GROUP WORK PROJECT # _1_ MScFE 652: PORTFOLIO MANAGEMENT
GROUP NUMBER: __5756__

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Portfolio Management, Group Work Project 1

May 3, 2024

1 Step 1

1.1 a. Definition of each of the 5 factors

Professors Eugene Fama and Kenneth French created the Fama-French model, which is essentially an asset pricing model, in the early 1990s. It improves on the Capital Asset Pricing Model (CAPM) by adding various other variables to provide a more thorough explanation of stock market investment returns. The said model suggests that the expected return of an investment should be proportional to its beta value, a measure of its sensitivity to every market movements. However, the Fama-French model asserts that other factors, beyond just the market risk, also play a significant role in determining returns of our stock market investments.

The following are the five factors of a Fama-French model. 1. Rm-Rf (Market Risk Premium) 2. Small Minus Big (SMB) 3. Higher Minus Low (HML) 4. Conservative Minus Aggressive (CMA) 5. Robust Minus Weak (RMW)

Below is an in depth explanation of each of the five factors.

Rm-Rf (Market Risk Premium) This factor represents the excess return of the overall market (usually proxied by a broad market index such as the S&P 500) over the risk-free rate of return (typically represented by the yield on their T-bills or ttreasury bills).

It captures the additional return investors demand for bearing systematic (market) risk beyond what they could earn from a risk-free investment.

Let's say the average return on the S&P 500 index over the past year was 10%, while the risk-free rate (e.g., the yield on 10-year Treasury bonds) was 3%. The market risk premium (Rm-Rf) would be 10% - 3% = 7%. This indicates that investors demanded a 7% premium for bearing the risk of investing in the stock market compared to the risk-free rate.

Small Minus Big (SMB) This factor accounts for the historical tendency of small-cap stocks to outperform large-cap stocks. SMB is one of the additional factors introduced by Fama and French in their model. In essence, it calculates the historical performance gap between large-cap and small-cap stocks.

Negative SMB implies that large-cap stocks have outperformed small-cap stocks, whereas positive SMB indicates that small-cap stocks have outperformed large-cap stocks.

This factor suggests that there's a size premium in the market, meaning smaller companies tend to offer higher returns relative to their larger counterparts.

Suppose over the past year, small-cap stocks, represented by an index like the Russell 2000, returned 15%, while large-cap stocks, represented by the S&P 500, returned 12%. The SMB factor would be 15% - 12% = 3%, indicating that small-cap stocks outperformed large-cap stocks by 3%.

High Minus Low (HML) This factor captures the tendency of value stocks (those with low price-to-book ratios) to outperform growth stocks (those with high price-to-book ratios). HML is another factor introduced by Fama and French. It compares the performance of value stocks (with low price-to-book ratios) to growth stocks (with high price-to-book ratios).

A positive HML basically suggests that value stocks have outperformed growth stocks, while a negative HML indicates the opposite: growth stocks have outperformed value stocks.

This factor suggests that there's a value premium in the market, meaning stocks with lower valuations tend to offer higher returns relative to stocks with higher valuations.

Consider comparing the performance of value stocks and growth stocks based on their price-to-book ratios. Suppose the average return of value stocks over the past year was 11%, while growth stocks returned 9%. The HML factor would be 11% - 9% = 2%, indicating that value stocks outperformed growth stocks by 2%.

Conservative Minus Aggressive (CMA) CMA is an additional factor proposed by Hou, Xue, and Zhang (2015), which extends the Fama-French framework as introduced before.

It measures the performance difference between conservative investment (low investment) and aggressive investment (high investment) firms. Positive CMA indicates that conservative firms have outperformed aggressive firms, while negative CMA indicates that aggressive firms outperformed conservative firms.

This factor suggests that there's a conservatism premium in the market, meaning firms with more conservative investment policies tend to offer higher returns relative to firms with more aggressive investment policies.

Imagine comparing the performance of conservative firms, which have lower levels of investment, with aggressive firms, which have higher levels of investment. Suppose conservative firms returned 13% over the past year, while aggressive firms returned 10%. The CMA factor would be 13% - 10% = 3%, indicating that conservative firms outperformed aggressive firms by 3%.

Robust Minus Weak (RMW) Same as Conservative Minus Aggressive (CMA), RMW is another factor introduced by Hou, Xue, and Zhang (2015) which extends the Fama-French model previously introduced.

It compares the performance of companies with robust (high-profitability) operating performance to those with weak (low-profitability) operating performance. Positive RMW indicates that companies with robust operating performance have outperformed those with weak operating performance, while negative RMW indicates the opposite, a positive RMW indicates that companies with weak operating performance have outperformed those companies with robust operating performance.

This factor suggests that there's a profitability premium in the market, meaning companies with higher profitability tend to offer higher returns relative to companies with lower profitability.

Let's say we compare the performance of companies with robust operating performance (high-profitability) to those with weak operating performance (low-profitability). Suppose companies with robust operating performance returned 14% over the past year, while companies with weak operating performance returned 11%. The RMW factor would be 14% - 11% = 3%, indicating that companies with robust operating performance outperformed those with weak operating performance by 3%.

1.2 b. For each factor, explain how it helps to explain returns

Those factors mentioned in the first part, along with market risk (as represented by beta), are part of the Fama-French model that seeks to provide a more comprehensive explanation for stock returns. It has become a widely used framework in both academic research and investment practice for assessing the performance of investment strategies and portfolios. Below are other scenarios and reasoning on why these factors contributed well in explaining the returns of an investment instrument.

A published research by Cao, et. al. last 2021 at the 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021) rearding the analysis of US consumption related industry based on Fama-French Model during COVID-19 shows how the different factors helps explains the returns. The CAPM model and Fama-French 3-factor model, Fama-French 5-factor model is another way to capture the return rates and their changes aside to asset pricing theory. In order to investigate the reasons behind the performance of the Fama-French 5 factors models on consumption-related industries in the US stock market before and after the COVID-19 outbreak, their paper primarily uses multiple linear regression. The findings demonstrate that the Fama-French 5-factor model accurately predicts stock returns in the US stock market. Regarding particular factors, market risk (MKT) has a strong correlation with stock return in the U.S. stock market and exhibits significance both before and after COVID-19. Its power of explanation also increases. Small minus big, or SMB, fluctuates greatly during a pandemic, loses significance afterward, and its negative coefficient suggests that a large company was responsible for the excess return. COVID-19 caused High minus Low (HML) to start having a positive impact on the soda and smoke markets. Robust Minus Weak (RMW) shifted and became weaker for the five-factor model. Conservative Minus Aggressive (CMA) maintained its original stance. Following the outbreak, CMA lost some of its significance.

According to a publication by Fama and French (1993), a five-factor model that supplements the three-factor model of Fama and French (1993) with variables for investment (CMA) and profitability (RMW) indicates a common explanation for a number of average return anomalies. More specifically, the high average returns linked to low market , share repurchases, and low stock return volatility are captured by positive exposures to RMW and CMA (stock returns that behave like those of profitable firms that invest prudently). On the other hand, low average stock returns linked to high , massive share issues, and extremely volatile returns can be explained by negative RMW and CMA slopes (such as those of generally unsuccessful enterprises that engage in aggressive investing). (Fama & French, 2014)

Another paper shows an evident application of Fama-French Model and why those parameters helps to explain returns. In this work. The five-factor approach is examined in 23 developed stock markets by Cakisi (2015). He creates the 25 size-book to market, 25 size-gross profitability (GP), and 25 size-investment (Inv) portfolios using firm level data from July 1992 to December 2014. employs both local and global components in the three, four, and five factor models to explain the performance on these portfolios. According to the five-factor model, the outcomes for the stock markets in North America, Europe, and other regions are comparable to those for the

United States. However, the results for investment (Inv.) and gross profitability (GP) indicate that these two additional factors are either clearly considerably weaker in the Asia Pacific and Japan portfolios, or they do not offer any explanatory power at all. His paper's findings also imply that localized models outperform global models in terms of performance. This could mean that market integration is still lacking. In contrast to the US market results, the value factor is still substantial in all locations even after the two additional Fama-French model variables are taken into account. (Cakici, 2015)

Additional evidence on why these factors helps to explain returns can be seen in the paper made by Alrabadi et. al., entitled "The Fama and French Five Factor Model: Evidence from an Emerging Market". The five-factor model that was recently created by French and Fama (2015) is tested in their study. They make use of daily data from 84 Amman Stock Exchange (ASE)-listed businesses from 2011 to 2015. The findings show that the common risk factors—excess market return (Rm-Rf), small minus big (SMB), high minus low (HML), robust minus weak (RMW), and conservative minus aggressive (CMA)—have a statistically significant impact on the cross section of daily returns in ASE. But over the course of the study period, the cross section of stock returns in ASE cannot be fully explained by the Fama and French five component model. These findings may be primarily explained by the fact that ASE is a developing market where stock returns may be impacted by a variety of unanticipated variables other than fundamentals. (Alrabadi & Alrabadi, 2018)

Those different papers shown above are evidences why and how those factors are being applied in financial markets and helps to explain returns.

2 Step 2

Download daily data from this site for a timeframe of 3 years

Below, we include all Python package that will be used.

2.1 a. Import, structure, and graph the daily factor returns

We begin by importing the `csv` file into a `pandas DataFrame`.

We set our timeframe of observation on the 3-year period that goes from March 1st, 2021 to February 29th, 2024.

The time series for each of the Fama-French (FF) factors in the timeframe considered are visualised below.

Some additional statistics regarding the time series of the 5 FF factors:

2.2 b. Collect and compute correlations of the changes in the factor returns.

As a preliminary to the analysis of their returns, we inspect the daily correlations of the five factors themselves:

From the above we can see that almost all of the factors, with the exception of the risk free rate RF, are heavily correlated, either positively or negatively.

The daily factor returns, expressed as percent change with respect to the previous day, are derived as:

Above,

- we dropped `NaN` values stemming from the first line (that lacks previous reference data) of the DataFrame, and
- we replaced $\frac{0}{0} = \text{NaN}$, mainly appearing in the RF column when both previous and current daily entries are $= 0$, with 0.

Plotting the time series of returns yields:

At first glance, the series look fairly stationary.

One can however observe imperfections in most of the graphs, in the form of gaps within plottings (for instance, in the plot for RF at about 2022-04). These are $-\infty$ or ∞ values in the time series originated from dividing from a previous daily value of 0. We correct this by setting infinity values to an arbitrarily large number, ± 1000.

Now we can finally compute the correlation matrix between the five factor returns.

The series of first differences of factor returns are uncorrelated, with just one exception of weak correlation between RMW and CMA.

However, for subsequent steps we will rely on the FF3/5 factors themselves, not on their first differences. This is because the latter do not lend themselves to be easily interpreted.

2.3 c. Collect economic data of your choice during that 3-year period

As a proxy for risk-free rate, we download from *Yahoo! Finance* data tracking the ^IRX index, which is based on yields from the 13-week US Treasury bills.

As could be expected, the graph below shows that this interest rates index increases in value following worldwide inflation due to - disruptions in global production and supply of goods and services after the Covid pandemic, and - sanctions to Russia which increased costs for raw materials.

3 Step 3

Find the betas of factors in the Fama-French 3 model.

3.1 a. Run both Least Squares and robust regressions on the data, and describe the train-test split.

3.1.1 Least Squares regression

For convenience, as a first step we add the 13-weeks Treasury bill index ^IRX to the `pandas` DataFrame of FF3 factors for the timeframe considered, then we plot the data.

Plots above show graphically how the FF3 factors are correlated among each other, but we can anticipate the dependent variable ^IRX, the Treasury bill rates is largely uncorrelated, i.e. independent from them.

Histograms on the main diagonal of the pairplot show distributions of the variables over the selected 3-year timeframe. The distribution histogram for ^IRX shows that the dependent variable in our incoming analysis is clearly not normally distributed.

Thus from the correlation and histogram plots above, we have just learned that - the dependent and independent variables of the incoming linear regression analysis are not in a linear relationship with each other - the three factors adopted as independent variables are fairly correlated with one another - the dependent variable ^IRX is not normally distributed.

These observations lead us to anticipate that the linear regression of ^IRX from the three factors of the Fama-French model will not be successful.

We see that the ordinary least squares (OLS) linear regression of ^IRX from the FF3 factors yields high to very high p-values for the estimates of the coefficients β_i, $i = 1, 2, 3$. This is true not only inside the testing period, but for the training period as well.

This means that none of the factors can explain the variation of the dependent variable ^IRX. Another indication that the OLS regression just performed is not significant is given by the very low value of the R^2 statistic which is practically ~ 0.

Below, for this model we plot the partial regression lines of the dependent variable, ^IDX, against each of the three independent variables of the FF3 model. The lines are obtained by plotting residuals of ^IRX against residuals of each factor, after having removed the effect of the after factors.

3.1.2 Robust regression

We will now regress the ^IRX index against the FF3 factors using a robust regression model(*M-Estimation*), in order to gain a better appreciation of the influence of outlying data points over the analysis.

We will leave the train-test split of the dataset at a 75/25 ratio.

The graph shown above - comparing regressions yielded by the ordinary least squares method against the robust Huber method - reveals results with marked differences in variance inside the training sample, but almost identical in testing. Robust regression mainly dampens the deleterious effects of outliers, and this shows in the above results, which however also exclude that the low quality of the regression is due to the impact of outliers.

But it was already evident that the bad fitting of the analysis is due to the short rates tracked by ^IRX being independent from the Fama-French factors, which are tailored to track market data, not macroeconomic.

Below, for this model we plot the partial regression lines of the dependent variable, ^IRX, against each of the three independent variables of the FF3 model. The lines are obtained by plotting residuals of ^IRX against residuals of each factor, after having removed the effect of the other factors.

The first series of figures below depicts partial regressions based on the Huber norm, while the second series is based on the bisquare norm.

3.2 b. Provide summaries of coefficients and metrics for the model

We provide a summary of the analysis below.

Refer to the equation below for naming parameters in the regression:

$$\text{IRX} = \alpha + \beta_0\,(\text{Mkt-RF}) + \beta_1\,(\text{SMB}) + \beta_2\,(\text{HML})$$

Summary of coefficients, with associated p-value in subsequent row.

Model	α	β_0	β_1	β_2
OLS	1.7562	-0.0516	0.0466	-0.1565
OLS p-value	0.000	0.481	0.708	0.048
Robust Huber	1.7554	-0.0522	0.0457	-0.1565
Huber p-value	0.000	-0.479	0.716	0.048
Robust Bisquared	1.6869	-0.0560	0.0530	-0.1612
Bisq. p-value	0.000	-0.482	0.695	0.06

We can appreciate from the table above that for all models, only a weakly significant dependence of IRX from factor HML can be theorised. All other factors are not statistically significant.

The table omits to report the standard deviation for the coefficients, in order to avoid data cluttering on parameters that in any case are not meaningful.

Summary of metrics for the OLS regression (values for the robust regressions are probably equal or very close, which would presumably be why no statistical metrics are available for them inside the `statsmodels` package).

Model	R^2	adj R^2	**JarqueBera**
OLS	0.007	0.002	74.664

R^2-based statistics close to 0 indicates that almost none of the variance in the dependent variable can be explained by the exogenous factors. The Jarque-Bera test result is far from 0, which means the dependent variable is not normally distributed.

4 Step 4

Find the beta factors in the FF5 model

4.1 a. Run both Least Squares and robust regressions on the data, and describe the train-test split.

4.1.1 Least Squares regression

Throughout this step, we follow the same procedure we have followed in step 3 in order to perform linear regressions on ^IRX. Only, this time we base the analysis on the full five factors of the Fama-French (FF5) model, instead of just three factors as before.

Factors added will be RMW - Robust Minus Weak - and CMA - Conservative Minus Aggressive.

In terms of coding, these two factors were already included inside the `df_daily` DataFrame we created, so all we have to do is to this time keep them instead of discarding them as done in the previous step, when they were not needed.

Plots above show how the FF5 factors are correlated among each other, but we can anticipate the dependent variable ^IRX, the Treasury bill rates is largely uncorrelated, i.e. independent from them.

Histograms on the main diagonal of the pairplot show distributions of the variables over the selected 3-year timeframe. The distribution histogram for ^IRX shows that the dependent variable in our incoming analysis is clearly not normally distributed.

Thus, similarly to what noticed in step 3, from the correlation and histogram plots above, we have just learned that - the dependent and independent variables of the incoming linear regression analysis are not in a linear relationship with each other - the five factors adopted as independent variables are fairly correlated with one another - the dependent variable ^IRX is not normally distributed.

These observations lead us to anticipate that the linear regression of ^IRX from the five FF5 factors will not be successful.

We keep the 0.75-0.25 split ratio between training and testing inside the data set.

In agreement with our pessimistic forecast, we observe that p-value statistics and metrics for the OLS FF5 regression model above are extremely poor.

Graphically, above, the training set shows no improvement here for FF5 model, with respect to what we found in the previous step for the FF3-based regression.

Let's produce results over the testing set.

Qualitatively, no improvement can be observed over the testing OLS performed in the previous step.

Again we can see that the ordinary least squares (OLS) linear regression of ^IRX from the FF5 factors yields high to very high p-values for the estimates of the coefficients β_i, $i = 1, \ldots, 5$. This is true not only inside the testing period, but for the training period as well.

This means that none of the factors can explain the variation of the dependent variable ^IRX. Another indication that the OLS regression just performed is not significant is given by the very low value of the R^2 statistic which is practically ~ 0.

Visually, the predictions over the testing period exhibit reduced variance with respect to those in the training period.

Below, for this model we plot the partial regression lines of the dependent variable, ^IDX, against each of the five independent variables of the FF5 model. The lines are obtained by plotting residuals of ^IRX against residuals of each factor, after having removed the effect of the after factors.

We see above that regression lines are nearly horizontal, a sign that independent and dependent variables are independent and thus uncorrelated.

4.1.2 Robust regression

We will now regress the ^IRX index against the FF5 factors using a robust regression model(*M-Estimation*), as did in point b of step 3.

We will leave the train-test split of the dataset at a 75/25 ratio.

All factors are not significant, according to the p-values of their respective parameters.

We deliberate to proceed with analysis only for the Huber robust regression, as the bisquare results will largely be similar.

We see in the plot above that the robust regression is way off the mark, analogously to what it was in step 3. Now, in addition we can observe how the robust regression predictions have a much lower variance than int was the case for the OLS regression. This derives from the feature of dampening the influence of outliers exhibited by robust regression methods.

In the figure above, the marked difference in variance between training and testing predictions from the robust regression, clearly stands out.

The graph shown above - comparing regressions yielded by the ordinary least squares method against the robust Huber method - reveals results with marked differences in variance inside the training sample, but almost identical in testing. Robust regression mainly dampens the deleterious effects of outliers, and this shows in the above results, which however also exclude that the low quality of the regression is due to the impact of outliers.

But it was already evident that the bad fitting of the analysis is due to the short rates tracked by ^IRX being independent from the Fama-French factors, which are tailored to track market data, not macroeconomic.

Below, for this model we plot the partial regression lines of the dependent variable, ^IRX, against each of the five independent variables of the FF5 model. The lines are obtained by plotting residuals of ^IRX against residuals of each factor, after having removed the effect of the other factors.

The first series of figures below depicts partial regressions based on the Huber norm, while the second series is based on the bisquare norm.

4.2 b. Provide summaries of coefficients and metrics for the model

We provide a summary of the analysis below.

Refer to the equation below for naming parameters in the regression:

$$\text{IRX} = \alpha + \beta_0\,(\text{Mkt-RF}) + \beta_1\,(\text{SMB}) + \beta_2\,(\text{HML}) + \beta_3\,(\text{RMW}) + \beta_4\,(\text{CMA})$$

Summary of coefficients, with associated p-value in subsequent row.

Model	α	β_0	β_1	β_2	β_3	β_4
OLS	1.7584	-0.0624	0.0422	-0.1065	0.0178	-0.1297
OLS p-value	0.000	0.410	0.768	0.998	0.899	0.527
Robust Huber	1.7580	-0.0625	0.0419	-0.1074	0.0179	-0.1285
Huber p-value	0.000	-0.412	0.772	0.397	0.899	0.534
Robust Bisquared	1.6889	-0.0654	0.0469	-0.1103	0.0130	-0.1276
Bisq. p-value	0.000	-0.427	0.764	0.421	0.932	0.569

We can appreciate from the table above that for all models, there is no significant dependence of IRX from any of the five factors in FF5. The table omits to report the standard deviation for the coefficients, in order to avoid data cluttering on parameters that in any case are not meaningful.

Summary of metrics for the OLS regression.

Model	R^2	adj R^2	**JarqueBera**
OLS	0.008	-0.001	74.899

R^2-based statistics close to 0 indicates that almost none of the variance in the dependent variable can be explained by the exogenous factors. The Jarque-Bera test result is distant from 0, which means the dependent variable is not normally distributed.

5 Step 5

5.1 c. Correlation matrix of factor returns

Below, we repeat the computation of the correlation matrix between the 5 factors in the Fama-French model.

Now Visualizing the Correlation Matrix of Factor Returns

5.1.1 1. Heatmap

A heatmap is an effective way to visualize the correlation matrix using colors to represent the correlation coefficients. The color palette of the heatmap shows, warmer colors represent positive correlations and cooler colors represent negative correlations.

5.1.2 2. Pairplot

A pairplot is used to visualize pairwise relationships between different factors. The grid of scatterplots for each pair of factors, showing their relationships along with histograms for each individual factor.

5.1.3 3. Clustermap

The clustermap visually organizes similar factors into clusters based on their correlation coefficients.

5.2 d. Covariance Matrix of Factor Returns

5.3 e. Comparison of the Two matrices

Correlation and covariance matrix for factors in the Fama-French model during timeframe specified (March 2021 - February 2024).

Correlation Matrix: The correlation matrix measures the linear relationship between pairs of factors, normalized to a scale of -1 to 1. Values closer to 1 indicate a strong positive linear relationship, while values closer to -1 indicate a strong negative linear relationship. The diagonal elements are always 1, indicating perfect correlation of a factor with itself. Example: The correlation between Mkt-RF and SMB is 0.184681, suggesting a weak positive linear relationship.

Covariance Matrix: The covariance matrix measures the extent to which two factors move together, regardless of the scale of their values. Larger values indicate greater variability between the factors, while values closer to zero indicate less variability. The diagonal elements represent the variance of each factor. Example: The covariance between Mkt-RF and HML is -0.43434, indicating a negative covariance (opposite movement).

6 Step 6

Effects of CMA and RMW

7 Step 7

7.1 f. Markowitz portfolio optimization

7.2 g. Portfolio dependence from factors in FF3

Robust FF3 Now we run a robust, Huber-normed regression of the portfolio returns based on the FF3 factors.

We do not notice appreciable differences with respects to the OLS analysis performed before.

Outliers in the database of portfolio returns evidently do not exert much of an influence.

Thus in the next section, we will only perform an OLS regression based on FF5 factors, and omit to simulate a redundant robust regression.

7.3 h. Portfolio dependence from factors in FF5

8 Step 8

Interpretation of results

Technology and growth-oriented companies (AAPL, AMZN) are significantly overweighted according to the optimum asset allocation weights, whereas TSLA, AAPL, and GOOGL are underweighted relative to the other stocks (AAPL, GOOGL). The indicated allocation is assumed to reflect the model's evaluation of the factor exposures and risk-return characteristics of these specific shares.

A. Expected Return and target (FF5 Model):

1. The target return of 10.00% indicates that the portfolio is specifically structured to achieve a certain return objective based on Fama-French factor exposures.
2. Volatility, often known as risk, is a concept that is measured and analysed using the FF5 model. The portfolio's volatility of 150.86% is caused by the combined impact of market risk (Rm-Rf), SMB, HML, CMA, and RMW factor exposures. The high degree of volatility suggests that the portfolio's performance is influenced by several variables, such as market sensitivity, growth, value, and other related risks.

B. Comparison of Models: FF3 Model vs. FF5 Model: The FF5 model includes additional components (CMA, RMW) that were not included in the FF3 model in order to provide a more precise representation of the portfolio's risk-return profile. The similarity in the optimum portfolio features (such as goal return, anticipated return, and volatility) between the two models indicates that factor exposures have a considerable influence on the portfolio's performance.

C: RMW: Fama-French factors include the Small Minus Big (SMB), High Minus Low (HML), Conservative Minus Aggressive (CMA), and Market Risk Premium. The Fama-French variables have an influence on both the projected return and risk of the portfolio.

As a case in point:

MSFT (Positive Market Risk Exposure): The significant magnitude of MSFT implies a positive susceptibility to market risk (Rm-Rf), therefore contributing to both the overall return and risk characteristics of the portfolio.

D: AMZN (Small and Medium-sized Businesses, Cost of Market Access, Risk-Managed Weight): The weight of AMZN is defined by its level of involvement in the conservative-minus-aggressive (CMA), small-cap premium (SMB), and possibly robust-minus-weak (RMW) components. These variables impact the risk and return characteristics of the portfolio.

The implications:

a. Understanding and managing the impact of Fama-French factors is crucial in diversifying portfolios based on variables, in order to achieve desired portfolio results while reducing risk.

b. Dynamic asset allocation, via the continuous monitoring and adjustment of portfolio allocations based on component analysis, may efficiently maximise returns by considering risk and aligning with investment goals.

c. To minimise the adverse effects of factor exposures, it is essential to use risk management measures such as asset allocation, hedging, and diversification, especially considering the significant volatility (150.86%).

d. The investment choices and performance results are significantly influenced by the Fama-French factors due to the optimum portfolio features and allocation.

By introducing factor analysis into the process of portfolio design, investors may enhance their understanding of the relationship between risk and return. This will enable them to make well-informed investment choices that match with their financial goals and risk preferences.

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