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Investment Weightings of Technology and Traditional Stocks: Investor Choice and Risk Management

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Abstract. In the era of big data, the financial landscape is undergoing transformative changes through the integration of advanced technologies. This research delves into the dynamic realm of asset portfolios within the information technology industry, traditional sectors, and amalgamated portfolios containing popular giant stocks. Employing Python and machine learning, the study focuses on predicting expected returns, comparing and analyzing diverse portfolios to identify optimal investment strategies for risk management. Evaluation metrics include annual return, annual volatility, Sharpe ratio, and statistical charts. The findings highlight the lucrative potential of investing in the information technology sector, revealing an impressive annual return rate of 40.1%. In contrast, traditional industry portfolios not only underperform but also exhibit high-risk profiles and diminished returns. This research underscores the critical role of technological advancements and data-driven methodologies in shaping contemporary financial strategies for robust portfolio management. his research advocates for the strategic incorporation of technology-driven insights in financial decision-making, emphasizing the significant outperformance potential of information technology portfolios in navigating the complexities of modern investment.

1 Introduction

During this age of constant development in the financial markets, quantitative trading has become a common practice. For example, in their study conducted in 2019, Chakrabarty and Biswas employed the strategic Markowitz portfolio optimization approach to construct a portfolio using the stock performance of eight companies [1]. The outcome yielded favorable investment returns. Investors also tend to use quantitative method to allocate their investment. According to the research of Goodell et al., the integration of AI and ML is fundamentally reshaping the landscape of trading and investment choices [2]. The quantitative portfolio allocation which is based on machine learning is gradually accepted by the investors.

In the finical industry, AI is widely used to manage portfolio. Beccalli et al. used AI to manage portfolio and discuss the ethics problems [3]. What's more, Nawrocka used neural networks for portfolio creation and trading strategies [4]. Even in 2002, Chan et al. applied artificial intelligence to portfolio management [5]. Therefore, using artificial intelligence for portfolio research has become a trend and hot topic.

During this research, researchers has divided random stock data into three groups as three different types of portfolio strategies. These three sets of data respectively include the following types of stocks: 30 traditional stocks, 30 technology stocks and a hybrid strategy of 30 traditional and technology stocks. The primary goal is to identify a suitable investment strategy, with the central challenge revolving around predicting the movements of the three stock portfolios [6]. In this research, machine learning will be employed to ascertain the optimal weights for the stocks.

2 Methodology

This section primarily focuses on presenting the experimental code, comprising four components: Data, Model, Portfolio Construction, and Portfolio Simulation. As mentioned earlier, the experimental data spans from January 1, 2015, to June 30, 2023, and is segmented into three portfolios: technological, traditional, and mixed. Each portfolio consists of 30 randomly selected stocks from the S&P500. The technological portfolio specifically encompasses stocks from the 'Information Technology' industry as categorized by S&P500. The traditional portfolio encompasses various traditional industries, such as industrials, healthcare, financials, materials, and others. All selections within this category are made randomly and are cross-checked by human review to ensure the absence of any controversial enterprises regarding industry classification. Examples include Google, Amazon, and Tesla, which are confirmed through human verification.

As for the "Mixed" portfolio, it consists of 20 randomly selected stocks from various industries, with an additional inclusion of 10 hot stocks to simulate fund manager selection. The list of hot stocks includes codes like NVDA, TSLA, QCOM, MSFT, NFLX, ADBE,

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AMD, AMZN, GOOG, and META. Following the data handling phase, the next step is the Model component.

The research team opted for the "Walking Forward Machine Learning Model." The walk-forward approach differs somewhat from traditional machine learning and may prove more fitting for dynamic market changes in terms of its modelling. In each iteration, the walking forward model is trained on known historical data and subsequently applied to predict the next time point or period. The actual results are then disclosed, and the model is updated with this new data before making the subsequent prediction. This process simulates real-time application, mirroring a scenario where each prediction is generated after the model has observed the latest data [7]. Nevertheless, traditional machine learning cross-validation proves unsuitable for the dynamic nature of the market due to several reasons. Firstly, in conventional machine learning, the dataset is typically divided into a training set and a test set. The model is trained on the entire training set and then assessed on the test set. Secondly, the model is trained only once on the training set without any simulation of model updates upon encountering new data. In essence, the fixed dataset and one-time training of traditional cross-validation methods make them ill-suited to adapt to market changes. For model fitting the team used Ridge regression. This kind of regression is an extension of linear regression that solves the problem by adding a regularization term to the cost function (loss function). The goal of Ridge regression is to minimize this cost function. The inclusion of regularization encourages the model to favor smaller parameter values during the data fitting process, effectively minimizing the risk of overfitting [8]. Through the manipulation of the regularization parameter alpha, experiments gain the ability to regulate the model's sensitivity to regularization.

Next part is about Portfolio Construction. It primarily delves into convex optimization problems utilizing the CVXPY library for portfolio optimization. The team configured the problem to maximize portfolio return while minimizing portfolio volatility. Moreover, the optimal weights derived from the convex optimization problem are applied to ascertain the optimal weights at the current time point. In essence, convex optimization is employed to dynamically calculate the weights of various assets, leveraging predicted returns and the covariance matrix.

3 Empirical results

Historical data for these stocks is downloaded using the “yfinance” library and the returns of these stocks are calculated and forecasted using the rolling window method.

The graphical results are mainly: (1) Calculate the return of the portfolio and plot the cumulative return curve. (2) Output the portfolio backtesting results using the “pyfolio” library.

3.1 Tech-stock portfolio

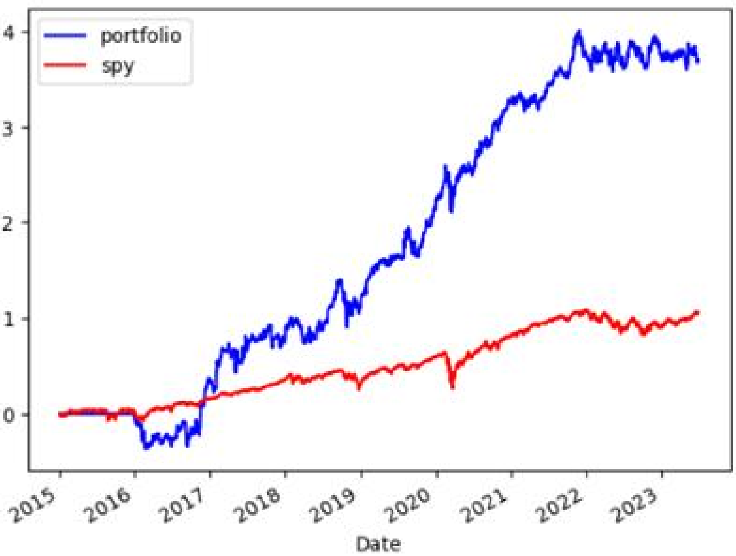

Fig. 1. Tech-stock portfolio return (Photo/Picture credit: Original).

In Figure 1 and Table 1, several key metrics are evident. The strategy demonstrates an annualized return of approximately 45.5%, while the total portfolio achieves a cumulative return of about 1,558.4% over the specified period. The portfolio's volatility is around 48.8% per year, indicating a potential monthly return fluctuation within a range of ±48.8%. The Sharpe ratio stands at 1.01, implying that the return per unit of risk taken surpasses the assumed risk-free rate (considered as 0%) by a factor of approximately 1.01 [9]. The Calmar ratio is 1.04, signifying that the investment return exceeds the risk-free rate plus one standard deviation of 4%. The maximum drawdown reaches a low of -43.7%, indicating a decline of 43.7% at its lowest point during this period. The maximum loss from a market peak to a market nadir, commonly called the maximum.

Table 1. Tech-stock portfolio result.

	Backtest
Annual return	40.1%
Cumulative return	1,558.4%
Annual volatility	48.8%
Sharpe ratio	1.01
Calmar ratio	1.04
Max drawdown	-43.7%
Omega ratio	1.20
Sortino	1.51
Kurtosis	5.88
Tail ratio	1.05
Daily value at risk	-6.0%

Drawdown (MDD), measures how sustained one's losses can be [10]. The Omega ratio is 1.20, suggesting an expected excess return of 120 basis points (or 1.2%) annually for the portfolio. The Sortino ratio is 1.51, meaning the portfolio's return on each unit of downside risk taken surpasses the risk-free rate plus 1.51 standard deviations. The portfolio exhibits no significant bias, as its skewness is close to zero. With a kurtosis of 5.88, its return distribution is considerably flatter than a normal distribution. The tail ratio is 1.05, indicating a slight right-skewness at the top of the return distribution. The portfolio's daily value at risk is -6.0%, suggesting an expected probability of a 6% loss under normal market conditions.

Fig. 2. Tech-stock cumulative return (Photo/Picture credit: Original).

Figure 2 illustrates the cumulative return over time, representing the total return of the investment or portfolio as time passes. This graph is useful for evaluating how well an investment performs, comparing different strategies, and analyzing the relationship between risk and return. According to the graph, the portfolio starts with an initial value of around 0.00 on the time axis, indicating no profit or loss initially. The highest point on the graph, situated beyond 25.00 on the time axis, reflects a cumulative return of 2500%. To put it simply, if the initial investment was $100, the portfolio would be valued at $2500 at that specific point in time. This visual representation provides a clear picture of how the investment evolves over the specified timeframe.

Figure 3(a) is rolling Sharpe Ratio (6 months): this is a line graph showing the Sharpe Ratio recalculated over 6 months. The portfolio's risk varies and reaches a peak (approximately 5.00) in the later months of the year, suggesting a gradual improvement in the portfolio's risk-adjusted return. Moreover, the average Sharpe ratio consistently exceeds 1.

Figure 3(b) is the percentage of underwater area, showing the portion of the portfolio's market value on a given day that is less than the initial market value. This chart aids in assessing the maximum decrease in the portfolio's value over time and quantifying the losses at different percentage levels. In the timeframe from 2022 to 2023, the portfolio experienced a more significant decline, exceeding 40%, and this decline persisted for an extended duration with substantial decreases.

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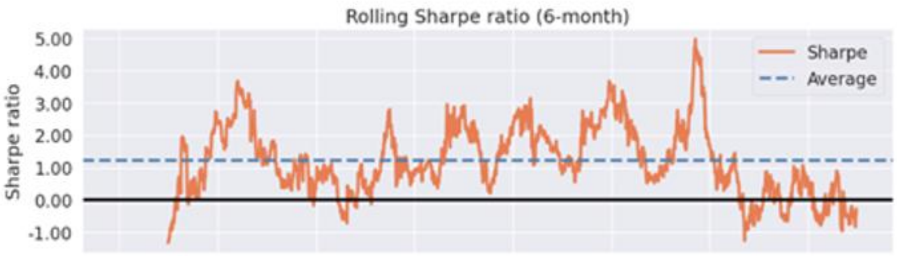
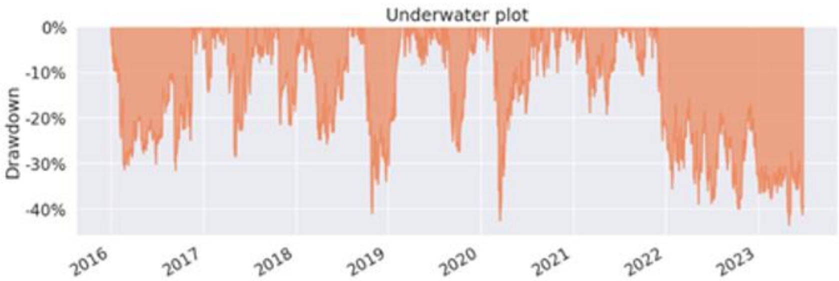


(a) Rolling Sharpe ratio



(b) Underwater plot
Fig. 3. Tech-stock rolling Sharpe ratio and the underwater plot (Photo/Picture credit: Original).

3.2 Traditional stock portfolio

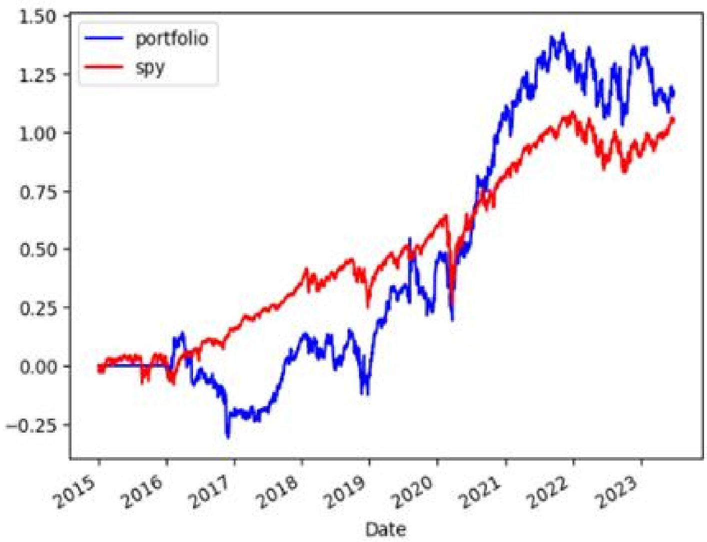


Fig. 4. Traditional stock portfolio return (Photo/Picture credit: Original).

Table 2. Traditional stock portfolio result.

	Backtest
Annual return	12.0%
Cumulative return	134.3%
Annual volatility	29.5%
Sharpe ratio	0.53
Calmar ratio	0.31
Max drawdown	-38.3%
Omega ratio	1.10
Sortino	0.80
Skewness	1.01
Kurtosis	18.90
Tail ratio	1.01
Daily value at risk	-3.7%

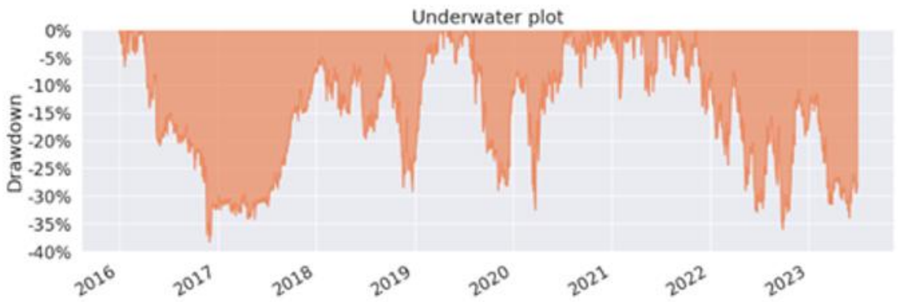
In Figure 4 and Table 2, the portfolio shows an annualized return of 12.0%. This implies that if someone had invested in this portfolio since December 31, 2015, the annual return on investment would have been 12.0%. As of June 29, 2023, the cumulative return for the portfolio is 134.3%. The annualized volatility is 29.5%, suggesting that the portfolio's prices have experienced higher fluctuations during this period, indicating a greater level of risk. The Sharpe ratio is 0.53, meaning that for every 1 unit of risk assumed, the portfolio earns an additional 0.53 units of return. The max drawdown, at -38.3%, represents the most significant loss the portfolio faced over the past few years. An Omega ratio of 1.10 indicates the excess return the portfolio has generated while enduring certain losses. The fact that it's greater than 1 suggests higher volatility compared to market levels and increased risk. The Sortino ratio of 0.80 indicates that the portfolio earns a higher excess return when exposed to a unit of downside risk. A skewness of 1.01 suggests a positively skewed return distribution, implying a longer right-hand tail and the possibility of some extreme positive returns. The kurtosis of 18.90 indicates a return distribution much steeper than the normal distribution. The tailed ratio of 1.01 suggests a slightly higher probability of the portfolio's return distribution being in the left tail compared to the normal distribution. The daily value at risk of -3.7% signifies the maximum potential daily loss the portfolio could incur.

Fig. 5. Traditional portfolio cumulative returns (Photo/Picture credit: Original).

In Figure 5, the portfolio starts with an initial value of 1.00. The peak on the time axis reaches 3.00, signifying a cumulative return of 300%. To put it differently, if the initial investment were $100, the portfolio's value at this specific point would be $300.

Figure 6(a) shows the rolling Sharpe ratio peaks (above 4.00) during the early and middle periods, fluctuating slightly in the later periods and frequently dipping below 0. Additionally, the average Sharpe ratio is less than 1. Figure 6(b) demonstrates a greater occurrence of assets declining below their initial market value in the years 2017, 2018, 2020, and 2023. Notably, in 2017, assets below the market value constituted 40% of the portfolio, indicating a more substantial decline during that particular period.

(a) Rolling Sharpe ratio



(b) Underwater plot

Fig. 6. Traditional portfolio rolling Sharpe ratio and the underwater plot (Photo/Picture credit: Original).

3.3 Mixed stock portfolio

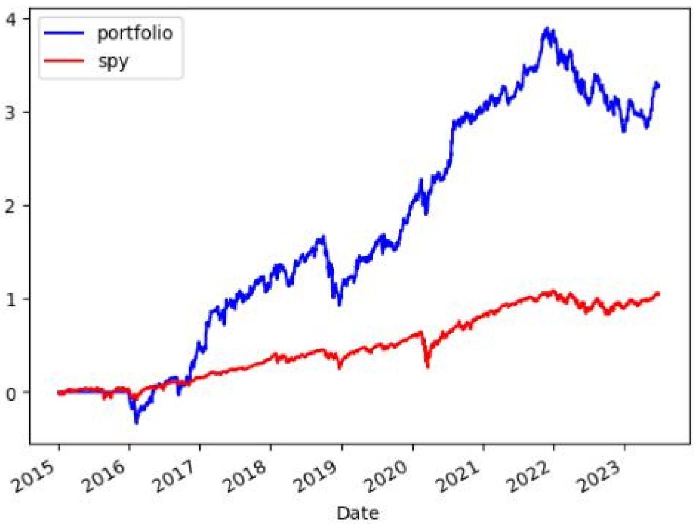


Fig. 7. Mixed stock portfolio return (Photo/Picture credit: Original).

Table 3. Mixed stock portfolio result.

	Backtest
Annual return	40.1%
Cumulative return	1145.6%
Annual volatility	45.0%
Sharpe ratio	0.97
Calmar ratio	0.56
Max drawdown	-71.7%
Omega ratio	1.19
Sortino	1.46
Skewness	0.17
Kurtosis	5.10
Tail ratio	1.15
Daily value at risk	-5.5%

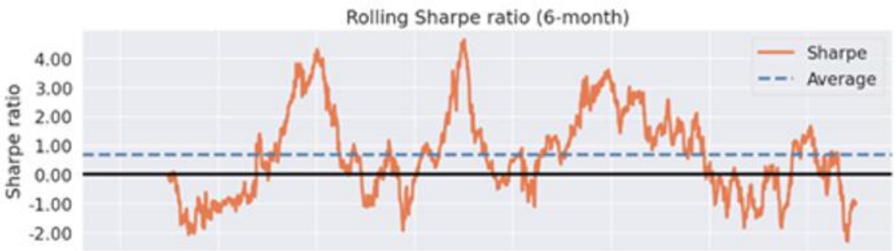
In Figure 7 and Table 3, the portfolio has an annualized return of 40.1%. The cumulative return is 1145.6%. The extent of the portfolio's annualized volatility is 45.0% showing the range of price changes. The Sharpe ratio is 0.97 which is smaller than 1 and means the diversity is not very well. The Calmar ratio is 0.56, indicating a higher risk. The max drawdown which is the largest decline in the portfolio's history, is -71.7% in this portfolio. The Omega ratio is 1.19 which is bigger than 1, indicating higher volatility than market levels and higher risk. 1.46 of the Sortino ratio means that taking 1 unit of downside risk can result in a return of 1.46 units. The skewness is 0.17, indicating the portfolio is relatively symmetrical and only slight leftward deviation. The kurtosis is 5.10 meaning that the shape of the return distribution is much steeper than normal. The tail ratio of 1.15 has a higher probability falls in the left tail rather. The daily value at risk that describes the maximum loss could face per day is -5.5%.

Fig. 8. Mixed portfolio cumulative returns (Photo/Picture credit: Original).

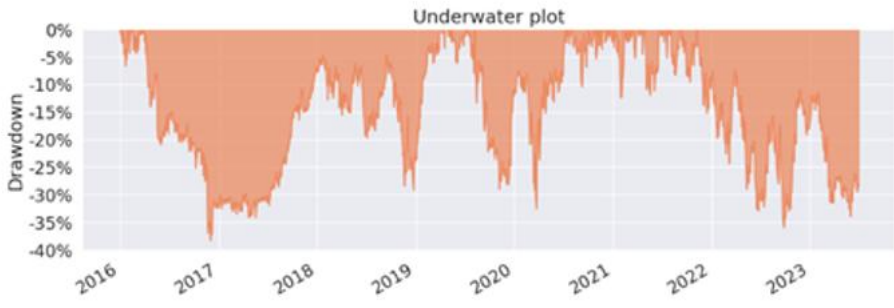
In Figure 8, the manifestation of cumulative return of the mixed stock is similar to that of tech-stock. The initial value of the portfolio is around 0.00, indicating no gain or loss. The highest point of the portfolio on the time axis is over 25.00, indicating a cumulative return of 2500%. This means that if the initial investment was $100, then at this point in time, the investment is worth $2500.

Figure 9(a) shows that the rolling Sharpe ratio fluctuates more gently, for the most part above the average ratio, with only a few instances where it falls below 0. In addition, the average Sharpe ratio is close to 1.

Figure 9(b) shows that the portion of the portfolio's market capitalization on a given day that is lower than the initial market capitalization is small, and only in 2019 and 2023 is the situation more pronounced, with a larger portion of the market capitalization loss.



(a) Rolling Sharpe ratio



(b) Underwater plot

Fig. 9. Mixed stock portfolio rolling Sharpe Ratio and the underwater plot (Photo/Picture credit: Original).

3.4 Comparison

The results include predictions of the technical, traditional, and mixed portfolios, each with a specified alpha value. This part will focus on analyzing and comparing the differences between the three results.

The first portfolio which needs to analyze is tech-portfolio. From the Graph 1, it has shown numerous useful information. From a temporal standpoint, the tech portfolio did not initially outperform the SPX500. However, two years later, it experienced explosive growth that far surpassed the market. This trend persisted until 2021 before showing signs of slowing down. In the last three years, the market exhibited fluctuations. Solely based on visual observations, the tech portfolio appears to be an outstanding investment at the moment. Table 1 reinforces this perspective, indicating an annual return rate of 40%, a cumulative return rate of 1558%, and an average Sharpe ratio of 1.01. Furthermore, Graph 3 illustrates numerous instances where the Sharpe ratio exceeds 4. Despite an annual volatility of 48.8%, most of the fluctuations, as depicted visually, are positive and consistently increasing. However, it's crucial to note that the maximum retracement has reached 43.7%, and the Daily Value at Risk has peaked at 6%. In summary, the tech portfolio represents a high-risk, high-reward investment.

The second portfolio which needs to analyze is traditional portfolio. Evaluating the statistical charts, the performance of the traditional portfolio appears less promising, as it consistently falls short of outperforming the market. It took six years from the outset to marginally surpass the market. During most of this period, its performance lagged behind, dealing a significant blow to investor confidence. It's highly likely that investors abandoned this portfolio a few years ago, opting instead for investments in the SPX500 index. By focusing solely on the data in Table 2, the traditional portfolio seems relatively stable, boasting a 12% annual return, a 29.5% annual fluctuation, and a maximum drawdown of only 38.3%. Indeed, when considering only these metrics, it appears more stable than the tech portfolio. However, this slight advantage in volatility comes at a cost—the cumulative return is significantly lower than that of the previous asset portfolio, and the risk remains considerable. The modest 5% reduction in the maximum drawdown results in prolonged underperformance compared to the market, with returns several times inferior to those of the tech portfolio. Clearly, the traditional portfolio exhibits high risk and low return characteristics.

The third portfolio is mixed portfolio. Considering the rate of return, the mixed portfolio stands out noticeably. Its returns are only slightly less than the first portfolio, and the Sharpe ratio has also reached 0.97. However, the portfolio's volatility and maximum drawdown rate are substantial, with the maximum drawdown even reaching 71.7%. In summary, the mixed portfolio represents a high-risk, high-return investment positioned between the tech portfolio and the traditional portfolio.

Based on the analyses of the three investment portfolios, the tech portfolio shows the highest performance according to the Sharpe ratio, followed by the mixed portfolio and, finally, the traditional portfolio.

3.5 Cumulative returns vs. holding period returns

In the section dedicated to portfolio simulation and backtesting, the returns of the portfolio are represented by both the blue and green lines in the result graphs, such as Graph 4 and Graph 5. However, their trends exhibit slight variations, which can be ascribed to the utilization of two distinct methods for calculating returns, as evident in the provided code. The blue line illustrates cumulative returns derived through "cumsum", while the green line depicts holding period returns calculated using "cumprod".

Cumulative return signifies the overall return across a specific time span and can be computed utilizing the "cumsum" function. This function adds up the returns at each time point, yielding the cumulative return over the entire designated time period.

Holding period return, on the other hand, refers to the total return over a specific holding period of an investment. It can be calculated using “cumprod”, where the returns at each time point are multiplied together to obtain the overall return over the holding period.

The computation of cumulative return presupposes a consistent principal amount. As such, the cumulative return for an investment signifies the overall gain or loss the investment has experienced over time, without considering the specific duration of the investment. In contrast, holding period return operates on the assumption of a growing principal over time. Consequently, holding period return exhibits exponential growth, while the growth of cumulative return appears comparatively subdued. Based solely on the observable trends in the chart, holding period return appears more favorable than cumulative return in the short term.

4 Conclusion

Based on the research findings, opting for an all-tech asset allocation appears to be the optimal choice given the same level of risk. Contrary to common investor beliefs, investing in traditional industries doesn't seem to translate into less risky or more stable returns; moreover, it might pose challenges for investments to outperform the market. Even a blend of technology stocks, traditional industries, and currently popular technology giants, as seen in the mixed portfolio, did not achieve the anticipated level of stability in fluctuations, despite yielding substantial returns. These outcomes serve as a reminder for investors to consider industries with promising development prospects. Simultaneously, the existence of traditional portfolios underscores that elevated risks do not necessarily equate to higher returns. Investors should use a cautious attitude and scientific concepts to make investments based on the market environment.

An inherent assumption in the code section involves liquidating all assets at the close of each month and reconstructing the portfolio at the start of the month. This practice is infrequent in actual trading scenarios, potentially introducing bias to the predictions. When computing the covariance matrix, it simplifies the model by abstracting it from the training data, utilizing the entire dataset instead. If the model were optimized using solely the training data, it might yield different outcomes.

Regarding the choice of asset portfolio data, relying solely on the information technology industry for constructing the tech-portfolio may seem somewhat limited. It would be beneficial to include recently popular AI-related companies, as certain entities excel in AI applications without being classified under the information technology industry—Tesla being a notable example. Moreover, given the random selection of companies, including numerous traditional industries, there is a challenge in ensuring the exclusion of companies from declining traditional sectors. This potential inclusion might adversely impact the performance of the traditional portfolio or mixed portfolio.

Although this study reveals the investment results for different types of portfolios, it also has some limitations and shortcomings. If research can classify the investment industries more carefully, set up more control groups and change the machine learning algorithm, paper may get more results. In addition, it is hoped that machine learning can be more widely used in related research.

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