Investments Project (Spring 2024)

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***Abstract*—This project addresses the construction and evaluation of optimal portfolios using management strategies based on signals such as beta, idiosyncratic volatility, and momentum. The aim is to apply theoretical finance concepts to practical portfolio management, considering transaction costs and variations in volatility. The main objective is to construct optimal portfolios by combining multiple signals and to analyze their performance using standard risk factors obtained from Ken French's website.**

I. Introduction

As part of this project, we collected financial data to analyze the monthly stock returns of common stocks listed on the NYSE and AMEX exchanges over the period from January 1, 1964 to December 31, 2023. The data was extracted from the CRSP database. We downloaded monthly common stock returns, as well as value-weighted market returns and 1-month T-bill returns to serve risk-free rate. The SQL queries and Python commands necessary for extracting and analyzing this data can be found in the IPython Notebook (.ipynb) file associated with this project.

II. Betting against Beta strategy (BaB)

To analyze the Betting against Beta (BaB) strategy, we calculated the time-varying market beta $\beta_{i,t}$ for each stock using monthly regressions of stock-specific excess returns on market excess returns over a 5-year rolling window, requiring at least 36 months of observations. The betas were winsorized to remove extreme values. Each month, stocks were sorted into deciles based on their beta, and monthly returns for these equally-weighted decile portfolios were calculated. The results, including annualized average returns, standard deviation, and Sharpe ratios for each decile, were plotted to assess portfolio performance.

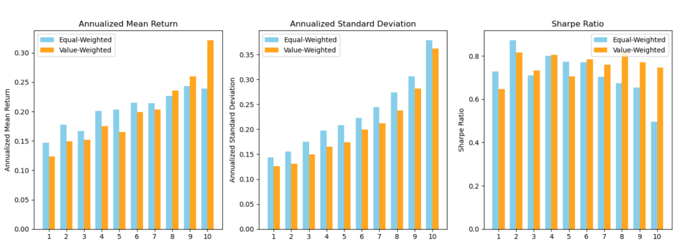

Figure 1. Average Annualized Metrics for the 10 Deciles Portfolios (BaB)

The analysis shows that portfolios generally achieve higher annualized mean returns with increasing beta, consistent with CAPM's prediction that higher risk (beta) warrants higher returns. Both types of portfolios display increased standard deviation with higher beta, aligning with CAPM expectations of higher risk with higher beta. However, we obtain a slightly decreasing Sharpe ratio, suggesting that the additional returns obtained for high beta stocks do not always compensate for the increased risk, which may contradict CAPM predictions. In summary, while higher beta portfolios support CAPM by exhibiting higher mean returns and risk, sharpe ratio results suggest additional factors influencing returns beyond what CAPM accounts for.

We constructed the Betting-Against-Beta (BaB) factor following Frazzini and Pedersen (2014). Each month, we formed a high-beta portfolio ($w_H = k(z-\bar{z})^+$) and a low-beta portfolio ($w_L = k(z-\bar{z})^-$) using cross-sectional beta ranks, where z represents beta ranks and $\bar{z}$ is the average rank. Then, the BaB factor return was calculated as $R^{BAB}_{t+1} = \frac{R^L_{t+1}-R_f}{\beta_L} - \frac{R^H_{t+1}-R_f}{\beta_H}$, where R^H_{t+1} and R^L_{t+1} are the returns of the high-beta and low-beta portfolios, and β_H and β_L are their respective betas. Below, we reported some interesting metrics which will allow us to draw conclusions about the effectiveness of this strategy.

Metric	Value	Metric	Value
Annualized Alpha of BaB Factor	0.0689	Beta BaB	0.4988
Sharpe Ratio of BaB Factor	0.7743	Market Risk Premium	0.0787
Idiosyncratic Volatility	0.1116	Market Volatility	0.1683

Figure 2. Performance Metrics of the BAB Factor

The BAB factor shows a positive annualized alpha, indicating outperformance, and a Sharpe ratio value that suggests reasonable risk-adjusted returns. With moderate idiosyncratic volatility and a beta below 1, it is less sensitive to market movements. The market risk premium and volatility provide context for the BAB factors performance. Overall, the BAB factor appears to offer potential benefits in terms of returns relative to its risk profile.

III. Momentum Strategy (Mom)

We also analyzed a long-short momentum strategy by sorting stocks into deciles based on their returns over the past 11 months, lagged by one month, and calculating monthly returns for these equally weighted decile portfolios. We've included value-weighted portfolios for comparison purposes. Here, we present the portfolio's average annualized mean, standard deviation, and Sharpe ratios for each decile to evaluate their performance and consistency with the CAPM.

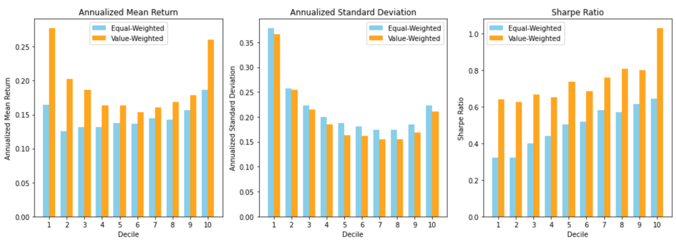

Figure 3. Average Annualized Metrics for the 10 Deciles Portfolios (Mom)

The CAPM predicts that expected returns of assets are proportional to their systematic risk (measured by beta) relative to the market. However, CAPM does not account for momentum effects, which are based on past stock performance. Our results demonstrate superior performance, with higher annualized returns and Sharpe ratios for stocks with high momentum, indicating significant excess returns when following a momentum strategy. This violates the CAPM assumption that expected returns depend solely on systematic risk. Momentum captures an additional effect not explained by the CAPM. So, our findings indicate that the momentum effect is both present and significant, which contradicts CAPM predictions and suggests that other factors, beyond systematic risk, influence stock returns.

We further studied the performance of the momentum strategy by constructing a long-short portfolio. This portfolio takes long positions in the three highest deciles and short positions in the lowest three deciles. We calculated and compared the mean, standard deviation, and Sharpe ratios for the long and short legs of the strategy, as well as the overall effectiveness of the momentum strategy itself. The results provide insight into the risk-adjusted performance of the momentum strategy.

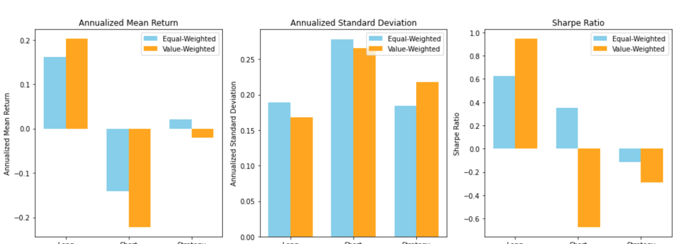

Figure 4. Performance Analysis for Momentum Strategy

The momentum strategy, which involves investing in the top three deciles and selling in the bottom three deciles, performs very poorly. The average return is close to or below zero, depending on the portfolio weighting, and the Sharpe ratio is negative, indicating poor risk-adjusted returns. Statistical tests confirm that the average returns of the momentum strategy are not significantly different from zero for both portfolio types, demonstrating that the implemented strategy does not produce significant excess returns and highlighting its limited effectiveness over the analyzed period.

IV. Idiosyncratic Volatility Strategy (IV)

Now, let's look at the idiosyncratic volatility strategy which evaluates the performance of portfolios based on their idiosyncratic volatility. To determine the effectiveness and validity of this strategy, idiosyncratic volatility was calculated from the residuals of five-year regressions, with winsorization at the 5th and 95th percentiles to reinforce the robustness of the data. Each month, stocks were ranked into deciles based on this volatility to examine the monthly returns, variance, and Sharpe ratios of the trained portfolios.

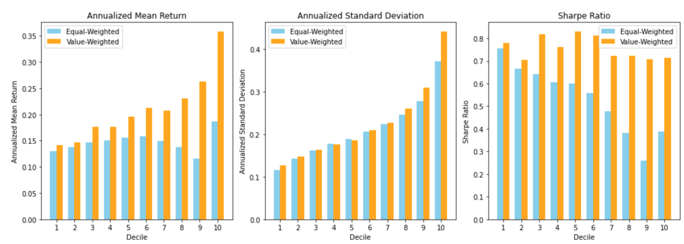

Figure 5. Average Annualized Metrics for the 10 Deciles Portfolios (IV)

The analysis shows that, for both portfolios with different weightings, annualized mean returns, standard deviations, and Sharpe ratios all increase across deciles, particularly for value-weighted portfolios. Higher idiosyncratic volatility is associated with higher returns and better risk-adjusted performance, which contradicts the CAPM. The CAPM, focusing solely on systematic risk (beta), fails to account for the significant role of idiosyncratic volatility in determining returns. These findings suggest that factors beyond systematic risk are influencing asset prices, highlighting the limitations of the CAPM.

We applied the method used for the momentum strategy to the idiosyncratic volatility strategy. Constructing a long-short portfolio helps understand the risk-adjusted performance of the overall strategy.

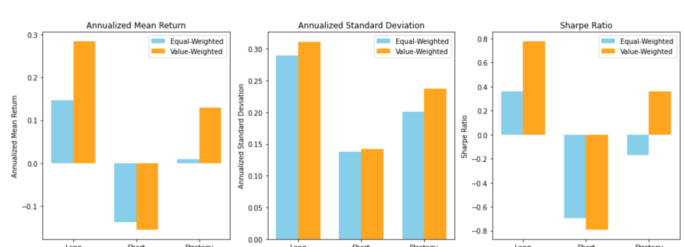

Figure 6. Performance Analysis for Idiosyncratic Volatility Strategy

Value-weighted portfolios have higher average annualized returns and Sharpe ratios than equally weighted portfolios, indicating better risk-adjusted performance. Statistical tests show that the returns of the value-weighted portfolios are significant, with p-values close to zero, while the equally weighted portfolios do not show significant returns. This suggests that the idiosyncratic volatility strategy works primarily for large-cap stocks, which are often better represented in value-weighted portfolios. In contrast, Ang, Hodrick, Xing, and Zhang's (2006) study found that stocks with high idiosyncratic volatility had lower future returns, which contrasts with our results. Differences may be due to sampling period, market conditions and methodology used.

V. Optimal Fund Portfolio Return (STRAT)

From now on, the objective is to construct an optimal portfolio by combining three investment strategies: Betting against beta (BaB), idiosyncratic volatility (IV) and momentum (MoM). To do this, we evaluated the performance of the portfolio using three different approaches: equal weighting, risk parity and mean variance optimization based on mean returns and covariance matrices of strategies. The first approach is to assign equal weight to each strategy. The second approach, risk parity, involves weighting strategies based on the inverse of their volatility, in order to fairly distribute risk between them. The third approach, mean-variance optimization, aims to find the combination of weights that maximizes the mean-variance utility, taking into account the average returns and the covariances of the strategies. After determining the optimal portfolios, we adjusted the portfolio returns to achieve a target volatility of 10%. Then we calculated the performance of metrics such as average return, volatility and Sharpe ratio for each strategy. The results below show the performance of value-weighted strategies with a target volatility of 10%.

	Equal Weight VW	Risk Parity VW	Mean-Variance Optimization VW
Mean Return	0.089038	0.094666	0.111048
Volatility	0.100000	0.100000	0.100000
Sharpe Ratio	0.467324	0.523608	0.691607

Figure 7. Performances of the 3 Approaches Combining all the Strategies

The final results show that the mean-variance optimization strategy shows the best annual average return. In terms of Sharpe ratio, mean-variance optimization outperforms the other two approaches indicating that mean-variance optimization provides the best risk-adjusted return. These results show that the mean-variance optimization approach outperforms other strategies.

VI. Fund Strategy

Let's move on to evaluating the performance and risks of our fund strategy. To do this, we carried out a regression of the strategy's returns on the returns of 12 industry portfolios, as well as on the five Fama-French research factors. This analysis allows us to identify the risk factors that significantly influence the strategy's returns and to evaluate whether these factors adequately explain the overall performance of the fund.

The results show that several factors are significant drivers of risk parity strategy returns. The factors “Durbl”, “Money” and “Other” turn out to be significant with relevant regression coefficients and t-values, explaining approximately 26.9% of the variance in strategy returns (R^2 = 0.269). Furthermore, the positive and significant alpha (0.005004) suggests that the strategy generates excess returns not explained by the sector risks included in the model. As for the factors Fama-French, Mkt-RF, SMB, HML and RMW, turn out to have a strong influence on the returns of the strategy. However, the CMA factor is not significant (t-value of -0.580). The R-squared of 0.285 indicates that the Fama-French factors explain approximately 28.48% of the variance in the strategy's returns, thus providing a partial but notable explanation of the strategy's performance.

VII. Summary

Our analysis of investment strategies—Betting against Beta (BaB), Momentum, and Idiosyncratic Volatility (IV)—yields insightful conclusions on their performance. The BaB strategy aligns with CAPM in terms of higher mean returns but shows a decreasing Sharpe ratio, indicating inadequate risk compensation. The Momentum strategy produces significant excess returns, challenging CAPM by highlighting additional influencing factors. The IV strategy shows better returns and risk-adjusted performance for higher idiosyncratic volatility portfolios, further exposing CAPM's limitations. Constructing an optimal portfolio using equal weighting, risk parity, and mean-variance optimization revealed that the mean-variance optimization approach delivers the highest returns and Sharpe ratio, demonstrating the superiority of advanced optimization techniques for enhancing risk-adjusted returns.

In summary, while traditional models like CAPM provide foundational insights, integrating additional factors and employing advanced optimization techniques are crucial for achieving superior investment performance and comprehensive risk management.