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Evaluating Time-Series Momentum in S&P 500 Stocks: Mean-Variance Optimization, Transaction Costs, and Market Regimes

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Abstract. As a classic trend-following strategy, the time-series momentum (TSMOM) strategy poses an empirical challenge to the efficient-market hypothesis. Most existing back-testing studies focus heavily on index and futures markets, while empirical research specifically targeting individual stocks remains limited, and the impact of trading costs on investment returns tends to be underestimated. Using daily data for S&P 500 constituent stocks covering 2015-2025, this paper constructs the baseline TSMOM strategy as well as the MVO-TSMOM strategy integrated with dynamic mean-variance optimisation. This study adopts a multi-layer trading-cost model and conducts tests under diverse market regimes, including bull, bear and range-bound markets. Empirical results indicate that the mean-variance optimisation strategy delivers a moderate improvement in risk-adjusted returns. Nevertheless, excess returns are substantially eroded owing to high portfolio turnover caused by monthly rebalancing. The strategy can only provide limited downside protection in bear-market environments when the round-trip transaction cost is extremely low (0.1%). No significant alpha is identified across the full sample period, suggesting that none of the strategies can consistently outperform the SPY index. Firstly, this paper provides empirical evidence for the real-world performance of the TSMOM strategy in global equity markets amid trade frictions. Secondly, it offers empirical evidence for the boundary conditions of the time-series momentum anomaly.

Keywords: Time Series momentum strategy, Mean-variance optimization, transaction cost, S&P 500 Index, trend-following strategy

1. Introduction

Persistent price trend anomalies in financial markets continuously challenge the Efficient Market Hypothesis. As a result, the Time-Series Momentum (TSMOM) trend-following strategy has garnered widespread attention from both academia and quantitative investment practitioners. Different from traditional cross-sectional momentum strategies, the TSMOM strategy generates long-short trading signals based on an asset's own historical return series, without requiring cross-asset relative strength comparison. Many early studies found that in a multi-asset and cross-market environment, the TSMOM strategy can yield significant returns after risk adjustment. However, most empirical studies rely on index and futures data, while systematic empirical evidence at the individual stock level for the U.S. stock market remains scarce. In addition, many backtest studies adopt overly idealized assumptions, which underestimate the impact of real-world trading frictions on the strategy's net performance. Furthermore, whether dynamic mean-variance optimization can improve the portfolio performance of the TSMOM strategy requires empirical verification.

This paper uses all S&P 500 Index constituent stocks from 2015 to 2025 as the research sample. This time frame covers major market volatility stages, including the pandemic-affected bear market, the prolonged slow bull market, and the highly volatile range-bound period, making it highly suitable for evaluating the performance of trend strategies under heterogeneous market cycles. This paper explores five core research questions: First, whether the stock-level TSMOM strategy can outperform the passive SPY benchmark index in the long run; Second, whether the weight allocation of dynamic mean-variance optimization can improve risk-adjusted return on investment; Third, how different levels of transaction costs erode the cumulative return of the strategy; Fourth, the heterogeneous performance of the TSMOM strategy in bull, bear, and range-bound markets, as well as its ability to mitigate drawdowns; Fifth, whether the empirical conclusions remain robust when the lookback window and risk aversion parameters change.

This study constructs a TSMOM portfolio using the complete sample of S&P 500 Index constituent stocks, and establishes two dual benchmarks: SPY and the equal-weighted TSMOM, which distinguishes it from previous research literature that focused on index backtesting. Secondly, this paper combines the rolling covariance mean-variance optimization method with TSMOM signals, and conducts comparisons using multiple risk aversion coefficients. In addition, this paper simulates three tiered transaction cost scenarios of 0.1%, 0.5% and 1.0% to quantify the return decay effect caused by portfolio turnover. Finally, the paper groups the samples according to market conditions, which can further explore the heterogeneity of portfolio strategies in bull, bear, and range-bound markets.

This paper complements the research on individual stock time-series momentum effects under real-world trading frictions, and helps define the boundary conditions of momentum anomalies. From a practical perspective, the research results can provide references for trend-oriented quantitative investors in aspects such as rebalancing frequency, cost management, and position weight optimization. The conclusion section of this paper discusses in detail the limitations of this study and optional future research directions.

2. Literature review

2.1. Momentum effect

The research on momentum effects mainly focuses on two major directions: cross-sectional momentum and time series momentum. The cross-sectional momentum theory was proposed by Jegadeesh and Titman [1]. Its core mechanism lies in buying stocks that have performed well in the past and selling those that have performed poorly based on the cross-sectional relative performance of assets. The time series momentum theory was proposed by Moskowitz et al. [2]. This theory generates long and short signals only based on the sign of the historical return rate of the asset itself, without the need for cross-asset comparison. Subsequent research has confirmed that this abnormal phenomenon is widespread in the stock, commodity and bond markets, and exhibits defensive characteristics during severe market downturns. Hurst et al. proposed trend-following strategies, providing empirical evidence at the long-term cross-asset level and emphasizing the downside hedging value of such strategies in bear markets [3].

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The profitability of the momentum strategy is conditional. Barroso and Santa Clara documented the time-varying risk characteristics and momentum crash risks in momentum strategies. The current explanation is that behavioral finance theory attributes the momentum premium to investors' "underreaction" and "delayed overreaction". The risk-based explanation regards momentum gains as compensation for tail risks. A large number of literatures point out that once the transaction friction factors in reality are taken into account, the theoretical momentum gains may be significantly reduced.

2.2. Mean variance optimization combined theory

Markowitz's mean-variance model is the cornerstone of modern portfolio theory [4]. This model solves for the optimal asset weight by maximizing investor utility and achieves a trade-off between risk and return under the given risk aversion coefficient. However, the mean-variance optimization method has some well-known drawbacks in practical applications. DeMiguel et al. pointed out that the estimation error in the covariance matrix often leads to extreme portfolio weights; in many cases, the optimized investment portfolio cannot go beyond the simple equal-weighted 1/N diversification strategy [5]. Therefore, in practical applications, improved methods such as rolling window covariance estimation, volatility anchoring, leverage constraints, and upper limits of position weights are usually employed to alleviate the instability of weight calculation results.

Kim et al. studied the momentum effect of time series on the volatility scale [6]. The results show that the position rules based on volatility anchoring help stabilize the portfolio risk in trend-following strategies. Combining mean-variance optimization with TSMOM signals is conceptually very attractive.

2.3. Research gap

A review of the existing literature has revealed four research gaps. A large number of empirical studies on TSMOM rely on index and futures datasets; However, comprehensive backtesting studies covering all the constituent stocks of the S&P 500 Index are still relatively scarce. At the same time, numerous backtesting studies have simplified or omitted the modeling of transaction costs, and have ignored the performance degradation problem caused by the stock turnover rate. In addition, the existing research on the MVO-TSMOM hybrid mainly focuses on index assets rather than individual stock portfolios, and rarely considers the estimation error risk contained in the MVO model. Finally, in the context of stratified trading friction, few studies have systematically decomposed the performance differences existing in different market scenarios such as bull markets, bear markets, and volatile markets.

3. Research design

3.1. Data and preprocessing

The sample period covers from January 2015 to December 2025. The source of the research data is the daily adjusted closing price of all S&P 500 index constituent stocks; this study relies on the Pandas-Data Reader data interface to complete the batch capture and import of all sample data, providing original data support for subsequent strategy backtesting and empirical analysis. The data comes from Yahoo Finance. The three-month U.S. Treasury yield is used as a risk-free interest rate when calculating excess returns. Data preprocessing includes missing value filling, daily logarithmic

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yield calculation and monthly compound yield calculation. All follow-up strategy backtests are based on the monthly rate of return. The comparison benchmark includes the SPY holding fixed portfolio and the weighted portfolio constructed from the component stocks of the S&P 500 index.

3.2. Strategy formulation and implementation rules

The MVO-TSMOM strategy selects valid stocks based on TSMOM trading signals and constructs optimal portfolios by maximizing standard investor utility function. The utility function is specified as follows:

$$U(\mu,\sigma) = \mu - \gamma\sigma^2 \tag{1}$$

where U refers to investor utility, μ represents the portfolio's expected return, σ denotes portfolio return variance, and γ is the investor's risk-aversion coefficient.

Based on the mean-variance theoretical framework, the optimal portfolio weight vector can be derived as:

$$W^* = \frac{\Sigma^{-1}\cdot\mu}{\gamma} \tag{2}$$

3.3. Performance evaluation system

Evaluation indicators are divided into three categories: income-related indicators include cumulative net asset value and annualised rate of return; risk indicators cover annualised volatility, maximum retreat and downward deviation; risk-adjusted yield indicators include Sharpe ratio and Sotino ratio; strategy A can be derived through CAPM regression analysis Lpha and Beta values are used for statistical inference of excess income.

The robustness test includes: parameter sensitivity analysis for the backtracking window and risk aversion coefficient; three levels of transaction cost scenario test; and institutional conditional backtracking test for three subsamples of bull market, bear market and interval fluctuation market.

4. Empirical results and tests

4.1. Full-cycle empirical result analysis

Under the low-friction assumption of a transaction cost of 0.1%, the cumulative net value of MVO-TSMOM and EW-TSMOM is slightly higher than the SPY benchmark. However, this advantage will quickly disappear as transaction costs rise. For instance, when the transaction cost reaches 0.5%, the annualized rate of return of the two strategies drops by 2 to 3 percentage points compared to the low-friction scenario. Or when transaction costs rise to 1.0%, the strategy's performance significantly underperforms that of SPY [7].

Backtesting statistics show that the average monthly turnover rate of the investment portfolio is approximately 28%. Monthly re-evaluation of the bullish and bearish signals for all individual stocks will lead to a high turnover rate. Frequent portfolio adjustments will continuously amplify transaction fees and slippage losses, which is also the core reason for the deviation between the idealized backtest results and the actual trading performance. Consistent with the research conclusion of Novy-Marx and Velikov, the theoretical gains of the high-turnover strategy examined in this paper will be completely eroded by real-market frictions [8]. The CAPM regression results show that within the full sample interval, the alpha estimates of EW-TSMOM and MVO-TSMOM

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are not significant, and the alpha is negative in some model Settings. The null assumption that the excess return of the strategy is equal to zero cannot be rejected.

4.2. Heterogeneous performance of strategies in different market environments

The backtesting results of market conditions show that the TSMOM strategy can effectively capture the upward trend of the market in a bull market, but its long-term returns are still lower than those of the SPY buy-hold strategy. During a bear market, the long-short switching mechanism can significantly reduce the maximum drawdown of an investment portfolio and has a certain value in protecting against downside risks. In a range-bound market, the repeated price reversals cause frequent switching of momentum signals, further pushing up the turnover rate and frictional losses, and significantly deteriorating the performance of strategies. This result is consistent with the view proposed by Barroso and Santa Clara that the risk of momentum strategies is time-varying [9].

4.3. Robustness test and practical implementation implications

The results of parameter sensitivity analysis show that the 12-month backtracking window takes into account both signal response speed and noise interference, achieving the best overall performance, which is consistent with the benchmark setting of Moskowitz et al. [2]. When the risk aversion coefficient is reached, the risk-adjusted return of the investment portfolio is optimal. Even after adjusting the backtracking window and risk aversion parameters, the core conclusion that "transaction costs erode returns and strategies fail in volatile markets" still holds true. Three sets of transaction cost robustness tests show that only in an environment with extremely low market friction can strategies achieve considerable positive returns. The backtest results provide feasible optimization ideas for the implementation of the TSMOM strategy. First, this paper recommends reducing the frequency of portfolio adjustments. For instance, changing the monthly portfolio adjustment to a bimonthly one can directly lower the monthly turnover rate and reduce frictional losses. Secondly, TSMOM can be combined with the time series mean reversion strategy to smooth out the overall volatility of the combination. This strategy has clear application limitations: it is suitable for low transaction cost environments and sustained one-sided trend market conditions. There is no advantage in a range-bound market [10].

5. Conclusion

Based on the data of S&P 500 component stocks from 2015 to 2025, this paper conducts a systematic evaluation of the backtest results of the equity-weight TSMOM and MVO-TSMOM strategies under multiple transaction cost assumptions, and obtains four core conclusions. First, at the individual stock level, TSMOM can only generate limited positive returns under the assumption of an extremely low transaction cost of 0.1%. Once transaction costs reach 0.5% or more, both types of strategies continue to underperform the SPY benchmark. Secondly, although dynamic mean-variance weight optimization can slightly improve risk-adjusted returns, it still cannot offset the transaction cost losses caused by high turnover rates. Thirdly, the core value of TSMOM lies in hedging against downside risks in a bear market, and it performs poorly in a range-bound market environment. Fourth, during the full sample period from 2015 to 2025, neither of the two strategies could generate statistically significant CAPM alpha.

There are several deficiencies in this study. Firstly, the research sample only includes the large-cap constituent stocks of the S&P 500, and does not include small and medium-sized stocks,

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commodities, bonds, or other alternative assets. Secondly, the MVO model does not introduce regularization processing and fails to fully address the issue of estimation error in the covariance matrix. Then, the backtesting framework adopts a pure long-short structure and does not set up corresponding risk control mechanisms such as volatility trigger stop-loss. Finally, this paper applies a unified transaction cost parameter, without taking into account the liquidity differences among various individual stocks, nor does it consider the market shock costs brought about by large-scale capital transactions.

For subsequent research, this paper identifies four directions in which this strategy can be further optimized. Firstly, certain improvements can be made to the model, such as introducing a regularized mean-variance model, multi-period momentum signal fusion, and a lightweight trend recognition model to alleviate the problem of estimation errors, etc. Secondly, this strategy has certain limitations in terms of sample scope. Therefore, the analytical framework of this paper can be transferred to the A-share market, indices of various countries around the world, and multi-asset futures datasets for comparative studies. For the improvement of the overall method, other ways of generating trend signals can be explored.

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