

Conditional Performance of Factor Portfolios – Factor Decomposition and Regime-Dependent Return Dynamics

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Abstract

This paper documents that the time variation in two major equity factor premia, Betting-Against-Beta and momentum, is systematically driven by distinct macroeconomic state variables that can serve as real-time timing signals. Using a bivariate double-regime framework applied to U.S. data from August 1964 to February 2026, paper demonstrates that BAB earns significant returns exclusively in high-term-spread environments regardless of concurrent market conditions, while momentum performance deteriorates sharply whenever inflation is near-zero or negative. A steep yield curve expands the carry margin of the leveraged low-beta strategy and maintains BAB profitability even during periods of elevated volatility, directly challenging the beta volatility puzzle. For momentum, moderate-to-high inflation buffers against the abrupt market reversals that generate crash risk, while deflationary environments consistently produce the strategy's worst outcomes across all macro combinations examined. Quintile-based timing strategies exploiting these signals improve risk-adjusted performance and substantially reduce drawdowns relative to unconditional exposure. Both findings motivate a broader research on volatility decomposition and the structural identification of the macro channels through which factor premia vary.

Keywords: factor timing, betting against beta, momentum, term spread, inflation, macroeconomic regimes, carry, crash risk, out-of-sample

JEL Classification: G11, G12, E44

Introduction

The empirical literature has well established doubt that the returns to equity risk factors vary over time, across business cycles, monetary policy regimes, and states of financial market stress. What remains far less understood is why they vary in the specific ways they do, which macroeconomic forces suppress a given factor's premium, which downgrade it, and whether those forces can be identified prospectively from information available to investors before the relevant month begins. This paper addresses that question for two of the most economically important and theoretically motivated factors in the asset pricing literature, Betting-Against-Beta (BAB) and momentum, by documenting that each factor's time variation is strongly and systematically linked to a distinct macroeconomic state variable that can serve as a real-time timing signal.

The finding that factor returns are state dependent has a long history. Fama and French (1989) show that the equity risk premium and the default premium are predictable from business-cycle variables, including the dividend yield and the term spread. Subsequent work demonstrates that momentum profits are highly sensitive to prevailing market conditions, with Cooper, Gutierrez, and Hameed (2004) documenting that momentum payoffs are concentrated in up-market states and near-zero or negative in down-market states, and Daniel and Moskowitz (2016) showing that momentum crashes cluster in specific macro environments characterised by sharp rebounds following bear markets. For BAB, the foundational contribution of Frazzini and Pedersen (2014) establishes that the low-beta premium reflects a structural funding-constraint mechanism. Investors who cannot use leverage overweight high-beta securities, causing their overpricing, and the premium earned by unconstrained arbitrageurs depends on the availability and cost of leverage. The implication is that BAB should be time-varying with the funding environment, but Frazzini and Pedersen (2014) test this using the TED spread as their proxy, which captures episodic interbank credit stress rather than the persistent carry conditions that drive the strategy's profitability across normal business cycles.

A growing literature specifically links factor time-variation to market volatility. Moreira and Muir (2017) show that scaling factor exposures inversely with lagged realised volatility substantially improves risk-adjusted returns for a broad set of factors including the market, value, momentum, and profitability premia, suggesting that volatility contains genuine predictive information about subsequent factor performance. Barroso and Santa-Clara (2015) apply a similar approach specifically to momentum, showing that volatility-scaled momentum eliminates the severe crash episodes that are characteristic to the unconditional strategy and approximately doubles the Sharpe ratio. These results have motivated the view that market volatility is the primary state variable for factor timing. Most recently, Barroso, Detzel, and Maio (2025) identify what they term the volatility puzzle of the beta anomaly. They claim that the BAB Sharpe ratios are systematically higher following low-volatility months, and the leading theoretical explanations collectively fail to account for this pattern.

This research argues that market volatility is not the primary conditioning variable for either BAB or momentum, and that treating it as such misses the specific macro channels through which each factor's premium varies. The central empirical contribution is a systematic bivariate double-regime analysis that crosses market volatility with four alternative macroeconomic state variables for both BAB and momentum over the full sample period from August 1964 to February 2026. The results reveal some consistent patterns for both portfolios. The effect of market volatility on factor premia is strongly contingent on the level of

macro variables, and in both cases the alternative variable undermines volatility as a stand-alone conditioning signal.

For BAB, the primary finding is that the term spread, defined as the ten-year Treasury yield minus the Federal Funds effective rate, is the decisive conditioning variable. BAB earns economically large and statistically significant positive returns in every High-TS regime cell across all four bivariate combinations examined, regardless of whether market volatility, credit spreads, inflation, or industrial production growth are simultaneously high or low. When the term spread is low or negative, by contrast, BAB consistently earns near-zero or negative factor-adjusted returns regardless of the secondary conditioning variable. The finding that BAB earns Sharpe 0.794 and significant FF5+Mom alpha of 8.35%** even in the high-volatility/high-term-spread intersection directly challenges the findings of Barroso, Detzel, and Maio (2025) and their demand driven explanation.

For momentum, the primary finding is that inflation is the decisive conditioning variable. Near-zero or negative inflation constitutes the primary adverse environment for momentum across all four bivariate combinations, producing Sharpe ratios between -0.170 and 0.110 and maximum drawdowns reaching 75.40% in the most extreme cell. High inflation, by contrast, substantially buffers the momentum crash risk that high volatility would otherwise generate, shown in the high-volatility/high-inflation intersection where momentum earns positive returns (Sharpe 0.359) while the high-volatility/low-inflation cell produces momentum's worst outcome (-1.32% annualised, Sharpe -0.080 , MDD 74.54%). This pattern is consistent with the inflation channel operating through trend persistence, as moderate-to-high inflation is associated with stable, demand-driven nominal growth, while near-zero inflation signals the demand-side dislocations that produce the abrupt market reversals documented by Daniel and Moskowitz (2016).

The double-regime evidence motivates implementable timing strategies that condition BAB exposure on the lagged term spread and momentum exposure on the lagged inflation rate. Three strategies are evaluated: a median-split rule, a quintile-based rule that exploits the full distributional shape of each signal, and an out-of-sample test in which all thresholds are fixed on the 1964–2004 training period and applied to the 2005–2026 test period without updating. In-sample, the median-split BAB strategy improves the Sharpe ratio from 0.812 to 0.869 relative to buy-and-hold and earns FF5+Mom alpha of 4.92%*** with significant reductions in maximum drawdown. The quintile-based Q3–Q5 strategy achieves Sharpe 0.886 and alpha 5.13%***. For momentum, the quintile strategy that avoids only the lowest inflation quintile achieves Sharpe 0.610 compared to 0.489 for buy-and-hold, reduces maximum drawdown from 57.82% to 35.94%, and earns FF5 alpha of 8.26%***. Out of sample, the BAB Q3–Q5 strategy earns significant alpha of 3.94%** ($t = 2.51$) in the 2005–2026 test period, while the momentum Q2–Q5 strategy earns OOS alpha of 3.64%** ($t = 2.32$) despite unconditional buy-and-hold momentum being entirely insignificant over the same period (alpha 3.76%, $t = 1.21$).

Both empirical findings appear novel relative to the published literature. No prior study documents the ten-year-minus-Federal-Funds term spread as a BAB predictor. The closest precedent is the TED spread in Frazzini and Pedersen (2014), which is a funding-stress indicator that spikes during crises rather than a persistent carry signal. For momentum, no prior study uses lagged CPI as the primary timing signal to the best of our knowledge.

Beyond the two timing results, this paper establishes a broader empirical pattern with implications for the research agenda on factor volatility and uncertainty decomposition. Aggregate market volatility has non-monotone, factor-specific, and interaction-dependent effects on factor premia — the same level of realised volatility can be associated with Sharpe ratios ranging from -0.080 to 2.530 for BAB and from -0.170 to 1.191 for momentum depending on the accompanying macro state. This heterogeneity motivates the next stage of research, which is decomposing volatility into cash-flow-driven and discount-rate-driven components following the Campbell et al. (2004, 2025) framework, and examining whether each factor's premium is differentially sensitive to these distinct sources of uncertainty.

The remainder of the paper is structured as follows. Section 1 describes the data sources and macroeconomic variables, Section 2 outlines methodology, including the bivariate regime framework and timing strategy construction. Section 3 reports the main results: double-regime motivating evidence for BAB (Section 3.1) and momentum (Section 3.2), in-sample quintile timing strategies (Sections 3.1.2 and 3.2.2), and out-of-sample results (Sections 3.1.3 and 3.2.3). Section 4 provides economic interpretation of both findings, discusses limitations and proposes extensions including continuous timing strategies, improved OOS design, and the volatility decomposition research agenda.

1. Data

1.1 Factor data

The empirical analysis combines data from three primary sources and spans the period from August 1964 to February 2026. Common asset pricing factor portfolios are obtained from the Kenneth French data library, including the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), momentum (MOM), and the risk-free rate (RF). The Betting Against Beta (BAB) factor is sourced from Andrea Frazzini's AQR website.

All factor series are measured at the monthly frequency and expressed in percentage returns. The underlying data extend from July 1963 to February 2026 to allow the construction of lagged variables and volatility measures beginning in August 1964. Daily market excess return data from the Fama–French library are additionally employed to estimate monthly realised market volatility (MVOL).

1.2 Macroeconomic Regime Variables

Five macroeconomic state variables are employed in the analysis: Term Spread (TS), Inflation (INFL), GARCH Market Volatility (MVOL), Credit Spread (CS), IP Growth. TS, INFL MVOL and CS components are sourced from FRED, while MVOL is calculated based on daily excess market returns data sourced from Kenneth French data library. All variables are lagged by one calendar month prior to use in any regime classification or timing strategy. The regime assigned to month t is therefore determined by information observable at the end of month $t-1$, ensuring that all results are real-time signals with no look-ahead bias.

Term Spread (TS) is computed as the 10-year constant-maturity Treasury yield (DGS10) minus the Federal Funds effective rate (FEDFUNDS). The term spread captures the slope of the risk-free yield curve and summarises the stance of monetary policy. A steep curve (high TS) reflects accommodative monetary policy, with the central bank holding short rates below the long-run neutral level and is associated with favourable funding conditions for leveraged strategies. An inverted curve (negative TS) has historically preceded recessions and signals tightening financial conditions.

Inflation (INFL) is computed as the year-over-year percentage change in the Consumer Price Index for All Urban Consumers (CPIAUCSL). Year-over-year rather than month-over-month inflation is used to eliminate seasonal noise and capture the sustained inflationary environment relevant to factor performance.

GARCH Market Volatility (MVOL) is approximated as the 12-month rolling conditional standard deviation using daily market excess returns. This variable captures aggregate equity market uncertainty.

Credit Spread (CS) is computed as the Moody's Baa seasoned corporate bond yield (BAA) minus the 10-year Treasury yield (DGS10). This variable captures the market price of corporate default risk and serves as a proxy for broader financial market stress. High credit spreads are associated with investor risk aversion, economic contraction, and tightening credit conditions.

IP Growth is computed as the year-on-year percentage change in the Industrial Production Index (INDPRO). IP growth captures the real economy cycle and provides an independent measure of the cash-flow channel.

2. Methodology

2.1 Regime Classification Framework

The empirical strategy proceeds through two stages of analysis that build sequentially on each other. The first stage is bivariate double-regime analysis, conducted by crossing pairs of lagged macro variables at their medians to produce four joint regime cells (Lo X / Lo Y, Lo X / Hi Y, Hi X / Lo Y, Hi X / Hi Y). Within each category both for univariate and bivariate analysis, the analysis reports annualised raw returns, standard deviations, Sharpe ratios, and maximum drawdowns for the factor series, along with t-statistics testing whether the mean monthly return within the cell is significantly different from zero. This provides a comprehensive description of how each factor's raw performance varies across macro states. The double-regime tables are primarily used to motivate the timing strategies by establishing which macro variables produce the most robusta and economically meaningful conditional performance differentials. A design feature throughout is that all regime signals are lagged by one month. The regime assigned to month t is computed from the macro variable(s) observed at the end of month $t-1$, which is known to the investor at the start of month t before the factor return is realised. This convention eliminates look-ahead bias from the regime classification. The signal lag also makes economic sense for investors who respond to macro data with a delay, and factor pricing adjusts to new information progressively rather than instantaneously.

The third stage translates the motivating evidence into implementable timing strategies and subjects those strategies to testing. The relationships that stand out are conditional performances of BAB under term spread regimes and of MOM under inflation regimes. For the test factors, standard empirical models are used to estimate regressions and test strategies' performances. For BAB, the benchmark is the six-factor FF5+MOM model. For MOM, the benchmark is the five-factor FF5 model. All regressions use Newey-West standard errors.

Three timing strategies are evaluated. All three share the same basic structure, which is that the investor holds the factor portfolio during in-regime months and holds the risk-free rate during out-of-regime months.

1) Median-split timing

The investor holds the factor when the lagged macro signal (TS for BAB; INFL for momentum) exceeds the full-sample median, and holds RF otherwise. This is the simplest implementable rule. A placebo inverse strategy is constructed alongside each timing strategy by inverting the investment rule (hold the factor when the signal is below the median). If the placebo earns comparable risk-adjusted returns to the correctly-timed strategy, the timing benefit is mechanical, arising from reduced time-in-market rather than signal informativeness. If the placebo earns substantially less, the signal contains genuine predictive content.

2) Quintile timing

The investor divides the lagged macro signal into five quintiles based on the full-sample distribution and invests in the quintiles identified as favourable from the per-quintile performance analysis. For BAB, invest in Q3, Q4, Q5 (avoid Q1 and Q2, where the term spread is below 0.70%); for momentum, invest in Q2, Q3, Q4, Q5 (avoid Q1, where inflation is below 1.89%) or in Q2, Q3, Q4 only (additionally avoiding Q5). The quintile strategy is designed to exploit non-linearities in the factor-macro relationship that binary timing rules necessarily miss.

Both the median threshold and the quintile boundaries are re-estimated using only the training period (August 1964 to December 2004). These thresholds are then held fixed and applied to the test period (January 2005 to February 2026) without any updating or look-ahead. The strategy return series in the test period is evaluated on all performance metrics and FF5(+MOM) alpha.

2.2 Performance Evaluation

Strategy performance is evaluated on three primary metrics: (1) annualised Sharpe ratio, computed as the ratio of mean monthly excess return to monthly standard deviation, multiplied by $\sqrt{12}$; (2) full-period maximum drawdown, the worst peak-to-trough loss in the strategy's cumulative return; (3) full-sample FF5+Mom alpha from Newey-West OLS regression.

A timing strategy is considered economically successful if it simultaneously improves the Sharpe ratio, reduces maximum drawdown, and earns a statistically significant positive alpha. The out-of-sample alpha t-statistic is given some weight since in-sample alpha is inherently optimistic when the threshold was estimated on the same data used for the regression but taken with caution due to the nature of the testing period. The 2005–2026 out-of-sample period contains several unusually extreme and persistent macroeconomic regimes that may materially influence factor timing results. Specifically, the sample includes the 2008 Global Financial Crisis, the prolonged zero-interest-rate and quantitative easing environment that followed, the COVID-19 market collapse and recovery, the sharp post-pandemic inflation surge, and the aggressive monetary tightening cycle of 2022–2023. These episodes generated unusually large fluctuations in liquidity conditions, risk aversion, funding costs, and inflation dynamics, all of which are economically related to the behavior of BAB and momentum strategies. Consequently, while out-of-sample alpha and Sharpe ratio improvements provide substantially stronger evidence than in-sample results alone, they may partly reflect the unique characteristics of this specific macroeconomic environment rather than a universally stable timing relation across all historical periods.

3. Results

3.1 Betting-Against-Beta and the Term Spread

3.1.1 Motivating Evidence: Double-Regime Analysis

Tables 1–4 present BAB performance across all bivariate combinations involving the term spread. The dominant empirical result is highly consistent across all specifications. High term spread regimes are systematically associated with stronger BAB returns, higher Sharpe ratios, and larger alphas, regardless of the control macroeconomic variable included in the interaction. For example, in every specification the high term spread states produce substantially larger annualised returns and alphas than the corresponding low term spread states.

In the $MVOL \times TS$ specification, BAB performs strongly whenever the term spread is high, even during periods of elevated market volatility. Although high volatility reduces performance relative to low-volatility environments, the BAB premium remains economically meaningful when the yield curve is steep. Specifically, the high TS / high MVOL regime still delivers an annualised return of 11.1%, a Sharpe ratio of 0.795, and an alpha of 8.1%, compared to only 3.1%, 0.177, and -2.0% in the low TS / high MVOL regime. At the same time, the difference between the two high TS states (18.1% vs 11.1% return; Sharpe 2.541 vs 0.795) indicates that aggregate volatility continues to materially affect BAB performance even when funding conditions are favourable. Overall, the evidence suggests that favourable funding conditions partially offset the adverse effects of elevated market volatility in determining BAB profitability.

The Credit Spread $\times$ TS interaction further reinforces the funding-based interpretation. BAB performance is strongest in the joint regime described by high term spread and high credit spread, where annualised returns reach 15.9% with an alpha of 13.1%. More importantly, both high term spread regimes substantially outperform the corresponding low term spread states regardless of the level of credit spreads (12.2% vs 4.4% under low CS; 15.9% vs 5.1% under high CS). This finding suggests that BAB profitability depends more heavily on the slope of the yield curve and implied funding conditions than on broad risk-aversion conditions alone.

The Inflation $\times$ TS and IP $\times$ TS interactions generate similar conclusions. Across both specifications, high term spread states consistently produce substantially larger returns, Sharpe ratios, and alphas than low term spread states. In the inflation specification, annualised returns increase from 6.4% to 15.7% under low inflation and from 3.3% to 13.2% under high inflation when moving from low to high term spread regimes. Similarly, in the IP specification, returns rise from 6.4% to 15.3% under low IP growth and from 2.6% to 14.1% under high IP growth. The consistency of the effect across all macro combinations suggests that the term spread contains the most robust information about BAB performance among the macroeconomic variables considered.

Collectively, the double-regime analysis establishes the term spread as the primary conditioning variable for BAB timing. Across all four specifications, high term spread regimes consistently generate economically and statistically stronger BAB performance, while low term spread environments are associated with materially weaker returns, Sharpe ratios, and alphas. The evidence therefore motivates a formal timing strategy that allocates to BAB only during sufficiently favourable term spread environments.

Table 1: BAB Returns by MVOL × TS Regime (Aug 1964 – Feb 2026)

	Ann. Ret (%)	Ann. Std (%)	Sharpe	MDD (%)		Ann. Alpha % (%)
Lo TS / Lo MVOL	6.2	7.8	0.731	-14.3		4.6**
Lo TS / Hi MVOL	3.1	14.6	0.177	-47.5		-2.0
Hi TS / Lo MVOL	18.1	7.0	2.541	-11.1		13.5***
Hi TS / Hi MVOL	11.1	13.7	0.795	-29.3		8.1**

Table 2: BAB Returns by Credit Spread × Term Spread Regime (Aug 1964 – Feb 2026)

	Ann. Ret (%)	Ann. Std (%)	Sharpe	MDD (%)		Ann. Alpha % (%)
Lo TS / Lo CS	4.4	8.8	0.435	-26.0		2.8
Lo TS / Hi CS	5.1	16.2	0.291	-48.1		-0.5
Hi TS / Lo CS	12.2	7.9	1.504	-13.4		10.4***
Hi TS / Hi CS	15.9	12.1	1.295	-29.8		13.1***

Table 3: BAB Returns by Term Spread × Inflation Regime (Aug 1964 – Feb 2026)

	Ann. Ret (%)	Ann. Std (%)	Sharpe	MDD (%)		Ann. Alpha % (%)
Lo TS / Lo INFL	6.4	11.7	0.522	-47.6		5.6**
Lo TS / Hi INFL	3.3	11.8	0.229	-36.9		-2.9
Hi TS / Lo INFL	15.7	11.5	1.355	-22.1		14.2***
Hi TS / Hi INFL	13.2	10.0	1.277	-22.7		9.3***

Table 4: BAB Returns by Term Spread × IP Growth Regime (Aug 1964 – Feb 2026)

	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)		Ann. Alpha % (%)
Lo TS / Lo IP	6.4	12.2	0.485	-22.0		0.3
Lo TS / Hi IP	2.6	11.2	0.188	-54.6		1.1
Hi TS / Lo IP	15.3	12.3	1.222	-29.9		10.3**
Hi TS / Hi IP	14.1	9.5	1.461	-17.7		9.1***

3.1.2 In-Sample Timing: BAB Against Term Spread

The double-regime evidence motivates a formal timing strategy based on the term spread. Table 5 decomposes BAB performance across term spread quintiles estimated in-sample using full-sample thresholds. The results reveal a strongly monotonic relationship between the term spread and BAB profitability. Annualised returns increase steadily from 4.4% in Q1 to 14.8% in Q5, while Sharpe ratios rise

from 0.357 to 1.290. Similarly, FF5+Mom alpha improves monotonically from -2.7% in the lowest quintile to economically large and statistically significant values in the upper quintiles (7.0% in Q3, 10.9% in Q4, and 9.9% in Q5). The strongest overall performance is concentrated in the highest term spread environments, indicating that BAB profitability is highly sensitive to the slope of the yield curve.

The lowest two quintiles produce weak performance and statistically insignificant alpha, identifying these environments as economically unattractive for BAB exposure. In particular, Q1 generates a Sharpe ratio of only 0.357 with negative alpha (-2.7%), while Q2 delivers the weakest raw returns in the sample (2.8%) alongside a Sharpe ratio of 0.283. By contrast, the upper quintiles exhibit materially stronger performance. Q4 and Q5 generate annualised returns of 12.3% and 14.8%, respectively, with economically large and highly significant alphas (10.9% and 9.9%). These results suggest that favourable funding conditions materially enhance BAB profitability beyond conventional factor exposures.

The intermediate Q3 regime is economically important because it marks the transition between weak and strong BAB environments. Q3 already produces substantially higher returns and Sharpe ratios than the lower quintiles (11.4% return; Sharpe ratio 1.067), while alpha becomes strongly statistically significant (7.0%). This finding suggests that the improvement in BAB performance begins before the most extreme term spread states are reached, motivating the comparison of broader and narrower investment rules in the subsequent timing analysis.

Table 6 evaluates several implementable timing strategies based on the term spread signal. The results show that timing substantially improves the risk characteristics of BAB exposure relative to the unconditional buy-and-hold benchmark. Although buy-and-hold BAB produces the highest unconditional Sharpe ratio overall (0.812), it is associated with extremely large drawdowns (-54.6%). By contrast, all timing strategies materially reduce maximum drawdown while preserving a large proportion of the BAB premium. For example, the median-split strategy reduces maximum drawdown almost by half (-29.3%) while maintaining a significant alpha of 5.0%, whereas the Q3–Q5 strategy generates an annualised return of 8.0%, a Sharpe ratio of 0.673, and a substantially smaller drawdown of -34.5%.

The comparison across strategies reveals an important trade-off between return retention and downside protection. Narrower strategies that allocate capital only during highly favourable term spread states improve drawdown outcomes but spend less time invested. The median-split strategy is invested only 50% of the time yet retains a Sharpe ratio close to the unconditional benchmark (0.689 vs 0.812) with materially lower volatility (8.0% vs 11.3%). Conversely, the broader Q2–Q5 strategy remains invested 80% of the time and preserves more raw return (8.2%) but experiences substantially larger drawdowns (-48.1%).

Importantly, the inverse placebo strategy performs poorly. Restricting exposure to the lowest term spread quintiles (Q1–Q2 only) generates weak returns (1.5%), a negative Sharpe ratio (-0.148), and insignificant negative alpha (-1.3%). This provides additional evidence that the predictive content of the term spread signal is economically meaningful rather than spurious.

At the same time, the quintile decomposition in Table 5 suggests that the underlying predictive relationship may be richer than what can be fully captured by simple threshold-based allocation rules. Performance improves almost monotonically across term spread quintiles, indicating a gradual strengthening of BAB profitability as funding conditions become more favourable. The strategies in Table 6 adopt simple and implementable decision rules, which still deliver economically meaningful improvements in drawdown and alpha preservation. However, because these rules group broad ranges of term spread states into binary

“invest” and “do not invest” decisions, they may not fully utilise the more continuous variation in performance documented across the quintiles. This suggests that the strong results achieved by the timing strategies could potentially be enhanced further through more flexible or dynamically scaled allocation approaches.

Table 5: BAB Performance by Term Spread Quintile — In-Sample

Q	TS Range	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5+Mom α (%)
Q1	−6.51% to −0.28%	4.4	12.4	0.357	−21.8	−2.7
Q2	−0.28% to 0.70%	2.8	10.1	0.283	−29.0	1.4
Q3	0.73% to 1.53%	11.4	10.7	1.067	−31.3	7.0***
Q4	1.54% to 2.37%	12.3	11.2	1.091	−22.6	10.9***
Q5	2.38% to 3.85%	14.8	11.5	1.290	−18.1	9.9***

Table 6: BAB Timing Strategies — In-Sample Comparison (Aug 1964 – Feb 2026)

Strategy	Invested	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5+Mom α (%)
Buy-and-Hold BAB	100%	9.2	11.3	0.812	−54.6	3.8**
Median split (Hi > 1.18%)	50%	7.2	8.0	0.689	−29.3	5.0***
Q3–Q5 (avoid Q1+Q2)	60%	8.0	8.8	0.673	−34.5	5.1***
Q2–Q5 (avoid Q1 only)	80%	8.2	9.9	0.526	−48.1	4.8***
Inverse: Q1–Q2 only	40%	1.5	7.2	−0.148	−33.8	−1.3

3.1.3 Out-of-Sample Results: BAB Timing

Table 7 evaluates BAB performance across term spread quintiles in the out-of-sample test period using thresholds estimated from the training sample. The results continue to support the central finding that the term spread contains economically meaningful information about future BAB profitability, although the monotonic relationship becomes weaker relative to the in-sample results. Performance remains substantially stronger in the middle and upper term spread regimes than in the lowest quintiles, indicating that favourable funding environments continue to improve BAB outcomes out of sample.

The weakest performance is concentrated in the low term spread states. Q1 and Q2 generate very poor results, with annualised returns of 3.1% and −1.8% alongside negative Sharpe ratios (−0.474 and −0.200). In contrast, Q3 and Q4 exhibit materially stronger performance, producing annualised returns of 7.0% and 8.7% with Sharpe ratios of 0.734 and 0.826, respectively. These findings remain broadly consistent with

the in-sample evidence and suggest that avoiding unfavourable funding environments improves the risk-adjusted performance of BAB strategies even in genuinely out-of-sample settings.

At the same time, the out-of-sample quintile structure is less cleanly monotonic than in the in-sample analysis. In particular, Q5 underperforms relative to Q3 and Q4, generating a lower annualised return (4.5%) and Sharpe ratio (0.490). This suggests that extremely high term spread environments do not necessarily correspond to proportionally stronger BAB performance out of sample. One possible interpretation is that very steep yield curves may sometimes coincide with periods of macroeconomic stress or recessionary conditions, partially offsetting the favourable funding effects associated with higher term spreads, which is very symptomatic for the observed period. Nevertheless, the overall pattern still indicates that low term spread environments remain economically unattractive for BAB exposure, while moderate-to-high term spread states deliver substantially better performance.

Table 8 evaluates the corresponding out-of-sample timing strategies. The results show that the term spread signal continues to improve BAB performance outside the estimation sample, although the magnitude of the improvement is naturally weaker than in-sample. The unconditional buy-and-hold strategy generates an annualised return of 4.6%, a Sharpe ratio of 0.491, and a maximum drawdown of -40.0%. Several timing strategies modestly improve these outcomes while simultaneously reducing downside risk.

The strongest overall out-of-sample performance is achieved by the Q3–Q5 strategy, which generates the highest annualised return (5.9%), the highest Sharpe ratio (0.570), and the only statistically significant alpha (3.94%). Importantly, this strategy also reduces maximum drawdown to -34.5%, demonstrating that the timing signal retains economically meaningful predictive content even after imposing a strict out-of-sample framework. The median-split strategy also performs well, improving the Sharpe ratio from 0.491 to 0.526 while reducing volatility from 9.3% to 7.0% and maximum drawdown from -40.0% to -29.8%. The broader Q2–Q5 strategy performs less favourably. Although it remains invested 86.6% of the time and therefore preserves exposure to the BAB premium, its Sharpe ratio (0.461) falls slightly below the unconditional benchmark while maximum drawdown remains very large (-40.4%). This result reinforces the importance of excluding the weakest funding environments identified in the quintile analysis, particularly the lowest term spread states, as well as the need for revised approach to the strategy construction and more frequent quintile revision.

Importantly, the inverse placebo strategy again performs poorly out of sample. Restricting BAB exposure to the lowest term spread quintiles (Q1–Q2 only) generates almost no return (0.4%), a near-zero Sharpe ratio (0.006), and negative alpha (-0.70%). The consistency of this result with the in-sample evidence strengthens the interpretation that the predictive content of the term spread signal is economically meaningful.

Table 7: BAB by TS Quintile in Test Period (Jan 2005 – Feb 2026, Training Thresholds)

Q	TS Range	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)
Q1	−1.49% to −0.42%	3.1	6.6	−0.474	−13.0
Q2	−0.37% to 0.61%	−1.8	9.1	−0.200	−25.2
Q3	0.62% to 1.46%	7.0	9.6	0.734	−9.6
Q4	1.48% to 2.37%	8.7	10.6	0.826	−22.6
Q5	2.42% to 3.65%	4.5	9.17	0.490	−13.7

Table 8: BAB OOS Strategy Comparison (January 2005 – February 2026)

Strategy	Invested	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5+Mom α (%)
Buy-and-Hold BAB	100.0%	4.6	9.3	0.491	−40.0	3.25
Median split (Hi > 1.05%)	56.7%	5.2	7.0	0.526	−29.8	3.14
Q3–Q5 (avoid Q1+Q2)	65.0%	5.9	7.9	0.570	−34.5	3.94*
Q2–Q5 (avoid Q1 only)	86.6%	4.8	9.0	0.461	−40.4	2.99
Inverse: Q1–Q2 only	35.0%	0.4	4.8	0.006	−23.7	−0.70

3.2 Momentum and Inflation

3.2.1 Motivating Evidence: Double-Regime Analysis

Tables 9–12 examine momentum performance across inflation-based double-regime specifications. Unlike BAB, momentum does not exhibit a single dominant conditioning variable. Instead, the results suggest that momentum profitability depends on the interaction between inflation and broader macroeconomic conditions, with low-inflation environments generally associated with weaker performance.

In the $MVOL \times \text{Inflation}$ specification, the weakest momentum performance occurs during the low inflation / high volatility regime, where returns become slightly negative (−0.6%), the Sharpe ratio falls below zero (−0.046), and drawdowns become extremely large (−72.0%). By contrast, performance improves materially when inflation is high even under high-volatility conditions (5.9% return; Sharpe ratio 0.314). The strongest overall performance is observed in the high inflation / low volatility regime, which delivers a 12.6% return, a Sharpe ratio of 1.073, and alpha of 14.5%.

Similar patterns appear in the $\text{Credit Spread} \times \text{Inflation}$ and $IP \times \text{Inflation}$ specifications. Momentum performs particularly poorly when low inflation coincides with adverse macroeconomic conditions such as high credit spreads or weak industrial production growth. For example, the low inflation / low IP regime produces only 1.12% returns with a Sharpe ratio of 0.054 and a drawdown of −69.4%. Conversely, the strongest performance generally occurs when inflation is high and macroeconomic conditions are more supportive, such as the high inflation / low credit spread regime (13.2% return; Sharpe ratio 0.994) and the high inflation / high IP regime (10.5% return; Sharpe ratio 0.765).

The $\text{Term Spread} \times \text{Inflation}$ specification produces weaker and less monotonic effects. While the low inflation / high term spread regime performs poorly (1.1% return; Sharpe ratio 0.062), momentum remains relatively resilient in low

term spread environments, particularly when inflation is high. In the high inflation / low term spread regime, momentum still delivers a return of 10.2% with a Sharpe ratio of 0.565, suggesting that elevated inflation helps sustain momentum profitability even when term spread conditions are less favourable. This further supports the view that inflation plays an important stabilising role for momentum performance across different macroeconomic environments.

Table 9: Momentum (MOM) Returns by Market Volatility × Inflation Regime (Aug 1964 – Feb 2026)

	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)		Alpha (%)
Lo INFL / Lo MVOL	9.6	9.8	0.955	-17.5		10.1***
Lo INFL / Hi MVOL	-0.6	18.3	-0.046	-72.0		4.0
Hi INFL / Lo MVOL	12.6	11.2	1.073	-12.1		14.5***
Hi INFL / Hi MVOL	5.9	17.4	0.314	-26.8		2.1

Table 10: Momentum (MOM) Returns by Credit Spread × Inflation Regime (Aug 1964 – Feb 2026)

	Ann Ret %	Std %	Sharpe	MDD %		Alpha %
Lo INFL / Lo CS	6.2	10.3	0.565	-23.7		8.5***
Lo INFL / Hi CS	3.0	17.4	0.163	-65.8		5.75
Hi INFL / Lo CS	13.2	12.8	0.994	-16.2		15.43***
Hi INFL / Hi CS	3.8	16.6	0.202	-27.9		5.86

Table 11: Momentum (MOM) Returns by Term Spread × Inflation Regime (Aug 1964 – Feb 2026)

Cell	Ann Ret %	Std %	Sharpe	MDD %		Alpha %
Lo INFL / Lo TS	8.6	13.2	0.632	-22.7		9.6***
Lo INFL / Hi TS	1.1	16.0	0.062	-65.8		1.5
Hi INFL / Lo TS	10.2	17.1	0.565	-25.7		9.5**
Hi INFL / Hi TS	8.2	9.7	0.799	-15.2		4.8

Table 12: Momentum (MOM) Returns by Inflation × IP Growth Regime (Aug 1964 – Feb 2026)

	Ann Ret %	Std %	Sharpe	MDD %		Alpha %
Lo INFL / Lo IP	1.12	17.5	0.054	-69.4		7.1*
Lo INFL / Hi IP	7.5	11.6	0.619	-30.5		8.5***
Hi INFL / Lo IP	8.3	15.9	0.490	-32.0		2.9
Hi INFL / Hi IP	10.5	13.0	0.765	-15.0		13.6***

3.2.2 In-Sample Timing: Momentum Against Inflation

Table 13 presents the quintile decomposition of momentum performance across inflation regimes using full-sample thresholds. The benchmark throughout is the FF5 model. The results show that momentum performance varies meaningfully across inflation environments, with the weakest outcomes concentrated in the lowest inflation quintile. Q1 produces very weak returns (2.0%), a low Sharpe ratio (0.115), and extremely large drawdowns (-60.2%), indicating that low inflation represents a particularly unfavourable environment for momentum investing.

Performance improves substantially in the middle inflation quintiles. Q3 delivers the strongest overall results, with annualised returns of 11.1%, a Sharpe ratio of 0.894, and highly significant FF5 alpha of 16.5%. Q4 and Q5 remain profitable and continue to generate significant alpha, although risk-adjusted performance moderates somewhat relative to Q3. In particular, the highest inflation quintile produces positive but less efficient performance (9.5% return; Sharpe ratio 0.625), suggesting that extremely high inflation may introduce greater macroeconomic uncertainty and reduce trend stability relative to moderate inflation environments.

Table 14 evaluates several implementable timing strategies based on the inflation signal. All timing strategies materially reduce drawdowns relative to unconditional momentum exposure. Buy-and-hold momentum produces a maximum drawdown of -57.8%, whereas all timing approaches reduce drawdowns to roughly the -25% to -35% range while preserving economically meaningful returns and alpha.

The strongest overall risk-adjusted performance is achieved by the strategy that excludes only the lowest inflation quintile (Q2–Q5). This strategy generates the highest Sharpe ratio (0.546), preserves almost the full unconditional return premium (7.0% vs 7.1%), and materially reduces drawdown (-34.2% vs -57.8%). The strategy excluding both the lowest and highest inflation quintiles (Q2–Q4) produces very similar results but does not materially improve performance relative to the simpler Q2–Q5 specification. This suggests that the primary source of improvement comes from avoiding the lowest inflation environments rather than excluding extremely high inflation states.

The median-split high-inflation strategy also performs well, substantially reducing volatility (10.2% vs 14.6%) and drawdowns (-25.7%), although it sacrifices more return due to lower market participation. By contrast, the inverse low-inflation strategy performs materially worse than all alternative specifications, generating a Sharpe ratio of only 0.230 alongside drawdowns comparable to unconditional momentum exposure (-59.5%).

Table 13: Momentum Performance by Inflation Quintile — In-Sample (Full-Sample Thresholds)

Q	INFL Range	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5 α (%)
Q1	-1.96% to 1.89%	2.0	17.6	0.115	-60.2	5.1
Q2	1.89% to 2.79%	7.4	13.3	0.354	-37/8	5.5
Q3	2.80% to 3.61%	11.1	12.4	0.894	-19.9	16.5***
Q4	3.61% to 5.50%	8.3	13.8	0.601	-25.3	6.92*
Q5	5.51% to 14.59%	9.5	15.2	0.625	-20.2	8.2*

Table 14: Momentum Timing Strategies — In-Sample Comparison (Aug 1964 – Feb 2026)

Strategy	Invested	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5 α (%)
Buy-and-Hold MOM	100%	7.1	14.6	0.489	-57.8	8.4***
Hi INFL median split	50%	6.1	10.2	0.461	-25.7	4.7***
Avoid Q1 only (Q2–Q5)	80%	7.0	12.3	0.546	-34.2	7.0***
Avoid Q1+Q5 (Q2–Q4)	60%	6.6	10.2	0.469	-34.2	5.1***
Inverse: Lo INFL (Q1)	50%	5.4	10.5	0.230	-59.5	3.7**

3.2.3 Out-of-Sample Results: Momentum Timing

The out-of-sample results in Tables 15 and 16 broadly confirm the inflation-based timing relationship. The lowest inflation quintile remains highly unfavourable for momentum, producing negative returns (-2.6%), a strongly negative Sharpe ratio (-1.58), and severe drawdowns (-57.8%). By contrast, the middle inflation regimes continue to generate the strongest risk-adjusted performance, particularly Q4, which delivers an annualised return of 11.4% and a Sharpe ratio of 0.813. The highest inflation quintile again produces weaker performance, suggesting that momentum performs best under moderate rather than extremely high inflation conditions.

The out-of-sample timing strategies materially improve downside risk relative to unconditional momentum exposure. Buy-and-hold momentum generates a Sharpe ratio of only 0.102 with a maximum drawdown of -57.8%, whereas all timing strategies reduce drawdowns substantially. The strongest overall performance is achieved by excluding both the lowest and highest inflation quintiles (Q2–Q4), which produces the highest Sharpe ratio (0.405) and reduces maximum drawdown to only -9.3%. The simpler strategy excluding only Q1 (Q2–Q5) also performs strongly, generating the highest alpha (3.5%) while materially improving Sharpe ratios and drawdowns.

Table 15: Momentum by Inflation Quintile in Test Period (Jan 2005 – Feb 2026, Training Thresholds)

Q	INFL Range (training thresholds)	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)
Q1	-1.96% to 2.52%	-2.6	16.7	-1.58	-57.8
Q2	2.54% to 3.16%	7.3	11.1	0.658	-8.6
Q3	3.21% to 4.29%	6.3	11.2	0.564	-7.7
Q4	4.35% to 6.24%	11.4	14.0	0.813	-9.2
Q5	6.33% to 8.98%	1.2	18.4	0.064	-16.2

Table 16: Momentum OOS Strategy Comparison (January 2005 – February 2026)

Strategy	Invested	Ann. Ret (%)	Std (%)	Sharpe	MDD (%)	FF5 α (%)
Buy-and-Hold MOM	100.0%	1.5	15.0	0.102	-57.82	3.8
Hi INFL median split	20.1%	2.8	6.8	0.238	-17.7	2.1*
Avoid Q1 only (Q2–Q5)	44.5%	3.5	8.4	0.356	-22.5	3.5**
Avoid Q1+Q5 (Q2–Q4)	38.8%	3.5	7.2	0.405	-9.3	3.1**
Inverse: Lo INFL	79.9%	0.4	13.4	-0.005	-57.8	1.6

4. Interpretation and discussion

4.1 Betting against Beta and Term spread

The finding that BAB performance is strongly and monotonically increasing in the term spread is related to, but distinct from, the leverage-constraint theory of the low-beta anomaly advanced by Frazzini and Pedersen (2014). In their model, investors who face binding constraints on the use of leverage overweight high-beta securities in an effort to achieve returns corresponding with their risk appetite without recourse to borrowing. This excess demand causes high-beta assets to become systematically overpriced relative to their fundamental risk, while low-beta securities are correspondingly underpriced. The BAB premium represents the equilibrium compensation earned by unconstrained arbitrageurs who lever up low-beta portfolios and short overpriced high-beta securities. Frazzini and Pedersen (2014) test this mechanism empirically using the TED spread, the difference between three-month LIBOR and the three-month Treasury bill rate, as their funding-cost proxy, showing that BAB earns less when TED rises and interbank funding conditions become stressed. The present analysis uses an economically distinct measure: the term spread, defined as the ten-year Treasury yield minus the Federal Funds effective rate. The term spread does not measure episodic interbank credit risk, but rather the persistent slope of the risk-free yield curve and thereby proxies the carry margin available to the BAB strategy across business and monetary-policy cycles. The empirical distinction matters, as the TED spread is near-zero in most months and spikes primarily during acute financial crises, making it predominantly a tail-risk signal. By contrast, the term spread varies continuously and persistently over the full sample, ranging from -6.51% to $+3.85\%$, and the monotone alpha pattern across its quintiles therefore reflects a continuous, cycle-length relationship rather than a purely crisis-driven one.

Within the broader Frazzini–Pedersen (2014) framework, the term spread proxies the net carry margin of the leveraged low-beta trade. When the yield curve is steep, short-term borrowing rates are low relative to the expected return from holding the scaled low-beta portfolio, expanding the profitability of the strategy for investors able to access leverage. This is economically equivalent to a persistent reduction in the shadow cost of leverage. As funding rates decline relative to longer-term yields, the set of investors for whom the BAB trade is economically attractive expands, arbitrage capital flows more easily toward the strategy, and the premium becomes both more reliably earned and more durably sustained throughout the business cycle. The large difference between the insignificant Q1 alpha of -2.7% and the highly significant Q5 alpha of $9.9\%^{***}$ is consistent with this mechanism operating across the full distribution of financing conditions rather than only during isolated episodes of market stress. The intuition underlying the empirical results is therefore that a steep yield curve simultaneously lowers the effective financing burden of leveraged low-risk portfolios and reflects broader macroeconomic conditions favourable to carry-style strategies. When short-term policy rates remain substantially below longer-term yields, leveraged investors can finance defensive low-beta portfolios at relatively low funding costs while maintaining exposure to higher expected-return assets, allowing the net carry available to the BAB trade to expand materially. Crucially, however, this interpretation is offered as economically consistent with rather than uniquely confirming the Frazzini–Pedersen (2014) channel, to the extent that the term spread captures broader features of the macroeconomic environment.

The most directly relevant recent contribution is Barroso, Detzel, and Maio (2025), who document what they term the volatility puzzle of the beta anomaly. Their central finding is that the leading theoretical explanations for time-varying BAB performance, including leverage constraints, limits to arbitrage, lottery preferences, analyst disagreement, and investor sentiment, collectively fail to explain BAB's performance conditional on volatility where they show that above-median volatility states deteriorate BAB's abnormal returns and Sharpe ratios. The evidence in this research speaks directly to the puzzle raised by Barroso, Detzel, and Maio (2025) and offers a partial resolution through the addition of the term spread as a conditioning variable. Their finding that BAB earns less in high-volatility states is confirmed. Pooling across all TS regimes, Hi MVOL months produce lower BAB returns than Lo MVOL months. However, the double-regime analysis of Table 3 reveals that the high-volatility underperformance of BAB is not uniform, but concentrated almost entirely in the Hi MVOL / Lo TS cell (Sharpe 0.177, alpha -2.0%), while the Hi MVOL / Hi TS cell continues to earn 11.1% annualised with Sharpe 0.795 and a significant FF5+Mom alpha of $8.35\%^{**}$ ($t=2.03$). This pattern is inconsistent with the institutional demand-shift explanation advanced by Barroso, Detzel, and Maio (2025) in its general form. If institutional flight-to-safety rebalancing toward low-beta stocks were the primary driver of reduced BAB returns in high-volatility periods, acting through price impact on the long leg of the portfolio, it should manifest regardless of the term spread, since institutional demand rebalancing is not directly conditioned on yield-curve slope. The fact that the term spread largely removes the high-volatility drag suggests that the term spread captures an additional economic dimension that mediates the volatility-BAB relationship, consistent with a carry or funding-cost mechanism that operates beyond institutional demand effects.

4.2 Momentum and inflation

The momentum results point toward a fundamentally different economic mechanism centered on the persistence of cross-sectional price trends and the conditions under which that persistence breaks down. The most robust finding across all four bivariate tables is that near-zero or negative inflation constitutes the primary adverse state for momentum profitability, a relationship that holds regardless of the secondary conditioning variable. Understanding why inflation should matter for momentum requires connecting the macro environment to the micro-level mechanism through which the momentum premium arises.

The original momentum evidence of Jegadeesh and Titman (1993) demonstrates that stocks with high returns over the prior three to twelve months continue to outperform stocks with low prior returns over the subsequent three to twelve months. Subsequent work has identified gradual information diffusion as a leading explanation. Hong and Stein (1999) develop a model in which information diffuses slowly across investors, generating under-reaction to fundamental news that causes prices to adjust towards their efficient level only gradually, creating exploitable return continuation. Under this mechanism, the momentum premium requires that the cross-sectional dispersion in firm-level fundamentals be sustained over the medium term. Winners must continue to have genuinely superior cash-flow prospects relative to losers, and this differential must be reflected in prices only progressively rather than immediately. Moderate inflation is supportive of this mechanism because it is associated with stable, demand-driven nominal growth in which firm-level revenue and earnings trends are persistent. In such environments, cross-sectional performance differentials in fundamentals are real and durable, and the market's gradual incorporation of this information generates the price continuation that momentum strategies exploit.

Near-zero or negative inflation environments are adverse to momentum through a distinct mechanism. They are typically associated with demand-side contractions, deflationary pressure, financial stress, or sharp policy interventions that generate abrupt and violent reversals in market leadership. Daniel and Moskowitz (2016) document that momentum crashes are not random but cluster in specific macro states. They occur predominantly during sudden market rebounds following bear markets, when highly shorted past-loser stocks rebound sharply and highly levered past-winner stocks are forced to delever. Critically, these rebounding environments are disproportionately concentrated in low-inflation or deflationary periods. The 2008–2009 episode, in which momentum lost approximately 55% peak-to-trough in the US, is the core example. It was preceded by falling inflation as commodity prices collapsed and aggregate demand contracted, and the subsequent reversal was driven by the violent rebound in beaten-down financial and cyclical stocks as credit markets recovered. The 2022 episode followed a similar pattern where lagged year-over-year CPI was still below the training-period Q1 threshold of 2.512% at the start of 2022, because the post-COVID inflation surge had only recently begun to register in annual comparisons, and momentum was long high-growth technology stocks that were severely repriced as rates rose. In both cases, the Q1 inflation signal correctly identified the environment as one in which momentum crash risk was elevated, and the OOS strategy avoided both episodes.

The interaction results further suggest that inflation contains information about the macroeconomic state beyond what is captured by volatility or credit conditions alone. Table 9 shows that the Hi INFL / Hi MVOL cell earns 12.6% annualised with positive momentum, while the Lo INFL / Hi MVOL cell earns −0.6% and incurs a 72.0% maximum drawdown. Both cells have above-median market volatility; the sole difference is the inflation state. Moderate-to-high inflation in a volatile environment suggests that economic uncertainty is demand-driven rather than recessionary, and that the repricing of risk assets does not necessarily involve the abrupt leadership reversals that destroy momentum positions.

4.3 Limitations and next steps

4.3.1 Points for improvement

The most significant methodological limitation of the timing strategies presented in this paper is the binary, discrete nature of the investment rule. Each strategy allocates either 100% to the factor portfolio or 100% to the risk-free rate, with no intermediate positions. This all-or-nothing construction has two practical deficiencies. First, it is discontinuous at the threshold, which means that a small mismeasurement or revision in the macro variable can produce a large and artificial swing in strategy returns, inflating the apparent precision of the timing rule. Second, it is unrealistic as an implementable allocation for institutional investors due to transaction costs, tracking-error constraints, and mandate. The strategies as constructed therefore provide an upper bound on attainable timing gains rather than a realistic estimate of implementable performance, and the Sharpe ratio improvements reported in Tables 6, 8, 14, and 16 are best interpreted as evidence of signal informativeness rather than as estimates of achievable investor returns.

The most immediate extension is to replace the binary threshold rule with a continuous allocation framework. Two natural approaches are available. The first, proposed by Moreira and Muir (2017) for volatility-managed portfolios, scales the portfolio weight inversely with the conditional variance of the factor, the investor holds a larger position when the signal indicates a favourable environment and a smaller

position when it does not, with the weight varying continuously rather than discretely. Adapting this to macro signals requires specifying how the factor weight maps to the level of the term spread (for BAB) or the inflation rate (for momentum). A linear specification is the natural starting point, while nonlinear specifications motivated by the quintile performance patterns could additionally account for the diminishing-returns structure at high TS levels and the hump-shaped momentum–inflation relationship.

The out-of-sample test employed in Sections 3.1.3 and 3.2.3 is genuine in the sense that thresholds are fixed on the training period and applied to the test period without updating. It is nonetheless subject to a design limitation, since the quintile boundaries are re-estimated only once, at the training-period cutoff. A more demanding as well as realistic alternative would be a recursive expanding-window design in which both the thresholds and the classification of quintile regimes as favourable or unfavourable are re-estimated using only data available up to each point in time, producing a genuine real-time allocation sequence. Under such a design, the strategy could revise its quintile classification as new data accumulate, responding to structural shifts in the factor–macro relationship over time.

A further interpretation caveat is the unusual nature of the test period itself. The January 2005 to February 2026 window encompasses several macroeconomic episodes of exceptional magnitude: the Global Financial Crisis of 2008–2009, the prolonged zero-interest-rate and quantitative easing environment of 2009–2015, the COVID-19 market collapse and recovery of 2020, and the aggressive monetary tightening cycle of 2022–2023. These episodes generated extreme and persistent deviations in yield-curve slope, inflation dynamics, funding conditions which the timing strategies condition on.

The out-of-sample design can be substantially strengthened by adopting a fully recursive expanding-window framework in which, at each month t , the quintile thresholds are re-estimated using all available data through month $t-1$, and the investment decision is based on the signal's position in the distribution estimated to that point. This ensures that the classification of regimes as favourable or unfavourable is itself out-of-sample at every point in the test period is re-evaluated as the macro-factor relationship evolves. If the identified relationships are genuinely structural rather than sample-specific, the recursive design should produce similar regime classifications to the fixed-threshold design while providing stronger validity. The second strengthening is to evaluate the OOS timing strategies against a direct benchmark.

4.3.2 Research agenda

The evidence in this paper reveals a pattern that motivates a broader research agenda. Aggregate market volatility does not affect factor premia monotonically, uniformly, or through a single channel. For BAB, high volatility is destructive when paired with a flat yield curve but largely benign when paired with a steep yield curve. For momentum, high volatility is deteriorating when paired with near-zero inflation but only modestly harmful when inflation is moderate or high. The same level of aggregate market volatility is therefore associated with radically different outcomes for different factors and in different macro contexts, implying that volatility as a scalar conditioning variable misses fundamental cross-sectional heterogeneity in how uncertainty is transmitted to factor premia. This heterogeneity reflects the distinct economic channels through which volatility affects different strategies. For BAB, volatility primarily influences the variance of returns rather than their expected level when funding conditions are favourable, consistent with the view that market turbulence widens the distribution of carry outcomes but does not eliminate the carry

itself when the yield-curve slope remains positive. For momentum, volatility is most destructive specifically when it accompanies demand-side dislocations signalled by near-zero inflation, because these are the environments that generate the abrupt reversals in market leadership that Daniel and Moskowitz (2016) identify as the source of momentum crashes. High volatility in a moderate-inflation environment, by contrast, may reflect supply-side uncertainty, sectoral rotation, or policy noise that disrupts individual stock trends without generating the systematic mean-reversion of the momentum portfolio. The channel through which volatility reaches factor returns is therefore as important as its level, and characterising these channels is the central goal of the proposed research agenda.

The proposed extension decomposes aggregate market volatility into economically distinct components and examines whether the macro-state dependence of factor premia identified in this paper can be mapped onto specific volatility sources. The decomposition draws on the Campbell and Shiller (1988) framework and its extensions. Under the Campbell and Vuolteenaho (2004) cash-flow and discount-rate decomposition, unexpected market returns are attributed to news about future cash flows (CF news) or news about future discount rates (DR news). These two components carry fundamentally different implications, where CF news is 'bad beta' in the sense of ICAPM, compensated in equilibrium by a risk premium, while DR news is 'good beta' as it does not forecast lower future investment opportunities and therefore commands no premium. The corresponding decomposition of market volatility into CF-driven and DR-driven components may explain the non-monotone volatility effects observed in the data. Importantly, the VAR methodology underlying the Campbell and Vuolteenaho (2004) decomposition is not restricted to the market return alone. The same framework can in principle be applied to decompose the unexpected returns of individual factor portfolios into their own cash-flow and discount-rate news components, thereby identifying whether each factor's premium is driven primarily by compensation for CF uncertainty, by DR fluctuations, or by some combination of the two. Such factor-level decompositions would provide direct structural identification of the channels documented descriptively in this paper. If BAB's return variation is predominantly DR-driven, consistent with the leverage-cost interpretation, and momentum's crash-prone variation is predominantly CF-driven in low-inflation environments, consistent with the trend-disruption interpretation, then the bivariate regime patterns reported reflect not merely empirical regularities but structurally grounded distinctions between economically distinct sources of factor risk. Extending the VAR state space to include macroeconomic variables such as the term spread and inflation alongside the standard financial predictors would further allow the decomposition to identify which macro conditions shift the relative importance of CF versus DR news for each factor, connecting the descriptive conditioning analysis of the present paper to a fully structural description of the macro-factor premium relationship.

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