Combination of Factor-Based Strategy and Asset Allocation

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1. Introduction

This paper develops and evaluates a quantitative investment strategy that combines factor-based stock selection with risk-focused portfolio allocation, offering a comprehensive approach to portfolio construction. The strategy aims to leverage the strengths of factor investing—identifying assets with desirable characteristics such as value and profitability—while optimizing portfolio risk and return profiles using advanced allocation methods like equal weight, Risk Parity, mean-variance optimization (MVO), and Minimum Variance. By integrating these two approaches, the study seeks to exploit the return-generating potential of factor exposures while systematically managing portfolio risk.

Our strategy is justified by the complementary nature of risk-based allocation and factor investing. By identifying stocks with sustained return premiums, factor techniques have continuously shown that they can generate alpha. However, they frequently overlook risk dynamics at the portfolio level, which can result in excessive concentration and inadequate diversification. On the other hand, risk-based allocation techniques are excellent at maintaining a portfolio's stability but use a different predictive power than factor-based asset selection. By striking a balance between return opportunities and efficient risk management, combining these two methodologies may provide a way to achieve better performance.

The study extends the work on factor-based and risk-based allocation by integrating dynamic adjustments to expected returns in MVO based on factor signals. Using a dataset spanning January 2000 to June 2023, the strategy is benchmarked against the S&P 500 and an equal-weighted portfolio of selected stocks to compare risk-adjusted returns and portfolio stability clearly. The portfolio value over time highlights the dominance of Mean-Variance Optimization in cumulative performance, particularly during bullish markets, while more conservative approaches like Minimum Variance provided steadier growth during periods of heightened volatility. These findings emphasize the trade-offs inherent in balancing risk and return. This study contributes a comprehensive framework for integrating factor-based selection with risk-focused allocation, offering actionable insights for portfolio management.

2. Strategy Design

2.1 Overview of the Strategy

2.1.1 Factor-based selection

To design our strategy, we will focus on two major factors: value and quality. In terms of value, we have decided to use an earnings-to-price ratio (E/P ratio). Companies with high E/P ratios will be considered as value companies. To calculate the E/P ratio for the CRSP monthly stocks dataset, we use the latest known value of earnings (column IB) divided by the corresponding market value (column MV) at the most recent fiscal year-end. We then lag this ratio by six months to account for the delay in earnings reporting after the quarter ends. To make the E/P ratio meaningful, we need to multiply it by 1000. This is because CRSP and Compustat use different units.

Concerning quality, profitability is a valuable indicator for quality criteria as a factor exposure because it captures key aspects such as operational efficiency, stability, financial resilience, cash flow generation, management competence, and the ability to grow and return value to shareholders. Profitable companies are often more robust and capable of surviving market challenges, making them suitable investments for those seeking quality exposure and long-term value creation. Using profitability as a measure of quality helps investors differentiate companies with sustainable advantages and financial stability from those whose earnings and financial health are less consistent or potentially more vulnerable. In this project, we have determined to use net income margin as a quality indicator. To calculate net income margin, we use the latest known value of earnings (column IB) divided by sales (column SALE) at the most recent fiscal year-end. After that, We then lagged this ratio by six months to account for the delay in earnings reporting after the quarter ends, as we did in the E/P ratio.

Later, we rank the first 100 stocks with the highest E/P ratio. Then, out of those 100 stocks, we select only 50 stocks that have a high net income margin. Additionally, we also make sure that the 50 stocks we have filtered are traded from 2000 onwards.

2.1.2 Risk-based allocation

After the stock selection has been made, we then allocate these 50 stocks using different risk-based methods, which include Risk Parity, Mean-Variance Optimization, and Minimum Variance as detailed below:

Risk Parity: Assets are weighted inversely to their volatility—higher volatility means lower weight, and vice versa. Weights are determined to balance each asset's risk contribution by minimizing variance.

Mean-Variance Optimization (MVO): MVO constructs a portfolio aiming for the highest return for a given risk or lowest risk for a given return, using expected returns, variances, and covariances for optimal allocation.

Minimum Variance (MV): MV constructs a portfolio to minimize risk without considering an expected return, making it ideal for risk-averse investors. Unlike MVO, MV focuses only on reducing portfolio volatility.

We have performed these three different methods for the purpose of asset allocation. The criteria we have set to decide which method has performed the best are annualized return, volatility, Sharpe ratio, and Max Drawdown. Additionally, we expect that the designed strategy, together with each risk-based allocation, will outperform the market and have equal weight as our benchmarks. In addition, we believe that risk-based allocation will optimize portfolio performance because it focuses on managing and balancing the risk contributions of these 50 stocks. By considering not just the allocation of capital but also how risk is distributed across different components, risk-based allocation enhances the stability and consistency of returns, especially during market volatility.

2.2 Implementation Details

In this project, we have done a monthly rebalancing in a long-only portfolio. Furthermore, the total weight of the portfolio always sums up to 100%. However, we found constraints such that for some certain stocks picked, they have not been traded every month since they are dynamic based on the factor or fundamental ranking process. Moreover, we also found that transaction costs are very low. That is a reason why we do not take transaction costs into account.

3. Data

This study utilizes data from three primary sources: the CRSP dataset for stock price and market capitalization information, the Compustat dataset for firm-level financial data, and the Fama-French dataset for factor returns and risk-free rate information. The dataset spans from January 2000 to June 2023, with all data organized on a monthly frequency to align with the rebalancing period of the portfolio. The combination of these datasets ensures a comprehensive view of stock characteristics and factor exposures, facilitating robust stock selection and portfolio evaluation.

To ensure data quality, missing values were filled with the most recent available data, following a last observation carried forward approach. Outliers were addressed by imposing realistic bounds: E/P ratios were constrained between 0.01 and 0.5, while net income margins were capped at 0.5 to avoid extreme values that could distort results. Lagging values for E/P ratios and net income margins by six months accounted for delays in financial reporting, preventing any look-ahead bias in the analysis. This rigorous data preparation ensured the integrity and reliability of the results derived from the backtesting and performance evaluation processes.

4. Backtesting and Performance Evaluation Framework

4.1 Simulate Portfolio Returns

Portfolio returns are calculated by multiplying the individual stock returns by their respective portfolio weights and summing these values. This ensures that each stock’s contribution to the portfolio’s performance is appropriately weighted, allowing for a precise representation of the overall return for each time period. The calculation is conducted with the following formula:

$$Portfolio\ Return_t = \Sigma\,(Picked\ Stock\ Return_{it}\ x\ Picked\ Stock\ Weight_{it})$$

Where: t = month period while i = picked stock

4.2 Simulate Portfolio Value

The portfolio value is updated iteratively by compounding the returns over time. Starting with an initial value, each subsequent value is computed as the product of the previous value and one plus the return for that period, reflecting the growth or decline in portfolio value.

$$Portfolio\ Value_{t+1} = Portfolio\ Value_{t}\ x\ (1 + Portfolio\ Value_{t})$$

Where: t = month period while i = picked stocks

4.3 Track Running Maximum

A running maximum of the portfolio value is maintained to identify the highest value achieved at any point in time. This is crucial for assessing drawdowns, as it provides a reference against which the current portfolio value can be compared.

$$Running\ Max_{t} = max(Portfolio\ Value_{0}, \ldots, Portfolio\ Value_{t})$$

4.4 Calculate Drawdown

Drawdowns are computed as the percentage drop from the running maximum value to the current portfolio value. This metric helps quantify the risk by measuring the extent of potential losses during the backtested period.

$$Drawdown_{t} = \frac{Portfolio\ Value_{t} - Running\ Max_{t}}{Running\ Max_{t}}$$

4.5 Evaluate Performance Metrics

Evaluating portfolio performance involves key metrics that capture risk, return, and efficiency. The Sharpe ratio measures risk-adjusted returns by dividing the excess portfolio return over the risk-free rate by its standard deviation, providing insight into the strategy's efficiency. Maximum drawdown quantifies the largest peak-to-trough decline, reflecting the portfolio's worst historical loss. Annualized returns offer a standardized measure of performance over a year, while volatility assesses the variability of returns, highlighting the risk inherent in the strategy.

In addition, factor regressions such as the Fama-French three-factor model (FF3) are used to identify whether the strategy generates alpha. These regressions decompose portfolio returns into contributions from market risk, size, and value factors, isolating the portion of returns unexplained by systematic risks. A statistically significant alpha indicates the strategy's ability to outperform its benchmarks, offering a robust evaluation of its effectiveness and uniqueness.

4.6 Benchmark Comparison

To assess the effectiveness of the strategy, its performance is benchmarked against the S&P 500 and an equal-weight portfolio. The S&P 500 serves as a market benchmark, representing the broad market's performance and providing a baseline for evaluating excess returns. Comparing to an equal-weight portfolio highlights the impact of the strategy's weighting methodology, as it allocates assets uniformly without regard to risk or return optimization. Key performance metrics, such as cumulative returns, Sharpe ratio, and drawdowns, are analyzed relative to these benchmarks to gauge risk-adjusted performance, stability, and value generation. These comparisons help contextualize the strategy's strengths and weaknesses in both market conditions and allocation approaches.

5. Results and Analysis

5.1 Portfolio Performances

The portfolio performance metrics demonstrate distinct characteristics across the allocation strategies. The Risk Parity strategy balanced risk and return, producing an annual return of 12.81% and a Sharpe Ratio of 0.47. Its volatility (24.09%) and drawdown (-56.99%) were moderate, positioning it as a middle ground between aggressive and conservative strategies.

Mean-Variance Optimization (MVO) achieved the highest annual return of 17.45% and the highest Sharpe Ratio of 0.49. However, this came at the cost of the highest volatility (32.42%) and the largest maximum drawdown (-63.17%). This highlights MVO's objective to maximize the Sharpe Ratio but also reveals its susceptibility to market downturns due to its focus on return optimization rather than risk control. Additionally, MVO demonstrated superior cumulative portfolio value growth over time, especially in bullish market conditions, showcasing its ability to capitalize on upward market trends effectively.

Conversely, the Minimum Variance strategy delivered the lowest volatility (21.65%) and the smallest drawdown (-43.65%), underscoring its effectiveness in minimizing risk and ensuring portfolio stability. While its annual return of 11.82% was lower compared to MVO and Risk Parity, it remains appealing for risk-averse investors seeking capital preservation during market turbulence.

Equal Weight and the Market benchmark underperformed all three allocation strategies, with Sharpe Ratios of 0.44 and 0.41, respectively, emphasizing the superiority of factor-based stock selection combined with optimized risk allocation.

Strategies/Market	Annual Return	Volatility	Sharpe Ratio	Max Drawdown
Market	8.05%	15.95%	0.41	-50.39%
Equal Weight	13.01%	26.00%	0.44	-56.69%
Risk Parity	12.81%	24.09%	0.47	-56.99%
Mean-Variance Optimization	17.45%	32.42%	0.49	-63.17%
Minimum Variance Optimization	11.82%	21.65%	0.47	-43.65%

Figure 1 shows the summary of all strategies' performances

5.2 Alpha Analysis (FF3 Regression Model)

The Fama-French 3-factor regression provides insights into the alpha generation and factor exposures of each strategy. For Risk Parity, the coefficients reveal a market beta (MktRF: 0.9904, p-value < 0.01), indicating alignment with market returns but not suggesting strong sensitivity, as the beta is close to 1. The positive SMB (size) beta of 0.6459 indicates a tilt toward smaller-cap stocks, while the HML (value) beta of 0.6499 highlights exposure to value factors. The R-squared (0.687) signifies robust alignment with systematic factors. Although the intercept (alpha) is positive, it is not statistically significant due to a small coefficient and a non-significant p-value. However, it does suggest the potential for added returns over systematic factors.

MVO's regression results indicate a similar market beta (MktRF: 0.9904, p-value < 0.01), consistent with exposure to market risk without indicating high volatility. The insignificant SMB beta (-0.2114, p-value > 0.05) suggests limited size factor reliance, while the significant HML beta (0.4929, p-value < 0.01) reflects a moderate value tilt. The lower R-squared (0.260) compared to Risk Parity suggests higher idiosyncratic risk, which aligns with MVO's focus on maximizing returns. The alpha for MVO is positive but not statistically significant, reflecting its potential for additional returns while emphasizing idiosyncratic drivers.

Minimum Variance exhibits the most defensive profile, with the lowest market beta (MktRF: 0.9264, p-value < 0.01), consistent with the strategy's risk-averse nature. Significant SMB (0.5961, p-value < 0.01) and HML (0.4645, p-value < 0.01) betas demonstrate exposure to smaller-cap and value factors. The high R-squared (0.703) highlights strong diversification across systematic risks. The positive alpha suggests some potential for excess returns, although it is not statistically significant, which aligns with the strategy's stability-oriented design.

In summary, all three strategies generate positive alpha, with MVO achieving the largest alpha among the three, despite none being statistically significant. Risk Parity and Minimum Variance emphasize diversification and stability, while MVO focuses on maximizing return potential by leveraging idiosyncratic factors. These findings highlight the effectiveness of combining factor-based selection with risk-focused allocation in achieving superior portfolio performance.

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                            OLS Regression Results
==============================================================================
Dep. Variable:              ExcessRET   R-squared:                       0.687
Model:                            OLS   Adj. R-squared:                  0.684
Method:                 Least Squares   F-statistic:                     202.6
Date:                Sun, 01 Dec 2024   Prob (F-statistic):           1.52e-69
Time:                        11:48:41   Log-Likelihood:                 513.93
No. Observations:                 281   AIC:                            -1020.
Df Residuals:                     277   BIC:                            -1005.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0016      0.002      0.682      0.496      -0.003       0.006
MktRF          0.9904      0.053     18.821      0.000       0.887       1.094
SMB            0.6459      0.077      8.368      0.000       0.494       0.798
HML            0.6499      0.067      9.639      0.000       0.517       0.783
==============================================================================
Omnibus:                       44.697   Durbin-Watson:                   2.023
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              176.780
Skew:                           0.579   Prob(JB):                     4.10e-39
Kurtosis:                       6.709   Cond. No.                         35.0
==============================================================================
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Figure 2 shows a regression analysis on risk parity over FF3

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                            OLS Regression Results
==============================================================================
Dep. Variable:              ExcessRET   R-squared:                       0.260
Model:                            OLS   Adj. R-squared:                  0.252
Method:                 Least Squares   F-statistic:                     32.47
Date:                Sun, 01 Dec 2024   Prob (F-statistic):           5.14e-18
Time:                        11:48:41   Log-Likelihood:                 310.36
No. Observations:                 281   AIC:                            -612.7
Df Residuals:                     277   BIC:                            -598.2
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0072      0.005      1.478      0.141      -0.002       0.017
MktRF          0.9904      0.109      9.121      0.000       0.777       1.204
SMB           -0.2114      0.159     -1.328      0.185      -0.525       0.102
HML            0.4929      0.139      3.542      0.000       0.219       0.767
==============================================================================
Omnibus:                      387.893   Durbin-Watson:                   1.838
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            67601.721
Skew:                           6.232   Prob(JB):                         0.00
Kurtosis:                      77.957   Cond. No.                         35.0
==============================================================================
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Figure 3 shows a regression analysis on mean-variance optimization over FF3

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                            OLS Regression Results
==============================================================================
Dep. Variable:              ExcessRET   R-squared:                       0.703
Model:                            OLS   Adj. R-squared:                  0.699
Method:                 Least Squares   F-statistic:                     218.2
Date:                Sun, 01 Dec 2024   Prob (F-statistic):           1.26e-72
Time:                        11:48:41   Log-Likelihood:                 550.89
No. Observations:                 281   AIC:                            -1094.
Df Residuals:                     277   BIC:                            -1079.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0016      0.002      0.753      0.452      -0.003       0.006
MktRF          0.9264      0.046     20.080      0.000       0.836       1.017
SMB            0.5961      0.068      8.809      0.000       0.463       0.729
HML            0.4645      0.059      7.857      0.000       0.348       0.581
==============================================================================
Omnibus:                       39.132   Durbin-Watson:                   2.043
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               91.306
Skew:                           0.673   Prob(JB):                     1.49e-20
Kurtosis:                       5.447   Cond. No.                         35.0
==============================================================================
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Figure 4 shows a regression analysis on minimum variance over FF3

6. Discussion and Implications

6.1 Key Insights

Our analysis reveals several critical insights into the performance and risk dynamics of the three portfolio allocation strategies: Risk Parity, Mean-Variance Optimization (MVO), and Minimum Variance. Among the strategies, MVO achieves the highest annualized returns at the cost of higher volatility and the largest maximum drawdown. However, the Sharpe ratio of MVO is still among the highest. This strategy prioritizes returns and is susceptible to market downturns.

Conversely, the Risk Parity and Minimum Variance portfolios exhibit superior risk-adjusted returns, reflected by their Sharpe ratios of 0.47. The Minimum Variance strategy shows the smallest drawdown, indicating stability and making it particularly effective during periods of heightened market volatility. These results emphasize the trade-offs between maximizing returns and managing risks inherent in portfolio construction.

The two-factor selection approach, focusing on value (E/P ratio) and quality (net income margin), significantly enhanced portfolio performance. In other words, we target stocks with strong fundamental metrics. This strategy aligned with proven drivers of alpha, as indicated by the Fama-French 3 factors regression results. In particular, both Risk Parity and Minimum Variance portfolios display a high R-squared, which showcases robust diversification across systematic risks. In contrast, for the MVO strategy, a low R-squared suggests that the returns are largely driven by idiosyncratic risks, such as stock-specific performance or noise in the optimization process.

Overall, in terms of risk-adjusted returns, all three strategies outperform the market benchmark. Therefore, factor-based stock selections combined with risk-based allocation strategies are proven to be effective in portfolio construction.

6.2 Implications and Applications

6.2.1 Target Audience

According to the analysis and results above, the adoption of specific strategies depends on the type of target audience. Specifically, institutional investors may be more appealing to Risk Parity and Minimum Variance strategies due to the characteristics of stability and alignment with systematic factors. These approaches are well-suited for long-term portfolios aiming to balance risk and return effectively. While for retail investors, although they may be constrained by time and resources, they are still able to benefit from the simplicity of factor-based stock selection. It is feasible to replicate aspects of this strategy to enhance their portfolio performance by focusing on value and quality metrics.

6.2.2 Risk Tolerance

Before investing, investors should carefully weigh their risk tolerance, return objectives, and investment horizon. For investors who are willing to tolerate high risks and larger drawdowns, such as hedge funds, MVO is better suited, as it offers the potential for the highest returns despite its higher volatility. In contrast, Risk Parity and Minimum Variance portfolios are ideal for risk-averse investors, such as pension funds, endowments, or individuals seeking stable, consistent returns over the long term.

6.2.3 Market Conditions

To achieve optimal outcomes, it is important to select strategies based on market cycles and conditions. MVO tends to excel during strong bullish markets. The focus on maximizing expected returns allows it to capitalize on upward trends. However, its high sensitivity to market fluctuations and idiosyncratic risks makes it vulnerable during bearish periods or market downturns. In contrast, Risk Parity and Minimum Variance portfolios are suitable for volatile or uncertain markets due to their emphasis on stability and risk diversification. They are a defensive choice for investors aiming to preserve capital during times of heightened volatility.

6.3 Limitations

6.3.1 Long-Only Constraint

The portfolios in this study are constructed under a long-only constraint, which restricts the ability to short-sell underperforming stocks. This limitation may reduce the potential for higher returns from hedging opportunities, especially in bearish markets where short-selling could mitigate losses.

6.3.2 Limited Factor Inclusion Constraint

During the stock selection process, we only include two factors: value and quality. This may lead to the overlook of other influential drivers of returns, such as momentum and ESG considerations.

7. Conclusion

This study evaluated the performance of a quantitative investment strategy combining factor-based stock selection with risk-focused portfolio allocation techniques. The results demonstrate that the choice of allocation method significantly impacts portfolio performance, with clear trade-offs between annualized returns, volatility, and drawdowns.

From the performance metrics and portfolio growth over time:

1. Mean-Variance Optimization (MVO): This method delivered the highest annual return (17.45%) and Sharpe Ratio (0.49) among all strategies, showcasing its ability to

maximize returns. However, it also exhibited the highest volatility (32.42%) and the largest maximum drawdown (-63.17%), indicating greater susceptibility to market downturns. This makes MVO suitable for return-focused investors willing to tolerate higher risk.

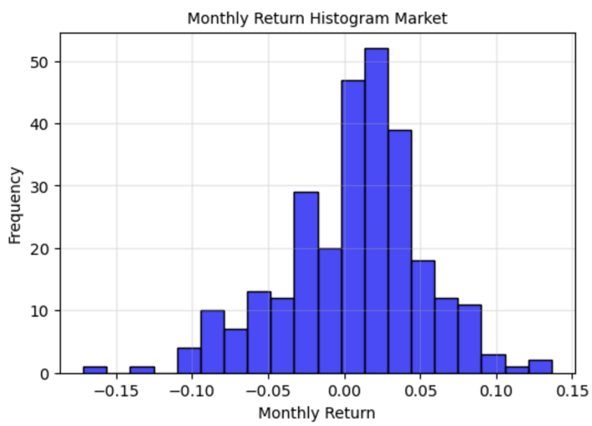
2. Minimum Variance: This strategy excelled in risk management, with the lowest volatility (21.65%) and a controlled maximum drawdown (-43.65%). Despite achieving lower annual returns (11.82%) compared to MVO and Risk Parity, it demonstrated strong stability, making it ideal for conservative investors focused on capital preservation.
3. Risk Parity: Balancing risk and return, the Risk Parity portfolio achieved a competitive annual return (12.81%) and a Sharpe Ratio of 0.47. Its volatility (24.09%) and drawdown (-56.99%) were moderate, indicating a middle ground between aggressive and conservative approaches.
4. Equal-Weight Portfolio: While straightforward to implement, the equal-weight strategy underperformed Risk Parity in risk-adjusted returns (Sharpe Ratio of 0.44) and showed relatively high volatility (13.01%) and drawdown (-56.69%), indicating that more sophisticated allocation methods can deliver better outcomes.
5. Market Benchmark (S&P 500): The market portfolio yielded the lowest annual return (8.05%) and Sharpe Ratio (0.41), with a drawdown of -50.39%. These results highlight the added value of factor-based selection and optimized allocation in generating alpha and managing risks.

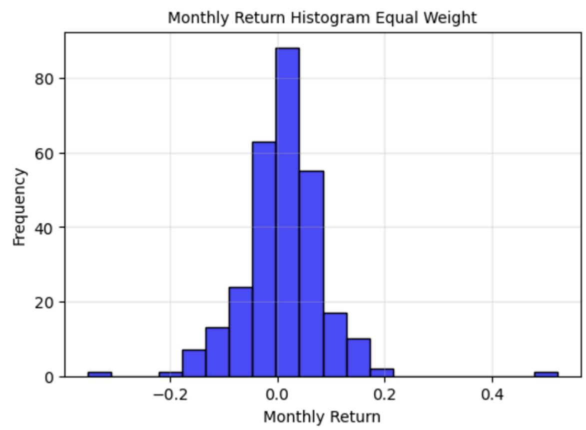
The portfolio value growth chart highlights the superior cumulative performance of MVO during bullish markets, while the stability of Minimum Variance is evident during periods of heightened market volatility. Risk Parity and Equal-Weight strategies provide intermediate performance, reinforcing the trade-offs between maximizing returns and minimizing risk.

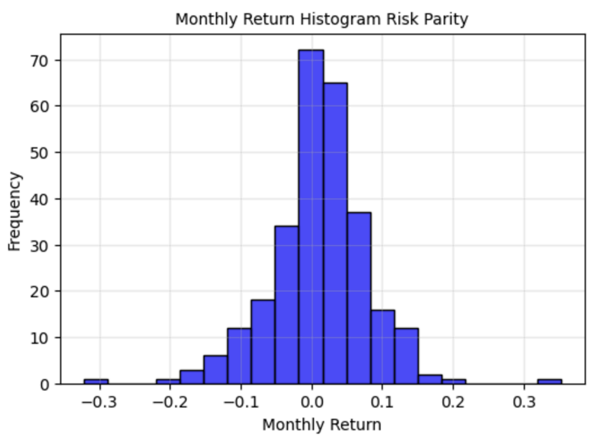
In conclusion, integrating factor-based selection with risk-based allocation provides a flexible framework for tailoring portfolios according to investor objectives and market conditions. Mean-variance optimization maximizes returns, while Minimum Variance and Risk Parity offer robust risk management. The results underscore the importance of selecting an appropriate allocation strategy based on the investor’s risk tolerance and market outlook, making this hybrid approach valuable for portfolio construction.

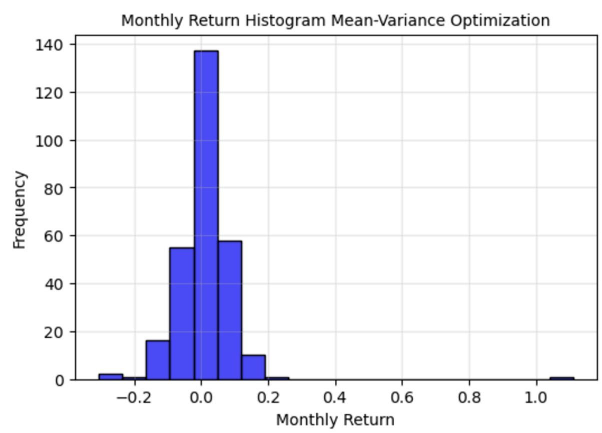
8. Appendix

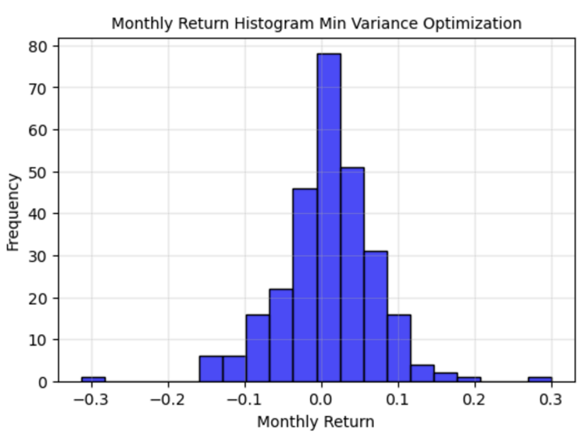
Monthly Portfolio Return Distribution from Each Portfolio Strategy











Portfolio Value Simulation Over The Time for Each Strategy