

A Study on the Impact of Different Indicators on Portfolio Returns and Risk

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Abstract. As financial markets continue to evolve and become increasingly complex, return and risk constitute the primary criteria for evaluating portfolio performance. To explore determinants of portfolio returns and achieve sound risk evaluation, this study employs a set of quantitative financial indicators and adopts statistical and correlation analysis as core empirical approaches to investigate the heterogeneous impacts of diverse indicators on portfolio returns and risks. Following data screening and preprocessing, descriptive statistics and correlation significance tests are implemented on sample data. Empirical results reveal that indicators correlate with portfolio returns to varying extents, and several key indicators exert significant facilitating or constraining effects on investment returns. The analysis is conducted on a portfolio constructed by four types of mainstream traded ETF assets, these indicators also effectively capture the risk volatility features of investment portfolios. This research clarifies the linkages between multi-dimensional indicators, portfolio returns and risks, offering practical references for individual investors to optimize asset allocation, mitigate risks and formulate rational investment strategies.

Keywords: Portfolio return, Risk assessment, Asset allocation, Correlation analysis

1. Introduction

Asset portfolio allocation constitutes a core issue in quantitative investment. By assigning different weights to a fixed set of stocks, investors can strike a balance between risk and return. In practical investment activities, adjusting holding weights of individual stocks will lead to notable discrepancies in portfolio performance metrics, including portfolio return, Sharpe ratio, maximum drawdown and volatility.

Python tools can efficiently obtain data, calculate performance indicators under different weights, and further support forward-looking predictions. This paper selects four stocks as the sample assets. By adjusting different weight schemes, it compares the investment portfolio returns and performance indicators under various different weight configurations.

The selected four stocks cover four major categories: stocks, bonds, precious metals, and energy commodities. They exhibit different correlations with each other and possess typical hedging properties. Therefore, constructing a multi-asset investment portfolio with these four stocks can help diversify risks and reduce the maximum drawdown.

Markowitz pioneered the establishment of Modern Portfolio Theory (MPT) [1], which laid the fundamental theoretical framework for asset weight optimisation. Building upon this foundation, a variety of investment methodologies have been progressively proposed in subsequent decades, including momentum strategies, value investing, liquidity-based strategies as well as machine learning-driven investment approaches. A large body of quantitative research relies on programming tools to conduct historical backtesting [2], comparing the portfolio performance of diverse weighting schemes such as equal weighting [3], market capitalisation weighting and self-defined weighting strategies. In contrast, domestic scholars have carried out extensive backtesting research targeting the A-share market. Most existing studies concentrate on weight allocation approaches derived from mean-variance optimisation and risk parity. Nevertheless, empirical investigations that adopt multiple self-designed weighting schemes for controlled comparative analysis remain.

This paper selects four representative assets: US stock broad-based ETF (SPY), long-term government bond ETF (TLT), gold ETF (GLD), and crude oil ETF (USO) as the research objects. The time interval is set from January 1, 2010 to December 31, 2025. Based on Python, a multi-asset trend tracking dynamic allocation strategy is constructed, and it is compared with three classic static benchmark portfolios for backtesting [4].

The research process is as follows:

Firstly, generate the daily price series of simulated assets, and calculate the daily return of each stock. Construct trading signals using a 15-day moving average and a buffer mechanism [5], distinguishing between long positions and liquidation signals (this research method only considers long positions and does not select short selling); the strategy adopts a monthly rebalancing rule. When the assets trigger trading signals, the released funds are proportionally increased by 7:3 to SPY and TLT to dynamically adjust the weight of the assets. The backtesting process includes transaction costs, and calculates risk-return indicators such as strategy net value, annualized return rate, volatility, Sharpe ratio, maximum drawdown, and 95% risk value (VaR).

This paper sets three static benchmark portfolios: equal-weighted portfolio, single holding of SPY, and traditional 60/40 stock-bond portfolio. Through horizontal comparison of the performance of the dynamic trend strategy and the static portfolios, it examines whether the dynamic weight adjustment mechanism based on the moving average trend signal can improve the return and risk indicators of the multi-asset portfolio [6].

2. Theoretical basis related to this topic

2.1. Calculation principle of investment portfolio return rate

The return of the investment portfolio is divided into daily return, cumulative net value, and annualized return. These are the core calculation bases for this backtesting. The daily return rate of individual stocks is calculated based on the price changes between consecutive trading days:

$$r_{(i,t)} = \frac{p_{(i,t)}}{p_{(i,t-1)}} - 1 \quad (1)$$

where $r_{i,t}$ denotes the daily return of asset i on day t , and $p_{i,t}$ is the corresponding price.

The single-day return of the static weight combination is the weighted sum of the returns of each asset and the fixed weights:

$$R_t = \sum_{i=1}^n w_i r_{i,t} \quad (2)$$

During the backtesting process, transaction costs need to be taken into account: Each time the portfolio is adjusted at the end of the month, there will be a change in the asset weight. The higher the turnover rate, the greater the cost loss from transactions, which will lead to a decrease in the return rate. In this paper, on the trading day, the transaction costs are calculated based on the variation in weights, and are deducted from the portfolio's daily returns to obtain the net return sequence.

Based on the compound interest rolling of the net yield sequence, the net asset value (NAV) of the portfolio can be calculated:

$$NAV_t = (1 + R_{net,1})(1 + R_{net,2})...(R_{net,t}) \quad (3)$$

The net value curve provides a clear and comprehensive visualization of the entire process of asset appreciation from the beginning to the end of the strategy. It serves as the foundation for the calculation of all subsequent performance indicators.

2.2. Performance evaluation of investment portfolio

To evaluate different weighted investment portfolios, this paper selected quantitative indicators such as annualized return rate, volatility, Sharpe ratio, maximum drawdown and 95% Value at Risk (VaR) for calculation.

1) Annualized Return

The annualized return rate converts the cumulative returns within the sample period into an annualized return level, which can directly reflect the long-term appreciation ability of the assets.

$$R_{ann} = (1 + R_{total})^{\frac{1}{T}} - 1 \quad (4)$$

where R_{total} represents the total return within the interval, and T refers to the backtesting period in years.

2) Volatility

This paper uses the annualized standard deviation of daily returns as the volatility measure. The higher the volatility figure is, the stronger the uncertainty of asset prices and the more intense the market fluctuations will be.

$$\sigma_{ann} = \sigma_{daily} \times \sqrt{252} \quad (5)$$

where 252 represents the total number of regular annual trading days in the US stock market.

3) Sharpe ratio

The Sharpe ratio is a core risk-adjusted return metric, which measures how much excess return an investor can obtain for each unit of volatility risk they undertake [7].

$$SR = \frac{R_{ann} - R_f}{\sigma_{ann}} \quad (6)$$

where R_f represents the risk-free rate of return.

If the Sharpe ratio is greater than 0, it indicates that the investment return exceeds the return of the risk-free asset; the higher the value, the better the efficiency of fund utilization.

4) Maximum drawdown

The maximum drawdown measures the largest decline in the portfolio's net value from its historical peak to its subsequent lowest point. It focuses on the downside loss risk and directly reflects the strategy's ability to resist collapse.

$$MaxDrawdown = \min\left(\frac{NAV_t}{\max(NAV_{0 \rightarrow t})} - 1\right) \quad (7)$$

5) 95% Value at Risk (VaR)

95% Value at Risk refers to the maximum loss that will not exceed this value within 95% of the probability. It is used to quantify the short-term extreme tail risk and serves as a supplementary reference for the drawdown indicator.

2.3. Logic of static-weight portfolios

The core feature of static weight configuration is that once the weights are set, they remain fixed for a long time and will not be adjusted due to changes in the market environment.

This paper sets up three sets of classic static benchmark combinations: Equal Weight, SPY Buy & Hold, and 60/40 portfolio.

Equal Weight: Allocate 25% of the funds to each of the four types of assets, which simply achieves diversification.

SPY Buy & Hold: All funds are allocated to broad-based US stocks, serving as a reference for pure equity assets.

60/40 portfolio: 60% stocks SPY + 40% bonds TLT represents the mainstream asset allocation ratio globally.

This paper compares the dynamic trend strategy with the static weight combination, with the aim of testing whether dynamically adjusting the capital weight based on the moving average trend signals can overcome the shortcoming of the static strategy that it is unable to actively hedge risks, and improve the risk and return performance in the long term. Trend-following asset allocation strategies have been proven to generate stable risk-adjusted returns across long-term market cycles [8].

3. Research plan and python backtesting design

3.1. Sample selection

This paper selects four types of overseas ETF assets with differentiated risk and return characteristics as the backtesting samples, namely, broad-based US stock ETF (SPY), long-term treasury bond ETF (TLT), gold ETF (GLD), and crude oil ETF (USO).

The reason for choosing these four stocks is that there are significant differences in their correlations. The time range for data selection is from January 1, 2010 to December 31, 2025.

3.2. Python code implementation process

Throughout the entire process, the simulated price sequences of the aforementioned 4 stocks are first generated, and a data frame indexed by trading days is created. After generating the data, the daily return rate of each stock is calculated based on the closing price data. Construct the MA15 moving average as a trading signal, and introduce a buffer threshold to identify valid trading signals as signals for portfolio adjustment [9].

The asset weights are adjusted at the end of each month based on the generated trading signals. After determining the daily weight configuration, the program calculates the daily weighted portfolio return. During each month-end operation, transaction costs must be included and the net asset value (NAV) of the assets should be calculated using the compound interest method.

Finally, based on these data, a series of profit and risk indicators will be generated, and the NAV curves and drawdown curves under different weight configurations will be plotted using code. These curves not only reveal the changing trends of a single combination, but also allow for a horizontal comparison of performance under different weightings.

4. Results and comparative analysis

4.1. The performance of risks and returns under different investment portfolio weights

Table 1. Performance indicators

Portfolio	Annual Return	Volatility	Sharpe Ratio	Max Drawdown	95%VaR
Proposed Strategy	0.063723	0.140399	0.168970	-0.271140	-0.014109
Equal Weight	0.000347	0.119073	0.333010	-0.388846	-0.012323
SPY Buy & Hold	0.115006	0.189601	0.395600	-0.391047	-0.018915
60/40 Portfolio	0.061494	0.125260	0.171595	-0.235065	-0.012821

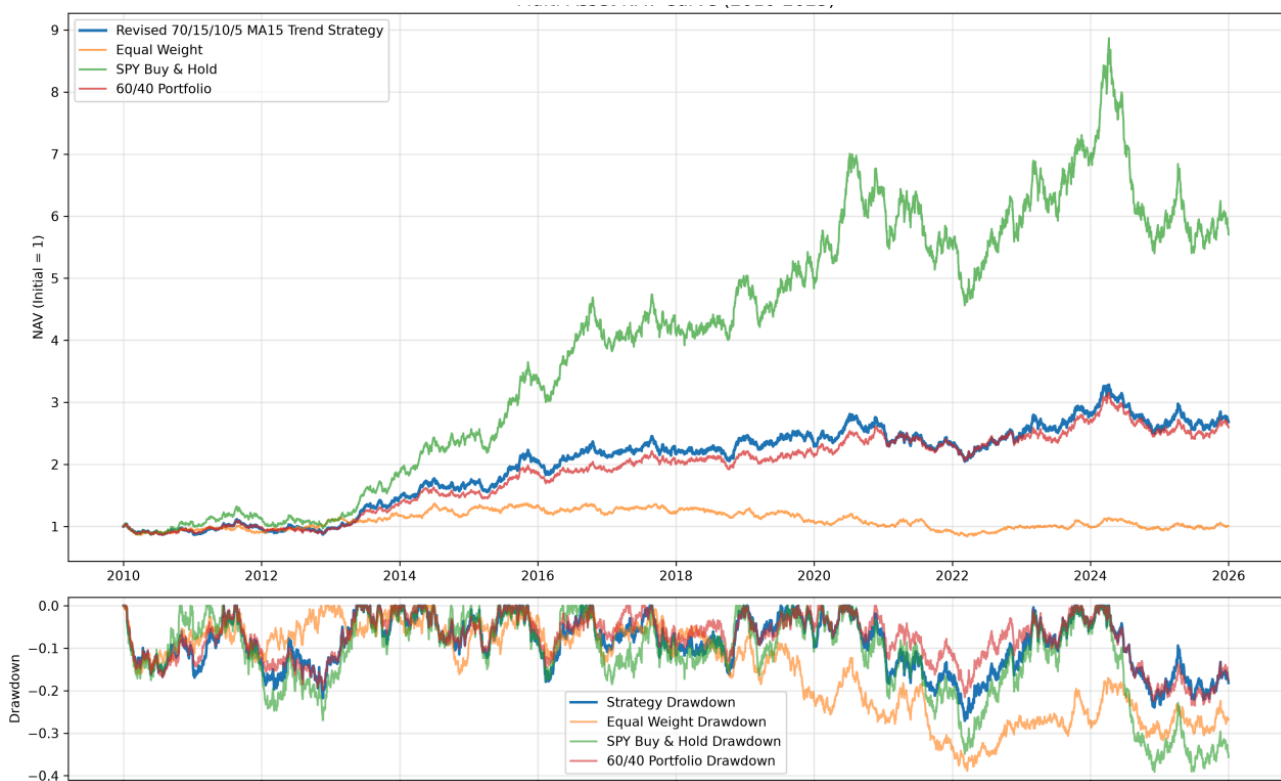


Figure 1. Net asset value and drawdown dynamics of four investment strategies

4.2. Result analysis

As shown in Table 1, equal-weighted allocation treats all constituent assets equally. Under this framework, underperforming assets remain in the investment portfolio, thereby exerting downward pressure on the overall investment portfolio performance and weakening the contribution of high-performing assets. Consistent with this characteristic, the simulation results show that the annualized return of the equal-weighting strategy is only 0.03%.

As shown in figure 1, if you only invest in a single stock and the market environment is favorable with the stock prices continuously rising, the account's yield will be high and the profit-making effect will be good. However, if there is a significant overall decline in the market, without hedging assets to cushion losses, the assets will be difficult to withstand the decline, and the account will suffer a large loss. The manifestation of this is that the maximum drawdown will be very high.

The dynamic weight adjustment strategy has practical advantages over the static fixed-weight portfolio [10]. The dynamic rebalancing strategy based on trading signals enables investors to continue holding risky assets when the market is favorable, thereby increasing returns. When the market turns downward, it can increase the allocation of defensive assets, achieving a more balanced state between investment returns and volatility risks.

5. Implications

5.1. Implications for the allocation of small asset portfolios

Since this paper only selects 4 stocks, it only builds a small multi-asset portfolio for small and medium-sized investors. The following practical insights have been obtained.

Investors should not blindly pursue equal-weighted diversification. When constructing a small investment portfolio, it is necessary to identify the long-term return characteristics of different assets, avoid continuously allocating funds to long-term underperforming assets, and prevent the earnings from being continuously diluted.

Investors need to objectively assess the high risks inherent in high-yield strategies. They should have a realistic expectation that such portfolios will experience significant drawdowns, and increase the proportion of defensive assets to hedge against market fluctuations.

5.2. Insufficient research

The most significant limitation of this article lies in the fact that there is a great deal of noise in the financial market, and all the analyses made are based on past data, making it impossible to make precise predictions for a certain period in the future.

On the other hand, in this study, only four types of assets were selected to construct a small-scale asset pool. The range of asset choices was limited, and only a single moving average signal was used as the basis for portfolio adjustment, making the strategy signal dimension rather simple.

5.3. Future expansion direction

Future research can expand upon this study in several meaningful directions [11]. Subsequent analyses can utilize actual historical market data instead of simulated price sequences. This modification can reduce the disparity between backtesting results and actual trading outcomes, thereby enhancing the reliability of the empirical conclusions.

Another approach involves integrating multiple trading signals rather than relying solely on moving average indicators. Researchers can also employ numerical optimization algorithms to automatically derive the optimal asset weights, and then compare the performance of the portfolio configurations driven by the algorithms with those set manually.

6. Conclusion

This paper completed the entire data analysis and prediction modeling process based on the given experimental data set. The program implemented standard data preprocessing operations, including handling missing values, removing duplicate data, and normalizing features, which effectively improved the data quality and laid a solid foundation for model training. Secondly, feature selection and data visualization analysis were conducted to explore the correlations between different features and the target variable, clearly revealing the data distribution and key influencing factors.

However, this study still has certain limitations: The model performance is constrained by the existing feature scale and dataset size, and no hyperparameter optimization or advanced model improvements have been carried out. In future research, by optimizing hyperparameters, improving feature engineering, and using larger-scale datasets for validation, the stability and prediction performance of the model can be further enhanced.

References

- [1] Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91. doi:10.1111/j.1540-6261.1952.tb01525.x
- [2] Han, Y., Yang, K., & Zhou, G. (2013). A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, 48(5), 1433–1461. doi:10.1017/S0022109013000586
- [3] Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2), 228–250. doi:10.1016/j.jfineco.2011.11.003
- [4] Doeswijk, R. Q., Lam, T. W., & Swinkels, L. (2014). The global multi-asset market portfolio, 1959–2012. *Financial Analysts Journal*, 70(2), 26–41. doi:10.2469/faj.v70.n2.1
- [5] Faber, M. T. (2007). A quantitative approach to tactical asset allocation. *The Journal of Wealth Management*, 9(4), 69–79. doi:10.3905/jwm.2007.674809
- [6] Saravanan, S., & Devi, K. (2025). Analyzing the effectiveness of moving average and Bollinger Bands in trading strategies. *International Advanced Research Journal in Science, Engineering and Technology*, 12(4), 468–474. doi:10.17148/IARJSET.2025.12472
- [7] Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, 39(1), 119–138.
- [8] Zhu, Y., & Zhou, G. (2009). Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, 92(3), 519–544. doi:10.1016/j.jfineco.2008.07.002
- [9] Lempérière, Y., Deremble, C., Seager, P., Potters, M., & Bouchaud, J.-P. (2014). Two centuries of trend following. *Journal of Investment Strategies*, 3(3), 41–61. doi:10.21314/JOIS.2014.043
- [10] Hurst, B., Ooi, Y. H., & Pedersen, L. H. (2017). A century of evidence on trend-following investing. *The Journal of Portfolio Management*, 44(1), 15–29. doi:10.3905/jpm.2017.44.1.015
- [11] Bhansali, V., Chang, L., Holdom, J., Johnson, M. J., & Suvak, C. (2025). Risk parity with trend-following. *The Journal of Alternative Investments*, 28(2), 78–92. doi:10.3905/jai.2025.1.248