Portfolio Optimization Based On 6 American Stocks

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Abstract. This paper constructs an optimal portfolio and compares the portfolio with the SPDR S&P 500 ETF Trust (SPY) using the maximum Sharpe ratio model. Six stocks from different sectors in the S&P 500 were selected: Apple Inc. (AAPL), JPMorgan Chase & Co. (JPM), Johnson & Johnson (JNJ), Nike Inc. (NKE), ExxonMobil (XOM), and Boeing (BA). Historical monthly data from January 2020 to December 2022 were used to calculate the optimal portfolio weights. The portfolio's cumulative return over the following two years (2023–2024) was -18.47%. In contrast, the SPY achieved a return of 53.26%. Although the model generated the highest Sharpe ratio within the in-sample period, the result did not extend to the out-of-sample test. The portfolio underperformed due to unstable returns, market shifts, and high exposure to volatile stocks. The findings indicate that market indices can provide more stable returns than individually constructed optimal portfolios in real investment environments.

Keywords: Portfolio optimization; Sharpe ratio; risk-return analysis; S&P 500.

1. Introduction

Portfolio construction is a key element of investment strategy. Investors aim to maximize return while minimizing risk [1-2]. Whether an individual portfolio can outperform a market index remains an open question. Market indices offer low cost and broad diversification [3]. These features attract investors seeking long-term stability. However, some prefer active allocation based on expected return and risk estimates [4]. The debate continues over which approach is more effective.

Two main points of view are presented by academic research on portfolio optimization and its comparison with market indices. From a capitalizing on stock selection and timing standpoint, one view holds that portfolios managed actively can outperform market indices, especially in certain market conditions [5]. In contrast, another viewpoint maintains that investing in market indices provides more stable returns with lower costs, as it eliminates the need for active management and associated fees [6]. While these points of view are strongly discussed, current studies indicate several limits. Most studies rely on theoretical models or back-tested simulations, with limited real-world empirical analysis, especially over extended periods [7]. This reduces the practical relevance of methods of portfolio optimization. Many studies also neglect to carefully examine the actual stocks in particular portfolios in favor of general market data, so neglecting the details of real-time performance [8]. The absence of out-of-sample testing and empirical evidence from diverse market conditions weakens the reliability of conclusions, particularly during periods of market instability [9]. Considering these gaps, this paper attempts to provide additional empirical insights on the effectiveness of optimal portfolios compared to market indices, especially in different market conditions.

This paper builds a portfolio using the maximum Sharpe ratio model. It chooses six stocks from the S&P 500, each from different sectors. Input for optimization comes from historical data covering 2020 through 2022. The portfolio's performance during 2023 and 2024 is evaluated in line with SPY. Under real market conditions, this comparison assesses the model's effectiveness [8]. The paper offers an understanding of risk-return tradeoffs between active and passive investment [4].

2. Data

This research downloaded the monthly data from Investing.com, starting from January 1, 2020, to December 1, 2024. In order to achieve a more effective risk diversification, six representative companies from different industries were meticulously chosen, including Apple Inc. (AAPL) in the technology industry, JPMorgan Chase & Co. (JPM) in the financial industry, Johnson & Johnson (JNJ) in the healthcare industry, Nike Inc. (NKE) in the consumer goods industry, ExxonMobil (XOM) in the energy industry, and Boeing (BA) in the industrial sector [10]. They are all representative firms in SPDR S&P 500 ETF Trust (SPY). The 5 years' monthly data was downloaded from the Investing.com website initially and then arranged in chronological order. Subsequently, the previous 3-year data's key risk-return metrics, including arithmetic returns, variance, standard deviation, covariance, along with a multitude of others, were computed. The following findings underscore distinct risk-return profiles and covariance-driven diversification constraints for equity groups.

Based on the summary statistics of stock returns, the following observations can be made. The average return of AAPL is the highest among the six companies, reaching 2.04%, while BA shows a negative mean return of -0.19%. JNJ, NKE, JPM, and XOM all present positive mean returns, with XOM close to AAPL at 1.96%. The standard deviation of BA is 0.1594, which is the highest, indicating greater volatility. In contrast, JNJ has the lowest standard deviation of 0.0529, suggesting more stable returns. The confidence interval at the 95% level is narrowest for JNJ and widest for BA, which is consistent with their respective standard errors. The skewness values are all close to zero, suggesting that most return distributions are relatively symmetric. Kurtosis values are generally low, and some are negative, such as AAPL (-1.1102), indicating a flatter distribution compared to the normal distribution. Maximum and minimum returns also show significant differences. BA has the widest return range, with a maximum of 45.93% and a minimum of -45.79%. In contrast, JNJ has the narrowest range. This further confirms the higher volatility in BA and the more stable performance in JNJ (See Table 1).

Table 1. Descriptive statistics for the monthly return of the 6 stocks

	BA return	JNJ Return	NKE return	APPL Return	JPM return	XOM Return
Mean	-0.19%	0.67%	0.85%	2.04%	0.28%	1.96%
Std Error	0.027	0.009	0.016	0.016	0.015	0.020
Median	-0.014	0.006	-0.005	0.024	0.012	0.021
Std Dev	0.159	0.053	0.095	0.097	0.089	0.119
Variance	0.025	0.003	0.009	0.009	0.008	0.014
Kurtosis	2.403	0.179	-0.499	-1.110	0.841	0.090
Skewness	0.171	0.295	-0.047	0.196	0.045	0.128
Max	45.93%	14.42%	18.35%	21.44%	20.46%	26.92%
Min	-45.79%	-9.67%	-21.92%	-12.23%	-22.46%	-26.19%
Cumulative Return	-41.51%	21.08%	15.50%	77.01%	-3.81%	58.11%
Confidence (95.0%)	0.0539	0.0179	0.0323	0.0328	0.0302	0.0401

The line chart below examines the cumulative returns of six stocks over a three-year period from January 1, 2020, to November 1, 2022. APPL demonstrates the most notable performance. Starting near 0% on January 1, 2020, its cumulative return peaks at approximately 100% to 150% and remains the highest by the end of the period, securing the top position. NKE exhibits an upward trajectory. Its cumulative return begins close to 0%, fluctuates moderately, and reaches approximately 50% to 100% by the endpoint, ranking second. Immediately following are JNJ and JPM, displaying stable trends. JNJ starts and ends within a range of 0% to 20%, while JPM fluctuates between -20% and 20%. XOM initially records negative cumulative returns, declining to -30% to -50%. It recovers gradually, concluding with a positive return of 0% to 20%, placing fifth. BA shows the weakest performance. Its cumulative return remains negative throughout, starting near 0% and dropping to -30% to -50%, ranking last (See Fig. 1).

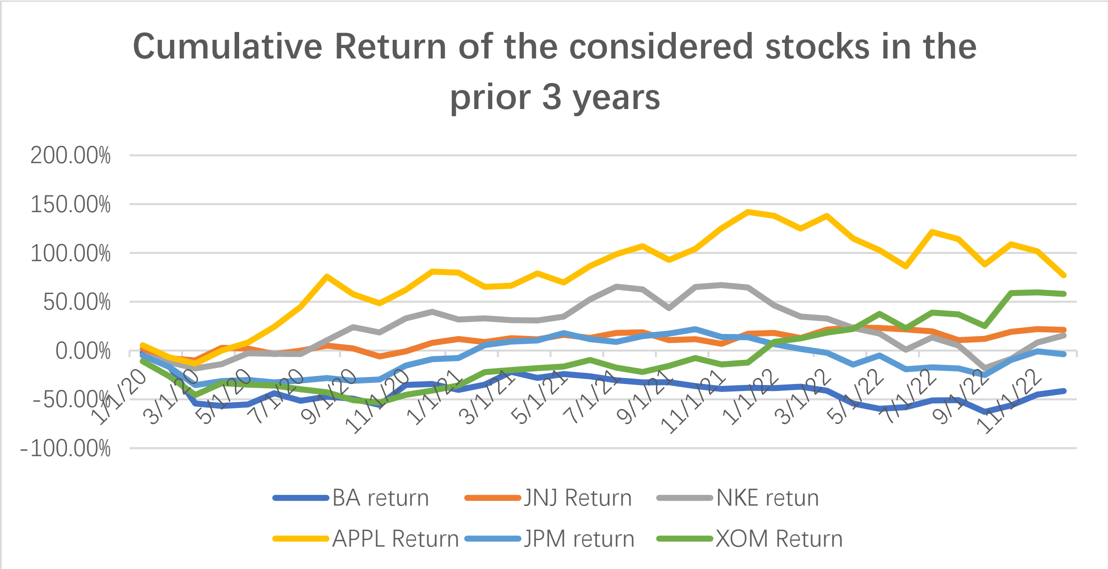

Fig. 1 Cumulative Return of the Considered Stocks in the Prior 3 Years

The variance-covariance matrix provides insights into the risk profiles and interdependencies among six equities: BA, JNJ, NKE, AAPL, JPM, and XOM. Covariance values reveal diversification potential. BA displays strong positive covariance with JPM (0.0089) and XOM (0.0084), suggesting limited risk reduction benefits when combined. JNJ exhibits low covariance with BA (0.0013) and JPM (0.0017), implying potential diversification advantages. AAPL shows moderate covariance with NKE (0.0047) and JNJ (0.0023), indicating partial correlation. XOM maintains relatively high covariance with JPM (0.0070), reducing portfolio diversification effectiveness (See Table 2).

These findings highlight BA and XOM as high-risk assets requiring careful allocation. JNJ serves as a stability anchor in portfolios. The strong BA-JPM-XOM covariance cluster necessitates complementary low-correlation assets for optimal risk management.

Table 2. Variance-Covariance Table of the Considered Stocks in the Prior 3 Years

	BA return	JNJ Return	NKE Return	APPL Return	JPM Return	XOM Return
BA return	0.0247	0.0013	0.0073	0.0052	0.0089	0.0084
JNJ Return	0.0013	0.0027	0.0014	0.0023	0.0017	0.0023
NKE Return	0.0073	0.0014	0.0089	0.0047	0.0042	0.0026
APPL Return	0.0052	0.0023	0.0047	0.0091	0.0030	0.0031
JPM Return	0.0089	0.0017	0.0042	0.0030	0.0078	0.0070
XOM Return	0.0084	0.0023	0.0026	0.0031	0.0070	0.0137

3. Method

The Sharpe Ratio is a measure of risk-adjusted return, indicating how much excess return an investment provides per unit of risk. Developed by economist William F. Sharpe, it is widely used in finance to compare the performance of investment portfolios [1].

The maximum Sharpe ratio model was selected for this study. The rationale is that it can identify the portfolio that can yield the maximum excess return for the same unit of risk assumed [2]. Within the efficient frontier, the portfolio selected by this model has the highest Sharpe ratio. A short-term model that allows short selling was employed in the analysis [11]. The basic equation of the model is shown below.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

R_p denotes the expected or actual return of the portfolio. R_f represents the risk-free rate of return, typically the return on short-term government securities such as U.S. Treasury bills. σ_p is the standard deviation of the portfolio's returns, representing the investment's total risk or volatility.

4. Results

The five-year data selected was split into two distinct parts, the first three-year period and the subsequent two-year period. By using the data from the initial three years, the optimal weights were obtained through the maximum Sharpe ratio model (See Table 3).

Table 3. Weights of the selected 6 stocks in the optimal portfolios

Portfolio	MAX SR(SR)
Weight BA	-0.621
Weight JNJ	-0.721
Weight NKE	0.504
Weight AAP	1.667
Weight JPM	-1.643
Weight XOM	1.815
SUM	1
Expected return	6.55%
variance	0.0473
std dev	0.2176
risk free rate	0.0025
Sharpe ratio	0.2896

The calculated weights were applied to construct investment portfolios for the subsequent two-year period. Monthly portfolio returns for each month of the following two years were derived using the actual return and the corresponding asset weight calculated by the specified formula [1]. Cumulative returns over the two years were computed (See Table 4). Portfolio performance was benchmarked against the SPY. The comparison revealed relative performance differences between the constructed portfolios and the market index [4].

Table 4. Cumulative Return of the Constructed Portfolio and SPY in the Latter 2-Year Period

Return	MAX SR(SR)	SPY	MAX SR(LR)
Cumulative Return	-0.184681597	0.532586589	0.561781406

Finally, based on the comprehensive analysis and comparison, the cumulative arithmetic return with the given weights for the subsequent two years is -18.47%. Meanwhile, for the SPY, its cumulative rate of return during the same period is 53.26%. It is concluded that investing in the SPY is a far more preferable choice than the constructed investment portfolio consisting of six stocks.

5. Conclusion

The constructed portfolio using the maximum Sharpe ratio model generated an expected return of 6.55% with a variance of 0.0473. The Sharpe ratio reached 0.2896 during the training period. However, the out-of-sample performance showed a cumulative return of -18.47%. In contrast, SPY achieved a return of 53.26% during the same period. The result demonstrates that the SPY outperformed the optimized portfolio. Although the model maximized return per unit of risk in-sample, it failed to provide better returns out-of-sample. The deviation highlights the risks of using static weights and relying on historical data. Index-based investment produced more favorable results under real market volatility.

The analysis has several limitations. The model excluded transaction costs, taxes, and other practical constraints. The use of fixed weights did not allow adjustments for changing market trends. The model did not include macroeconomic or behavioral factors that influence return. These factors may explain the underperformance in the test period. Future research should consider dynamic portfolio construction. Additional inputs such as time-varying covariances and macroeconomic signals may improve predictive power and result consistency.

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