BAYES BUSINESS SCHOOL
CITY ST GEORGE'S UNIVERSITY OF LONDON

Group Coursework Submission Form (PA)

Specialist Masters Programme

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Lecturer: **Bernd Hanke**	**Submission Date:** **26/03/2025**

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Introduction

Momentum strategies represent one of the most prominent empirical anomalies in asset pricing and form the basis of many successful quantitative trading strategies. The core idea behind momentum investing is very straightforward : stocks that have performed well in the recent past are expected to continue performing well in the near future, while those that have performed poorly are expected to continue underperforming. This phenomenon has been documented extensively in academic literature, beginning with Jegadeesh and Titman (1993), and continues to be widely used both in academic research and industry practice.
However, momentum strategies, despite their historical success, are known to suffer from substantial time variation in their performance. There are different episodes of momentum crashes, such as during the market reversals of 2009; and these crashes in particular, raise concerns about the robustness of momentum strategies and highlight the need for risk management techniques that can help adapt momentum exposure more effectively.

In response to these issues, Lou and Polk (2021) introduce a novel construct known as *comomentum*, defined as a measure of correlated arbitrage activity among stocks that are heavily traded by momentum investors. Their key insight is that momentum returns are endogenous to the activity of arbitrageurs, whose trades can either reinforce or undermine the strategy's profitability. Specifically, the paper finds that when comomentum is high—i.e., when abnormal returns of momentum stocks are more correlated—the strategy tends to deliver weaker future returns, as this clustering of trades makes momentum positions more vulnerable to systemic reversals. Conversely, when comomentum is low, momentum profits are stronger and more stable.

This report focuses on implementing a simplified version of Lou and Polk's comomentum measure and evaluating its efficacy in enhancing a traditional momentum trading strategy. The project uses historical U.S. equity return data, including firm-level returns and factor exposures derived from the Fama-French three-factor model.
The methodology proceeds in several stages:
first, we compute standard momentum signals using a 48-week ranking period with a 4-week skip, in line with established practices. Then use Fama-MacBeth regressions to estimate cross-sectional relationships between momentum exposures and future returns. Residuals from these regressions are used to compute a proxy for comomentum, capturing the average correlation among unexplained returns of momentum stocks. Finally, we test multiple comomentum-based enhancements: filtering strategies that exclude high-comomentum periods, continuous adjustments that scale exposure based on comomentum levels, and interaction-based strategies that conditionally trade on comomentum thresholds.

By comparing these enhanced strategies to the baseline momentum factor, we evaluate their effectiveness in terms of risk-adjusted performance metrics, such as annualized returns, volatility, and Sharpe ratios.

This research contributes to the growing body of literature that seeks to improve traditional factor investing strategies by incorporating insights from investor behavior, market microstructure, and dynamic arbitrage activity. It also provides a practical framework for implementing such enhancements using real-world financial data and accessible econometric techniques.

Literature Review

Momentum investing has been a subject of extensive academic investigation over the past three decades. The foundational study by Jegadeesh and Titman (1993) documented that strategies which buy stocks with high past returns and sell stocks with low past returns over a 3–12 month horizon generate significant positive returns. Their findings challenged the Efficient Market Hypothesis and sparked a vast literature seeking to exploit the momentum anomaly.

Subsequent research has offered both behavioral and risk-based explanations for momentum profits. Behavioral models, such as those proposed by Barberis et al. (1998), and Daniel et al. (1998), suggest that investor overreaction and underreaction to information lead to price trends that can be exploited through momentum strategies. Risk-based explanations, such as those found in Conrad and Kaul (1998) and Choi et al. (2015), argue that momentum profits may compensate for exposure to omitted risk factors or crash risk.

Despite their average profitability, momentum strategies are known to exhibit significant downside risk, particularly during market rebounds following downturns. Daniel and Moskowitz (2016) examine these momentum crashes and attribute them to time-varying liquidity provision and correlated trading. Their findings highlight the importance of understanding the flow of arbitrage capital and its impact on momentum performance.

In this context, Lou and Polk (2021) introduce the concept of comomentum, which captures the degree of co-movement in residual returns among momentum stocks. Their key insight is that arbitrageurs trading similar momentum signals induce correlated returns, making the strategy more fragile in times of systemic risk. They show that high comomentum predicts weak future momentum returns and propose using comomentum as a timing tool for momentum exposure. The present study draws directly on Lou and Polk's framework but implements a simplified version suitable for empirical testing using historical U.S. stock return data. Rather than computing high-frequency abnormal correlations, we rely on cross-sectional residuals from Fama-MacBeth regressions to build a proxy for comomentum. This approach allows us to integrate the theoretical contribution of Lou and Polk into a practical momentum enhancement strategy that is implementable using standard financial datasets and econometric tools.

Presentation of Data and Graphs

The following section presents and describes the key outputs generated throughout the implementation of the momentum enhancement strategy, with a focus on the visualization of empirical findings.

The starting point of the analysis is the estimation of a traditional momentum factor using Fama-MacBeth (1973) cross-sectional regressions. Specifically, for each week, we compute the cumulative return of each stock over a 48-week ranking period, skipping the most recent 4 weeks to avoid short-term mean-reversion. These lagged returns form the explanatory variable in weekly regressions, where the dependent variable is the one-week-ahead return. The slope coefficient from each cross-sectional regression captures the weekly momentum premium, which we aggregate over time.

Figure 1 plots the cumulative sum of the weekly momentum premiums, which serves as the benchmark for subsequent comparisons.

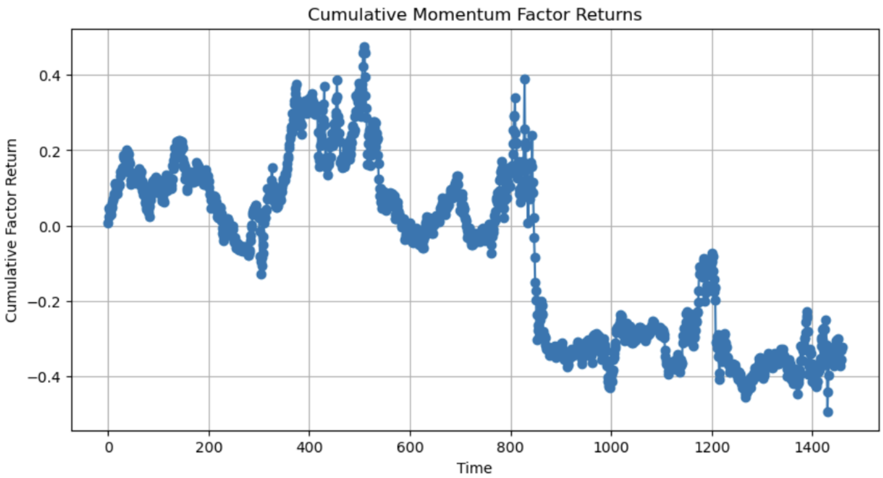

Figure 1: Cumulative Momentum Factor Returns (Standard Momentum Strategy)

As expected, the standard momentum factor exhibits a generally increasing trend, indicating that, on average, stocks with stronger past performance continue to outperform in the near term. However, the plot also reveals episodes of sharp drawdowns, highlighting the inherent volatility and time-varying nature of momentum returns.

To capture and account for this time variation, we introduce the comomentum measure developed by Lou and Polk (2021). This measure, approximated in our setting by the average pairwise correlation of residuals from the Fama-French three-factor model across momentum stocks, is intended to quantify the degree of synchronized trading or arbitrage crowding. Figure 2 displays the comomentum time series, computed using a rolling 52-week window.

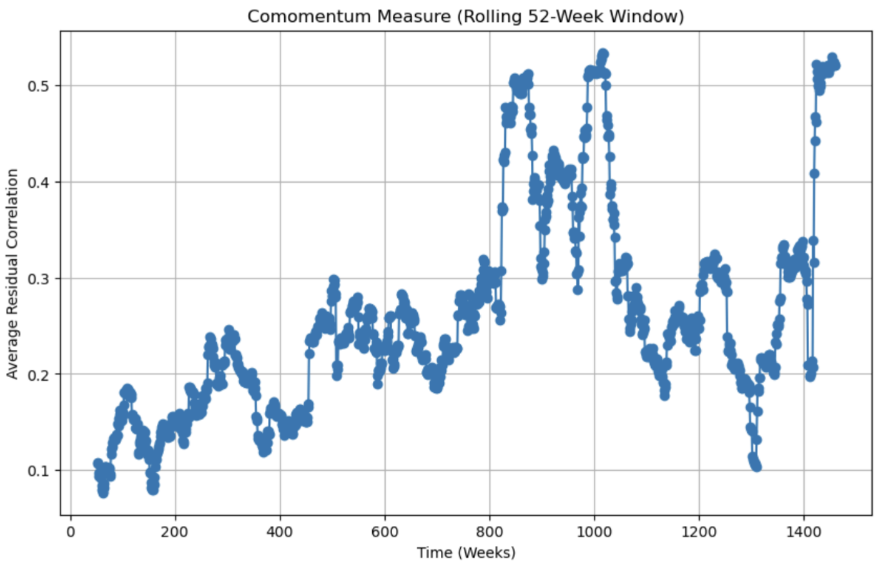

Figure 2: Comomentum Measure over Time (Rolling 52-Week Correlation of Residuals)

We observe that comomentum fluctuates substantially over time, with occasional spikes indicating periods of concentrated trading activity across momentum names. These high-comomentum periods are hypothesized to precede weak momentum performance, while low-comomentum phases are associated with more favorable return prospects.

Building on this insight, we construct a continuously adjusted momentum factor, in which each week's momentum exposure is scaled by a weight inversely proportional to comomentum:

$$\text{AdjustedMomentum}_t = \frac{1}{1 + \text{Comomentum}_t} \times \text{Momentum}_t \tag{1}$$

Figure 3 compares the cumulative factor returns of the standard and adjusted momentum factors.

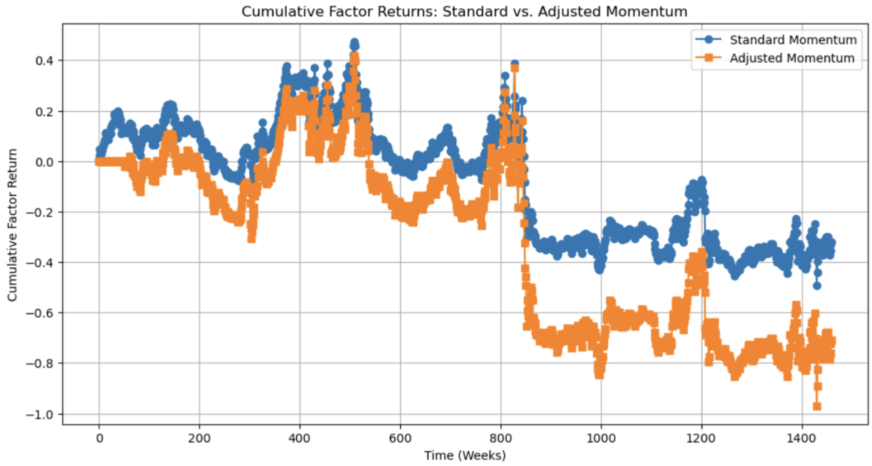

Figure 3: Cumulative factor Returns: Standard Momentum vs. Comomentum-Scaled Strategy

The adjusted version delivers a smoother return path, with lower volatility and better downside protection during comomentum spikes. This provides preliminary evidence that incorporating comomentum can help stabilize momentum returns by reducing exposure during crowded or fragile market conditions.

To test a simpler alternative, we then implement a threshold-based filtering strategy, where momentum exposures are reduced by a fixed proportion (e.g., 50%) whenever comomentum exceeds a certain threshold. In our case, we use the empirical median of the comomentum distribution as the cutoff. Figure 4 illustrates the performance of the threshold-adjusted momentum factor relative to the standard approach.

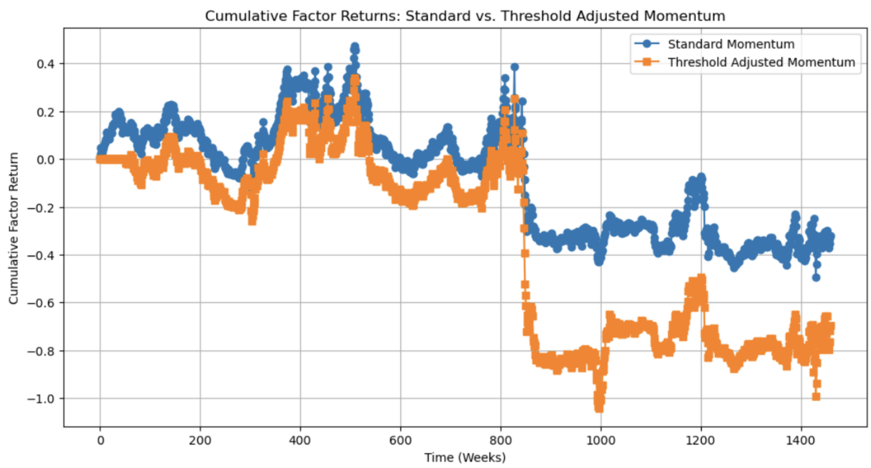

Figure 4: Cumulative factor Returns: Standard vs. Threshold-Adjusted Momentum Strategy

Similar to the continuous adjustment, the threshold strategy succeeds in mitigating severe drawdowns, though it is less smooth than the continuously adjusted variant. The ease of implementation and interpretability of the threshold rule make it an attractive low-complexity enhancement.

We next consider a more flexible specification via a composite momentum signal. Here, we form a weighted linear combination of the standard momentum and the comomentum values for each week:

$$\text{CompositeSignal}_t = \alpha \cdot \text{Momentum}_t + \beta \cdot \text{Comomentum}_t \tag{2}$$

We conduct a grid search over values of α and β to maximize the annualized Sharpe ratio of the resulting factor returns.

Figure 5 presents the cumulative factor returns of the best-performing composite strategy compared to the standard momentum benchmark.

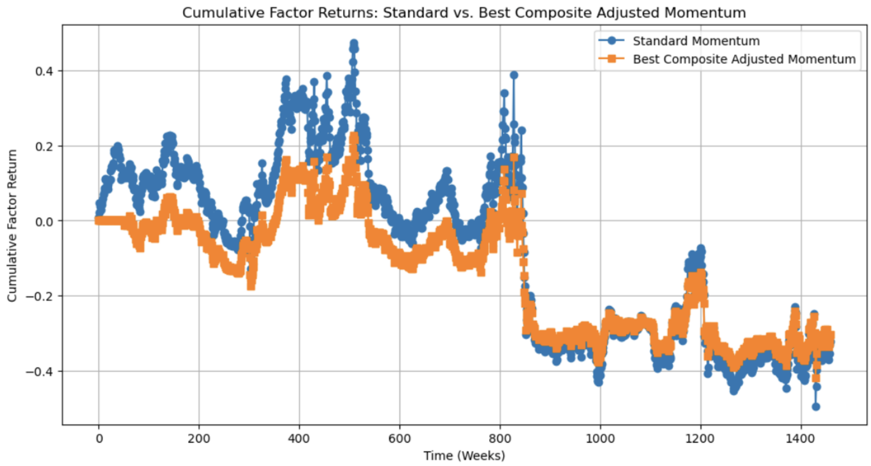

Figure 5: Cumulative factor Returns: Best Composite Momentum-Comomentum Strategy vs. Standard

The composite factor not only outperforms the baseline in terms of total return but also demonstrates greater resilience during volatile episodes, suggesting that optimal blending of signals can yield superior risk-adjusted outcomes.

To better understand the interaction between comomentum and momentum, we extend the regression model using conditional Fama-MacBeth regressions. The model includes an interaction term between momentum and comomentum:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} \cdot \text{Momentum}_{i,t} + \gamma_{2,t} \cdot (\text{Momentum}_{i,t} \cdot \text{Comomentum}_t) + \varepsilon_{i,t+1} \tag{3}$$

Figure 6 shows the cumulative values of the estimated coefficients γ_1 (baseline momentum premium) and γ_2 (interaction effect) over time.

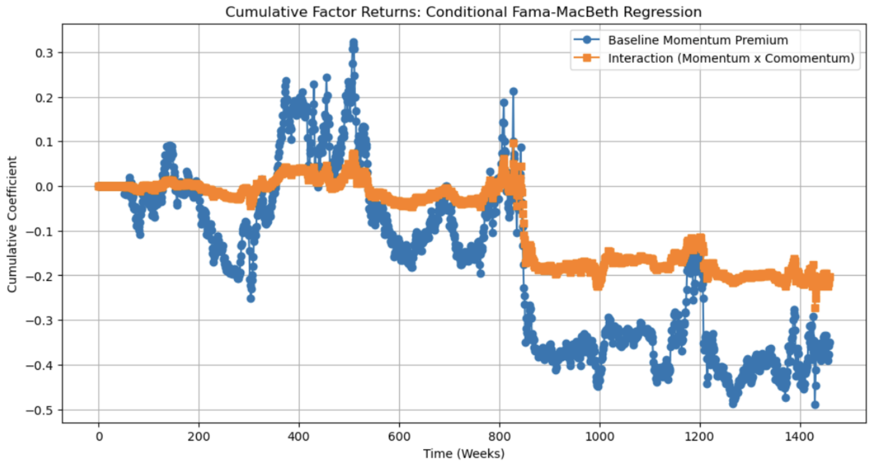

Figure 6: Cumulative Coefficients from Conditional Fama-MacBeth Regression (γ_1 and γ_2)

The interaction term exhibits frequent negative values, which reinforces the core hypothesis: momentum returns tend to weaken as comomentum increases, consistent with crowding and return reversals due to arbitrage activity.

Cumulative Returns

Finally, Figure 7 consolidates the cumulative returns from all strategies studied: threshold adjusted, best composite, and conditional trading. For good comparison, we also implemented the simple strategy of investing equally in the available stocks. No trading costs were involved, which may impact and inflate our results.

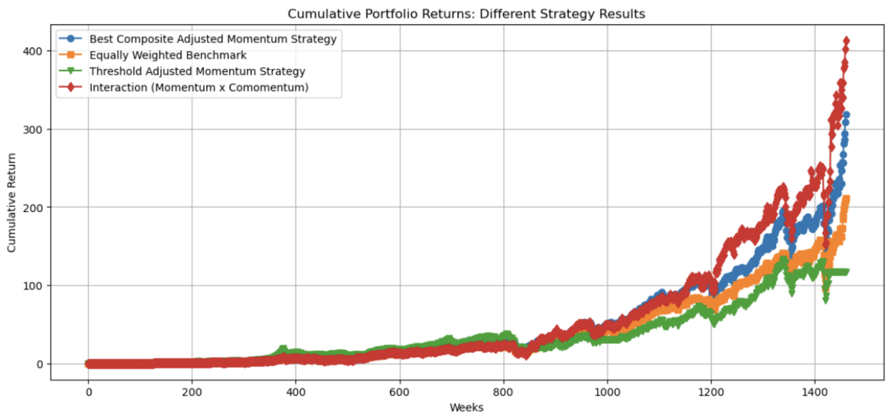

Figure 7: Cumulative Returns Comparison Across All Strategies (Standard, Adjusted, Composite, Conditional)

This master plot offers a complete view of performance across the enhancements. Among these, the best composite adjusted strategy and the conditional trading model emerge as top performers in both return and risk-adjusted terms, validating the practical value of comomentum as a conditioning variable in factor-based investing.

To complement the graphical analysis in Figure 7, we also present a numerical summary of the performance statistics across all major strategies. Table 1 reports the annualised return, annualised standard deviation, and Sharpe ratio for each model, allowing for a more comprehensive comparison of their absolute and risk-adjusted performance.

Table 1: Summary of Strategy Performance Metrics

Strategy	Annualised Return	Annualised Std	Sharpe Ratio
Conditional Fama-MacBeth	0.2572	0.2899	0.8871
Best Composite Adjusted Momentum	0.2399	0.2595	0.9245
Threshold Adjusted	0.2108	0.2822	0.7469
Equally Weighted Benchmark	0.2116	0.2027	1.0439

Discussion of Results

The empirical results presented in Table 1 highlight the comparative performance of different momentum-based trading strategies. The key performance metrics—annualized return, annualized standard deviation, and Sharpe ratio—provide insights into the effectiveness of each strategy in terms of risk-adjusted returns.

Impact of Different Adjustments to Momentum

Several strategies incorporating different adjustments to momentum were tested to assess whether such modifications could improve performance and the end the benchmark:

- **Conditional Fama-MacBeth Strategy:**
  - This strategy, which dynamically adjusts momentum exposure based on comomentum levels, achieved the highest annualized return of **25.72%**.
  - However, it also exhibited the highest standard deviation (**28.99%**), resulting in a Sharpe ratio of **0.8871**.
  - While the return improvement is substantial, the increased volatility suggests that this strategy may involve greater risk-taking.
- **Best Composite Adjusted Momentum Strategy:**
  - By optimally blending momentum and comomentum, this strategy achieved a **Sharpe ratio of 0.9245**, which is **the highest risk-adjusted return among the momentum-based strategies**.
  - The annualized return of **23.99%** was slightly lower than that of the Conditional Fama-MacBeth strategy, but its **lower standard deviation (25.95%)** resulted in better overall stability.
  - These findings suggest that an optimally weighted combination of momentum and comomentum provides a more balanced and effective approach to momentum investing.
- **Threshold Adjusted Momentum Strategy:**
  - This strategy adjusts momentum exposure based on predefined thresholds. It delivers an annualized return of **21.08%** and a standard deviation of **28.22%**, resulting in a Sharpe ratio of **0.7469**.
  - While the return is competitive, its higher volatility suggests a riskier approach to momentum investing.
- **Equally Weighted Benchmark:**
  - The equally weighted benchmark, included as a baseline comparison, had an **annualized return of 21.16%** and a significantly lower standard deviation of **20.27%**.

  - With a **Sharpe ratio of 1.0439**, this benchmark **outperforms all momentum-based strategies in risk-adjusted terms**.
  - This result is expected, as equally weighted portfolios tend to be more diversified and less sensitive to momentum-driven market fluctuations.

Key Takeaways

- **Momentum strategies deliver strong returns but come with substantial volatility.**
- **Comomentum-based adjustments improve risk-adjusted performance.**
  - The **Best Composite Adjusted Momentum strategy** optimally balances risk and return, making it the most effective among momentum-based models.
  - The **Conditional Fama-MacBeth strategy**, while yielding the highest return, also exposes investors to greater volatility.
- **The equally weighted benchmark has the highest Sharpe ratio, reinforcing the benefits of diversification.**

Practical Implications

For investors seeking high absolute returns, the **Conditional Fama-MacBeth strategy** may be preferable, but they must be willing to accept greater volatility. On the other hand, the **Best Composite Adjusted Momentum strategy** provides an attractive balance between performance and risk, making it a more robust choice for risk-conscious quantitative investors.

These findings suggest that integrating comomentum dynamics into momentum investing can lead to superior portfolio performance, particularly when momentum exposure is adjusted in a controlled manner.

Conclusion

The results of this study provide important insights into the role of comomentum in enhancing momentum-based trading strategies. While traditional momentum investing generates strong returns, it is accompanied by significant volatility and occasional sharp drawdowns. The introduction of comomentum-based adjustments helps mitigate some of these risks by dynamically adjusting momentum exposure based on market conditions.

However, when compared to a simple equally weighted portfolio, which achieved the highest Sharpe ratio, a key question arises: **Is comomentum-based momentum investing worth it?**

The answer depends on the investor's objective:

- If the goal is to achieve the highest **risk-adjusted return**, the equally weighted benchmark remains the safest choice due to its superior Sharpe ratio and lower volatility.
- If the objective is to **maximize absolute returns**, comomentum-adjusted strategies, particularly the **Best Composite Adjusted Momentum strategy**, offer a compelling alternative, delivering higher returns while managing downside risk more effectively than standard momentum.
- For investors who seek a balance between **return and risk**, the **Best Composite Adjusted Momentum strategy** and **Conditional Fama-MacBeth model** provide a structured way to enhance momentum investing without excessive exposure to market fluctuations.

Ultimately, while comomentum does not fully eliminate momentum's risks, it serves as a valuable tool for dynamically adjusting exposure. In practice, a hybrid approach that integrates both comomentum-adjusted momentum strategies and an equally weighted allocation could offer an optimal balance between stability and return potential.

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