The return data were obtained by transforming the analysis tools and using the calculation of functions such as MEAN and SQRT. Expression-based statistics for some of these selected assets are shown in the table below.

Table 1. Descriptive statistics of the selected assets

	HES	PFIZER	F	AMZN	MSFT
mean return	0.0255551	0.01216720	0.01352	0.02201809	0.0250955
geometric mean	0.0160309	0.00963499	0.00707	0.01754927	0.0234153
variance	0.0192932	0.00532687	0.01305	0.00925916	0.0034993
standard deviation	0.1389001	0.07298543	0.11427	0.09622457	0.0591548
MAX	0.4718653	0.22839498	0.31985	0.27059597	0.1762911
MIN	-0.407262	-0.1352216	-0.3060	-0.2375250	-0.099866

By visualising the above data, it can be concluded that the mean return is the largest for HES at 0.255551. mean return is the smallest for F at 0.01352. In terms of variance, HES has the most significant variance, while MSFT has the minor variance. Regarding return size, HES has the highest return, while MSFT has the lowest return. Conversely, HES has the most significant minimum return, and MSFT has the minor minimum return.

2.2 Method

The capital asset pricing model and the Fama-French three-factor model are utilized in this paper.

2.2.1 capital asset pricing model (CAPM)

The capital asset pricing model describes the connection between systematic investment or half the risk of an investment and the anticipated return on an asset. A theory (CAPM formula). For a given hazardous asset, S (think of S as security)

$$E[r_S] = r_f + \beta_S \cdot (E[r_M] - r_f) \tag{1}$$

Where,
r_s is the return variable associated with portfolio S.
r_M is the market portfolio return variable ;
r_f is the risk-free rate on the market;
β_S is the portfolio S's market risk sensitivity, calculated as

$$\beta_S = \frac{Cov(r_S, r_M)}{Var(r_M)} \tag{2}$$

From this, the Sharpe ratio can also be introduced here for risk assessment of returns

$$Sharp(S) = \frac{E[r_S] - r_f}{\alpha_S} = Corr(r_M, r_S) \cdot Sharape(M) \tag{3}$$

According to this calculation, the correlation between S and M increases the Sharpe ratio of S and the risk-return ratio. Using a technique such as the capital asset pricing model (CAPM), only systematic risk is considered, avoiding excessive involvement of other threats. As a result, the discount rate used for valuation is higher [6]. It is, therefore, a more basic method of calculating the required rate of return, allowing investors to choose between competing offers of financial assets based on absolute risk to solve general problems in investment decisions.

2.2.2 Fama-French three-Factor model

The Fama-French 3-Factor Model is an extension of the traditional Capital Asset Pricing Model (CAPM) that explains the returns of a diversified stock or bond portfolio relative to market returns. In addition to market risk, upgrading takes size risk and value risk into account [7]. The formulae are：

$$r = r_f + \beta_3(r_m - r_f) + \beta_2 \cdot SMB + \beta_3 \cdot HML + \alpha \quad (4)$$

Where,

- r is the portfolio's projected rate of return
- r_f is the market risk-free rate
- $\beta$is the coefficient factor, representing sensitivity
- $(r_m - r_f)$is the premium for market risk
- SMB (Small Minus Big) represents the historical excess return of small-cap stocks over large-cap equities.
- HML (High Minus Low) is the difference between the portfolio returns of firms with high book values and those with low book value.
- α is the excess return

The Fama-French three-factor model is considered as the most resilient economic model [8], in which the volatility of the important elements is correlated with macroeconomic risk and projected returns rise as GDP increases and stock prices decrease. Nonetheless, investing in companies that have a high tableic novel ratio is nonetheless hazardous. Additionally, this model captures a somewhat greater average return on small-cap stocks [9-10].

3. Results

Firstly, an analysis of the covariance tool was used to calculate the correlations between the five selected stocks from different sectors. As shown in the table below, the correlation coefficients between all stocks are non-zero, and all are positive. This means that the stocks in this portfolio are positively correlated with the exact change trend. However, as the results are all less than 0.01, the correlations are small, and the likelihood of the industries influencing each other is low.

Table 2. Calculating the correlation coefficient using covariance

	HES	PFIZER	F	AMZN	MSFT
HES					
PFIZER	0.001027796				
F	0.006687292	0.001068345			
AMZN	0.004391432	0.001923831	0.00277249		
MSFT	0.002325998	0.001089084	0.00240374	0.004178024	

Using the regression analysis tool, the beta and E(R) of the capital asset pricing model for the five stocks HES, PFIZER, F, AMZN and MSFT were calculated using the market data () in preparation for the subsequent calculation of the CAPM portfolio weight. The results are shown in the table below.

Table 3. Using regression to calculate the factors required for the CAPM model

	HES	PFIZER	F	AMZN	MSFT
mkt RP	0.0066907	0.00669079	0.00669	0.00669079	0.0066907
RF	0.0008385	0.00083859	0.00083	0.00083859	0.0008385
CAMP beta	1.6329656	0.63951815	1.15892	1.20783300	0.8806221
CAMP E(R)	0.0117644	0.00511748	0.00859	0.00891996	0.0067306

In preparation for the subsequent computation of the FF3F portfolio weight, the varied beta and E(R) required by the Fama-French three-factor model for the SMB and HML. The results are shown in the table below.

Table 4. Using regression to calculate the factors required for the FF3F model

	HES	PFIZER	F	AMZN	MSFT
SMB RP	0.0019081	0.00190816	0.00190	0.00190816	0.0019081
HML RP	0.0035420	0.00354201	0.00354	0.00354201	0.0035420
FF3F MKT beta	1.3964825	0.74453524	0.98151	1.30494641	0.9547493
FF2F SMB beta	1.2294387	-0.6251179	0.94469	-0.4499758	-0.369588
FF3FHML beta	1.3664507	-0.0994409	0.93000	-0.7354389	-0.411597
FF3F E (R)	0.0173681	0.00427508	0.01250	0.00610617	0.0050635

The maximum portfolio sharp ratio calculated under the CAPM is 0.11909271, as shown in the two charts below. "In addition to this, the F weighting in the automotive sector is also minimal at 0.0727, which indicates that the automotive and retail sectors are not dominant in this portfolio.

Table 5. CAPM portfolio weight at maximum Sharpe ratio

	HES	PFIZER	F	AMZN	MSFT
CAPM portfolio weight	0.1571	0.2107	0.0727	0.0155	0.5438

Table 6. Other CAPM portfolio results at maximum Sharpe ratio

	Value
CAPM port return	0.00735137
CAPM port variance	0.00299062
CAPM port standard deviation	0.05468656
CAPM port sharp ratio	0.11909271

The maximum Sharpe ratio calculated under the FF3Fmodel is 0.13742245, as shown in the two figures below. The largest weight that should be invested at this point is HES in the energy sector, with a ratio of 0.3504. The smallest weight is AMZN, which reaches 0, meaning its participation in the portfolio can be dropped. However, the F in the automotive sector, which has a minimal weight in the CAPM, has the second largest weight in the model at 0.2629. Finally, PFIZER in the pharmaceutical sector and MSFT in the retail sector have equal weight. In contrast to the CAPM, this weight shift is probable given that the FF3Fmodel incorporates scale risk and significance risk in in addition to market risk, and macro variables impact swings in investment weightings.

Table 7. FF3F portfolio weight at maximum Sharpe ratio

	HES	PFIZER	F	AMZN	MSFT
FF3F portfolio weight	0.3504	0.1974	0.2629	0	0.1890

Table 8. Other FF3F portfolio results at maximum Sharpe ratio

	Value
FF3F portfolio return	0.0111766
FF3F portfolio variance	0.00565923
FF3F portfolio standard deviation	0.07522789
FF3F portfolio sharp ratio	0.13742245

As shown in the two tables below, the figure is calculated to be approximately 0.00253812 when the variance is minimised under CAMP, at which point AMZN's portfolio share is minimised, falling to zero. In contrast, MSFT has the most significant proportion of the portfolio, more than half of the total, at around 0.5758, while PFIZER also has a high proportion of the portfolio, at around 0.3500. This suggests that, at least in terms of CAPM, AMZN, which belongs to the retail sector, is more affected when the data is at its minimum, while MSFT in the technology sector and PFIZER in the pharmaceutical sector are more stable. PFIZER is more stable.

Table 9. CAPM portfolio weight at minimum variance

	HES	PFIZER	F	AMZN	MSFT
portfolio weight	0.02794393	0.35001897	0.04620667	0	0.57583045

Table 10. Other CAPM portfolio results at minimum variance

	Value
CAPM port return	0.00639272
CAPM port variance	0.00253812
CAPM port standard deviation	0.05037974
CAPM port sharp ratio	0.11024522

The two figures below show that the minimum variance calculated under the FF3F model is approximately 0.00253812. At this point, the proportion of investment accounted for by AMZN remains the smallest, also at zero. In contrast, the ratios accounted for by MSFT and PFIZER are also higher. This is very similar to the results obtained from the CAPM analysis in the previous paratable.

Table 11. FF3F portfolio weight at minimum variance

	HES	PFIZER	F	AMZN	MSFT
portfolio weight	0.0279388	0.35001897	0.04620667	0	0.5758306

Table 12. Other FF3F portfolio results at minimum variance

	Value
FF3F portfolio return	0.00547512
FF3F portfolio variance	0.00253812
FF3F portfolio standard deviation	0.05037974
FF3F portfolio sharp ratio	0.09203145

4. Conclusion

In summary, this paper uses stocks from five different sectors in more active markets to form different portfolios, which are analysed by the CAPM and FF3F models to determine the proportion of the portfolio that should be invested when they generate the maximum Sharpe ratio and minimum variance, respectively. At the CAPM level of analysis, the automotive and retail sectors do not dominate the portfolio, while the technology and pharmaceutical sectors are more stable under market volatility and should account for a more significant proportion of the portfolio. On the other hand, at the analytical level of the FF3F model, in addition to the above results, the energy sector should also account for a portion of the portfolio. This result would allow investors interested in these sectors or already in the financial markets to allocate their capital better and reduce their investment risk.

However, there are weaknesses in this paper, such as the fact that the CAPM is based on the best efficient market portfolio and that the FF3F model does not explain the market capitalisation premium, which suggests that more data and models are needed for further research.

References

[1] Abba Ahmed, B. Impact of COVID-19 Pandemic on Global Economy. SSRN Electronic Journal. 2020.

[2] King, D. Portfolio optimisation and diversification. Journal Of Asset Management, 2007, 8(5): 296-307

[3] Phylaktis, K., Ravazzolo, F. Stock market linkages in emerging markets: implications for international portfolio diversification. Journal Of International Financial Markets, Institutions And Money, 2005,15(2): 91-106

[4] Ali, F., Jiang, Y., Sensoy, A. Downside risk in Dow Jones Islamic equity indices: Precious metals and portfolio diversification before and after the COVID-19 bear market. Research In International Business And Finance, 2021, 58, 101502.

[5] Yahoo Finance. URL: https://finance.yahoo.com/. Retrieved 15 September 2022,

[6] Olubukola Otekunrin, A., Chinoda, T., Matowanyika, K. The Nexus Between Economic Growth, Financial Development, Financial Inclusion and Financial Innovation in Africa. Asian Economic And Financial Review, 2021, 11(8): 672-681.

[7] Piela, K. Evaluation of Efficiency and Explanatory Power of the CAPM and the Fama-French Asset Pricing Models: Evidence from the U.S. Equity Markets. SSRN Electronic Journal, 2013

[8] Tram Anh, L. Comparison of the Capital Asset Pricing Model and the Three-Factor Model in a Business Cycle: Empirical Evidence from the Vietnamese Stock Market. VNU Journal Of Science: Economics And Business, 2020, 36(2).

[9] Lippi, M. VALIDATING DSGE MODELS WITH SVARS AND HIGH-DIMENSIONAL DYNAMIC FACTOR MODELS. Econometric Theory, 2021: 1-19.

[10] Mukherji, S., Jeong, J. Long-term international diversification of equities. Global Finance Journal, 2021, 50, 100584.