Momentum-Based Trading Strategies

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19/09/2024

1 Introduction

This report presents an in-depth analysis of momentum-based trading strategies applied to S&P 500 equities. The objective of this study is to evaluate the performance of various momentum horizons, investigate the impact of rebalancing frequencies, and assess the role of smoothing techniques in calculating momentum z-scores. By calculating momentum over different time horizons (1, 3, 6, and 12 months) and conducting a backtest framework, we analyze key performance metrics such as cumulative returns, Sharpe ratio, and turnover for each strategy.

Additionally, the analysis explores the effect of lagging momentum signals and compares their performance to real-time signals. The results are visualized across multiple dimensions, including cumulative returns and performance metrics, to provide a comprehensive view of how momentum strategies perform under varying conditions.

2 Data Fetching

The data fetching process involves several key steps to gather historical financial data for the S&P 500 momentum factor analysis. First, a list of S&P 500 companies is scraped from Wikipedia. Historical stock data for these companies is then retrieved using the Tiingo API, with Yahoo Finance acting as a fallback in case of API limitations of 500 stock tickers per month, since S&P 500 has 503 stock tickers due to the different classes of 3 stocks. In addition to individual stock data, historical price data for the S&P 500 index is collected from Yahoo Finance. Lastly, economic data such as the risk-free rate is fetched from the Federal Reserve's FRED database.

3 Data Cleaning

The data cleaning process involves loading, cleansing, and aligning financial datasets for further analysis. First, stock, index, and risk-free rate data are loaded from CSV files. The stock data undergoes cleaning by removing rows with missing values and outliers, ensuring sufficient historical data for each ticker. The following stock tickers were removed due to lack of sufficient data (i.e., less than 1 year worth of data): `["AMTM", "GEV", "SOLV", "SW"]`, therefore the backtesting is essentially done on 499 stocks in the S&P 500 Index. The dates across all datasets are aligned to a common range to ensure consistency. Additionally, returns are calculated from adjusted closing prices.

4 Momentum Calculations

The momentum calculation process involves determining stock momentum and lagged momentum for multiple horizons using cleaned stock data. Momentum is calculated using the formula:

$$M_n = P_t - P_{t-n} \tag{1}$$

Where:

- M_n: Momentum over n periods
- P_t: Price at time t
- P_{t-n}: Price at time $t-n$

For this analysis, horizons of 1, 3, 6, and 12 months are used.

Lagged momentum is calculated as:

$$LM_{(1,t)} = P_{t-\text{lag}} - P_{t-\text{lag}-1} \tag{2}$$

Where:

- $LM_{(1,t)}$: Lagged momentum at time t
- $P_{t-\text{lag}}$: Price at time $t - \text{lag}$
- $P_{t-\text{lag}-1}$: Price at time $t - \text{lag} - 1$

This method calculates both momentum and lagged momentum for the given horizons and lag periods.

5 Backtesting Framework

The backtesting framework implements a momentum-based trading strategy using cross-sectional z-scores of stock returns to generate trading signals. The strategy first calculates momentum for each stock over different time horizons (e.g., 1, 3, 6, or 12 months). Momentum values are taken from the column specified in the data. To standardize these momentum values across all stocks for a given date, **z-scores** are calculated using the following formula:

$$z_i = \frac{M_i - \bar{M}}{\sigma_M} \tag{3}$$

Where:

- z_i: Z-score for stock i
- M_i: Momentum value for stock i
- $\bar{M}$: Mean momentum across all stocks
- σ_M: Standard deviation of momentum across all stocks

In cases where smoothing is applied, the momentum values are first smoothed using a rolling mean with a specified window (e.g., 5 days). This results in a smoother series of momentum values, reducing short-term noise before calculating the z-score.

The strategy rebalances the portfolio at a fixed frequency (weekly or monthly). On each rebalance date, stocks with z-scores exceeding a user-defined threshold (e.g., $z > 1$) are selected for inclusion in the portfolio. The backtesting framework only takes long positions with equal weights assigned to the selected stocks. If no stocks meet the z-score threshold, the portfolio remains unchanged.

For each day between rebalancing dates, the portfolio return is calculated based on the stock prices:

$$R_t = \sum_i w_i \times \left(\frac{P_{i,t+1}}{P_{i,t}} - 1 \right) \tag{4}$$

Where:

- R_t: Portfolio return on day t
- w_i: Weight of stock i in the portfolio
- $P_{i,t+1}$: Price of stock i at time $t + 1$
- $P_{i,t}$: Price of stock i at time t

The backtesting framework avoids **data leakage** and **look-ahead bias** by carefully slicing the data based on valid trading dates. It ensures that all stock selections and return calculations are based only on information available at the time. Specifically:

- The data is filtered by date so that no future information is used for stock selection or portfolio construction.

- The framework only uses momentum and price data from prior periods when rebalancing the portfolio, ensuring no future returns are incorporated into the decision-making process.

- Rebalancing happens at the end of the trading period, based on momentum values observed **prior** to the rebalance date, ensuring the strategy mimics realistic, real-time decision-making.

At the end of the backtest, daily portfolio returns are aggregated, and performance metrics are calculated, including annualized returns, volatility, Sharpe ratio, and maximum drawdown. Additionally, portfolio turnover is tracked after each rebalance to measure how much the portfolio composition changes over time. By carefully managing the data flow and ensuring that only past information is used, this backtesting framework provides reliable and realistic results free from data leakage.

However, there are plenty of limitations that should be kept in mind regarding the backtesting framework before moving on to the analysis of the results section. The backtest is only carried out for a 5 year period from 2019-10-09 to 2024-10-09 where the entire stock market has been in the bull market phase due to the intial quantitative easing during the pandemic and then the potential of interest rate cuts in the near future, a cumulative return of 93% in the last 5 years. Thus the data is highly skewed for momentum based trading strategies. Also there are several assumptions made along the way which do not hold in the real world workings of the financial markets.

6 Analysis of Results

For the sensitivity analysis of the different parameters of the trading strategy, I have assumed the 1-month horizon, weekly rebalancing, no smoothing of z-scores to be the default (i.e. benchmark strategy).

6.1 Momentum Horizon Sensitivity Analysis

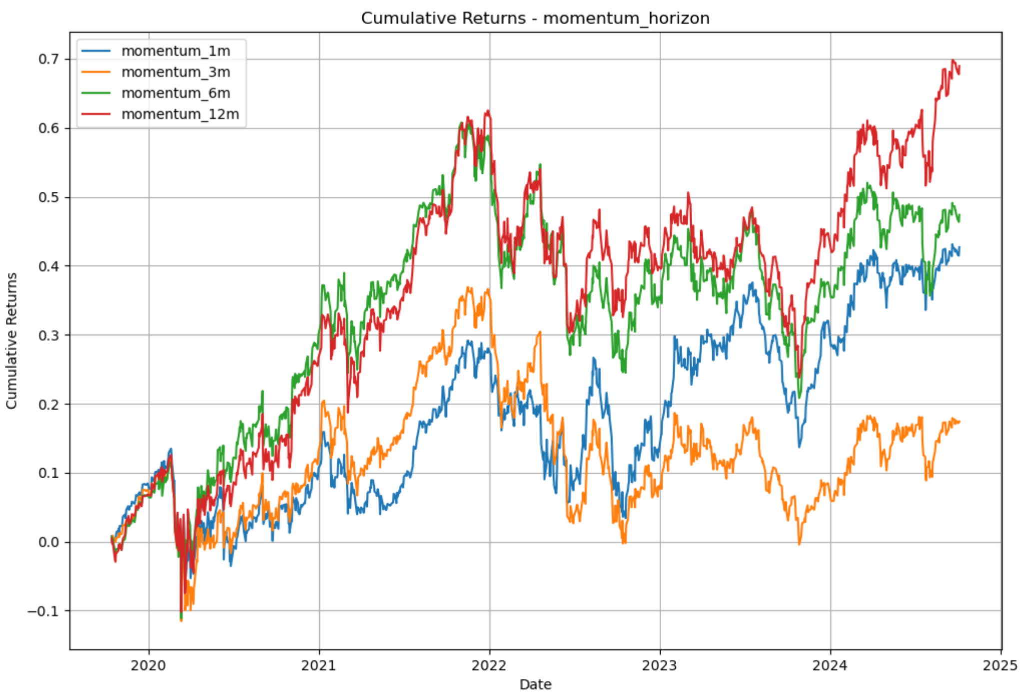

Figure 1: Cumulative Returns for Momentum Horizons

Figure 1 shows the cumulative returns for the different momentum horizons from 2020 to 2024. Across all horizons, momentum strategies outperformed the initial value (cumulative return = 0), indicating that all strategies added value over time.

Metric	Momentum 1m	Momentum 3m	Momentum 6m	Momentum 12m
Cumulative Returns	42.69%	17.41%	47.38%	68.94%
Annualized Return	9.54%	4.20%	10.45%	14.39%
Annualized Volatility	19.67%	20.03%	20.52%	21.07%
Annualized Sharpe Ratio	0.4851	0.2097	0.5095	0.6829
Maximum Drawdown	-19.95%	-27.28%	-24.85%	-23.83%
Average Turnover	41.59%	25.16%	18.00%	13.99%
22-day Holding Period Avg Return	0.72%	0.62%	0.80%	0.91%
66-day Holding Period Avg Return	2.36%	2.14%	2.48%	2.45%
132-day Holding Period Avg Return	4.73%	4.81%	5.43%	4.90%
252-day Holding Period Avg Return	10.71%	11.21%	11.69%	10.70%

Table 1: Momentum Horizon Performance Metrics

The 12-month momentum strategy consistently performed the best, showing the highest cumulative return throughout the period, particularly in 2024. It reached a peak cumulative return of nearly 0.7, while the shorter horizons exhibited lower cumulative returns, especially in volatile periods, such as early 2022.

The 1-month strategy generally lagged behind the others up until mid-2022 but it remained competitive, showing similar trends to the other horizons from there on out. The complete opposite happened with the 3-month strategy where it consistently outperformed the 1-month strategy, but post mid-2022 it was heavily underperforming compared to all the strategies as shown in Table 1.

The Sharpe ratio is a key indicator of risk-adjusted performance, where a higher value indicates better returns for the risk taken. One key assumption made when calculating the Sharpe ratio is that the risk-free rate is assumed to be 0. The 12-month strategy again outperforms the others with a Sharpe ratio of 0.6829, followed by 6-months at 0.5095. These results suggest that longer momentum horizons offer better risk-adjusted returns compared to shorter horizons. The 1-month and 3-month strategies have lower Sharpe ratios of 0.4851 and 0.2097, respectively, indicating that these shorter-term strategies may not justify their volatility.

Turnover is a critical metric for understanding trading costs. Shorter-term momentum strategies, particularly momentum_1m, have significantly higher turnover (41.59%) compared to momentum_12m (13.99%). This suggests that the shorter-term strategies require more frequent trading, leading to potentially higher transaction costs, which could diminish their net performance over time. The backtesting framework, I have assumed transaction costs to be 0.

While the momentum_12m strategy offers the highest returns and risk-adjusted performance, the relatively high volatility and drawdown associated with it are concerns. Investors seeking more stability may prefer the momentum_6m strategy, which balances returns and risks better than the shorter-term strategies. There is no noticeable relationship in terms of the drawdown and the momentum horizon. Since increasing the momentum horizon does increase the drawdown (from 1-month to 3-months), but then the drawdown decreases as the momentum horizon is increasing (from 3-months to 12-months). This suggests that the drawdown is highly dependent on the time period with which the backtesting is performed.

6.2 Rebalancing Frequency Sensitivity Analysis

Now as one can observe from both the Table 2 and Figure 2 that the monthly rebalacing frequency strategy significantly outperforms the weekly rebalancing strategy. It not only has higher cumulative returns but it also has a slightly lower drawdown. However, the turnover is greater for the monthly frequency strategy by approximately a staggering 35%. This suggests that with monthly rebalancing the portfolio needs a larger reconstruction due to the changes in the momentum signal. This is contrary to the belief that a strategy with a lower rebalancing frequency should have a lower turnover, but due to the market being very volatile the landscape changes with a high intensity requiring the portfolio construction to be modified by a lot. The higher turnover means that the strategy is more costly due to the transaction costs that will be incurred so, the cumulative return performance metrics needs to be taken at face value with a pinch of salt. Morevover, there is not a significant improvement in the different holding period returns even though the rebalancing frequency is different.

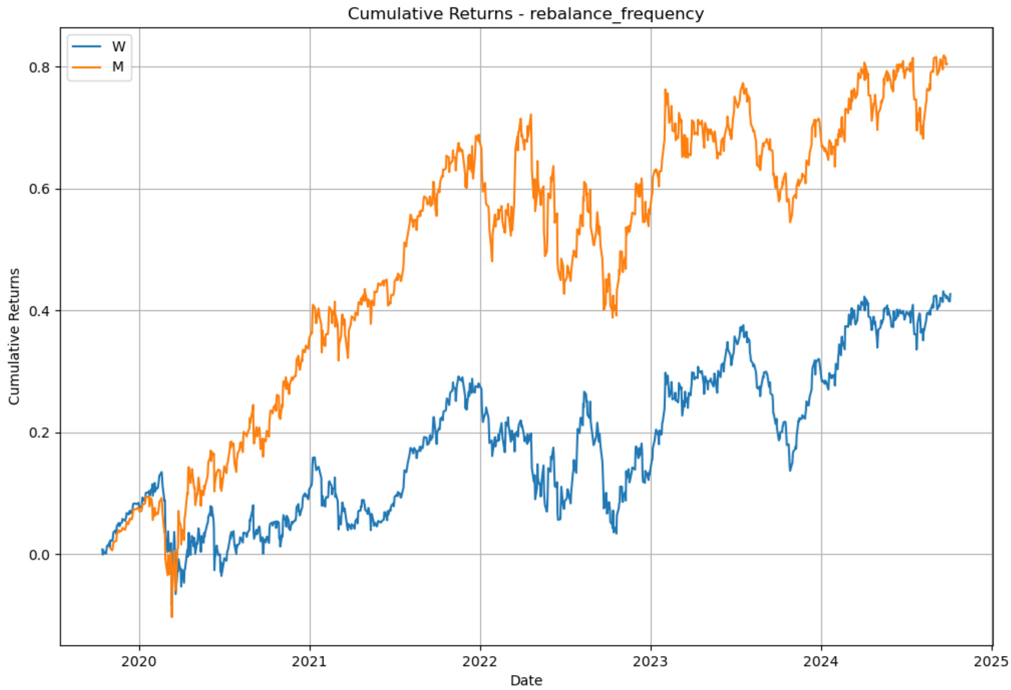

Figure 2: Cumulative Returns for Rebalacing Frequency

6.3 Smoothing of Z-scores

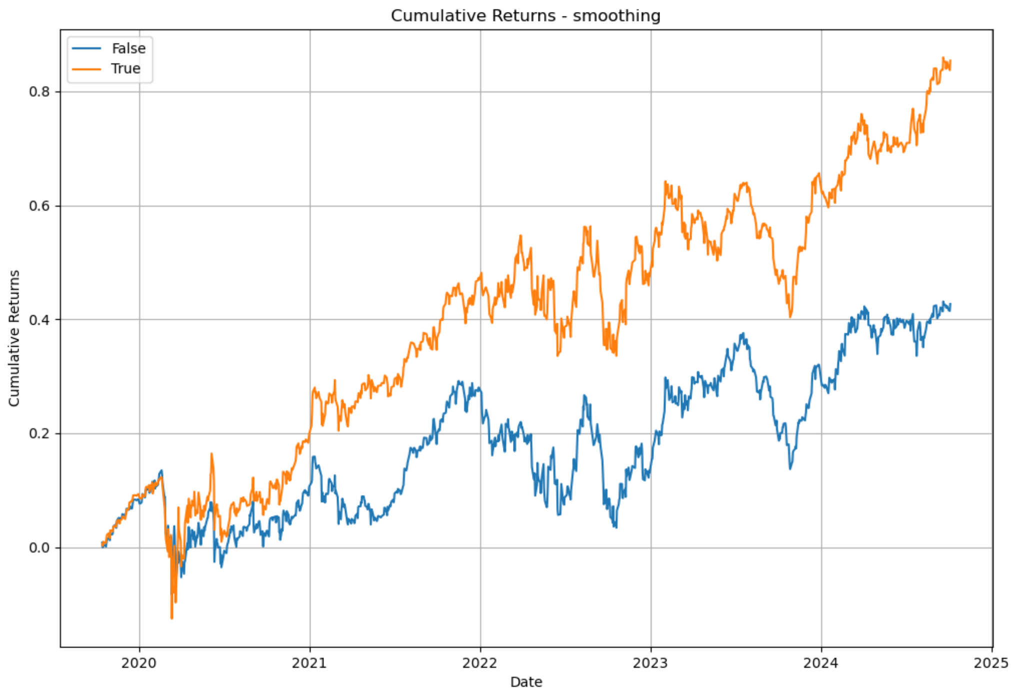

Figure 3: Cumulative Returns with and without Smoothing

Metric	Weekly Rebalance	Monthly Rebalance
Cumulative Returns	42.69%	80.43%
Annualized Return	9.54%	16.61%
Annualized Volatility	19.67%	20.54%
Annualized Sharpe Ratio	0.4851	0.8086
Maximum Drawdown	-19.95%	-19.35%
Average Turnover	41.59%	76.36%
22-day Holding Period Avg Return	0.72%	0.79%
66-day Holding Period Avg Return	2.36%	2.48%
132-day Holding Period Avg Return	4.73%	5.01%
252-day Holding Period Avg Return	10.71%	10.78%

Table 2: Rebalancing Frequency Performance Metrics

The cumulative returns plot in Figure 3 clearly demonstrates that applying smoothing (window size = 5 days) to the z-scores in the momentum strategy yields significantly higher returns compared to the non-smoothed approach. The strategy with smoothing consistently outperforms the non-smoothed strategy over the entire backtesting period from 2020 to 2024. This outperformance can be attributed to several factors. Firstly, smoothing helps reduce the impact of short-term market noise and volatility on the momentum signals, allowing the strategy to capture more persistent trends. By using a rolling window to calculate the z-scores, the strategy likely becomes less sensitive to sudden, temporary spikes or dips in momentum, which could otherwise lead to false signals and unnecessary trading. This reduced sensitivity to noise may result in more stable and reliable stock selection, potentially lowering turnover and associated transaction costs. Additionally, smoothing may help in identifying stocks with more consistent momentum characteristics, rather than those experiencing short-lived momentum bursts. This could lead to selecting stocks with more sustainable performance trends, contributing to the strategy's improved long-term returns. The substantial gap in cumulative returns between the smoothed and non-smoothed approaches, particularly widening from 2022 onwards, suggests that the benefits of smoothing become more pronounced over time, possibly due to compounding effects and the strategy's ability to better navigate various market conditions.

6.4 Smoothing Window Sensitivity Analysis

Metric	Smoothing Window 5 days	Smoothing Window 22 days	Smoothing Window 132 days
Cumulative Returns	85.40%	120.70%	142.46%
Annualized Return	17.15%	22.50%	25.49%
Annualized Volatility	20.86%	21.12%	21.79%
Annualized Sharpe Ratio	0.8219	1.0655	1.1697
Maximum Drawdown	-22.13%	-22.24%	-22.27%
Average Turnover	42.39%	44.94%	45.95%
22-day Holding Period Avg Return	0.98%	1.15%	1.26%
66-day Holding Period Avg Return	2.74%	3.09%	3.22%
132-day Holding Period Avg Return	5.14%	5.98%	5.98%
252-day Holding Period Avg Return	11.46%	13.00%	13.46%

Table 3: Smoothing Window Performance Metrics

The impact of different smoothing windows on the momentum strategy's performance is clearly illustrated in Figure 4 and Table 3. Figure 4 demonstrates that longer smoothing windows generally lead to higher cumulative returns, with the 132-day window (green line) consistently outperforming the 22-day and 5-day windows over the backtesting period from 2020 to 2024. This visual trend is quantitatively supported by Table 3, which shows that the 132-day smoothing window achieved the highest cumulative return of 142.46%, compared to 120.70% for the 22-day window and 85.40% for the 5-day window. Interestingly, the difference in annualized volatility across the three windows is relatively small, suggesting that the improved returns from longer smoothing windows do not come at the cost of significantly increased risk. The trade-off appears to be slightly higher turnover for longer windows, which may be offset by the improved returns. These results suggest that longer smoothing windows

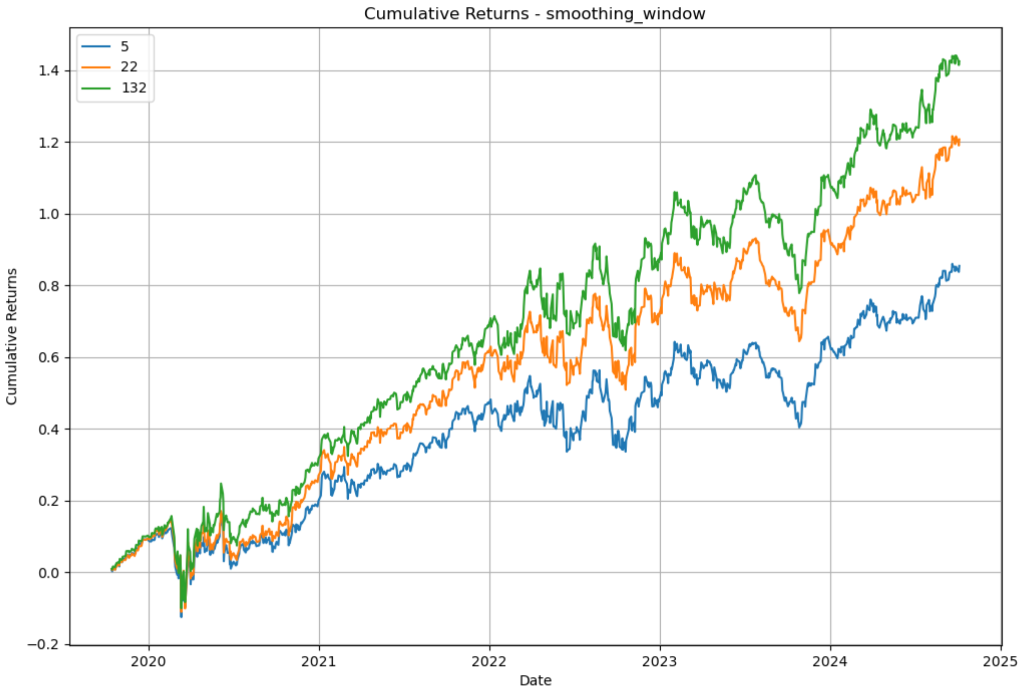

Figure 4: Different Smoothing Window Cumulative Return

may be more effective at filtering out short-term noise and capturing more persistent momentum trends, leading to more robust stock selection and ultimately higher returns in the momentum strategy.

6.5 Current Momentum vs. Lagged Momentum Strategy

Metric	**Lagged Momentum: 1m_1m, 1m_2m**
Rebalancing Frequency	Weekly
Z-score Threshold	1
Z-score Smoothing	False
Smoothing Window (days)	5
Cumulative Returns	91.24%
Annualized Return	18.08%
Annualized Volatility	23.34%
Annualized Sharpe Ratio	0.7747
Maximum Drawdown	-20.09%
Average Turnover	35.90%
22-day Holding Period Avg Return	1.04%
66-day Holding Period Avg Return	2.38%
132-day Holding Period Avg Return	5.52%
252-day Holding Period Avg Return	10.96%

Table 4: Lagged Momentum Performance Metrics

The lagged momentum trading strategy is developed with a slightly different methodology as compared to using the current momentum signal. The strategy calculates lagged momentum indicators over

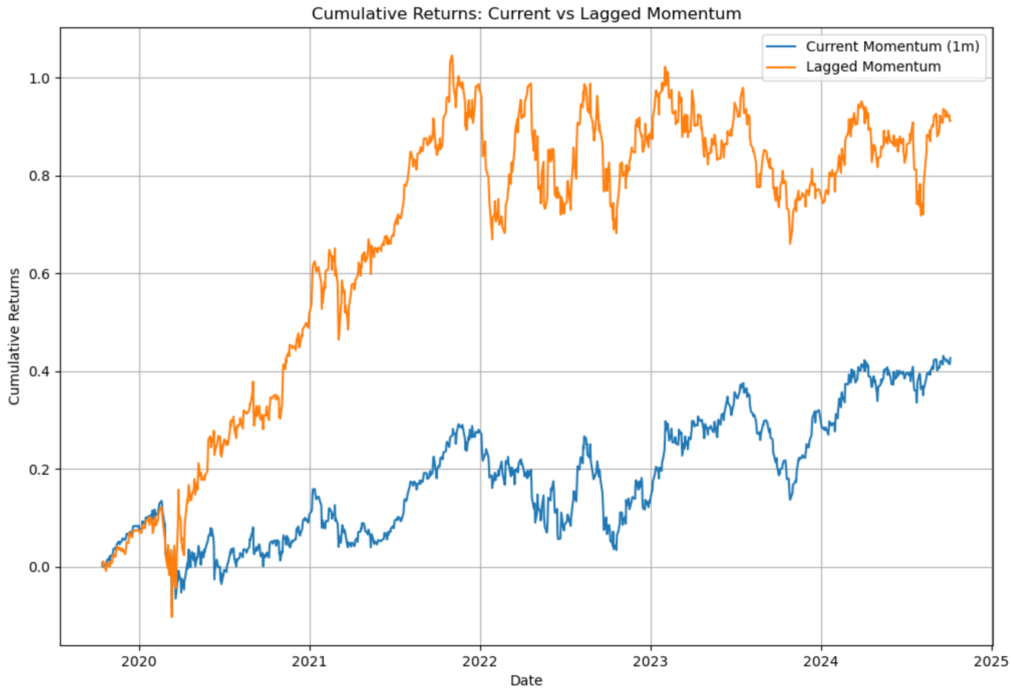

Figure 5: Current Momentum vs. Lagged Momentum Cumulative Return

different time periods, specifically using 'lagged_momentum_1m_1m' and 'lagged_momentum_1m_2m'. These indicators capture price trends that may persist over time, potentially offering more stable signals compared to traditional momentum strategies. The strategy then applies a z-score transformation to these momentum values, standardizing them across the universe of stocks. Then the average of the two z-scores (i.e. using each lagged momentum) are taken into consideration. The rest of the backtesting framework has been kept the same for fair comparison of the performance metrics.

The results of the lagged momentum strategy demonstrate significant outperformance compared to the current momentum approach, as illustrated in Figure 5. The cumulative returns plot shows that the lagged momentum strategy consistently outperforms the current momentum strategy over the entire period from 2020 to 2024. By the end of the period, the lagged momentum strategy achieves a cumulative return of 91.24%, more than double the current momentum strategy's return of about 42%.

Table 4 provides detailed performance metrics for the lagged momentum strategy. When compared to the results of Table 1, that the maximum drawdown is only slightly higher and the turnover is signifcantly lower by about 5%. This suggests that the lagged momentum signals act as a more robust signal in terms of the continued momentum into the future for the stocks. Even the average holding period returns across different periods are higher.

6.6 Optimal Strategy

Now through recursive nested loops, one obtains the optimal strategies based on different targeted performance metrics. The one prevailing fact that emerges from Table 5 is that all the optimal strategies are when the Z-scores are smoothened with the window size of 132 days. This underlines the fact that when the backtest is introduced with more past data for the computation of the Z-scores the strategy performs significantly very well. Also for the case of backtesting the strategy using the data from 2019-10-09 to 2024-10-09 the highest cumulative return generating strategy is the same as the highest Sharpe ratio strategy. Inspecting deeper in to the performance of the strategy in Figure 6 one observes that the strategy was very closely performing the same as the S&P 500 Index until the start of 2022 when the rise of geopolitical issues occurred between Russia and Ukraine. The S&P 500 index did suffer in the year of 2022 where as the optimal strategy kept on performing well. This can also be seen from the drawdown of the strategy which was is in mid-2020 due to the pandemic but compared to the S&P 500 index the strategy did not suffer that big of a drawdown.

Figure 6: Highest Cumulative Return Strategy

Metric	Highest Cumulative Return	Highest Sharpe Ratio	22d Holding Period	66d Holding Period	132d Holding Period
Momentum Horizon	momentum_1m	momentum_1m	momentum_6m	momentum_6m	momentum_3m
Rebalancing Frequency	Weekly	Weekly	Weekly	Monthly	Monthly
Z-score Threshold	1	1	0.5	0.5	1
Z-score Smoothing	True	True	True	True	True
Smoothing Window (days)	132	132	132	132	132
Cumulative Returns	142.46%	142.46%	118.42%	120.31%	119.54%
Annualized Return	25.49%	25.49%	22.17%	22.83%	22.72%
Annualized Volatility	21.79%	21.79%	21.92%	22.18%	22.36%
Annualized Sharpe Ratio	1.1697	1.1697	1.0114	1.0293	1.0158
Maximum Drawdown	-22.27%	-22.27%	-23.15%	-23.14%	-22.73%
Average Turnover	45.95%	45.95%	13.89%	25.04%	55.26%
22-day Holding Period Avg Return	1.26%	1.26%	1.27%	1.03%	1.10%
66-day Holding Period Avg Return	3.22%	3.22%	3.49%	3.85%	3.79%
132-day Holding Period Avg Return	5.98%	5.98%	6.51%	6.68%	6.78%
252-day Holding Period Avg Return	13.46%	13.46%	13.99%	14.48%	14.96%

Table 5: Optimal Strategy's Performance Metrics

7 Conclusion

This comprehensive analysis of momentum-based trading strategies applied to S&P 500 equities has yielded several significant insights. The study evaluated various momentum horizons, rebalancing frequencies, and smoothing techniques, providing a nuanced understanding of their impact on strategy performance.

Key findings include:

- Longer momentum horizons, particularly the 12-month strategy, consistently outperformed shorter horizons in terms of cumulative returns and risk-adjusted performance (Sharpe ratio).
- Monthly rebalancing showed superior performance compared to weekly rebalancing, albeit with higher turnover, suggesting a trade-off between performance and transaction costs.
- Applying smoothing to z-scores significantly enhanced strategy performance, with longer smoothing windows (132 days) yielding the highest cumulative returns.
- The lagged momentum strategy demonstrated substantial outperformance compared to the current momentum approach, achieving more than double the cumulative return over the backtesting period.
- The optimal strategy, combining a 12-month momentum horizon, monthly rebalancing, and 132-day smoothing window, showed remarkable resilience during market downturns, outperforming the S&P 500 index significantly from 2022 onwards.

These results underscore the potential of momentum-based strategies in capturing persistent market trends and generating alpha. However, it's crucial to note that the backtesting period (2020-2024) coincided with a largely bullish market, which may have influenced the strategies' performance. The higher turnover associated with some of the better-performing strategies also highlights the importance of considering transaction costs in real-world applications.

8 Next Steps

While this analysis provides valuable insights into momentum-based trading strategies, several avenues for further research and refinement exist:

1. **Extended Backtesting:** Due to computational restrictions, this study was limited to a 5-year backtest. To gain a more comprehensive understanding of the strategies' performance across different market cycles, future research should:
   - Conduct backtests over longer periods (10-15 years).
   - Perform multiple 5-year backtests across different time periods (e.g., 2012-2017, 2007-2012) to assess strategy performance in various market conditions.
2. **Econometric Analysis:** To ensure the predictability of momentum factors is statistically significant and not due to chance or high correlation with the S&P 500 index, further econometric analysis should be conducted. This could include:

- Time series analysis to test for factor persistence.
- Cross-sectional regressions to control for other known factors.
- Tests for statistical significance of momentum predictability.

3. **Combined Momentum Signals:** Given the superior performance of lagged momentum, future research could explore:
   - Constructing trading signals that combine current and lagged momentum.
   - Optimizing the weighting between current and lagged signals.
4. **Incorporation of Fundamental Signals:** To enhance strategy robustness during structural breaks (e.g., COVID-19 crash), consider:
   - Integrating macroeconomic indicators into the signal generation process.
   - Developing a multi-factor model that combines momentum with fundamental factors.
5. **Leverage and Short Positions:** To potentially enhance returns and provide downside protection:
   - Explore the use of leverage in the strategy.
   - Incorporate short positions based on negative z-scores.
6. **Alternative Portfolio Construction:** Instead of equal weighting, investigate:
   - Weighting based on the strength of momentum signals (z-scores).
   - Risk-parity or minimum variance approaches to portfolio construction.
7. **Advanced Smoothing Techniques:** Experiment with different methods for smoothing z-scores:
   - Exponentially weighted moving averages.
   - Kalman filters or other adaptive smoothing techniques.
8. **Robust Performance Metrics:** Enhance the performance evaluation by:
   - Incorporating a realistic risk-free rate in Sharpe ratio calculations.
   - Including additional risk-adjusted metrics such as Sortino and Calmar ratios.
   - Accounting for transaction costs (e.g., 5 bps per trade) to provide a more realistic assessment of strategy profitability.
9. **Advanced Data Visualization:** Deepen the analysis through:
   - Sector-based analysis of portfolio weights over time.
   - Correlation analysis with market indices and other factors.
   - Interactive visualizations to explore strategy behavior under different parameters.

By pursuing these next steps, future research can build upon the findings of this study to develop more robust, reliable, and profitable momentum-based trading strategies. The integration of additional data sources, advanced statistical techniques, and consideration of real-world constraints will be crucial in translating these theoretical insights into practical investment applications.