Sector-Relative Momentum Acceleration Strategy

Nicholas Delianedis
Julia Figueros
Sven Hauksson
Pranay Kumar

UCLA Anderson School of Management

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1 Introduction

Momentum based strategies have been a cornerstone of quantitative investing for many years. They consistently deliver excess returns across asset classes and periods. However, momentum approaches mainly rely on past return levels, potentially overlooking some important characteristics which could improve performance.

This project presents an investment strategy that aims to enhance momentum investing by introducing two additional concepts: sector-relativity and second order momentum, or 'acceleration'. The idea is that not only do stocks that have performed well tend to continue performing well, but those stocks whose momentum is accelerating, especially relative to their peers, may offer early and stronger signals of future overperformance.

To implement this idea, we develop a long-short equity strategy using U.S. common stocks, identifying the top and bottom deciles based on sector-standardized momentum acceleration, and using the excess returns of the top decile minus the bottom decile.

We evaluate the strategy's performance through return metrics and risk-adjusted alphas, demonstrating its potential as a practical and interpretable enhancement to traditional momentum investing.

2 Literature and Strategy Context

Momentum strategies were first documented by Jegadeesh and Titman (1993), and they have become one of the most well-known anomalies in finance, delivering positive abnormal returns across different time periods and different financial markets.

Other research (e.g., Fama and French, 1996) used momentum in multi-factor models, while others explored enhancements through risk-adjusted ranking and signal smoothing. Recent papers have begun to research momentum acceleration, the rate of change in momentum, as a higher-order signal capable of predicting turning points or amplifying alpha (e.g., Chen and DeBondt, 2004; Gutierrez and Pirinsky, 2007). Meanwhile, sector-neutral or sector-relative momentum approaches (e.g., Moskowitz and Grinblatt, 1999) have shown that adjusting for sector effects improves performance by filtering out common trends.

Our strategy builds on these ideas by combining acceleration with sector-relative momentum to refine the signal further. To the best of our knowledge, the combination of these techniques has not been previously implemented in the academic literature, making this project both incremental and practical.

3 Strategy Description

Our strategy enhances traditional momentum by integrating two extra dimensions: second-order momentum acceleration and sector-relative adjustment.

We started by calculating momentum, and then building a signal based on the monthly change in momentum, which we refer to as second order momentum, or acceleration. In addition, we grouped the stocks in each month by industry, and adjusting the stock returns by the industry average of that month. Then, we created a number of other signals based on these two signals to compare.

Each month, we sorted stocks into deciles based on these signals using the Daniel-Moskowitz (DM) methodology, and form a long-short portfolio by taking a long position in decile 10 and a short position in decile 1. Returns are value-weighted using lagged market capitalization.

4 Discussion

4.1 Strategy Strengths

Of the signals we tested, the two WML strategies based on the nonlinear combinations of first and second order momentum both outperformed vanilla momentum's Sharpe Ratio, while the `VolAdjMom` signal did similarly well, as shown in Table 1. In addition, the skewness for most of these strategies is on the order of 15-20, indicating an unbalanced return distribution. However, our `Rank_Order_2_Adj` and `VolAdjMom` signal strategies have a much lower magnitude skew, indicating a more balanced portfolio. In addition, the `VolAdjMom` signal boasts a high Fama French 3-Factor regression alpha of 0.89 (Table 3), and an improved Sharpe Ratio post-2000 per our robustness testing, indicating that it performs well in modern markets (Table 4).

4.2 Costs and Risks

The largest cost of this strategy is its volatility. As shown in Table 1, the volatilities of our WML portfolios can get as high as 36.85%. One plausible explanation for the alpha that this strategy generates is that it is compensation for the large amounts of risk taken by investors who are more risk averse than the CAPM model accounts for.

Another major cost of this strategy is its turnover rate, which, as we see in Table 6, is relatively high for all of our best performing strategies. For example, the 20% momentum/80% acceleration signal's strategy has a monthly turnover rate of 97.89%, as compared to first order momentum's 68.41% and `Rank_Order_2_Adj`'s 61.91%. The high turnover rates seen here, especially for the blended signal, would quickly eat into any profits made, and would need to be taken into consideration by anyone considering implementing one of these strategies.

4.3 Investor Rationale

The strategy is implementable and scalable for institutions. It effectively captures momentum while mitigating noise from market trends by adjusting to specific sector dynamics. It can avoid overexposure to any single industry and has enhanced signal precision. The strong alpha of this strategy suggests that it takes advantage of pricing inefficiencies not captured by other standard risk models.

Our original second order momentum signal (`Delta_Ret`) and other pure second order momentum signal strategies' WML portfolios have negative excess return, as exemplified in Table 1 by the performance of `Rank_Blend_20/80`, the most heavily weighted of the blended portfolios towards pure second order momentum. These negative returns can be explained by mean reversion, as stocks that overperform come back down to the mean. These signals are still useful because they, for the most part, have statistically significant alphas, and thus provide useful information for our more complex strategies, such as the one generated with the `Rank_Order_2_Adj` signal, which adjusts momentum by subtracting half of the square of adjusted second order momentum, which has generates a Sharpe Ratio of 0.38, which is higher than regular momentum's Sharpe Ratio of 0.36.

4.4 Robustness

To determine how robust these signals and strategies are, we split are sample by time at the year 2000 to compare how they performed before and since that year. The results are displayed in Table 4 and in Table 5, where we see that the returns and Sharpe Ratios are still significant both pre- and post-2000, but that the momentum and second order nonlinearly combined signals do significantly worse post-2000 than they did pre-2000, while the blended signal and `VolAdjMom` did somewhat better. This phenomenon is well known with regards to first order momentum, but we can determine from these results that this may be due to excess risk being taken, as the volatility-adjusted momentum did not show this effect.

5 Conclusion

In conclusion, the strategy delivered high excess returns and Sharpe ratios with statistically significant alpha. The signal is transparent, scalable, and straightforward to compute, making the strategy a good fit for institutional quantitative implementation. As mentioned before, the strategy has consistently performed well across decades of data. In the future, we could extend this strategy framework to global equity markets, integrate transaction costs into the model, or use alternative weights using machine learning for signal optimization.

A Appendix I

This appendix outlines the methodology used to construct momentum-based signals, form decile portfolios, and evaluate the performance and robustness of our investment strategies.

1. Data Preprocessing

We began with monthly stock return data from the CRSP database, including both standard returns and delisting returns to avoid survivorship bias. These were merged and cleaned to handle missing values and ensure accuracy, especially for firms that were delisted. SIC industry codes were included, and firms with invalid or missing codes were excluded. We computed market capitalization using the absolute price times shares outstanding (in millions of USD), which was critical for both value-weighting and forming breakpoints in portfolio construction.

2. Signal Construction

We constructed a set of momentum-based signals aimed at capturing different predictive features of stock returns:

- **Base Momentum (Ranking_Ret):** The 12-month cumulative return from months $t-12$ to $t-2$, excluding the most recent month to mitigate short-term reversals.
- **Second-Order Momentum (Rank_Order_2):** Enhances the base momentum by incorporating the change in return (acceleration).
- **Sector-Relative Adjusted Momentum (Rank_Order_2_Adj):** Adjusts second-order momentum by subtracting the average within-sector acceleration, allowing for sector-relative comparisons.
- **Volatility-Adjusted Momentum (VolAdjMom):** Divides cumulative return by the 12-month rolling standard deviation, filtering out high-risk or "lottery" stocks.
- **Blended Signals:** Weighted combinations of the above signals, such as 80% base momentum and 20% sector-relative momentum, to explore hybrid predictive power.

All signals were ranked cross-sectionally each month to facilitate decile sorting.

3. Portfolio Formation

Stocks were assigned to deciles each month based on their signal values using two sorting methodologies:

- **Daniel & Moskowitz (DM):** Stocks ranked using the full sample of available firms.
- **Kenneth French (KRF):** NYSE stocks used to determine decile breakpoints; applied to the full universe to avoid size bias.

Returns within each decile were computed using lagged market capitalization for value-weighting.

4. Performance Evaluation

For each signal, we calculated monthly returns for each decile and formed a **Winner-minus-Loser (WML)** portfolio as Decile

10 minus Decile 1. The following statistics were then computed (annualized where applicable):

- Average excess return
- Volatility (standard deviation)
- Sharpe ratio
- Skewness

These metrics allowed us to assess both return potential and risk characteristics of each strategy.

5. Factor Regressions

To identify sources of return, we regressed the WML portfolio returns against:

- **CAPM:** Market excess return.
- **Fama-French 3-Factor Model (FF3):** Market, size (SMB), and value (HML) factors.

We reported alpha (intercept), factor loadings, and R^2 to evaluate whether excess returns could be explained by traditional risk factors.

6. Robustness Checks

To test the stability of signal performance, we divided the sample into two periods:

- **Pre-2000:** Captures performance in early, high-growth, and less efficient markets.
- **Post-2000:** Covers the more recent, potentially more efficient market regime.

All performance metrics and regressions were re-estimated in each period to assess consistency over time.

7. Turnover Calculation

To estimate the implementation costs associated with each strategy, we calculated **average monthly turnover** for each WML portfolio. Turnover is defined as the percentage of stocks entering or exiting the top and bottom deciles between two consecutive months. A higher turnover implies more trading and higher potential transaction costs.

B Appendix II

B.1 Summary Statistics

Table 1: Performance Metrics for WML Portfolios across Momentum Signals

Signal	Excess Return (%)	Volatility (%)	Sharpe Ratio	Skewness
`Ranking_Ret`	13.15	36.85	0.36	15.88
`Rank_Order_2`	14.28	35.83	0.40	17.62
`Rank_Order_2_Adj`	7.49	19.53	0.38	-2.35
`VolAdjMom`	6.41	18.06	0.35	-3.08
`Rank_Blend_80/20`	9.08	36.24	0.25	16.78
`Rank_Blend_50/50`	4.83	35.12	0.14	18.50
`Rank_Blend_20/80`	-0.24	34.36	-0.01	19.73

Note: All statistics reported are computed for the WML (Winner Minus Loser) portfolios constructed using each signal.

B.2 Factor Regressions

Table 2: Fama-French 3-Factor Regression: `Rank_Blend_80/20` WML Portfolio

Factor	Coefficient	t-stat	p-value
Alpha	0.0076	3.82	0.000
Market Minus Rf	-0.0421	-1.13	0.258
SMB	0.1265	2.15	0.032
HML	0.2019	3.90	0.000

Note: This table presents results from a Fama-French 3-Factor regression run on the monthly returns of the `Rank_Blend_80/20` WML portfolio. The alpha is statistically significant and robust to factor loadings, making this blended strategy a strong performer among those evaluated.

Table 3: Alpha and t-statistics from FF3 Regression

Signal	Alpha (%)	t-stat(Alpha)
`Ranking_Ret`	0.71	2.41
`Rank_Order_2`	0.77	2.67
`Rank_Order_2_Adj`	0.66	4.30
`VolAdjMom`	0.89	6.69
`Rank_Blend_20/80`	-0.34	-1.21

B.3 Robustness Testing

Table 4: Pre- vs Post-2000 WML Sharpe Ratios by Signal

Signal	Pre-2000 Sharpe Ratio	Post-2000 Sharpe Ratio
Ranking_Ret	0.39	0.25
Rank_Blend_80/20	0.25	0.41
Rank_Order_2_Adj	0.42	0.20
VolAdjMom	0.31	0.46

Table 5: Pre- vs Post-2000 WML Excess Returns by Signal

Signal	Pre-2000 Excess Return (%)	Post-2000 Excess Return (%)
Ranking_Ret	15.77	5.33
Rank_Blend_80/20	10.05	8.16
Rank_Order_2_Adj	8.08	3.41
VolAdjMom	5.69	6.65

B.4 Turnover Rates

Table 6: Average Monthly Turnover of WML Portfolios

Signal	Turnover (%)
Ranking_Ret	68.41
Rank_Order_2_Adj	61.91
VolAdjMom	72.28
Rank_Blend_20/80	97.89