Exploring Macro Factor-Driven Multi-Asset Tactical Allocation Strategies with Machine Learning

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Abstract. This study constructs a machine learning-based tactical asset allocation (TAA) framework to address the limitations of traditional strategic asset allocation (SAA) in a volatile macro environment. The study obtains macroeconomic indicators from FRED and combines Exchange Traded Fund (ETF) historical data with lagged and rolling standardization methods to avoid forward-looking bias. In this paper, ridge regression, random forest, and XGBoost prediction models are compared, and a model selection mechanism based on prediction accuracy is proposed. The results show that ridge regression is the most robust in terms of forecasting accuracy and directional consistency. Based on the forecast signal, two types of portfolio strategies are designed: the Top-N equal-weight strategy and the mean-variance optimization strategy. The empirical results show that the mean-variance optimization strategy outperforms the 60/40 benchmark portfolio in terms of risk-return performance: its annualized return rate is 15.86%, slightly higher than 15.73% of the 60/40 benchmark portfolio; The Sharpe ratio reached 1.564, up about 16.9% from 1.338 of 60/40; Volatility also decreased from 11.75% to 10.14%, significantly improving risk control. These findings verify the potential of machine learning-driven asset rotation, provide practical reference for investors and asset managers, and lay a methodological foundation for future research introducing more factors, more complex models, and cross-market validation.

Keywords: Tactical Asset Allocation; Macro Factor; Machine Learning; Ridge Regression; Mean-Variance Optimization.

1. Introduction

The global investment environment is facing multiple challenges like high inflation, monetary tightening, geopolitical conflict, and economic uncertainty, revealing the limitations of the strategic asset allocation (SAA) model [1]. The 2022 pullback of a 60/40 equity-bond allocation highlights its vulnerability, emphasizing the increasing importance of tactical asset allocation (TAA), a dynamic portfolio model.

SAA relies on long-term mean expectations and cannot ensure the timely reflection of economic cycle changes [1]. Asset classes diverge as economies switch between recovery, overheating, stagflation, and recession. If the macro cycle conversion signal can be captured and dynamically allocated, the stability and return of the portfolio will be significantly improved. Macro factors such as the term structure of interest rates, inflation, unemployment rate, and Purchasing Managers' Index (PMI) not only affect policy and earnings expectations, but also directly determine asset valuation, which helps to improve allocation foresight [2].

In practice, macro factors are often high-dimensional and nonlinear, making them difficult to translate into allocation signals through traditional linear models. Recent achievements in machine learning (ML) have shown advantages in extracting predictive information from complex macro data. Therefore, this study develops an ML framework to convert macro factors into tactical signals for dynamic asset rotation and evaluates its performance against static benchmarks.

Modern portfolio theory (MPT) underpins asset allocation by emphasizing risk reduction and return enhancement through diversification, while SAA and TAA, respectively, focus on long-term allocation and dynamic adjustment strategies [3]. Recent research shows that a TAA method based on a deep reinforcement learning model (using the A2C algorithm) achieved a Sharpe ratio of 0.406 in the investment portfolio from 2018 to 2020 and recovered its maximum drawdown within 99 days after the 2020 crash, significantly demonstrating its advantages in risk-adjusted returns and recovery efficiency [4].

Regarding the impact of macroeconomic indicators on asset pricing, research shows that interest rate, inflation, and employment data have a significant influence on asset returns [2][5]. With growing data complexity, ML has shown strong advantages in financial prediction, and studies confirm that both linear and tree models improve forecasting accuracy [6]. Chen et al. further demonstrate that their ML model achieved an out-of-sample Sharpe ratio of 2.6, compared with only 0.8 for the Fama–French five-factor model, highlighting the superiority of ML in asset pricing and portfolio optimization [7].

Despite significant progress in areas such as asset allocation, macro factor analysis, and the application of machine learning, research on comprehensive multi-factor and dynamic models remains relatively limited. Therefore, this study will explore a dynamic asset allocation model that combines machine learning with macroeconomic factors, aiming to improve portfolio risk–return balance and offer practical solutions for asset management.

The main contribution of this paper lies in establishing a comprehensive model evaluation system. It compares ridge regression, random forest, and XGBoost to build a prediction-based model selection mechanism, thereby providing a reliable model screening method for macro factor prediction. Meanwhile, this paper adopts factor lag and rolling standardization processing in methodology to avoid information leakage and ensure the reproducibility of the research. In addition, the research develops an end-to-end framework from factor processing to portfolio optimization. Finally, this paper empirically verifies the feasibility of a multi-asset rotation strategy driven in a complex macro environment through machine learning and provides investors with a forward-looking asset allocation approach.

2. Methodology

2.1. Data Description

2.1.1 ETF price data

The ETF price data used in this study were obtained from Yahoo Finance, and six representative ETFs were selected: SPDR S&P 500 ETF Trust (SPY), iShares Australia ETF (EWA), SPDR Dow Jones Industrial Average ETF Trust (DIA), Invesco QQQ Trust (QQQ), iShares MSCI EAFE ETF (EFA), and SPDR Gold Shares (GLD). The reason for choosing these ETFs is that they cover different markets and investment themes, including a wide range of US markets (SPY, DIA, QQQ), international markets (EWA, EFA), and gold (GLD), thus helping to construct a diversified portfolio. The time frame of the data is from January 1993 to November 2021[8].

2.1.2 Macroeconomic indicator data

Macroeconomic indicator data come from FRED, including key indicators such as 10-year and 2-year Treasury bond yield spread (T10Y2Y), consumer price index (CPIAUCSL), VIX index, unemployment rate (UNRATE), industrial production index (INDPRO), etc. The indicators cover monthly data from January 2000 to December 2023 to provide rich background information on the economy [9].

2.2. Data Processing

Data obtained from Yahoo Finance and FRED were cleaned to remove missing values and outliers. To make the data consistent, the daily frequency data of ETF is converted into monthly frequency data, and then ETF price data and macroeconomic indicator data are merged by date alignment. Fig. 1 presents a comparison of the performance of selected ETFs over time, covering normalized price trends, monthly return distributions, and correlation matrices with key economic indicators from FRED [2].

To avoid look-ahead bias, all macroeconomic indicators are lagged by one period before being used as model inputs. In addition, features are standardized using a rolling window approach to ensure consistency across time while preventing information leakage from future data.

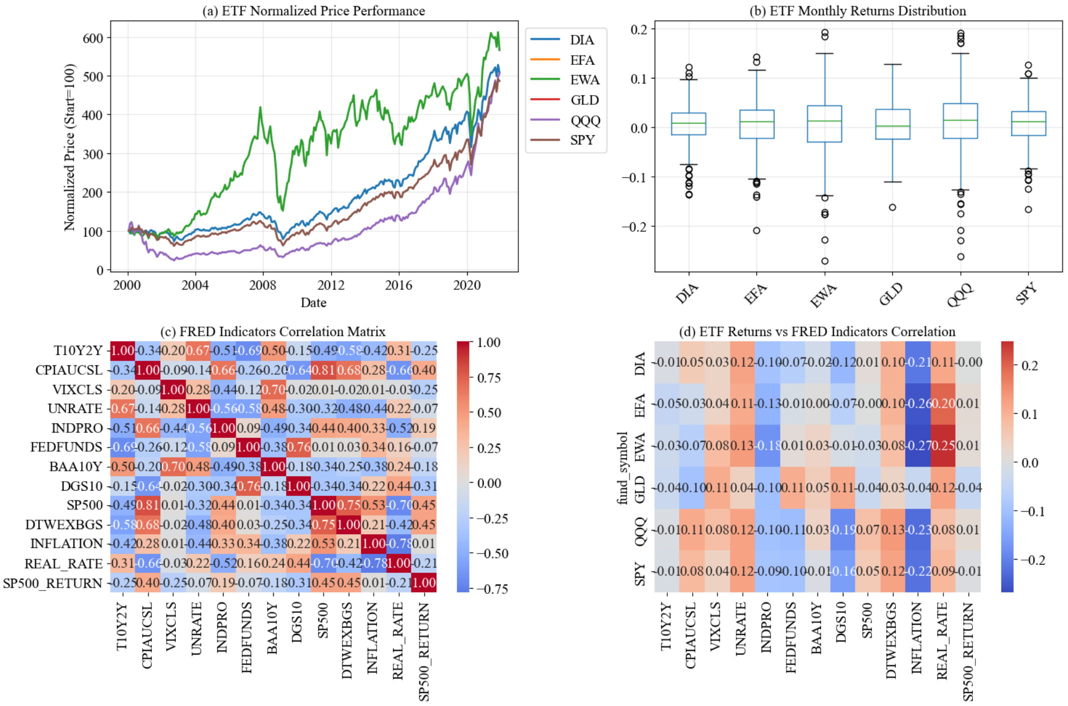

Fig. 1 The Various Indicators of the Two Datasets, (a)ETF Normalized Price Performance; (b)ETF Monthly Returns Distribution; (c)FRED Indications Correlation Matrix; (d)ETF Returns vs FRED Indicators Correlation (Picture credit: Original)

2.3. Division of Characteristics and Target Variables

The feature set includes various features extracted from ETF prices and macroeconomic indicators, while the target variable is the predicted future ETF returns. The division of characteristics and target variables ensures that the model accurately captures the characteristics of the time series data.

2.4. Model And Algorithm

In this paper, three machine learning models, ridge regression, Random forest, and XGBoost, are used to forecast ETFs based on macroeconomic data from FRED, and the prediction results are systematically evaluated. Using the optimal forecast data, the 60/40 strategy, the Top-N equal weight strategy, and the mean-variance strategy are used to generate portfolios and backtest them. Fig. 2 shows the flow of various data forecasting methods and asset allocation strategies adopted in this study.

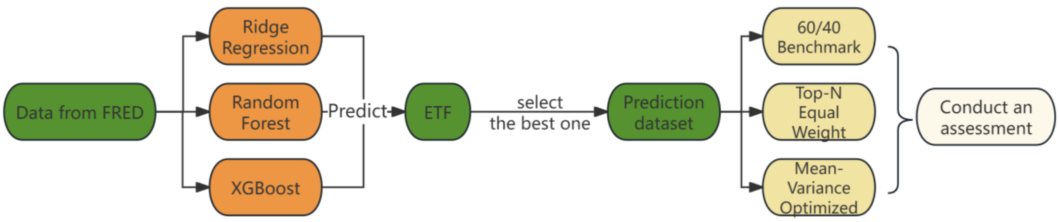

Fig. 2 Data forecasting method and asset allocation strategy process (Picture credit: Original)

2.4.1 Prediction Model

This study employs ridge regression, random forest, and XGBoost to forecast ETF returns based on macroeconomic indicators. Firstly, the ridge regression model is chosen for its ability to address multicollinearity in high-dimensional macroeconomic data, providing stable and reliable forecasts.

Secondly, the random forest model is employed because its ensemble of decision trees captures nonlinear relationships and improves generalization across complex datasets. Finally, the XGBoost model is included for its efficient gradient boosting framework, which enhances predictive accuracy and effectively handles intricate interactions among features. Combining these three models, we hope to achieve higher accuracy and stability in the prediction of ETF returns, and also provide a more reliable basis for investment decisions.

Models were trained and tested using a rolling-window approach, ensuring that only historical information was used at each step to mimic real-time forecasting [6].

2.5. Performance Evaluation Metrics

This study used three performance evaluation metrics to evaluate the forecasting performance of the model. Root mean square error (RMSE) measures the deviation between predicted and actual values, reflecting overall forecasting accuracy. The coefficient of determination (R^2) assesses the proportion of variance explained by the model, indicating its explanatory power. Directional accuracy captures whether the model correctly predicts the sign of returns, which is especially relevant for investment decisions. Together, these metrics provide a balanced evaluation of both numerical precision and practical applicability.

2.6. Portfolio Construction and Backtesting Strategies

Based on the model prediction signals for the next year, two investment strategies are designed. The first is the Top-N equal weight strategy, which aims to select the ETFs with the highest return forecast and assigns them equal weight. In this way, investors are able to fully participate in the yield opportunities of high-potential assets without having to worry about the risk of a single investment. The second is the mean-variance optimization strategy, which optimizes the portfolio according to the predicted return rate and covariance matrix, so as to seek the best return at different risk levels. This strategy combines the effectiveness of risk and return, allowing investors to maximize return while controlling investment risk.

Backtesting is conducted using a rolling-window framework on historical data. Performance is assessed through cumulative returns, volatility, Sharpe ratio, and drawdown, with portfolios rebalanced periodically according to the forecasts.

3. Results

3.1. Comparison of Model Prediction Performance

This study investigates the prediction accuracy of three prediction models, ridge regression, Random forest, and XGBoost, within a rolling window. The performance of each model was evaluated by RMSE, R-squared, and directional accuracy. Table 1 shows the performance evaluation metrics of these models.

Table 1. Summary of Model Prediction Accuracy

Model	RMSE	R^2	Direction Accuracy
Ridge Regression	0.0424	0.6339	0.7694
Random Forest	0.0508	0.3991	0.4861
XGBoost	0.0533	0.5667	0.6000

It can be seen from Table 1 that ridge regression has the best performance in terms of RMSE (0.0424) and R-squared (0.6339), showing its high prediction accuracy. At the same time, the direction accuracy is 0.7694, indicating that the model also has advantages in direction prediction. In contrast, the RMSE of random forest is 0.0508 and R-squared is 0.3991, showing relatively low predictive power, while the RMSE of XGBoost is 0.0533 and R-squared is 0.5667, which is slightly worse than ridge regression, but still has a certain predictive effect. These results indicate that ridge regression is the most effective model in this study, which is important for improving the prediction accuracy.

3.2. Analysis of Portfolio Performance

3.2.1 Dynamic strategy vs. benchmark strategy

In the performance analysis part of the portfolio, the research focuses on the performance of the dynamic strategy versus the benchmark strategy. Table 2 compares the key performance indicators of the Top-N equal-weight strategy, mean-variance optimization strategy, and 60/40 benchmark strategy, including annualized return %, annualized volatility, Sharpe ratio, maximum drawdown, win ratio, Sortino ratio, and Calmar ratio:

Table 2. Strategies performance comparison

	Top-N Equal Weight	Mean-Variance Optimized	60/40 Benchmark
Annual Return	0.1562	0.1586	0.1573
Annual Volatility	0.1059	0.1014	0.1175
Sharpe Ratio	1.4756	1.5640	1.3385
Max Drawdown	-0.0466	-0.0462	-0.0468
Win Rate	0.7273	0.7723	0.6264
Sortino Ratio	2.0706	2.2153	NaN
Calmar Ratio	3.3534	3.4347	NaN

It can be seen from the Table 2 that the mean-variance optimization strategy performs better than the Top-N equal-weight strategy in terms of annualized return, Sharpe ratio, and Calmar ratio, and the maximum recluse is smaller, indicating that it is more effective in risk control.

Fig. 3 presents the cumulative return curves and retracement curves for different strategies based on ridge regression forecasts. In the Fig. 3, the green line represents the mean-variance optimization strategy, the red line is the Top-N equal weight strategy, and the yellow line is the 60/40 benchmark strategy. It can be seen that the mean-variance optimization strategy maintains a relatively high cumulative return in most periods, while the retracement range is relatively small, showing its good risk management ability.

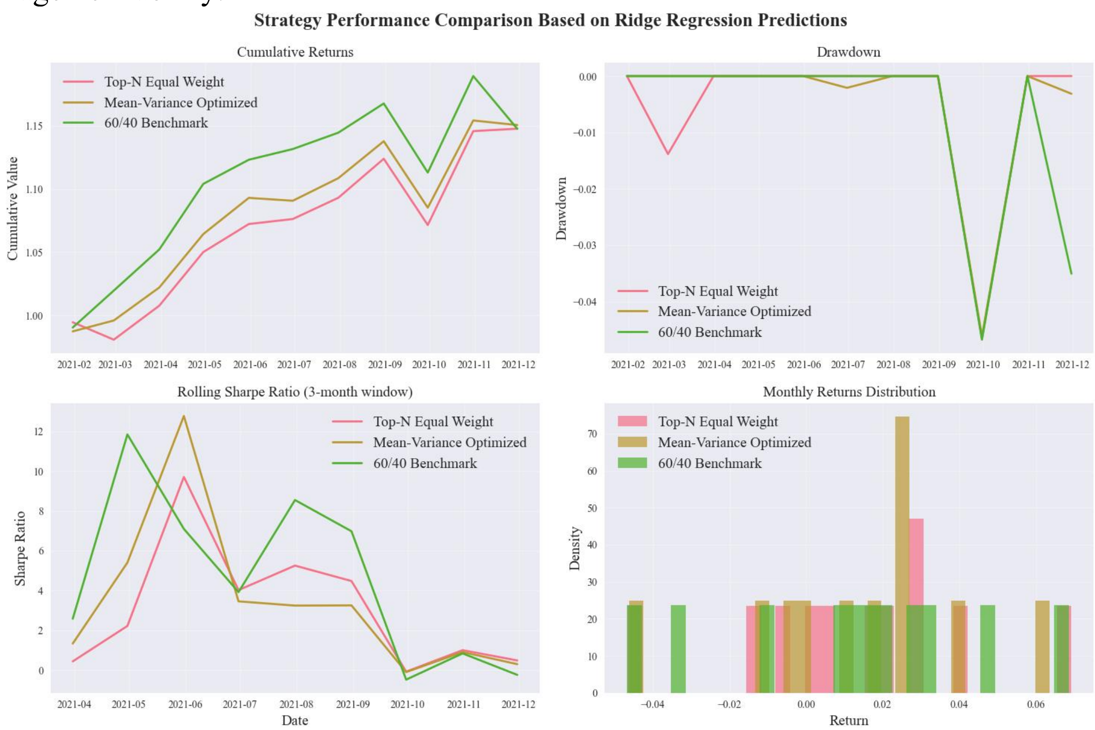

Fig. 3 Strategy Performance Comparison Based on Ridge Regression Predictions (Picture credit: Original)

3.2.2 Weight change analysis

Fig. 4 presents the portfolio weight changes for the Top-N equal-weighted strategy and the mean-variance optimization strategy. It can be observed that the Top-N strategy shows obvious asset rotation behavior in different time periods, showing the dynamic response of market conditions to the strategy. The adjustment of weights becomes more pronounced when the macroeconomic environment is volatile.

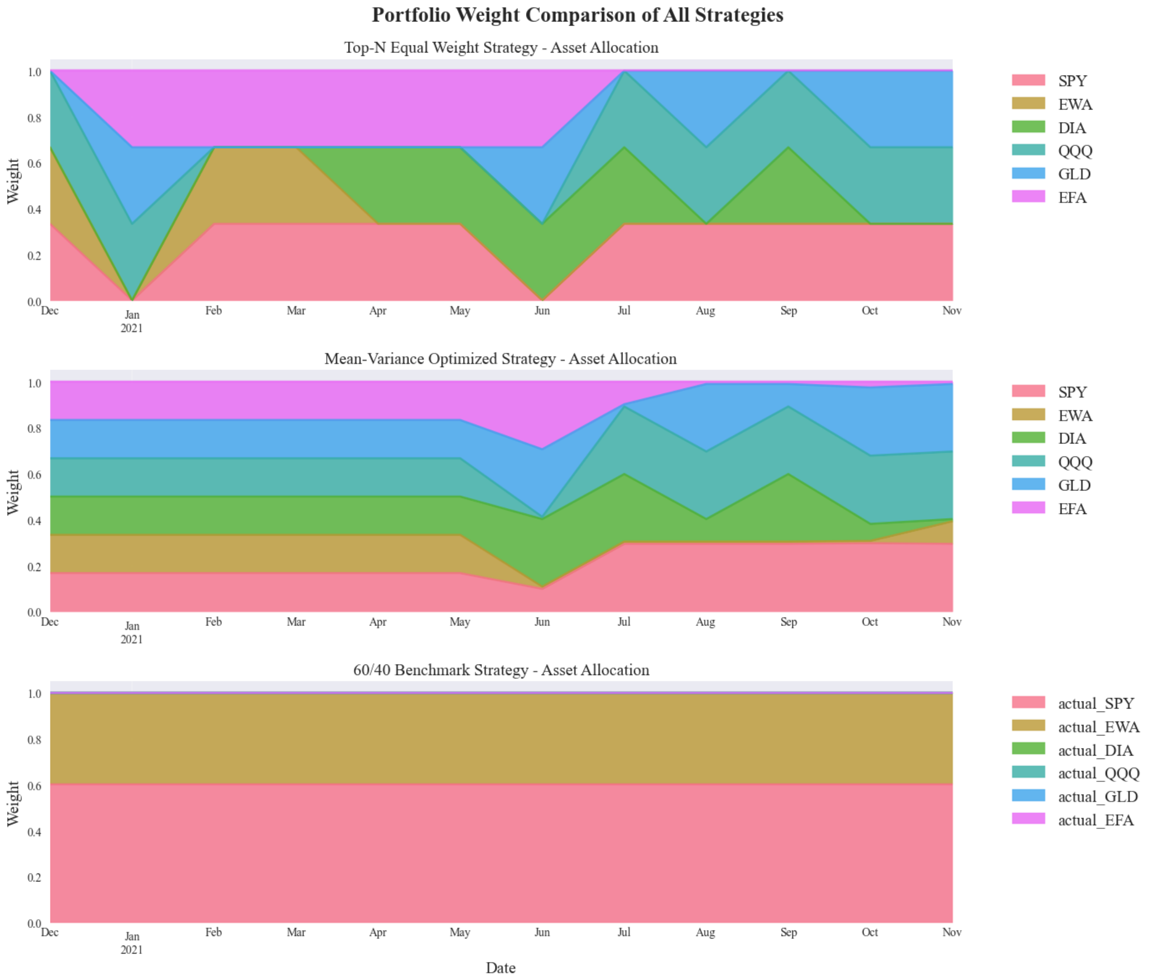

Fig. 4 Portfolio Weight Comparison of All Strategies (Picture credit: Original)

3.3. Summary of Results

Based on the above analysis, the ridge regression model performs best in terms of forecasting performance, especially in terms of RMSE and directional forecasting accuracy, indicating that it has a stronger ability to explain data. In the process of portfolio construction, the mean-variance optimization strategy provides superior performance in risk-adjusted returns. The analysis of changes in the weights of dynamic strategies and their association with macroeconomic cycles provides an important reference for future investment decisions.

3.4. Discussion

This study shows that combining macroeconomic factors with machine learning methods can provide effective signals for tactical asset allocation. Empirical results show that compared with traditional benchmarks, predictive models can enhance the risk-adjusted returns of investment portfolios. However, there are still several limitations.

First of all, the factor subset used in this study is mainly limited to traditional macroeconomic indicators, and the frequency is monthly data, which makes it difficult to fully reflect the rich information and high-frequency dynamics in the market. In the future, alternative data, such as market sentiment and remote sensing images, can be introduced, and high-frequency data can be considered to improve the timeliness and effectiveness of prediction [10][11].

In addition, the backtesting framework does not take into account transaction costs and liquidity constraints, which may lead to an overestimation of investment performance. If these market frictions are included in the model evaluation, it will be more in line with the actual application environment [12].

Finally, the empirical analysis in this paper is limited to a single market environment and lacks external applicability. Cross-market and multi-asset class robustness tests will help verify the universality of the model [13].

Therefore, future research can further improve factor expansion, high-frequency and alternative data utilization, market friction modeling, and explore advanced methods such as deep learning and ensemble learning to improve the stability and promotion value of a multi-asset allocation strategy.

4. Conclusion

This paper proposes and verifies a machine learning-based tactical asset allocation framework to cope with the shortcomings of traditional strategic allocation in complex macro environments. Firstly, the macro factors are lagged and standardized to avoid information leakage. Then, the prediction performance of ridge regression, random forest, and XGBoost models is compared, and a model selection mechanism based on prediction accuracy is established. On this basis, two types of investment strategies are designed: Top-N equal weight and mean-variance optimization. Through rolling backtest and 60/40 benchmark comparison, the results show that the machine learning-driven strategy has advantages in return and risk-adjusted performance, and the mean-variance strategy achieves the best effect. Therefore, the framework transforms changes in macro factors into adjustments of asset allocation weights, supports the implementation of low-turnover ETFs and risk budgets, provides investors with a predictive asset allocation method in a complex macro environment, and helps stably obtain risk-adjusted excess returns in different economic stages.

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