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Risk-Adjusted Returns in S&P 500 with Long-Only Cross-Sectional Momentum Strategy

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Abstract. Cross-sectional momentum has been used widely, but there are few researches to find the impact of portfolio concentration to long-only momentum strategy. This Paper examines how varying the number of stocks affects the performance of long-only momentum strategy in S&P 500 universe from 2000 to 2026. This study uses the standard 12-month period and skip the recent month to filter out the microstructure noises. Through picking the top n historical winners, the results show a significant balance between risk and return. Considering that evidence indicates that concentrated portfolios carry distinct trade-offs, a highly concentrated portfolio may have the highest return but also the risk of large drawdowns and elevated volatilities. However, the study may indicate that when the size of portfolio increases to n=6, the strategy could reach the optimal balance between the momentum premium and the diversification benefits. Additionally, this strategy reaches the highest Sharpe Ratio of 1.04 and shows a significant alpha of 30.84%. Therefore, these findings show that for the institutional investors who use long-only strategies, mechanically picking the extreme winners is not the best option, rather, changing the portfolio to a proper size may be the key to maximize the risk-adjusted returns.

Keywords: cross-sectional momentum, long-only strategy, S&P 500, risk-adjusted return

1. Introduction

Jegadeesh and Titman first introduced the cross-sectional momentum strategy to the academic literature [1], and the momentum effect—buying historical winners and selling historical losers—has established itself as one of the most robust anomalies in modern finance and asset pricing. However, the extensive empirical research conducted over the past few decades may suggest that momentum premiums appear pervasive across global equities. The results might indicate that quantitative investment theories were profoundly reshaped by this evidence. Moreover, the data could show that this influence is most notably included in the Carhart four-factor model [2]. And the research also shows that momentum effect proves robust across markets.

Wall Street hedge funds are still widely using this strategy to get profits by going long on winners and shorting losers. However, Daniel and Moskowitz claimed that momentum strategies have some substantial losses when the market rebounds in the periods of distress [3]. And, some traditional zero-investment, long-short framework also have severe practical limitations that are difficult to overcome. For example, mutual funds and pension funds have strict regulatory constraints, like high

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borrowing costs, and the unlimited downside risk because of short-selling, so these companies often cannot apply such strategies freely. Long-only momentum strategy reduces the short leg and holds far more practical significance for constrained asset managers.

In this paper, the study examines the performance of equal-weighted, long-only momentum strategies for the S&P 500 stock universe by the way of 12-1 to reduce microstructure noises [4]. This paper also tries to quantify how the portfolio concentration affects the risk-adjusted returns. But the research findings may indicate that there exists a trade-off between maximizing momentum premium and diversification, and the results show that the factors would influence the overall portfolio outcomes.

Markowitz claims that investors can improve the risk-return trade-off by constructing diversified portfolios of assets with imperfectly correlated return [5]. Based on these evidences of momentum, Jegadeesh and Titman show that momentum profits continue to exist in later out-of-sample periods, indicating that the effect is not just a result of data mining [6]. Additionally, this work also finds that although the highly concentrated portfolios could make the highest annualized raw returns, undiversified idiosyncratic risk would lead to severe volatility and reduce risk-adjusted performance. When expanding the portfolio size, the strategy could achieve an optimal balance between the momentum premiums and the diversification effect, which leads to the maximized annualized Sharpe Ratio. Furthermore, the OLS regression shows that even the strategy removes the systematic market risk, the optimally diversified long-only strategy makes a significant alpha. And this also indicates that the strategy's excess returns are the results of genuine momentum anomaly instead of passive exposure of market beta.

2. Data and methodology

This section details the data sample used in the empirical research, the mathematical construction of the momentum signal, the dynamic portfolio rebalancing rules, and the core econometric models employed to evaluate the strategy's risk-adjusted performance.

2.1. Data description

This study uses the stocks of the S&P 500 index—the most used benchmark in the U.S. equity market—as the base investment universe. This paper uses monthly closing price data to get medium-term to long-term cross-sectional momentum premium. Moreover, the backtesting period could indicate robustness because the time period spans from January 2000 to July 2026. Furthermore, this time period may suggest that the results cover multiple complete economic cycles, including the 2008 financial crisis.

Fama and French show that the momentum anomaly occurs in microcap, small-cap, and big-cap stocks. Since this study focuses on a large-cap U.S. equity universe, this work uses SPDR S&P 500 ETF Trust (SPY) as the market benchmark [7]. The monthly price and volume data for all individual stocks, along with the SPDR S&P 500 ETF Trust, are sourced from Alpha Vantage. In the data preprocessing stage, value-missed months are excluded to ensure the calculations are correct.

(Note: This study relies on the static S&P 500 constituent list as of the end of the backtesting period, given that point-in-time historical constituent data proved difficult to obtain. This may introduce a certain degree of survivorship bias into the results. However, the bias does not appear to alter the core directional conclusions when comparing the relative sensitivity of strategies across different n values.)

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2.2. Momentum signal construction

To accurately gauge the momentum trend of individual stocks while mitigating the negative interference of microstructure noise and the short-term reversal effect, this study follows the conventions of classic asset pricing literature, such as Fama and French, by adopting the standard "12-1" momentum model.

The study calculates the momentum sorting signal for stock i, denoted as $Ret_{i,t}$, at the start of each rebalancing month (month t) as the cumulative return over the past 12 months, excluding the most recent month (month $t-1$). The formula is:

$$Ret_{i,t} = \prod_{k=2}^{12}(1 + r_{i,t-k}) - 1 \tag{1}$$

where $r_{i,t-k}$ represents the actual monthly return of stock i in month $t-k$. Considering that the product's starting index is $k = 2$, the month before the rebalancing date is deliberately skipped. Moreover, this exclusion could indicate that the researchers wanted the signal to avoid short-term reversal effects that might otherwise contaminate the measure. Therefore, the momentum signal captures medium-term price continuation trends.

2.3. Portfolio construction

After calculating the momentum signal $Ret_{i,t}$ for all valid stocks in the cross-section, this study adopts a long-only implementation rather than the traditional zero-investment long–short winner–loser portfolio documented by Jegadeesh and Titman.

Each month t, S&P 500 constituents get sorted in descending order based on their $Ret_{i,t}$. The top n ranked stocks are then selected to build the Winner Portfolio. Given that value-weighting could concentrate risk heavily in mega-cap stocks, the strategy instead allocates capital using an equal-weighting scheme. The actual return of this portfolio in month t, denoted $R_{p,t}$, may be calculated using the formula:

$$R_{p,t} = \frac{1}{n} \sum_{i=1}^{n} R_{i,t} \tag{2}$$

where $R_{i,t}$ is the actual return of the selected stock in month t.

To limit concentration in the largest S&P 500 constituents, the strategy allocates capital using an equal-weighting scheme. This choice is also supported by DeMiguel, Garlappi, and Uppal, who show that the naive $\frac{1}{N}$ allocation rule is not consistently outperformed by more complex portfolio-optimization approaches in out-of-sample test [8].

2.4. Performance evaluation metrics

This study examines strategy performance across different n values, focusing not only on absolute return levels but, more importantly, on risk-adjusted performance.

The Annualized Sharpe Ratio is used first to measure the excess compensation the strategy earns per unit of total risk [9]:

$$SR = \frac{\sqrt{12} \times \overline{R_p}}{\sigma_p} \tag{3}$$

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where $\overline{R_p}$ is the average monthly return of the strategy over the sample period, and σ_p is the standard deviation (volatility) of the strategy's monthly return series. Given that empirical simplicity is the goal here, the risk-free rate is assumed to be zero. The multiplier $\sqrt{12}$ annualizes the monthly metric, conforming to international industry standards.

This study also strips away systematic market risk to examine whether the strategy shows genuine, absolute stock-picking ability, using the single-factor framework of the Capital Asset Pricing Model (CAPM). An Ordinary Least Squares (OLS) regression is conducted:

$$R_{p,t} = \alpha + \beta R_{m,t} + \epsilon_t \tag{4}$$

where $R_{p,t}$ is the monthly return of the long-only momentum portfolio, and $R_{m,t}$ is the market benchmark return (proxied by SPY). Given that this regression setup isolates systematic exposure, the intercept, α, could reasonably be considered the paramount parameter of interest in this study [10]. Moreover, the findings may suggest that α quantifies the pure excess return generated by the cross-sectional momentum stock selection mechanism. Alpha reflects return after adjusting for equivalent market beta risk.

3. Empirical results

3.1. Base case performance

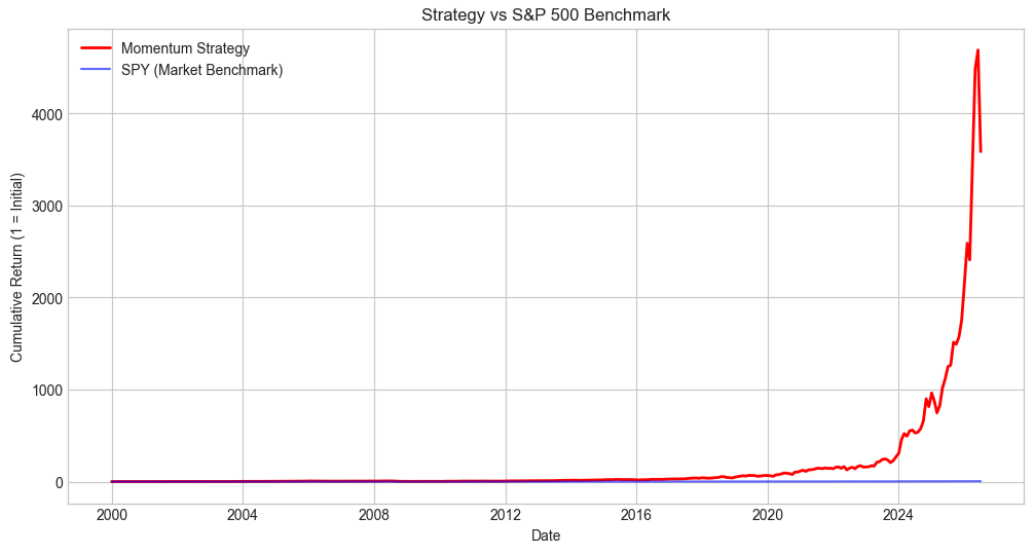


Figure 1. cumulative return trajectory of SPY and the strategy of n=6

To visually illustrate the long-only momentum strategy, this work first establishes a base-case scenario by setting the portfolio concentration at an optimal level of $n = 6$. Figure 1 plots the cumulative return trajectory of this base strategy against the S&P 500 market benchmark (SPY) over the sample period from 2000 to 2026.

From an absolute return perspective, the long-only momentum strategy generates a robust annualized return of 35.41%, significantly outperforming the market benchmark. In addition, during the periods of severe market downturns, the strategy still showed remarkable resilience. By systematically rotating into relative historical winners, the strategy avoided the most severely

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depreciating assets, therefore, demonstrating strong defensive characteristics alongside its capacity for excess return generation.

3.2. Sensitivity analysis on portfolio concentration

This study tests the sensitivity of this strategy with respect to parameter n. Figure 2 shows a dual-axis chart of the Annualized Return (solid red line) and the Annualized Sharpe Ratio (dashed blue line) against n moving from 1 to 100.

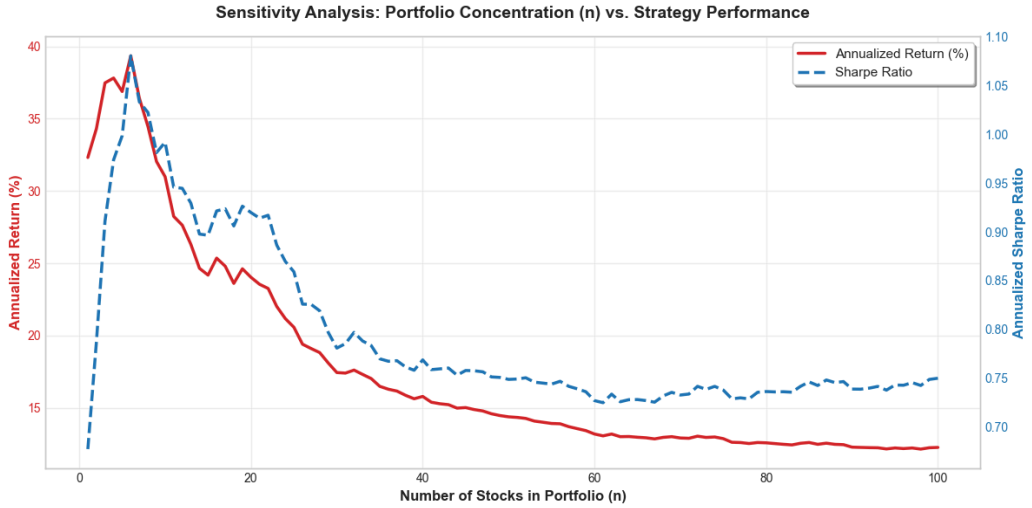


Figure 2. Annualized return and sharpe ratio from n=1 to n=100

Figure 2 shows that as n increases, the annualized return increases and then decreases. Considering that the theoretical prediction of the most extreme momentum premiums concentrates in a small range of good-performing assets, this pattern can indicate that adding lower-ranked stocks to diverse the portfolio would reduce the return. However, the risk-adjusted performance may suggest that it is different. Moreover, the evidence shows that the Sharpe Ratio does not peak at the minimum n. Small n causes volatility, and it will lose some returns. Nevertheless, as n increases to approximately $n = 6$, the strategy could achieve an optimal equilibrium between capturing the momentum premium and benefiting from diversification, and this could make the Sharpe Ratio to its global maximum of 1.04. Therefore, the findings may suggest that for long-only institutional investors, moderately expanding the portfolio size appears crucial for maximizing risk-adjusted efficiency.

3.3. Risk-adjusted alpha regression analysis

To further isolate the strategy's true stock-picking ability from systematic market exposure, Table 1 presents the results of the OLS regression based on the single-factor CAPM model for the optimal portfolio.

Table 1. Performance metrics and CAPM regression results for the optimal portfolio

Annualized return	*35.79%*
Annualized Volatility	*0.358*

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Table 1. (continued)

Beta	1.37
Alpha	30.84%

Table 1 shows that the strategy makes a market beta of 1.37, and it means a strong positive correlation with the broader market, which fits the nature of a long-only equity portfolio. However, the strategy might still generate a substantial alpha of 30.84% after controlling for this systematic market risk. Given that this alpha appears positive and statistically significant, the evidence could suggest that the excess returns stem from the genuine efficacy of the cross-sectional momentum sorting mechanism. Moreover, the results indicate that this effect may reflect something more than passive exposure to the market benchmark. Findings support momentum mechanism drives returns.

4. Conclusion

In this paper, the research examined the efficacy of the long-only cross-sectional momentum strategy for the S&P 500 universe from January 2000 to July 2026. However, these findings also may suggest that there exists a profound balance the momentum premium and the portfolio concentration. Considering that the extreme concentration makes the highest annualized return, it may indicate that the portfolio may own some idiosyncratic risk and higher volatility. Additionally, the results show that when the portfolio size is changed to $n = 6$, it would achieve the optimal equilibrium and the Annualized Sharpe Ratio is the maximum of 1.04 and CAPM regression shows alpha of 30.84%, driven by stock-picking rather than passive exposure.

Furthermore, the study may claim that these findings have significant implications for quantitative assets management companies, especially for those who are restricted by short-selling bans like traditional mutual funds and Smart Beta ETF providers. Based on these results, it is not optimal enough to mechanically chase highest returns by choosing the top momentum winners. Therefore, the evidence may indicate that selecting a broader set of winners would enhance the risk-adjusted return and widen the strategy's capacity. Nevertheless, the findings may suggest that a larger portfolio size could reduce market impact and get momentum premiums. A larger stock set could make monthly rebalancing easier and reduce the liquidity friction.

Although these findings are robust, there are still some limitations about the study. The significant evidence may show that there may exist survivorship bias because the backtesting framework relies on the current static S&P 500 constituent list. Considering that the calculated returns are gross of transaction costs, the actual alpha would be overstated and lower than the reported one. Therefore, the high turnover of this momentum strategies means that the bid-ask spreads and commissions would reduce the total gains. So, in practice, these costs cannot be ignored. Future research could address these limitations by incorporating point-in-time constituent data and explicit transaction cost models, and testing this long-only framework across mid-cap or international markets would further validate the robustness of the findings.

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