# A Research of the Investment Weights of Technology Stocks and Traditional Stocks

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**Abstract.** This paper delves into the intricate realm of investment strategies, with a specific focus on navigating the dynamic landscapes of technology stocks and traditional stocks. The paramount considerations revolve around investor selection and risk management, pivotal elements for achieving sustainable growth. The study meticulously examines three distinct portfolio strategies: technology stocks, traditional stocks, and a synergistic hybrid of the two. In an innovative approach, machine learning algorithms are deployed to predict and optimize portfolio changes, adding a layer of adaptability to the investment landscape. A comprehensive analysis employs various financial indicators to gauge the performance of these portfolios, shedding light on their risk-reward profiles. The study not only caters to investors with different risk appetites but also underscores the significance of machine learning in dynamically adjusting portfolios to match the evolving market conditions. This adaptability is crucial for striking a delicate balance between growth and stability, aligning with individual risk preferences. Moreover, the research scrutinizes cumulative returns in contrast to holding period returns, providing nuanced insights into the efficacy of each strategy over time. In essence, the document offers a multifaceted perspective, leveraging machine learning to empower investors in navigating the complex interplay of technology and traditional stocks, fostering informed decision-making in an ever-changing financial landscape.

**Keywords:** Investment Strategy, Technology Stocks, Traditional Stocks, Risk Management, Machine Learning.

## 1. Introduction

Risk and return are the two main contents in investment decisions. Rational investors need to pursue maximizing returns at a given level of risk, or minimizing the level of risk at the same level of return. This need drives the development of investment portfolio theory. With the advancement of information technology and the gradual improvement of financial markets, the cost of information transmission between various financial products has also been significantly reduced. The space for arbitrage that used time and space information differences in the past has also been gradually compressed. Therefore, how to carry out scientific and Effective investment decision-making is a problem that every investor must face. Portfolio theory is a decision-making methodology for investment collections of stocks, bonds, financial derivatives and other securities held by individual and institutional investors. The reduction of information circulation costs and the development of computing power have made the information on risky assets increasingly Transparency makes investors more efficient when making decisions. Correspondingly, portfolio theory has also made great progress in the context of technological progress [1].

Classic asset allocation models (such as mean-variance models, etc.) usually adopt a two-step strategy, which first estimates the distribution of returns (i.e., the mean and covariance matrix of returns), and then determines the portfolio weight [2-4]. Among them, returns the estimation of the distribution will produce errors and ultimately affect portfolio decisions [4]. At the same time, there are a large number of literatures that estimate the distribution of returns through asset characteristics. After predicting the distribution, equal weight or market capitalization weighted long-short combinations are usually used to judge the accuracy of the prediction [5-7].

Random stock selection means that investors do not rely on any specific investment strategy during the investment process, but choose investment objects by randomly selecting stocks [8, 9]. There are several reasons to use ransom stock picking. First, it reduces investors' reliance on specific strategies,

leading to a more open mind to face market changes without being limited to a specific investment philosophy [10, 11]. Secondly, it reduces human intervention. Compared with human investment strategies, random stock selection reduces the factor of human intervention [12]. It avoids investment mistakes caused by personal emotions, errors in judgment and other factors. In addition, it reduces investment risks and the impact of market fluctuations to a certain extent by providing more opportunities and diversified investment options [13].

This paper will randomly select three different types of investment portfolio strategies and discuss them, 30 traditional stocks, 30 technology stocks and a mixed strategy of 30 traditional stocks and technology stocks. The main goal is how to choose a suitable investment strategy and the main problem is to predict the movements of these three stock portfolios. This study will use machine learning to determine the weighting of stocks.

## 2. Methodology

### 2.1. Data Selection

As mentioned above, the experimental data from 2015-01-01 to 2023-06-30 are divided into three investment portfolios: technology, traditional and mixed. Each portfolio contains 30 stocks from the S&P 500 Index. The Technology portfolio has only one industry, which is classified by the S&P 500 as "Information Technology." These 30 stocks are randomly selected. Tradition includes traditional industries. Such as industry, healthcare, finance, materials, etc. They are all traditional businesses. What's more, they are also randomly selected and manually checked to confirm that there are no companies that dispute the industry classification. For example: Google, Amazon, Tesla. The mixed portfolio includes 20 stocks randomly selected from various industries, and 10 popular stocks are manually added to simulate the fund manager's selection. Here is a list of popular stock symbols: NVDA, TSLA, QCOM, MSTF, NFLX, ADBE, AMD, AMZN, GOOG, META.

### 2.2. Modelling

The stock prediction model to be used in this study selected the "walking machine learning model". Walking is somewhat different from traditional machine learning and may be more suitable for the dynamics of the market from a modeling perspective. In each iteration, a forward model is trained based on known historical data and then used to predict the next point in time (or period). The actual results are then revealed and the model is updated with this new data before making the next prediction. It simulates using the model in a real-time environment because each prediction is made after the model "sees" the data. However, traditional machine learning cross-validation is not suitable for use in changing markets. Here are some reasons why. First, the data set of traditional machine learning is usually divided into a training set and a test set. The model is trained on the entire training set and then evaluated on the test set. Second, the model is trained only once on the training set and then evaluated on the test set. Simulations without model updates after seeing new data. In short, due to fixed data sets and one-time training, traditional cross-validation methods cannot adapt well to market changes. For model fitting, the team used ridge regression. This kind of regression is an extension of linear regression that solves this problem by adding a regularization term to the cost function (loss function). The goal of ridge regression is to minimize this cost function. The existence of regularization makes the model more inclined to choose smaller parameter values when fitting the data, thereby reducing the risk of overfitting. By adjusting the regularization parameter alpha, experiments can control the sensitivity of the model to regularization.

## 3. Empirical Results

Obtain information about S&P 500 stocks from Wikipedia, screen for stocks in technology stocks, traditional stocks and mixed industries, and randomly select 30 stocks. The historical data of these stocks are downloaded using the "y finance" library, and the rolling window method is used to

calculate and predict the returns of these stocks. The graphical results are mainly:(1) Calculate the return of the investment portfolio and draw the cumulative return curve. (2) Use the "Portfolio" library to output the backtest results of the portfolio.

### 3.1. Technology Stock Investment Portfolio

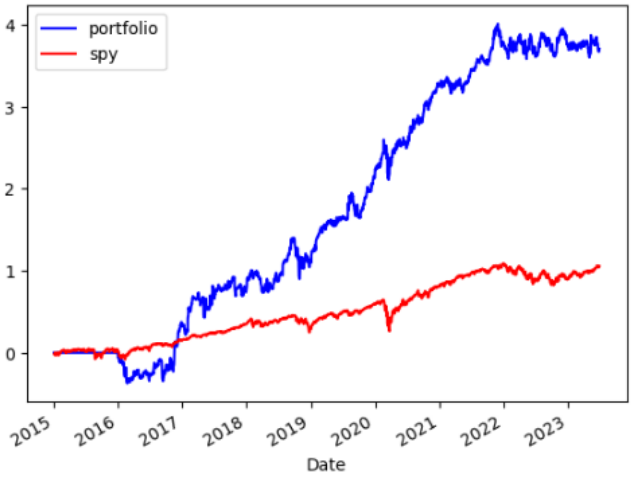



**Figure 1.** Tech-stock portfolio return.

From Figure 1, the strategy's annualized return is approximately 45.5%. During this period, the total portfolio's cumulative return was approximately 1,558.4%. The portfolio's volatility is approximately 48.8%, which means the portfolio's return could vary between ±48.8%. The Sharpe ratio is 1.01 (see Table 1), which means that the return per unit of risk taken by the investor exceeds the risk-free rate (assumed to be 0%) by approximately 1.01 times. The Calmar ratio is 1.04, which means the investment return exceeds the risk-free rate plus a standard deviation of 4%. During this period, the largest drawdown was -43.7%, meaning the portfolio was down 43.7% at the worst possible time. Omega's ratio is 1.20, which means the portfolio's expected excess return per year is 120 basis points (or 1.2%). The Sortino ratio is 1.51, which means that the portfolio's return for each unit of downside risk exceeds the risk-free rate plus 1.51 standard deviations. And this portfolio is not significantly skewed because its skewness is close to zero. The kurtosis is 5.88, meaning its returned distribution is much flatter than the normal distribution. The tail ratio is 1.05, which means the portfolio is slightly right-skewed at the top of the return distribution. The portfolio has a daily value risk of -6.0%, which means that under normal market conditions, the expected probability of loss in a day is 6%.

**Table 1.** Tech-stock portfolio result.

| | |
|---|---|
| Start date | 2015-12-31 |
| End date | 2023-6-29 |
| Total months | 89 |
| | Backtest |
| Annual return | 45.5% |
| Cumulative returns | 1558.4% |
| Annual volatility | 48.8% |
| Sharpe ratio | 1.01 |
| Calmar ratio | 1.04 |
| Stability | 0.95 |
| Max drawdown | -43.7% |
| Omega ratio | 1.20 |
| Sortino ratio | 1.51 |
| Skew | -0.00 |
| Kurtosis | 5.88 |
| Tail ratio | 1.05 |
| Daily value at risk | -6.0% |

In Figure 2, it shows a plot of cumulative returns over time. Cumulative return is the total return of an investment or portfolio over time. This chart can be used to evaluate the performance of an investment or portfolio, to compare different strategies, or to analyze risk and return. According to this graph, the initial value of the portfolio is around 0.00, indicating no gains or losses. The portfolio's highest point on the timeline was over 25.00, indicating a cumulative return of 2500%. This means that if the initial investment is $100, then at this point, the investment is worth $2,500.

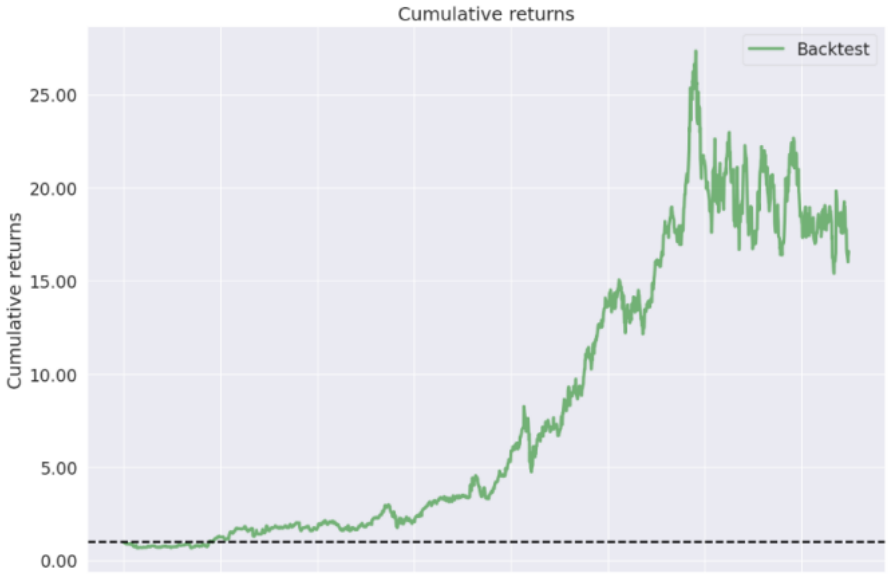
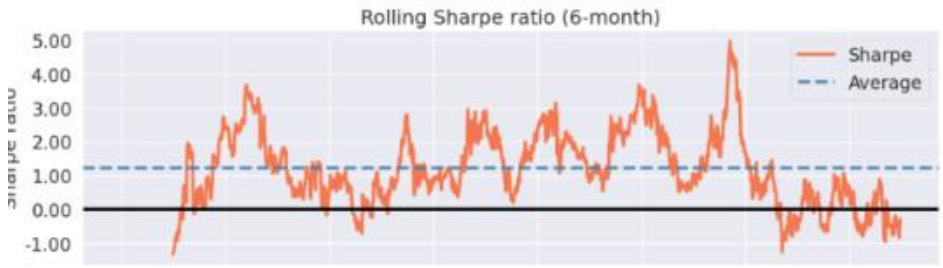



**Figure 2.** Tech-stock cumulative returns.

Figure 3 (a) is the Rolling Sharpe Ratio (6 Months): This is a line graph showing the Sharpe Ratio recalculated over a 6-month period. The portfolio's risk continues to fluctuate and reaches a peak (around 5.00) in the middle to late part of the year, indicating a gradually increasing risk-adjusted return for the portfolio. In addition, the average Sharpe ratio is also greater than 1. Figure 3(b) is the percentage of underwater area, showing the portion of the portfolio's market value on a given day that was below its initial market value. This chart helps analyze a portfolio's maximum drawdown over a period of time, and how much it lost in different percentages. From 2022 to 2023, the portfolio has fallen even more, exceeding 40%, and has fallen sharply over a longer period of time.




(a) Rolling Sharpe ratio




(b) Underwater plot

**Figure 3.** Tech-stock rolling Sharpe Ratio and the underwater plot.

### 3.2. Traditional Stock Investment Portfolio

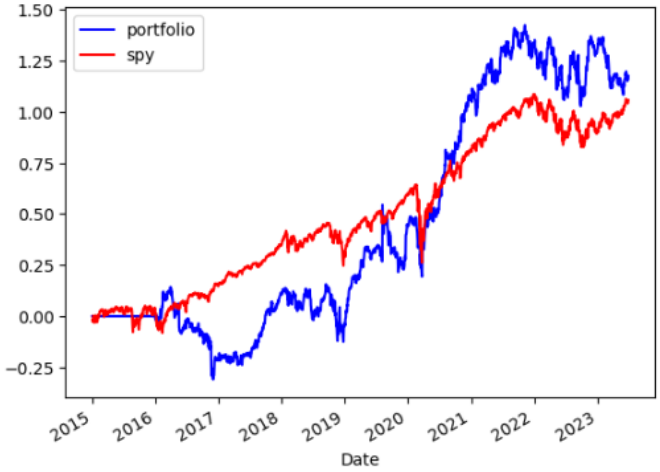



**Figure 4.** Traditional stock portfolio return.

In Figure 4, the portfolio's annualized return is 12.0%. This means that if the portfolio had been held since December 31, 2015, it would have earned an annual return on investment of 12.0%. As of June 29, 2023, the portfolio's cumulative return was 134.3%. The portfolio's annualized volatility is 29.5%, indicating that the portfolio's price has experienced greater volatility and a higher level of risk during this period. The Sharpe ratio is 0.53 (see Table 2), which means that for every unit of risk the portfolio takes on in addition, a return of 0.53 units was obtained. -38.3% represents the worst loss scenario the portfolio has experienced in the past few years. An Omega ratio of 1.10 represents the excess return a portfolio can achieve while maintaining a certain loss. 1.10 is greater than 1, indicating that the volatility is higher than the market level and the risk is higher. A Sortino ratio of 0.80 indicates that when faced with one unit of downside risk, the portfolio earned higher excess returns. A skewness of 1.01 indicates that the portfolio's return distribution is positively skewed, meaning that the right tail is long and there may be some extreme positive returns. The kurtosis is 18.90, indicating that the shape of the returned distribution is much steeper than the normal distribution. The tail ratio is 1.01, indicating that the probability that the portfolio's return distribution is in the left tail is slightly higher than the normal distribution. A daily value risk of -3.7% represents the maximum loss a portfolio can face on a daily basis.

In Figure 5, the initial value of the portfolio is 1.00. The portfolio's highest point on the timeline is 3.00, indicating a cumulative return of 300%. This means that if the initial investment was $100, the value of that investment at this point is $300.

**Table 2.** Traditional stock portfolio result.

| | |
|---|---|
| Start date | 2015-12-31 |
| End date | 2023-6-29 |
| Total months | 89 |
| | Backtest |
| Annual return | 12.0% |
| Cumulative returns | 134.4% |
| Annual volatility | 29.5% |
| Sharpe ratio | 0.53 |
| Calmar ratio | 0.31 |
| Stability | 0.82 |
| Max drawdown | -38.3% |
| Omega ratio | 1.10 |
| Sortino ratio | 0.80 |
| Skew | 1.01 |
| Kurtosis | 18.90 |
| Tail ratio | 1.01 |
| Daily value at risk | -3.7% |

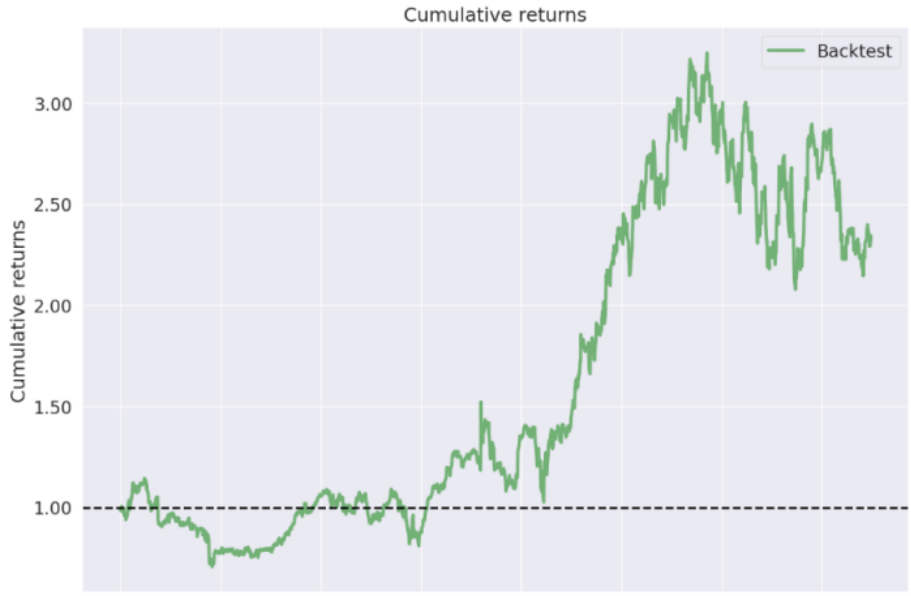
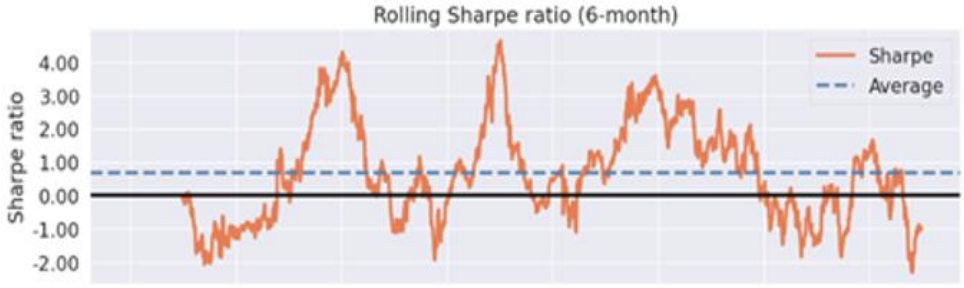



**Figure 5.** Traditional portfolio cumulative returns.

Figure 6(a) shows the rolling Sharpe ratio peak (above 4.00) in the early and mid-term, with slight fluctuations in the later period, often falling below 0. In addition, the average Sharpe ratio is also less than 1. Figure 6(b) shows that 2017 to 2018, 2020 and 2023 have seen more severe undervaluations of assets below their initial market capitalization. In 2017, below-market assets accounted for 40% of the portfolio, suggesting greater asset declines during this period.




(a) Rolling Sharpe ratio




(b) Underwater plot

**Figure 6.** Traditional portfolio rolling Sharpe Ratio and the underwater plot.

### 3.3. Mixed Stock Portfolio

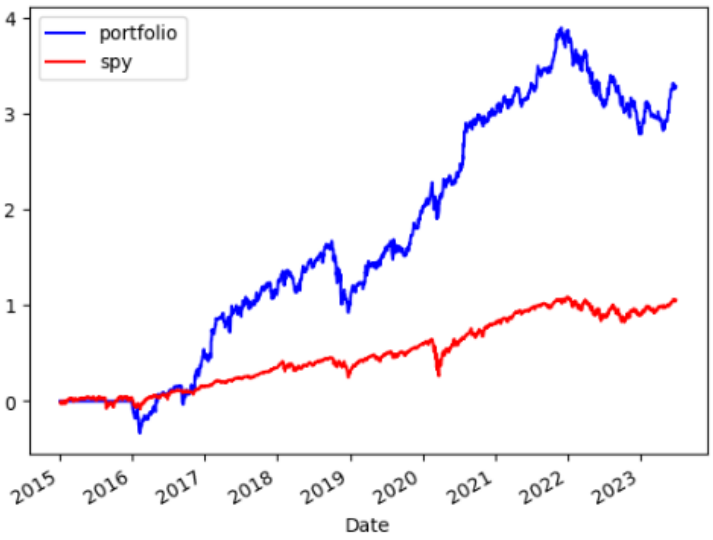



**Figure 7.** Mixed stock portfolio return.

**Table 3.** Mixed stock portfolio result.

| | |
|---|---|
| Start date | 2015-12-31 |
| End date | 2023-6-29 |
| Total months | 89 |
| | Backtest |
| Annual return | 40.1% |
| Cumulative returns | 1145.6% |
| Annual volatility | 45.0% |
| Sharpe ratio | 0.97 |
| Calmar ratio | 0.56 |
| Stability | 0.85 |
| Max drawdown | -71.7% |
| Omega ratio | 1.19 |
| Sortino ratio | 1.46 |
| Skew | 0.17 |
| Kurtosis | 5.10 |
| Tail ratio | 1.15 |

In Figure 7, the portfolio's annualized return is 40.1%. The cumulative return is 1145.6%. The portfolio's annualized volatility is 45.0%, showing the range of price changes. The Sharpe ratio is 0.97 (see Table 3), which is less than 1, meaning the diversity is not very good. The Calmar ratio is 0.56, indicating higher risk. The largest decline in the portfolio's history was -71.7% for the portfolio. The Omega ratio is 1.19, which is greater than 1, indicating higher volatility than market levels and higher risk. A Sortino ratio of 1.46 means that taking 1 unit of downside risk can result in 1.46 units of return. The skewness is 0.17, indicating that the portfolio is relatively symmetrical with only a slight leftward bias. The kurtosis is 5.10, i.e. the shape of the returned distribution is much steeper than the normal distribution. 1.15 is more likely to be in the left tail. The daily risk value describing the maximum loss that may be faced each day is -5.5%.

In Figure 8, the cumulative return performance of hybrid stocks is similar to that of technology stocks. The initial value of the portfolio is around 0.00, indicating no gains or losses. The portfolio's highest point on the timeline was over 25.00, indicating a cumulative return of 2500%. This means that if the initial investment is $100, then at this point, the investment is worth $2,500.

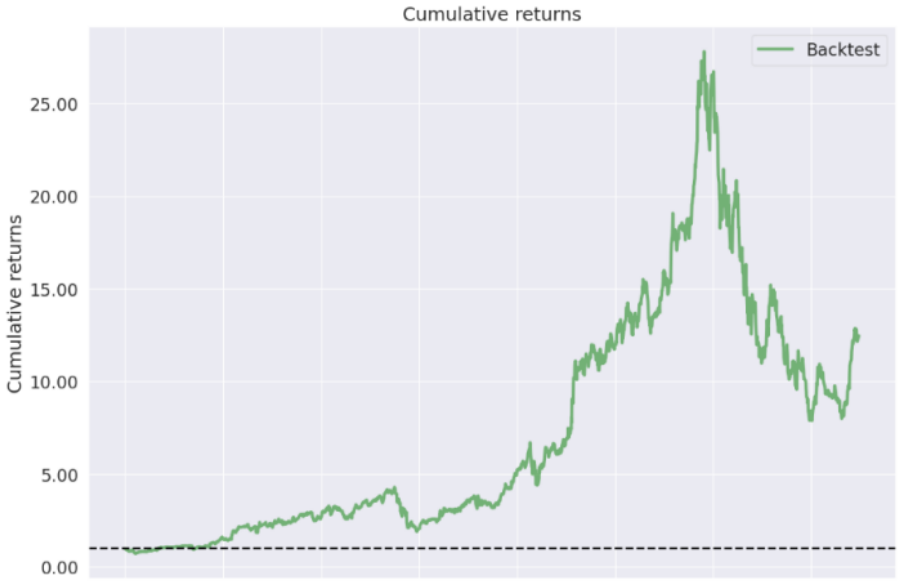
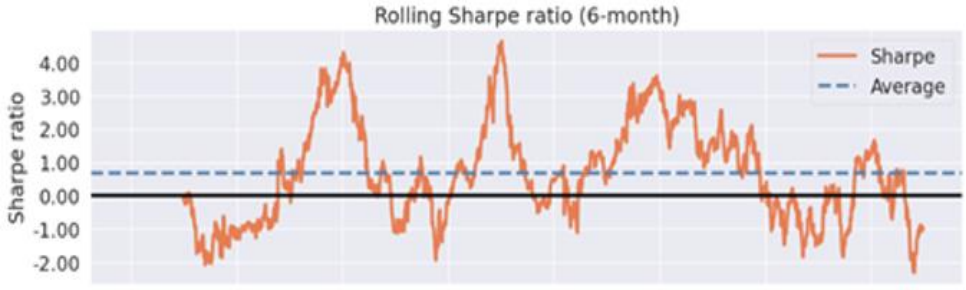



**Figure 8.** Traditional portfolio cumulative returns.

Figure 9(a) shows that the rolling Sharpe is milder than the volatility, mostly above the average ratio, with only a few cases where it is below 0. Furthermore, the average Sharpe ratio is close to 1. Figure 9(b) shows that the market capitalization of parts of the portfolio falls slightly below the initial market capitalization on a given day, with this only becoming more pronounced in 2019 and 2023, with a larger proportion of market capitalization being lost.




(a) Rolling Sharpe ratio




(b) Underwater plot

**Figure 9.** Traditional portfolio rolling Sharpe Ratio and the underwater plot.

The experiment used data from January 1, 2015, to June 30, 2023, and created three portfolios (Technology, Traditional, and Hybrid) with stocks in the S&P 500 Index. Each portfolio contains 30 stocks and is selected by industry category.

A "forward walking machine learning model" was chosen in the experiment. This model is different from traditional machine learning because it is more suitable for dynamic market changes. This section can give the final results of the experiment, including simulation of portfolio performance. Results include forecasts for technology, traditional and hybrid portfolios, each with an assigned alpha value.

This hybrid portfolio combines technology elements with traditional investment portfolios. A technology portfolio focuses solely on information technology stocks, whereas a traditional portfolio may include a more diverse range of sectors. This difference in composition can significantly affect the risk-return profile of each portfolio.

Use metrics such as maximizing returns and minimizing volatility. These metrics are critical to understanding how each portfolio performs under different market conditions. These notebooks may contain code for calculating these metrics, allowing direct comparison of performance between hybrid, technology, and traditional portfolios.

When comparing these three investment approaches, it can be seen that the all-tech portfolios have much higher annualized returns and cumulative returns than the all-traditional stock portfolios and the hybrid portfolios, but they also have higher annualized returns Volatility, which means greater risk. A higher Sharpe ratio indicates that returns are higher when risk is taken into account. The largest declines give investors a perspective on potential losses. While the entire traditional stock portfolio provides total cumulative returns and low volatility, this may indicate a relatively conservative investment strategy.

If it follows typical financial metrics and normal market conditions, a blended portfolio may offer a moderate risk/reward ratio. An all-tech portfolio may have the highest returns during certain periods, but will also have higher return risk. An all-traditional stock selection portfolio may be the most conservative, but has lower returns and lower risk. When making a decision, if investors prefer riskier stocks and higher returns, an all-tech portfolio may be the first choice. On the other hand, if an investor prefers a stable and low-risk investment, then an all-traditional stock portfolio may be a more suitable choice. Mixed portfolios offer a middle-of-the-road option with moderate risk and reward.

### 3.4. Cumulative Return vs. Hold Cycle Return

In the portfolio simulation and back testing sections, both the blue and green lines in the results graph represent the portfolio's returns. However, their trends are slightly different, as shown in Figure 3 and Figure 4. This difference can be attributed to the use of two different methods to calculate returns, as shown in the code. The blue line represents the cumulative return obtained through Accumulation, while the green line represents the holding period return calculated using Accumulation.

Cumulative income refers to the total income within a period of time, which can be calculated using "fuyu". “Cumsum” adds the returns at each point in time to obtain the total return for the entire time period. Cumulative return is expressed as a percentage and is the raw mathematical return calculated from:

$$\text{Cumulative return} = \frac{\text{Current Price of Security} - \text{Original Price of Security}}{\text{Original Price of Security}} \quad (1)$$

Holding period return, on the other hand, refers to the total return of an investment over a specific holding period. It can be calculated using "cumprod" where the returns at each point in time are multiplied together to get the total return over the holding period. The annualized HPR for holding period returns and multi-year returns can be calculated as follows:

$$\text{Holding Period Return} = \frac{\text{Income} + (\text{End of Period Value} - \text{Initial Value})}{\text{Initial Value}} \quad (2)$$

The calculation of cumulative returns assumes a constant principal. Thus, an investment's cumulative return is the total amount gained or lost by an investment over time, regardless of the investment's duration. Holding period returns, on the other hand, assume that principal increases over time. This results in exponential growth in holding period returns and relatively flat growth in cumulative returns. If it only takes the information from the trend in the chart, then in the short term, holding period returns appear to be better than cumulative returns.

## 4. Conclusion

The main goal of this article is to study the investment strategies of technology stocks and traditional stocks, focusing on investor selection and risk management. It explores three portfolio strategies: technology stocks, traditional stocks, and a mixture of the two. The study leverages machine learning, using a "walking machine learning model" to predict movements in these portfolios. Adapt to dynamic markets. The report analyzes the performance of these portfolios using a variety of financial metrics, discusses their risk-reward profile, and provides insights for investors with varying risk appetites. Finally, cumulative returns are compared to holding period returns, providing a nuanced view of investment results.

Based on the above research content, it is recommended that investors' choice of investing in technology stocks and traditional stocks should be guided by risk tolerance and investment objectives. Technology stocks offer higher growth potential, but with increased volatility, making them suitable for risk-tolerant investors looking for higher returns. Traditional stocks are more stable but have lower growth, catering to risk-averse investors who prioritize safety over high returns. Using machine learning models for dynamic portfolio adjustments highlights the importance of remaining adaptable in changing market conditions. This approach can help investors strike a balance between growth and stability, optimizing investment results based on personal risk appetite.

This paper demonstrates its broad scalability and practical application value. On the one hand, with the rapid progress in the field of artificial intelligence, especially machine learning technology, the ML-AC model combined with the latest machine learning technology will continue to innovate investment strategies, and can make innovative adjustments to the strategy based on actual market trading needs. On the other hand, due to the rapid growth in data volume, the data features used to predict portfolio weights can be further expanded to include non-traditional data features such as text and video, as well as features of other related assets such as bonds and options, to adapt to the needs of the artificial intelligence era. Wealth management and portfolio selection needs.

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