Quantitative Trading Report

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Abstract

Lou and Polk [2021] propose a novel measure, *comomentum*, to enhance momentum strategies by capturing return comovement among crowded trades. While theoretically appealing, we find no out-of-sample evidence that comomentum improves risk-adjusted returns or adds predictive power beyond standard momentum. Our results indicate comomentum is not a robust signal.

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1 Introduction

In *Comomentum: Inferring Arbitrage Activity from Return Correlations*, Lou and Polk [2021] suggest a novel framework for assessing when momentum factors will perform well, and when momentum factors will perform worse. They call this *Comomentum*. In this paper, we respond that this **does not hold out of sample.** Comomentum has a weak correlation of *-26%* with Momentum, and a formal hypothesis test confirms **Comomemtum has no predictive power**.

2 Methodology

2.1 Data Preprocessing

Our investment universe consists of *7,216* stocks, with a horizon of *1,513* weeks, roughly *29* years of returns data. Financial data is seldom clean, often suffering from missing values or periods of stock inactivity and ours is no exception. To address this, we introduce a 'live indicator' to track the activity of each stock. We identify and exclude *45* 'dead' stocks, those that exhibit no activity (i.e., a live indicator sum of zero) over the sample period, to focus on active assets only. For stocks which are 'live' but its return or factor exposure data is missing, we mark that observation as 'invalid', potentially arising from corrupt or incomplete data sources. Only fully valid entries are included in the subsequent analysis. After preprocessing, our final investment universe consists of *7,171* stocks with *1,513* weekly returns data.

2.2 Momentum

Following [Jegadeesh and Titman, 1993], we compute a standard momentum factor over 48 weeks, by finding the cumulative return over the period excluding the most recent 4 weeks; where exclusion offsets microstructure effects or short-term reversals. The momentum of stock i at time t is computed as:

$$\text{Momentum}_i(t) = \sum_{s=t-48}^{t-5} r_i(s) \tag{1}$$

Momentum is calculated for each stock, ensuring that only windows with complete data (i.e., no missing values) are included.

2.3 Fama-Macbeth Style Regression

We perform adapted weekly Fama and MacBeth [1973] regressions, where one-week ahead stock returns are regressed on one-week lagged momentum exposures[1]. While the original Fama-MacBeth framework uses factor coefficients, β_f, as regressors, our setup instead uses momentum directly, following standard predictive cross-sectional methods. This structure remains consistent with the Fama-MacBeth spirit of estimating and averaging time-arying coefficients.

For each week, we include only stocks that satisfy the following:

[1]Further citations of Fama-Macbeth are excluded.

1. The stock is *live*, i.e., its live indicator equals 1.

2. Both its momentum exposure and return data are non-missing.

3. It has a valid next-week return.

For each period, t, we run a cross-sectional regression across all qualifying stocks i:

$$r_{i,t+1} = \alpha_t + \gamma_t \cdot \text{Momentum}_{i,t} + \varepsilon_{i,t},$$

where γ_t is the regression coefficient for momentum at time t, and $\varepsilon_{i,t}$ is the error term. A t-statistic is computed over the time series γ_t to assess the overall significance of the momentum factor:

$$t\text{-stat} = \frac{\bar{\gamma}}{SE(\overline{\gamma})},$$

where $\bar{\gamma}$ is the mean of the regression coefficients, and $SE(\overline{\gamma})$ is the standard error computed as $\frac{\sigma(\gamma)}{\sqrt{T}}$ where $\sigma(\gamma)$ is the standard deviation of γ_t, and T is the number of valid cross-sections where Momentum is computed.

We note that a minimum number of stocks with valid momentum factors, (`min_obs`), is required to ensure that t-statistics are based on a sufficiently large sample. For example, if only one stock, i, has a valid momentum factor at time t then the coefficient γ_t is driven entirely by $Momentum_{i,t}$ and is not a sound estimate for the momentum factor globally. Generalising this, having too few stocks in the regression can lead to estimates driven by noise or outliers and unreliable t-statistics.

2.4 Multi-Factor Regression

Multi-Factor Fama-MacBeth performs the same analysis as before, but with multiple independent variables regressed simultaneously to assess their impact on stock returns. There is one caveat, however: the factors are standardised to affect larger numerical values from dominating the regression results, leading to inaccurate estimates. We use the three standard factors from the *Fama-French 3 Factor model* to perform this calculation: *Market Excess Returns* (ExRetM), *Small-minus-big* (SMB), and *High-minus-low* (HML). Mathematically:

$$r_{i,t} = \alpha_t + \gamma_{1,t} \cdot \text{ExRetM}_t + \gamma_{2,t} \cdot \text{SMB}_t + \gamma_{3,t} \cdot \text{HML}_t + \varepsilon_{i,t},$$

where, for stock i at time t, $\gamma_{f,t}$ is the regression coefficient for factor f shared across all stocks in week t, and $\varepsilon_{i,t}$ is the residual for stock i.

2.5 Comomentum

Comomentum, as introduced by Lou and Polk [2021] is a measure of abnormal return comovement among momentum stocks, used to detect *crowding* in momentum strategies. When Comomentum is high, many investors are simultaneously chasing the same winners and shorting the same losers, increasing the risk of sharp reversals and weaker momentum performance. Conversely, low comomentum suggests less crowding and stronger, more reliable momentum returns.

To replicate this strategy, we compute comomentum over a 52-week rolling window. At each period t, we perform a rolling multi-factor regression for each stock over the past 52 weeks using the Fama-French 3-Factor Model. The residuals $\epsilon_{i,t}$ from these regressions are gathered. At the same date t, we rank all live stocks by their standard momentum measure. The bottom 10% of stocks form the 'Loser' decile, and the top 10% form the 'Winner' decile. For the Loser decile, we compute the average of the off-diagonal entries in the correlation matrix of their 52-week residuals, denoted as $\text{CoMOM}_L(t)$. The same procedure is applied to the Winner decile to obtain $\text{CoMOM}_W(t)$. The overall comomentum measure is then calculated as the simple average:

$$\text{CoMOM}(t) = \frac{\text{CoMOM}_L(t) + \text{CoMOM}_W(t)}{2}.$$

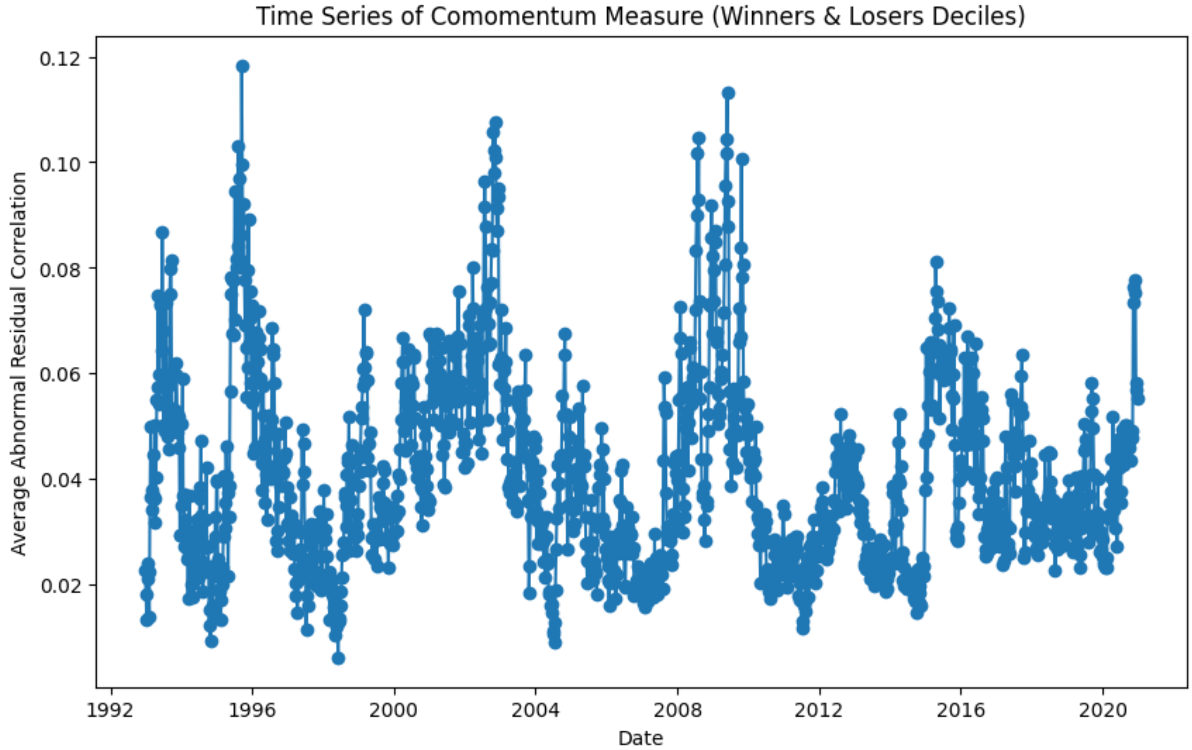

Figure 1: Time Series of Comomentum Measure (Winners and Losers Deciles)

3 Results and Analysis

3.1 Threshold Tuning and Data Availability Constraints

Before presenting our results, we explore a practical limitation that influenced our regression framework. In Section 2.3, we require a minimum number of stocks with valid momentum values per period, (`min_obs`), to ensure that each cross-sectional regression is statistically significant. We conducted a grid search over different thresholds for `min_obs`, to identify the smallest value which resulted in a statistically significant t-statistic. This occurred at `min_obs` = 1800, with the factor achieving weak significance at the 10% level.

However, when comomentum was introduced, we required both a 48-week momentum factor and a 52-week window of residuals from Section 2.5. Our data availability sharply

Table 1: Grid Search for Minimum Observation Threshold and Corresponding t-Statistics

Minimum obs	**t-statistic**	**Significance**
800	1.0346	Not significant
900	0.5164	Not significant
1000	0.5885	Not significant
1100	0.4117	Not significant
1200	0.7705	Not significant
1300	1.0717	Not significant
1400	1.4663	Not significant
1500	1.1876	Not significant
1600	1.0360	Not significant
1700	1.1199	Not significant
1800	**1.8636**	**Significant at 10% level**
1900	-0.6211	Not significant

declined and applying the same `min_obs` threshold resulted in insufficient valid cross-sections, missing γ values and undefined t-statistics.

To address this, we temporarily relax `min_obs` to compare comomentum-adjusted strategies with standard momentum. Even under these more lenient conditions, comomentum failed to produce stronger performance and, in fact, is shown to be statistically insignificant (see Section 3.4).

3.2 Performance of Comomentum-Adjusted Momentum Strategies

We create two comomentum-adjusted variations of momentum, attempting to create a novel signal that incorporates crowding into our trading strategy.

Continuous Weight Adjustment. We modify momentum by applying a weight based on the comomentum level. This involves downweighting the momentum exposure during high-comomentum periods and upweighting it during low-comomentum periods. A possible functional form is:

$$\tilde{M}_t = M_t \cdot f(C_t), \quad \text{where} \quad f(C_t) = \frac{1}{1 + \lambda(C_t - \bar{C})} \tag{2}$$

where M_t is the standard momentum factor, C_t is the comomentum measure, $\bar{C}$ is a benchmark (we take the median of C_t), and λ is a tuning parameter.

Threshold-Based Adjustment. A simpler approach is to 'switch off' the momentum when comomentum is high. This is defined by:

$$\tilde{M}_t = M_t \cdot \mathbf{1}_{\{C_t \leq T\}}, \tag{3}$$

where $\mathbf{1}$ is the *Indicator Function* and T is a threshold of the comomentum distribution.

We perform a *Grid Search* to tune the optimal value of λ and the optimal threshold T (see Section 3.3).

Table 2 reports summary statistics for the unadjusted and adjusted strategies. While the continuously-adjusted momentum factor achieves a marginally higher mean return and lower standard deviation than the standard factor, the differences are minor. The threshold-adjusted signal suffers slightly lower returns but also shows reduced volatility.

Table 2: Performance Summary of Momentum Variants

Statistic	Standard	Adjusted (Continuous)	Adjusted (Threshold)
Annualised Mean	7.27%	7.33%	6.38%
Annualised Std Dev	0.970	0.945	0.885
Sharpe Ratio	0.75	0.78	0.72
T-statistic	1.0788	0.9005	1.1724

Cumulative return plots (see Figure 2) show similar growth patterns across all three strategies. That is, while comomentum may adjust the risk profile of momentum-based signals slightly, it does not lead to material improvements in performance. The threshold-adjusted signal performs remarkably worse, almost certainly caused by the shrinking of the standard momentum factor to *0* when comomentum is high.

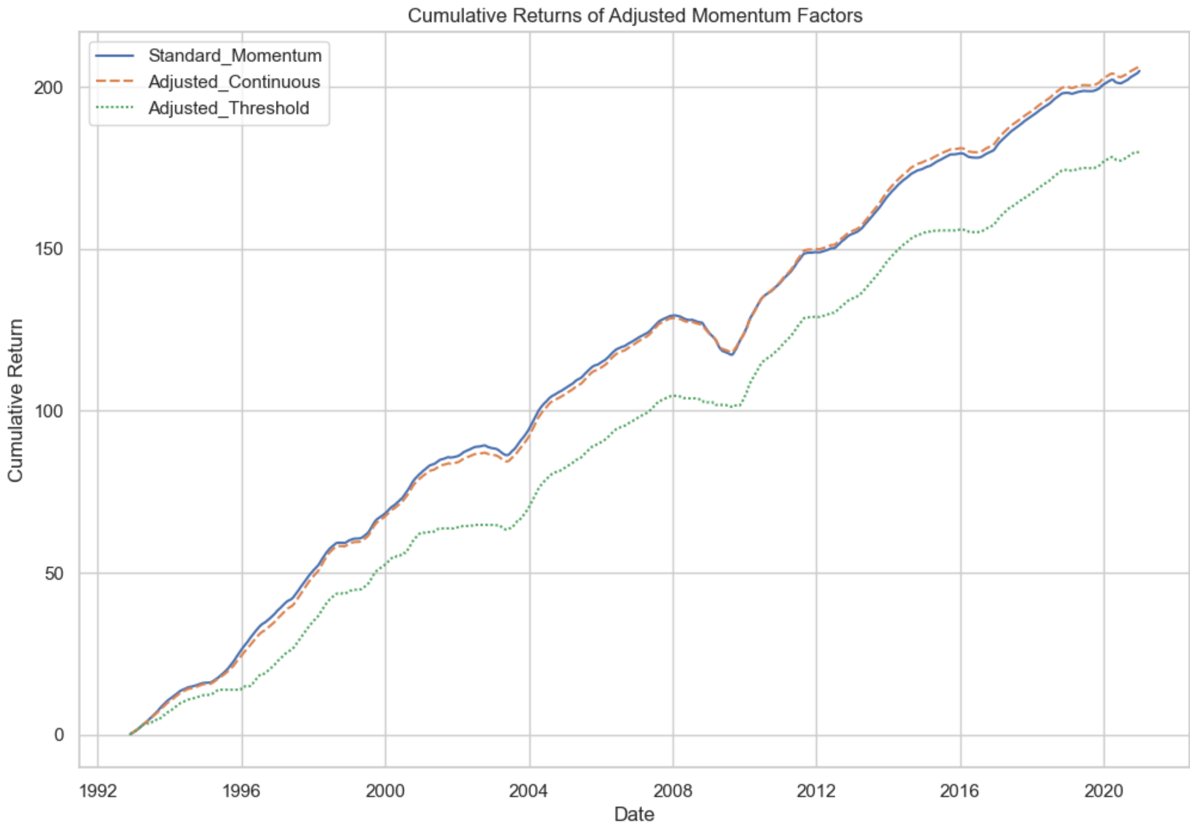

Figure 2: Cumulative Returns for Standard and Adjusted Momentum Strategies

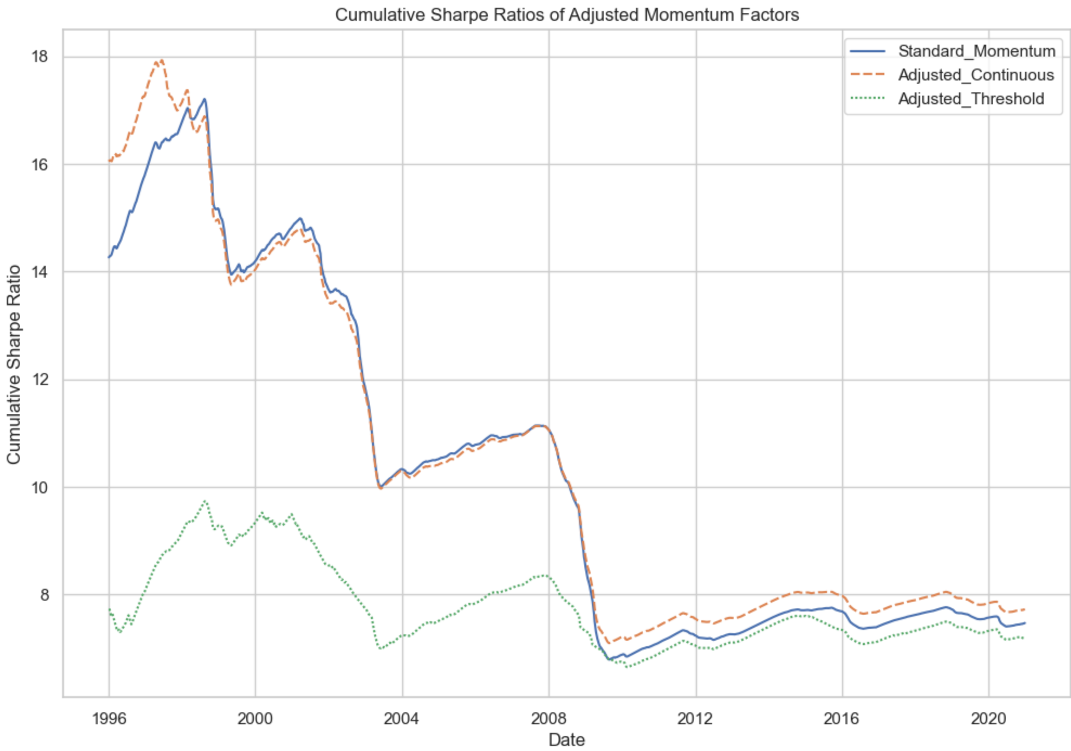

Figure 3: Cumulative Sharpe Ratios of Standard and Adjusted Momentum Strategies.

Note: The first 4 years are redacted as a lack of available data led to unstable estimates.

The cumulative sharpe ratios in Figure 3 show a significantly reduced and smoother risk profile for the threshold-adjusted signal towards the start of our horizon. But after 2008, Sharpe ratios converge across all strategies. This flattening likely reflects suppressed excess returns during the Financial Crisis, which disproportionately affected active signals, while the threshold-adjusted strategy was mostly deactivated during high-comomentum periods.

As a final step, we re-run the Fama–MacBeth regressions described in Section 2.3 using each of the comomentum-adjusted factors as the regressor in turn. Both the continuously-adjusted and threshold-adjusted factors suffer from insignificant t-statistics, reinforcing our prior conclusion: comomentum-adjusted strategies do not outperform the standard momentum factor in an out-of-sample evaluation.

3.3 Walk-Forward Parameter Tuning

We perform walk-forward tuning over rolling windows to identify the optimal λ and threshold values.[2] For each iteration, we record the best-performing parameters and associated returns.

Interestingly, the results for λ show a bimodal pattern; either very small ($\lambda \to 0$) or very large ($\lambda \geq 90$) values are selected. A notable concentration also occurs at $\lambda = 40$, although the reason for this remains unclear.

Threshold-based adjustment tuning was more stable. The *79.5th* percentile threshold was selected in over *90%* of cases.

[2]For a full introduction to walk-forward tuning in Quantitative Finance, see Sullivan et al. [1999].

Table 3: Top 3 λ Values Selected in Walk-Forward Tuning

Lambda	Frequency	Avg. Return
0.1	41	1.50
100.0	39	9.93
90.0	13	12.87

Table 4: Top 3 Threshold Values Selected in Walk-Forward Tuning

Threshold Quantile	Frequency	Avg. Return
0.795	131	1.20
0.815	3	0.87
0.800	2	0.84

However, even after tuning, the performance of adjusted-momentum strategies remains weak, leading us to test whether these patterns could be attributed to chance.

Note that we can further interpret these tuning results by recosndiering Equation 2 which defines the adjustment function used.

Case 1: λ is small ($\lambda \to 0$)

When λ is close to zero, the adjustment factor simplifies:

$$f(C_t) \approx \frac{1}{1 + 0 \cdot (C_t - \bar{C})} = 1$$

and

$$\tilde{M}_t \approx M_t$$

Hence, momentum is effectively unadjusted.

Case 2: λ is large ($\lambda \to \infty$)

For $C_t > \bar{C}$,

$$\lambda(C_t - \bar{C}) \to \infty \quad \Rightarrow \quad f(C_t) \to 0 \quad \Rightarrow \quad \tilde{M}_t \to 0$$

That is, when comomentum is high, momentum is suppressed.

For $C_t < \bar{C}$,

$$\lambda(C_t - \bar{C}) \to -\infty \quad \Rightarrow \quad f(C_t) \to \infty \quad \Rightarrow \quad \tilde{M}_t \to \infty$$

That is, when comomentum is low, momentum is amplified.

The distribution of λ values exhibits a very extreme split, with momentum either being shrunk aggressively to *0*, preserved at intermediate levels, or amplified significantly. This aligns with the theoretical role of λ in governing persistence or trend-following dynamics. However, the sharpness of the transitions between these states and the lack of intermediate momentum values from Case 1 raises the question that this split may be down to chance or overfitting. As a result, we conduct a hypothesis test.

3.4 Does Comomentum Add Predictive Value? Hypothesis Test

We perform a formal test of whether comomentum contributes genuine predictive value to momentum.

Null Hypothesis ($\mathcal{H}_0$): Comomentum contains no predictive signal. Any observed improvements from tuning are due to noise, randomness, or overfitting.

Alternative Hypothesis ($\mathcal{H}_1$): Comomentum carries genuine predictive information. Tuning with the true comomentum series should produce better out-of-sample performance than tuning with a randomised series.

To test this, we randomised the comomentum time series, preserving distribution, destroying time structure, and repeated the walk-forward tuning. Table 5 shows the top λ values selected under $\mathcal{H}_0$:

Table 5: Top λ Values from Randomised Comomentum (Null Hypothesis)

Lambda	**Frequency**	**Avg. Return**
60.0	31	11.19
80.0	24	15.69
50.0	20	29.41

Clearly, large λ values are selected under both the true and randomised comomentum series. The discrepancy, however, is significantly higher and unbelievable average returns under the null. We conclude that parameter tuning is driven more by noise than by any meaningful comomentum signal. Further, the case for comomentum as a predictive signal is undermined. Stronger performance under $\mathcal{H}_0$ suggests that tuning is overfitting to spurious patterns, and that comomentum-adjusted strategies do not offer consistent out-of-sample improvements over standard momentum.

4 Conclusion

Lou and Polk [2021], propose a novel measure of crowded markets to enhance traditional momentum strategies. We replicate and extend the original methodology, implementing both continuous and threshold-based Comomentum-adjusted momentum strategies. Despite walk-forward tuning, these adjusted signals fail to outperform standard momentum in terms of return, Sharpe ratio, or statistical significance. Thus, while momentum remains a powerful signal on its own, the case for modifying it via Comomentum is unconvincing.

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