

The winner takes it all: asymmetric drivers of momentum's conditional performance

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This Draft: January 2026

Abstract

Momentum generates significantly higher abnormal returns and Sharpe ratios following months with below-median realized volatility. The conditional difference in alphas between low- and high-volatility states is economically significant and amplifies when market volatility is high. We show that the long leg of the strategy predominantly drives this conditional performance, challenging conventional views on the origins of the momentum risk-return trade-off: while the loser portfolio's alpha remains consistently negative across volatility regimes, the winner portfolio's alpha nearly triples in low-volatility states. These findings are robust to alternative explanations, including trend-following, liquidity risk, investor sentiment and idiosyncratic volatility. They suggest that momentum volatility timing offers a distinct, implementable mechanism to maximize alpha capture, even in the presence of trading costs and leverage constraints.

Keywords: Momentum crashes; Volatility timing; Winner-loser asymmetry; Conditional performance

JEL classification: G11, G12, G14

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1 Introduction

The momentum anomaly remains one of the most enduring and widely researched puzzles in asset pricing. Defined as the tendency for recent winners to outperform recent losers, the strategy relies on the predictive power of past returns for future cross-sectional performance. Initially identified in U.S. stocks ([Asness, 1994](#); [Jegadeesh & Titman, 1993](#)), its profitability has been validated across nearly a century of U.S. data ([Israel & Moskowitz, 2013](#)). Momentum is a ubiquitous phenomenon found in markets worldwide and across all major asset classes: it has been documented in international equities ([Rouwenhorst, 1998, 1999](#)), currencies ([Okunev & White, 2003](#)), commodities ([Erb & Harvey, 2006](#)), bonds ([Asness, Moskowitz, & Pedersen, 2013](#)), cryptocurrencies ([Tzouvanas, Kizys, & Tsend-Ayush, 2020](#)), as well as factor and industry portfolios ([Arnott, Kalesnik, & Linnainmaa, 2023](#); [Ehsani & Linnainmaa, 2022](#)).

However, the robustness of this anomaly is complicated by its dynamic risk profile. [Daniel and Moskowitz \(2016\)](#) highlight that momentum effectively behaves like a short call option on the market. During bear markets, the strategy often ends up shorting the market by selling high-beta losers that have dropped significantly. Consequently, when the market rebounds abruptly, the short side of the momentum portfolio suffers massive losses. This mechanism drives the severe crashes observed in the data, notably in 1932 and 2009, suggesting that momentum returns exhibit substantial tail risk.

These severe crashes render momentum unappealing to many investors, despite its higher Sharpe ratios than those of market, size, or value factors. However, [Barroso and Santa-Clara \(2015\)](#) argue that the crashes are avoidable because momentum risk is highly predictable over time. They introduce a volatility-scaled momentum strategy that dynamically adjusts exposure, thereby virtually eliminating crash risk and nearly doubling the Sharpe ratio. This strategy resolves the issue of negative skewness while introducing a new

theoretical challenge: the volatility-managed version performs so well that it constitutes an even greater anomaly than the original strategy.

Recent literature has expanded the debate surrounding momentum risk beyond the strategy’s crash proclivity to encompass a broader range of explanations and mechanisms. [Ruenzi and Weigert \(2018\)](#) provide a risk-based rationale, linking momentum profits to a wider systematic market crash risk. [Jacobs, Regele, and Weber \(2015\)](#) uncover a strong link between expected skewness and cross-sectional momentum. Liquidity also plays a central role: [Butt and Virk \(2022\)](#) and [Avramov, Cheng, and Hameed \(2016\)](#) argue that aggregate market illiquidity, alongside optionality, is a key predictor of momentum crashes.

Challenging the universality of the crash mechanism, [Grobys, Ruotsalainen, and Äijö \(2018\)](#) find that alternative strategies, such as industry or 52-week high momentum, do not exhibit the same option-like payoffs as standard price momentum. Furthermore, [Ehsani and Linnainmaa \(2022\)](#) and [Arnott et al. \(2023\)](#) suggest that momentum profits, and potentially their risk, are primarily driven by autocorrelations in systematic factors rather than distinct idiosyncratic anomalies. Finally, [Bianchi, De Polis, and Petrella \(2024\)](#) argue that the risk-return trade-off of momentum depends critically on conditional skewness rather than volatility alone. They show that a dynamic skewness-adjusted strategy significantly outperforms standard volatility scaling, as momentum’s time-varying skewness cannot be fully reconciled with asymmetric exposure to market risk.

The prevailing view in the literature tends to be defensive, implying that volatility timing works primarily by avoiding crash states in which the loser leg rebounds violently. While this option-like behavior explains the reduction in tail risk, it does not fully account for why volatility-managed momentum generates such massive unexplained alpha relative to the standard factor models. We address this gap by showing that volatility timing is not merely a defensive mechanism to avoid crashes, but also an *offensive* mechanism that

capitalizes on conditional mispricing. We find that the strategy concentrates exposure in calm (low-volatility) states where winner stocks generate outsized alpha, and reduces exposure in turbulent states where winner alpha evaporates. Our finding thus contrasts sharply with the loser-centric view. While loser alphas are relatively stable across regimes, the benefits of volatility timing are driven primarily by the asymmetric risk sensitivity of the winner leg.

Our results hold after accounting for transaction costs and leverage constraints and are distinct from liquidity or sentiment effects. Specifically, we investigate several alternative explanations and mechanisms. We control for the time-series momentum factor of Moskowitz, Ooi, and Pedersen (2012) to demonstrate that our results are not merely capturing trend-following effects. To ensure that winners in high-volatility states are not simply suffering a liquidity discount or driven by investor overreaction, we control for the Pástor and Stambaugh (2003) liquidity factor. To verify that the high alpha observed in low-volatility states does not solely reflect periods of high investor confidence or overreaction, we demonstrate that our results remain robust after controlling for the Baker and Wurgler (2007) investor sentiment index. Furthermore, double sorts on momentum and idiosyncratic volatility confirm that the effect is distinct from the low-volatility anomaly.

We also perform additional robustness checks, including break-even turnover analysis to demonstrate that the alpha survives realistic trading costs, and tests with weights capped at 2.0, 1.5 and 1.0 to show that extreme leverage outliers do not drive the results. Finally, we present international evidence from Europe and Asia-Pacific confirming that volatility timing remains effective globally (except for Japan), and that it is driven by the exact asymmetric mechanism observed in the U.S. – the outperformance of winner stocks following low-volatility periods.

This paper makes three specific contributions to the literature on momentum and

volatility timing. First, we document the asymmetry of the volatility effect, driven principally by the long leg. By decomposing the strategy, we show that winner portfolio alpha nearly triples in low-volatility states, suggesting that momentum volatility timing acts as an alpha enhancement mechanism for the long side.

Second, our findings challenge the standard intertemporal risk-return trade-off in the context of momentum. While classic asset pricing theory suggests that periods of high variance should be associated with higher expected returns to compensate for risk, our results support the volatility puzzle documented by [Moreira and Muir \(2017\)](#). We find that momentum creates significant alpha only in low-volatility states. In high-volatility states, the strategy loads on risk factors but generates no abnormal return. The market thus creates a “sweet spot” in low-volatility environments where momentum yields high returns with low factor exposure.

Third, we provide evidence of an interaction effect between momentum and market volatility: the spread in alphas between low- and high-momentum volatility states is most pronounced (1.20% per month) following periods of high market volatility. This interaction refines the timing signal, suggesting that the benefit of differentiating between momentum states is maximized when the market’s systemic risk is elevated, precisely when unmanaged momentum is most prone to failure.

The remainder of this paper is structured as follows. [Section 2](#) outlines our data sources, the methodology for constructing portfolios and the volatility-scaling approach. [Section 3](#) analyzes the unconditional and conditional performance of the volatility-managed strategy. In [Section 4](#), we present our core contribution by decomposing the strategy into its winner and loser components, where we demonstrate that the benefits of volatility timing are asymmetric. [Section 5](#) validates these findings against alternative explanations, including time-series momentum, liquidity risk, sentiment and idiosyncratic volatility, and presents

robustness checks related to transaction costs, leverage constraints and international markets. Finally, Section 6 summarizes our key findings and concludes.

2 Data and methodology

2.1 Data

Our primary analysis focuses on the U.S. equity market. We obtain daily and monthly returns for all common stocks (share codes 10 and 11) listed on the NYSE, AMEX and NASDAQ from the Center for Research in Security Prices (CRSP). The sample period spans from January 1927 through October 2025. The market portfolio is defined as the CRSP value-weighted index of all eligible stocks. We compute excess returns by subtracting the one-month U.S. Treasury bill rate. To ensure data quality, we require firms to have a valid share price and number of shares outstanding as of the portfolio formation date. Furthermore, we require at least eight valid monthly returns over the prior 11 months, excluding the most recent month used for the formation period. Consistent with standard conventions and CRSP availability, we calculate returns on a close-to-close basis.

To construct and evaluate our factor models, we source daily and monthly returns for the [Fama and French \(2015\)](#) five factors (MKT, SMB, HML, RMW, CMA) and the one-month U.S. Treasury bill rates from the [Kenneth French Data Library](#). We use the same source for our international analysis, which is based on the momentum factor and six portfolios formed by sorting on size and momentum for three additional regions: Europe, Asia-Pacific (excluding Japan), and Japan. This dataset covers the period between November 1990 and October 2025.

We augment this dataset with several factors to test alternative explanations for our results. We obtain the monthly time-series momentum factor of [Moskowitz et al. \(2012\)](#)

from [AQR Capital Management’s data library](#) to control for trend-following effects distinct from cross-sectional momentum. To account for liquidity risk, we use the traded liquidity factor of [Pástor and Stambaugh \(2003\)](#), obtained from [Luboš Pástor’s website](#). Finally, to examine the role of investor sentiment, we use the monthly sentiment index of [Baker and Wurgler \(2007\)](#), orthogonalized to macroeconomic conditions, available on [Jeffrey Wurgler’s website](#).

2.2 Portfolio formation

We construct the Winner and Loser portfolios following the methodology of [Fama and French \(1996\)](#). At the beginning of each month t , we create six value-weighted portfolios from the intersection of two portfolios formed on market capitalization (Size) and three portfolios formed on prior returns. We rank stocks based on their cumulative return between months $t-12$ and $t-2$, skipping the most recent month ($t-1$) to avoid microstructure biases and short-term reversals documented by [Jegadeesh \(1990\)](#) and [Lehmann \(1990\)](#). The Winner portfolio is defined as the equally-weighted average of the two high prior-return portfolios, and the Loser portfolio is the average of the two low prior-return portfolios:

$$\text{Winner}_t = \frac{1}{2} (\text{Small High}_t + \text{Big High}_t), \quad (1)$$

$$\text{Loser}_t = \frac{1}{2} (\text{Small Low}_t + \text{Big Low}_t), \quad (2)$$

where Small and Big denote stocks with market capitalization below and above the NYSE median, respectively. High and Low denote stocks with prior returns above the 70th and below the 30th NYSE percentiles, respectively. We note that this construction differs from [Daniel and Moskowitz \(2016\)](#), who utilize the top and bottom deciles of a univariate sort. However, we employ the definitions in Eqs. (1) and (2) to maintain consistency with the standard momentum factor (MOM) used in the [Fama and French \(2018\)](#) six-factor model,

defined as:

$$\text{MOM}_t = \text{Winner}_t - \text{Loser}_t, \quad (3)$$

i.e., a portfolio long on the Winner leg and short on the Loser leg.

To form the volatility-managed momentum portfolio, we follow the methodology of [Barroso and Santa-Clara \(2015\)](#), dynamically adjusting exposure to the original (unmanaged) momentum factor based on its realized volatility in the prior month:

$$\text{MOM}_{t+1}^\sigma = \frac{c}{\hat{\sigma}_t} \text{MOM}_{t+1}, \quad (4)$$

where $\hat{\sigma}_t$ is the realized volatility of the last 21 daily returns $\text{mom}_{d,t}$ of the prior month t :

$$\hat{\sigma}_t = \sqrt{\sum_{d=1}^{21} \text{mom}_{d,t}^2}. \quad (5)$$

The constant c in Eq. (4) is chosen such that the managed and the unmanaged momentum have the same sample variance.¹ As argued by [Barroso, Detzel, and Maio \(2025\)](#), the scaling in Eq. (4) avoids look-ahead biases documented by [Liu, Tang, and Zhou \(2019\)](#) and produces more stable weights than the standard alternative of scaling by realized variance.

Fig. 1 displays a monthly time series of the momentum realized volatility defined by Eq. (5). The spikes coincide with periods of extreme market stress and subsequent reversals, most notably the 1937 echo of the Great Depression, the bursting of the Dot-Com bubble in 2000, the post-crisis period in 2009, and the 2020 market’s volatile reopening phases following the COVID-19 pandemic. In these periods, the Loser leg, typically comprised of distressed assets, generated massive variance as markets rebounded.²

¹The scaling constant c is, anyway, arbitrary and bears no impact on statistical inference. We applied an alternative definition with c calibrated using only a 36-month burn-in period, on an increasing-window basis and on a 36-month rolling-window basis. The paper’s main results do not differ dramatically.

²Daniel and Moskowitz (2016) identify three distinct phases of momentum crashes: (1) panic states, (2)

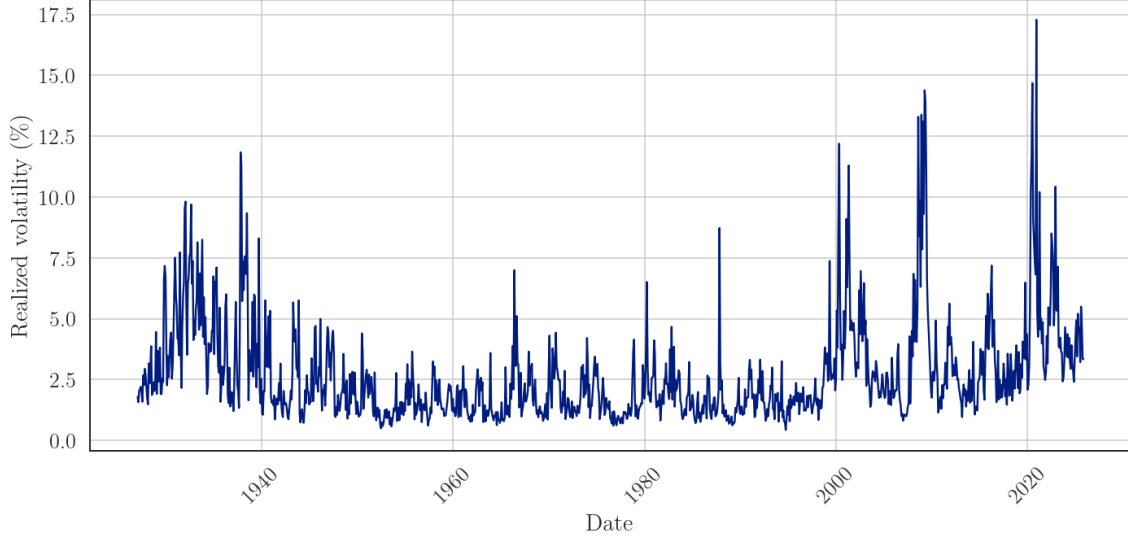


Figure 1: MOM realized volatility. This figure depicts the monthly time-series of realized volatility of the momentum, defined in Eq. (5), in percent. The sample period is January 1927 to October 2025.

We also define the volatility-managed Winner and Loser portfolios in analogy with Eq. (4):

$$\text{Winner}_{t+1}^{\sigma} = \frac{c^W}{\widehat{\sigma}_t^W} \text{Winner}_{t+1} \quad (6)$$

$$\text{Loser}_{t+1}^{\sigma} = \frac{c^L}{\widehat{\sigma}_t^L} \text{Loser}_{t+1}, \quad (7)$$

post-crisis market rebounds, and (3) sector-specific volatility dislocations.

where the unmanaged returns Winner_t and Loser_t are defined in Eqs. (1) and (2). Similarly,

$$\hat{\sigma}_t^W = \sqrt{\sum_{d=1}^{21} \text{winner}_{d,t}^2} \quad (8)$$

$$\hat{\sigma}_t^L = \sqrt{\sum_{d=1}^{21} \text{loser}_{d,t}^2}, \quad (9)$$

are the corresponding realized volatilities, while $\text{winner}_{d,t}$ and $\text{loser}_{d,t}$ are the prior-month daily returns of the constituent legs. The constants c^W and c^L in Eqs. (8) and (9) are calibrated analogously with Eq. (5) to match the same sample variances of the managed and the unmanaged portfolio.

3 The performance of volatility-managed momentum

3.1 Unconditional performance and risk profile

Table 1 reports descriptive statistics for the performance of the unmanaged momentum factor (MOM) and its volatility-managed counterpart (MOM^σ). The statistics shown are the mean return (Mean), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), and the annualized Sharpe ratio (SR). By construction, the scaling constant c in Eq. (4) ensures that MOM^σ has the same standard deviation as MOM. Despite maintaining the same level of volatility, the managed strategy delivers a dramatically superior return profile: the mean monthly return of MOM^σ is almost double that of the unmanaged MOM (1.21% versus 0.61%). Consequently, volatility management essentially doubles the annualized Sharpe ratio from 0.45 to 0.89. The economic and statistical significance of this improvement is noteworthy, particularly in light of Cederburg, O’Doherty, Wang, and Yan (2020), who find that the vast majority of volatility-managed factors fail to improve their Sharpe ratios over their unmanaged counterparts.

Table 1: Performance of MOM and its volatility-managed counterpart.

This table shows descriptive statistics of the returns on MOM and MOM^σ , which scales MOM each month by its realized volatility estimated over the previous month (see Eq. 4). The statistics are: mean return (Mean), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), and the annualized Sharpe ratio (SR). The sample period is January 1927 to October 2025. The bracket reports the studentized difference in Sharpe ratios between MOM^σ and MOM obtained from the bootstrap method of [Ledoit and Wolf \(2008\)](#).

	Mean (%)	SD (%)	Skew	Kurt	SR
MOM	0.61	4.69	−3.06	28.02	0.45
MOM^σ	1.21	4.69	−0.39	2.98	0.89
					[4.92]

Volatility scaling also fundamentally alters the higher-moment risk profile. The unmanaged strategy exhibits significant negative skewness (−3.06), reflecting its tendency to experience sudden, deep crashes relative to its average performance. This crash risk intuition of [Daniel and Moskowitz \(2016\)](#) implies that the strategy collects steady premia but faces catastrophic losses during sharp market reversals. Volatility scaling reduces this negative skewness in absolute terms to −0.39. The unmanaged strategy also exhibits extreme excess kurtosis (approximately 28), indicating a high probability of extreme events. Volatility scaling drastically lowers this statistic to roughly 3. By dampening exposure during turbulent periods, the managed portfolio avoids the extreme outliers that drive fat tails, transforming momentum from a strategy characterized by rare, devastating losses into one with a much more stable risk profile.

The dramatic improvement in risk-adjusted performance is visualized in Fig. 2, which plots the cumulative wealth of a \$1 investment in the unmanaged (red line) and volatility-managed (blue line) momentum portfolios on a logarithmic scale. While both strategies generate substantial long-term wealth, their paths diverge significantly during periods of market stress. The unmanaged strategy suffers from severe drawdowns that can take

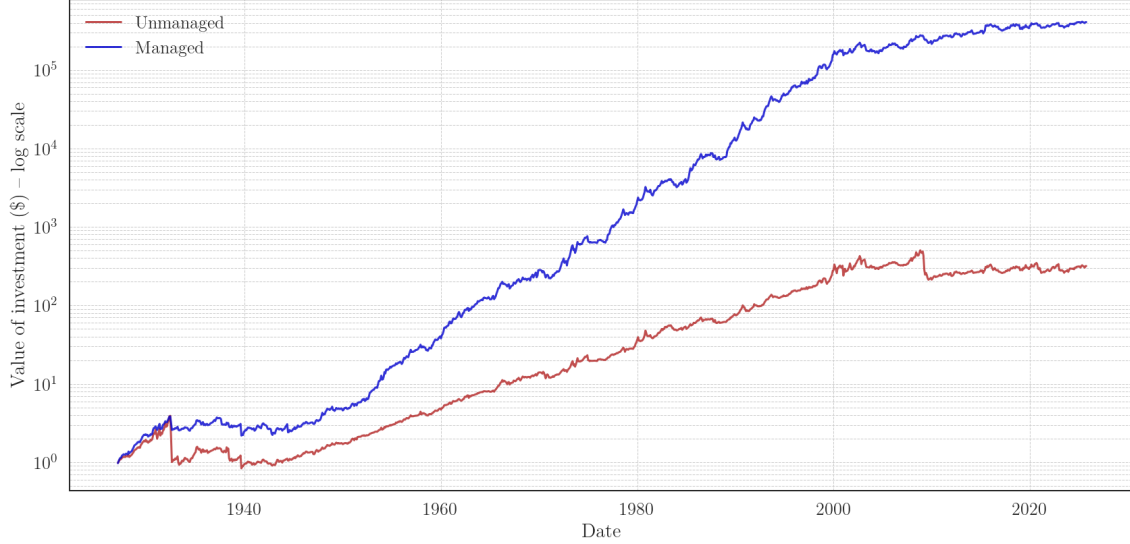


Figure 2: Cumulative returns for MOM and MOM^σ . The figure shows the growth of a \$1 investment from January 1927 to October 2025. The red line is the unmanaged momentum (MOM). The blue line is the volatility-managed momentum MOM^σ , obtained by scaling MOM by its realized volatility estimated over the previous month (see Eq. 4). The investment values on the vertical axis are in a log scale.

decades to recover. For instance, after the Great Depression crash, the unmanaged wealth index did not permanently surpass its September 1929 peak until the mid-1940s. More strikingly, the unmanaged strategy has effectively eroded since the Global Financial Crisis. After peaking at \$503.1 in November 2008, the wealth index plunged to \$212.2 by September 2009. Remarkably, as of October 2025, the unmanaged strategy has yet to recover this high-water mark – at \$317.6, it is still 37% below its peak from nearly 17 years earlier. In sharp contrast, the volatility-managed portfolio avoids these deep plummets, exhibiting a smoother upward trajectory that consistently compounds wealth even through the volatile post-2009 and post-2020 periods.

The mitigation of this tail risk is explicitly detailed in Fig. 3, which plots the monthly

drawdowns of both portfolios over the whole sample period. The unmanaged strategy displays the severe crash risk documented by [Daniel and Moskowitz \(2016\)](#). The data reveals a devastating maximum drawdown of 78.6% during the Great Depression era, culminating in September 1939, and a 57.8% drawdown in 2009. By mechanically reducing exposure when realized volatility spikes, the managed portfolio effectively navigates these turbulent periods. Fig. 3 shows that the volatility-scaled strategy transforms deep, multi-decade losses into manageable corrections with significantly shorter recovery times. This preservation of capital during the crashes of 1932 and 2009, and the volatile post-2020 period, explains the dramatic difference in terminal wealth and ties to the Sharpe ratios reported in Table 1.

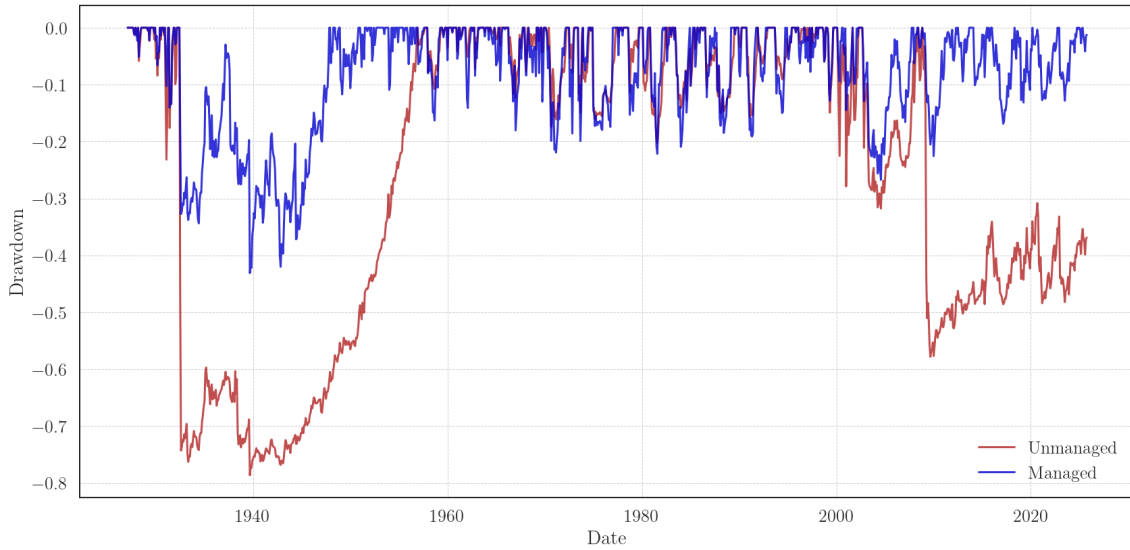


Figure 3: Historical drawdowns of MOM and MOM^σ . This figure displays the monthly drawdowns between January 1927 and October 2025. The red line is the unmanaged momentum. The blue line is the volatility-managed momentum MOM^σ , obtained by scaling MOM by its realized volatility estimated over the previous month (see Eq. 4). Drawdowns are calculated as the percentage decline of the cumulative wealth index from its running historical maximum.

To determine whether the superior performance of volatility-managed momentum can be explained by exposure to standard risk factors, Table 2 presents the results of factor regressions of MOM^σ using several asset pricing models. The models include the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (FF4), the Fama and French (2015) five-factor model (FF5) and the Fama and French (2018) six-factor model (FF6). The results show that MOM^σ generates highly significant abnormal returns across all specifications. Under the CAPM and FF3 models, the strategy delivers annualized alphas of approximately 1.30% and 1.38% per month (t -statistics > 9.0), respectively. The FF5 model, which accounts for profitability and investment factors, leaves an unexplained alpha of 1.31% per month. Most notably, the strategy retains a large, statistically significant alpha even after controlling for the unmanaged momentum factor. In the FF6 model, MOM^σ generates an alpha of 0.64% per month ($t = 5.60$). Similarly, the univariate spanning regression in the last column shows that the unmanaged momentum factor cannot span the managed strategy: MOM^σ earns an abnormal return of 0.72% per month ($t = 6.98$) over the unmanaged benchmark. Thus, the main benefits of volatility scaling constitute a distinct source of return that is not captured by the static momentum factor or other standard risk premia.

3.2 Conditional performance: the volatility states

To understand the economic drivers behind the success of volatility scaling, we analyze the performance of the underlying unmanaged momentum strategy conditional on its own volatility states. By construction, the volatility-managed portfolio aggressively overweights months following low volatility and underweights months following high volatility. Therefore, for volatility scaling to generate the massive alphas documented in the previous subsection, the unmanaged strategy must exhibit a specific non-linearity: it must generate

Table 2: Unconditional performance of the volatility-managed MOM.

This table shows the intercept (alpha) and the coefficients obtained by regressing the returns of MOM^σ on those of Fama-French factors and the momentum. MKT, SMB and HML are from Fama and French (1993), RMW and CMA are from Fama and French (2015) and MOM is from Carhart (1997). MOM^σ is obtained by scaling MOM by its realized volatility estimated over the previous month. The last column displays the result of a univariate spanning regression of MOM^σ on MOM. The sample period is January 1927 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). We also report the R^2 and the root mean square error (RMSE). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	CAPM	FF3	FF4	FF5	FF6	Spanning
Alpha (%)	1.30*** (0.13)	1.38*** (0.13)	0.57*** (0.09)	1.31*** (0.19)	0.64*** (0.11)	0.72*** (0.10)
MKT	-0.14*** (0.04)	-0.07** (0.03)	0.13*** (0.02)	-0.07 (0.05)	0.08*** (0.02)	
SMB		-0.13** (0.07)	-0.08** (0.03)	-0.06 (0.08)	-0.07 (0.05)	
HML		-0.31*** (0.05)	0.09** (0.04)	-0.36*** (0.08)	0.10** (0.05)	
RMW				0.13 (0.10)	-0.01 (0.06)	
CMA				0.14 (0.13)	-0.16** (0.07)	
MOM			0.87*** (0.05)		0.94*** (0.07)	0.80*** (0.07)
R^2	0.03	0.09	0.66	0.04	0.68	0.64
RMSE	4.63	4.48	2.75	4.58	2.66	2.83

superior risk-adjusted returns precisely in those low-volatility states where the managed strategy concentrates its exposure. If the risk-return trade-off were constant, such that returns increased proportionally with volatility, scaling would merely stabilize the variance without enhancing the Sharpe ratio or alpha.

Table 3 presents the results of regressing unmanaged momentum returns on the Fama-French five factors, conditional on whether the prior month's realized volatility was be-

low (Low) or above (High) the sample median. The results reveal a striking dichotomy in the strategy’s performance. In low-volatility states, momentum acts as a source of pure abnormal return: it generates a statistically significant alpha of 1.09% per month (t -statistic > 6.0) with negligible exposure to standard risk factors. In sharp contrast, during high-volatility states, the alpha collapses to a statistically insignificant 0.24% per month. Furthermore, in these turbulent periods, the strategy loses its anomalous characteristics. It loads heavily on standard risk factors, exhibiting significant negative exposure to the market (-0.21) and value (-0.66) factors, and positive exposure to investment (0.53). Consequently, the annualized Sharpe ratio collapses from 1.27 in the low-volatility regime to just 0.19 in the high-volatility regime, a difference that is statistically significant at the 1% level. The superior performance of the managed portfolio, therefore, arises from selectively targeting conditions in which momentum offers high abnormal returns, while avoiding regimes where the strategy generates no compensation beyond its inherent risk.

One explanation for the predictive power of momentum volatility is that it merely proxies for broader market risk (Moreira & Muir, 2017). Since asset volatilities are highly correlated, periods of high momentum volatility often coincide with periods of high market volatility. To disentangle these effects and ensure the benefits of scaling momentum are not a simple byproduct of market timing, Table 4 presents the FF5 alphas of unmanaged momentum across four regimes defined by the intersection of high/low momentum volatility and high/low market volatility. The results indicate that the volatility puzzle is specific to the strategy’s own risk profile and not subsumed by the market. When momentum volatility is high, alphas are statistically insignificant regardless of the market state. Conversely, when momentum volatility is low, the strategy generates significant abnormal returns in both market regimes. The spread in alphas between low- and high-momentum volatility states is statistically insignificant (0.17%) when the market is calm, but surges

Table 3: Performance of MOM conditional on volatility.

This table shows the intercept (alpha) and the coefficients obtained by regressing the unmanaged momentum returns on five factors of [Fama and French \(2015\)](#) over the subsample period of months with below-median lagged volatility (Low), the subsample period with above-median volatility (High), and the corresponding low-minus-high differences. The sample period is July 1963 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). We also report the R^2 , the root mean square error (RMSE) and the annualized Sharpe ratio (SR). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%. The significance of the difference in Sharpe ratios between Low and High volatility states was obtained via the bootstrap method of [Ledoit and Wolf \(2008\)](#).

	Low	High	Low – High
Alpha (%)	1.09*** (0.17)	0.24 (0.28)	0.84*** (0.32)
MKT	−0.05 (0.05)	−0.21*** (0.07)	0.16* (0.09)
SMB	−0.11 (0.07)	0.10 (0.12)	−0.21 (0.14)
HML	−0.13 (0.11)	−0.66*** (0.12)	0.53*** (0.16)
RMW	−0.10 (0.18)	0.27* (0.15)	−0.37 (0.24)
CMA	−0.18 (0.15)	0.53*** (0.18)	−0.71*** (0.24)
R^2	0.04	0.16	
RMSE	2.51	4.94	
SR	1.27	0.19	1.08***

to a statistically significant 1.20% per month when market volatility is high. Hence, the benefit of volatility timing is amplified by market turbulence.

The four regimes shown in [Table 4](#) thus exhibit distinct behaviors. When both realized momentum and market volatility were high in the previous month (HH), the strategy encounters a classic crash scenario akin to 2009. The market is turbulent, and the momentum portfolio itself is highly unstable. In this state, the alpha collapses, offering maximum

Table 4: Abnormal returns of MOM in periods of high- and low- own-factor and market volatility. This table assigns months to one of four regimes based on whether prior-month realized market volatility and realized momentum volatility are above or below their median value and presents alphas (in percent per month) obtained by regressing the unmanaged momentum returns on five factors of Fama and French (2015) in each of the four regimes. Regression slopes and intercepts are estimated separately in each regime. The sample period is July 1963 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Market volatility	Momentum volatility			
	Low	High	Low – High	Average
Low	0.76*** (0.16)	0.59* (0.32)	0.17 (0.35)	0.67*** (0.18)
High	1.37*** (0.30)	0.17 (0.36)	1.20** (0.47)	0.77*** (0.24)
High – Low	0.61* (0.34)	−0.42 (0.48)	1.03* (0.59)	0.09 (0.30)
Average	1.06*** (0.17)	0.38 (0.24)	0.69** (0.30)	

risk with no abnormal return. Volatility scaling acts defensively here by reducing exposure, helping investors avoid the crash. The state where momentum volatility is high but market volatility is low (HL) presents a different challenge. While it lacks the disastrous potential of the HH state, it remains suboptimal: unmanaged momentum captures some premium, but at a higher-than-necessary internal risk level, resulting in attenuated alpha. Here, the managed strategy correctly reduces exposure, avoiding insufficient premia. When both volatilities are low (LL), momentum operates in its calm baseline scenario. The unmanaged strategy performs well, delivering a significant alpha of 0.76% per month, which is further amplified by increasing momentum exposure in the managed portfolio. Finally, the most lucrative environment for the strategy is when prior momentum volatility is low

despite high market volatility (LH). While broad market turbulence may scare away general investors, the momentum portfolio itself remains stable. In this counterintuitive state, unmanaged momentum generates a massive 1.37% monthly alpha. Crucially, volatility scaling also increases exposure in this regime, functioning as an offensive mechanism that enables investors to capture outsized returns when risk aversion is high.

4 Decomposing the source: asymmetric sensitivity

Having established that the effectiveness of momentum volatility management arises from timing specific volatility regimes, we now investigate the mechanical drivers of this performance. If momentum risk is primarily a short-side phenomenon, the benefits of volatility scaling should be almost entirely defensive, driven by mitigating losses of the short leg. However, our findings presented in Table 4 suggest a more complex dynamic. In this section, we decompose the strategy into its long and short components to determine whether the leg asymmetry drives the conditional outperformance.

Table 5 presents descriptive statistics for the Winner and Loser portfolios, alongside their volatility-managed counterparts, defined in Eqs. (6) and (7). The results reveal a striking asymmetry in how volatility scaling affects the two legs. The unmanaged Loser portfolio exhibits the hallmarks of the option-like profile described by Daniel and Moskowitz (2016): extreme excess kurtosis (19.45) and high positive skewness (1.89). Such a return distribution reflects the tendency of Loser stocks, which are often distressed firms, to experience violent upward price spikes during market rebounds. While volatility scaling successfully tames this tail risk by reducing kurtosis to 2.24, it does not improve the risk-adjusted return: the Sharpe ratio of the managed Loser leg (0.19) is statistically indistinguishable from the unmanaged version (0.21). In sharp contrast, the benefits of volatility management are concentrated in the Winner portfolio. The managed Winner strategy achieves

Table 5: Performance of Winner and Loser portfolios and their volatility-managed counterparts. This table shows descriptive statistics for portfolios obtained by sorting stocks on their prior returns, as described in Section 2. The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). Winner ^{σ} and Loser ^{σ} are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). The statistics are: mean excess return (Mean), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), and the annualized Sharpe ratio (SR). The sample period is January 1927 to October 2025. The bracket reports the studentized difference in Sharpe ratios between managed and unmanaged portfolios obtained from the bootstrap method of Ledoit and Wolf (2008).

	Mean (%)	SD (%)	Skew	Kurt	SR
Winner	1.11	6.10	−0.06	5.31	0.63
Winner ^{σ}	1.32	6.10	−0.40	1.64	0.75 [2.20]
Loser	0.50	8.11	1.89	19.45	0.21
Loser ^{σ}	0.44	8.11	−0.27	2.24	0.19 [−0.43]

a significantly higher Sharpe ratio (0.75) compared to its unmanaged counterpart (0.63), with a studentized difference of 2.20. This discrepancy suggests that the offensive power of volatility timing originates from the long side: the strategy aggressively increases exposure to Winner stocks during low-volatility regimes when their risk-adjusted returns are highest. While managing the short side is necessary to prevent crashes, managing the long side is what drives the superior performance of the overall strategy.

To formally test whether the volatility-managed legs offer abnormal returns beyond their static benchmarks, Table 6 reports the results of univariate spanning regressions. Specifically, we regress the excess returns of the volatility-managed Winner and Loser portfolios on their respective unmanaged counterparts. The results reinforce the asymmetry identified in the descriptive statistics. For the Loser leg, the intercept is statistically indistinguishable from zero (0.04%), indicating that volatility scaling does not generate

Table 6: Spanning regressions for the volatility-managed Winner and Loser portfolios.

This table shows the intercept and the slope obtained by regressing the excess returns of Winner $^\sigma$ and Loser $^\sigma$ on their unmanaged counterparts. The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). Winner $^\sigma$ and Loser $^\sigma$ are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). The sample period is January 1927 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). We also report the R^2 and the root mean square error (RMSE). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	Winner $^\sigma$	Loser $^\sigma$
Intercept	0.36*** (0.09)	0.04 (0.14)
Unmanaged	0.86*** (0.04)	0.80*** (0.06)
R^2	0.74	0.64
RMSE	3.13	4.88

alpha on the short side – it simply scales exposure to the same underlying risk driver. Conversely, the managed Winner portfolio generates a highly significant alpha of 0.36% per month relative to the unmanaged Winner portfolio. This stark difference confirms that the exceptional performance of the volatility-managed momentum strategy is not merely a byproduct of hedging the option-like crash risk of Losers. Instead, it is driven by a distinct timing benefit on the long side: the strategy successfully identifies and overweights periods where Winner stocks generate outstanding risk-adjusted returns that the static portfolio fails to capture.

Table 7 disaggregates the conditional performance of the Winner and Loser portfolios by conditioning on three different volatility measures: the portfolio’s own volatility (Panel A), the overall momentum factor volatility (Panel B), and the market volatility (Panel C). The results clearly highlight the asymmetric sensitivity of the two legs.

Table 7: Abnormal returns of the Winner and Loser portfolios in periods of high- and low- own-factor, momentum and market volatility.

This table presents alphas (in percent per month) obtained by regressing the unmanaged Winner and Loser portfolio excess returns on five factors of [Fama and French \(2015\)](#) over the subsample period of months with below-median lagged volatility (Low), the subsample period with above-median volatility (High), and the corresponding differences. In Panel A, we split the subsamples based on the own-factor (“self”) volatility, i.e., the lagged realized volatility of the Winner and the Loser portfolio, respectively (Eqs. 8 and 9). In Panel B, we split the subsamples based on the lagged realized momentum volatility (Eq. 5). In Panel C, we split the subsamples based on the lagged realized market volatility. The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). The sample period is July 1963 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Panel A: Self volatility			
	Low	High	Low – High
Winner	0.37*** (0.07)	0.21** (0.10)	0.16 (0.12)
Loser	−0.54*** (0.10)	−0.29* (0.17)	−0.25 (0.20)
Panel B: Momentum volatility			
	Low	High	Low – High
Winner	0.42*** (0.07)	0.16 (0.10)	0.25** (0.12)
Loser	−0.54*** (0.09)	−0.15 (0.19)	−0.39* (0.21)
Panel C: Market volatility			
	Low	High	High – Low
Winner	0.29*** (0.06)	0.31*** (0.10)	0.02 (0.12)
Loser	−0.49*** (0.09)	−0.24 (0.20)	0.24 (0.22)

Panel A, conditioning on the portfolio’s own lagged volatility, defined by Eqs. (8) and (9), shows that while Winner alpha is higher in low self-volatility states (0.37% versus 0.21%), the difference is not statistically significant. Loser alpha also shows no significant conditional pattern based on its own volatility.

Panel B, which conditions on the lagged momentum volatility (Eq. 5), provides the most compelling evidence. In low-momentum volatility states, the Winner portfolio generates a substantial, highly significant alpha of 0.42% per month, almost three times the alpha observed in high-momentum volatility states. The 0.25% difference is statistically significant, demonstrating that the Winner portfolio’s profitability is acutely sensitive to the overall momentum environment. Conversely, the Loser portfolio’s alpha remains negative across regimes, but becomes less negative (i.e., performs better) in high-momentum volatility states (−0.15%) than in low-momentum volatility states (−0.54%). The reduction of 0.39% indicates that the Loser leg’s primary function is not alpha generation but rather mitigating downside exposure during high-volatility periods.

Panel C, conditioning on lagged market volatility, further clarifies that Winner alpha is consistently positive and significant (around 0.30%) regardless of market turbulence, with no significant difference between the high- and low-volatility regimes. As in Table 4, the momentum volatility signal is distinct from broader market risk.

Taken together, these findings reinforce the view that momentum volatility timing is primarily driven by the ability to identify and concentrate exposure in low-risk momentum environments, where Winner stocks generate robust, excessive alpha. These differential performance patterns across volatility regimes are visually confirmed in Fig. 4, which displays the cumulative excess returns of a \$1 initial notional investment in the Winner (blue line) and Loser (red dashed line) portfolios, conditional on the lagged realized momentum volatility (Eq. 5).

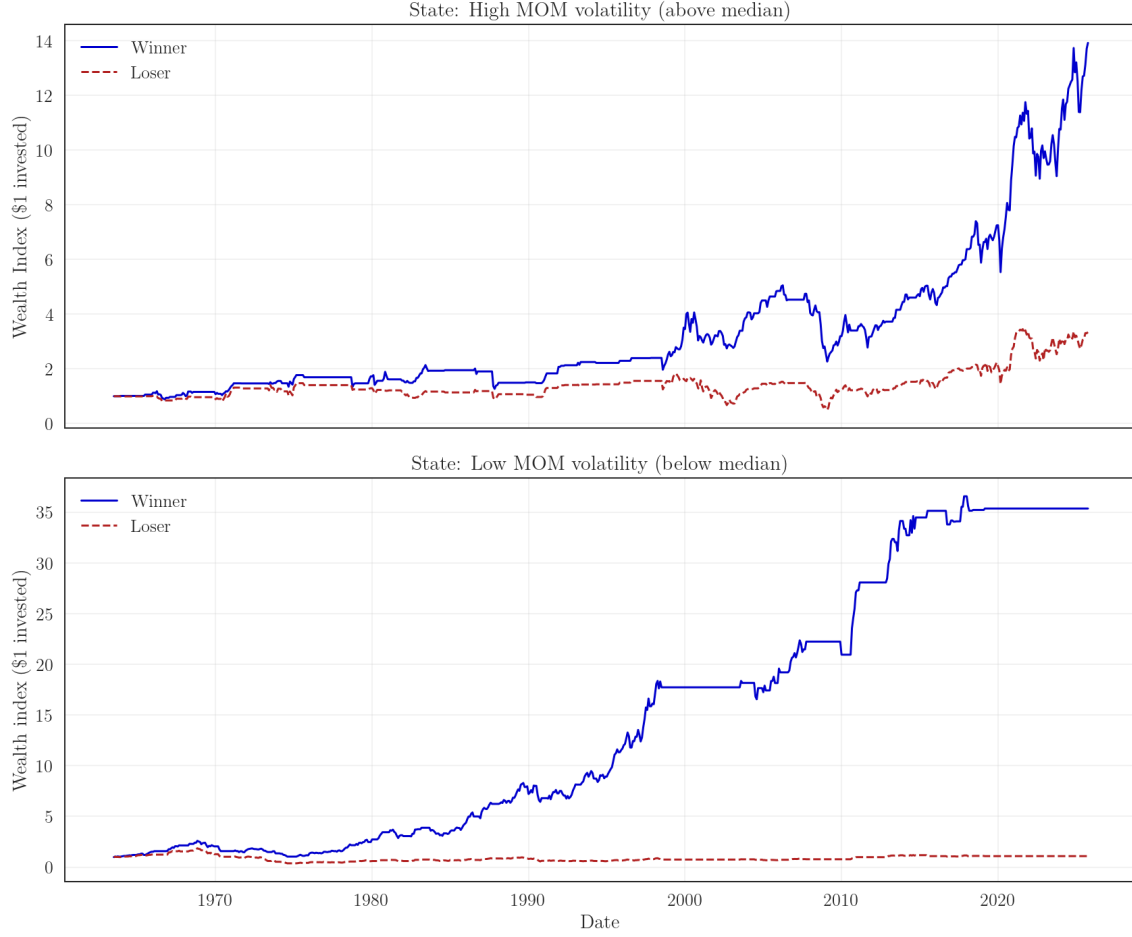


Figure 4: Cumulative excess returns of Winner and Loser portfolios conditional on momentum volatility. This figure plots the cumulative wealth of an initial \$1 investment in the Winner (blue line) and Loser (red dashed line) portfolios. The sample period from January 1927 to October 2025 is partitioned into two states based on the median of the lagged realized momentum volatility (Eq. 5). The top panel displays cumulative excess returns during months following high momentum volatility (above the sample median), while the bottom panel displays cumulative excess returns during months following low momentum volatility (below the sample median). In months where the volatility condition is not met, the excess return is set to zero for the accumulation calculation.

The top panel shows that when momentum volatility is high, both the Winner and Loser portfolios exhibit subdued cumulative returns, with the Winner leg barely surpassing 14 times its initial notional value and the Loser leg showing modest appreciation. The bottom panel illustrates the strategy’s truly offensive nature. During periods of low momentum volatility, the Winner portfolio generates outstanding cumulative growth, reaching a peak of over 35 times its initial notional investment. In stark contrast, the Loser portfolio generates almost no cumulative excess return growth in this regime, essentially earning the risk-free rate and remaining close to its initial \$1 notional value. The substantial alpha and wealth generation of volatility-managed momentum are overwhelmingly concentrated in specific low-volatility environments for the Winner leg.

5 Mechanisms and robustness

Having established that the conditional outperformance of volatility-managed momentum is driven by the asymmetric sensitivity of the Winner leg, it is critical to determine that these results are not merely manifestations of other well-known anomalies and are robust to market frictions. First, we investigate whether the alpha generated in low-volatility states can be explained by alternative factors such as time-series momentum, liquidity risk, investor sentiment, or idiosyncratic volatility. Second, we address practical implementation concerns by evaluating the impact of transaction costs and strict leverage constraints on the strategy’s profitability. Finally, we examine the universality of the volatility-timing benefit and its underlying mechanisms by extending our analysis to international markets.

5.1 Alternative explanations

We first address two prominent alternative explanations: time-series momentum (TSMOM) and liquidity risk. Volatility timing might be an indirect way to exploit time-series momen-

tum, as both strategies are trend-following: volatility timing increases exposure when risk is low, which is often a characteristic of trending markets. At the same time, Moskowitz et al. (2012) demonstrate that TSMOM directly capitalizes on past price trends. To ascertain if the volatility-managed strategy provides information distinct from TSMOM, Panel A of Table 8 reports spanning regressions of Winner^σ , Loser^σ , and MOM^σ on their unmanaged counterparts, augmented with the TSMOM factor.

The results confirm that the volatility-managed strategies deliver significant spanning regression alphas beyond both the static momentum and TSMOM factors. MOM^σ exhibits a highly significant alpha of 0.56% per month, even after controlling for the substantial explanatory power of unmanaged MOM and a statistically significant TSMOM factor. Volatility timing clearly captures a distinct source of return that is not subsumed by general trend-following strategies. Similarly, Winner^σ generates a significant positive alpha of 0.23% per month, while Loser^σ shows a significant negative alpha of -0.40% per month. The TSMOM factor is not sufficient to capture this asymmetry.

Another primary concern, particularly relevant during volatile market conditions, is liquidity risk. Standard momentum strategies, which typically short illiquid Loser stocks and go long crowded Winner stocks, can face substantial liquidity constraints or premia. This issue is highlighted by Pástor and Stambaugh (2003), who demonstrate that illiquidity is a priced factor, and by Asness et al. (2013) and Sadka (2006), who argue that a significant portion of momentum profits may represent a compensation for this liquidity risk. It is plausible that the efficacy of volatility timing stems from exploiting liquidity premia implicitly, as low-volatility states may coincide with high-liquidity states. Panel B of Table 8 addresses this by reporting spanning regressions including the traded liquidity factor (TLiq). The results demonstrate that the volatility-managed alpha is not encompassed by liquidity risk. MOM^σ continues to generate a large and highly significant alpha of 0.67%

per month. Although the unmanaged momentum factor remains a dominant explanatory variable, the liquidity factor is statistically insignificant, confirming that the benefits of volatility timing are orthogonal to the market’s common liquidity premium. Winner $^{\sigma}$ yields a significant alpha of 0.29% per month, while the coefficient of TLiq is negative and highly significant. This negative exposure suggests that volatility-managed Winner stocks tend to perform better when illiquid assets outperform liquid assets, potentially indicating a tilt towards bearing illiquidity risk during calm periods. Loser $^{\sigma}$ also maintains a negative and significant alpha. While both individual legs show significant negative liquidity exposures, these effects largely cancel out in the combined MOM $^{\sigma}$ portfolio, resulting in an insignificant TLiq factor. Therefore, the volatility-managed momentum strategy is not driven by implicitly exploiting a liquidity premium.

While the conditional performance of momentum is strongly linked to its own volatility, another concern is whether this effect merely proxies for broader investor sentiment. [Antoniou, Doukas, and Subrahmanyam \(2013\)](#) and [Stambaugh, Yu, and Yuan \(2012\)](#) suggest that momentum profits are often highest during periods of high investor sentiment, as optimistic investors may overreact to news, and short-sale constraints can prevent price correction. Since volatility is often low when sentiment is high, one might argue that our low MOM volatility state is simply a high sentiment state in disguise. To address this, [Table 9](#) presents FF5 alphas of unmanaged momentum in months divided into four regimes, based on whether prior-month [Baker and Wurgler \(2007\)](#) sentiment index and realized momentum volatility are above or below their respective medians.

The table clearly shows that sentiment does not capture the same effects as momentum volatility. Momentum generates significant alphas only in low-volatility states, regardless of sentiment levels. For instance, in the low sentiment / low MOM volatility regime, alpha is 1.14% per month ($t = 5.60$), and in the high sentiment / low MOM volatility

regime, it is 0.79% per month ($t = 3.34$). Conversely, in high-volatility states, alphas are substantially lower and insignificant. More importantly, the average alpha spread between low- and high-momentum volatility states is 0.76% per month ($t = 2.31$), demonstrating the consistent predictive power of momentum volatility. While a positive average alpha is observed across both sentiment regimes, the difference between these sentiment-conditional spreads is statistically insignificant, confirming that sentiment does not explain away the volatility timing effect. This evidence suggests that the low MOM volatility state is not merely a proxy for investor optimism but a distinct structural regime in which arbitrage is less risky, and Winner momentum persists, independent of aggregate investor mood.

Another potential explanation for the conditional alpha of volatility-managed momentum relates to the idiosyncratic volatility (IVOL) puzzle. [Ang, Hodrick, Xing, and Zhang \(2006\)](#) famously documented that stocks with high IVOL earn abnormally low subsequent returns, contrary to traditional risk-return paradigms. This puzzle is often attributed to limits to arbitrage, as theorized by [Shleifer and Vishny \(1997\)](#) and further explored in the context of anomalies by [Pontiff \(2006\)](#). It suggests that arbitrageurs avoid shorting high-IVOL, overvalued stocks due to the high costs and risks associated with trading such volatile securities, thereby allowing mispricing to persist. Since low-volatility momentum states might inadvertently select for portfolios composed of low-IVOL stocks, one could argue that the observed conditional alpha is merely a proxy for the IVOL effect rather than a distinct timing signal. This concern is particularly relevant given conflicting evidence on the interaction between momentum and IVOL. At the same time, the low-IVOL anomaly predicts underperformance for high-IVOL stocks. [Arena, Haggard, and Yan \(2008\)](#) find that momentum profits are actually *higher* among high-IVOL stocks.

To definitively disentangle these effects, we perform a double sort on momentum and idiosyncratic volatility, investigating whether our findings remain robust across IVOL cat-

egories. Table 10 presents the Fama-French five-factor alphas (Panel A) and annualized Sharpe ratios (Panel B) for nine portfolios formed from the intersection of three momentum groups (Low, Medium, High) and three IVOL groups (Low, Medium, High). The breakpoints for these groups are the 30th and 70th NYSE percentiles for both momentum and IVOL. The results strongly suggest that the momentum premium is not merely a byproduct of the low-IVOL anomaly. The interaction is, rather, more nuanced. Holding IVOL constant, high-momentum (Winner) stocks consistently outperform low-momentum (Loser) stocks. However, within the High IVOL bucket, the spread between Winner alpha (0.53%) and Loser alpha (−0.57%) is 1.10% per month. This finding aligns with [Arena et al. \(2008\)](#) and contradicts the concern that volatility timing harvests the low-IVOL premium. If volatility timing were merely screening for low-IVOL stocks, we would expect the best performance in the Low IVOL rows. Instead, we see that high idiosyncratic volatility amplifies the momentum signal – Winners win more, and Losers lose more when IVOL is high. This pattern is further corroborated by Panel B, which shows that Sharpe ratios generally increase with momentum (moving from left to right across rows). Sharpe ratios exhibit an apparent monotonic decrease as IVOL increases across Low MOM (Loser) and Medium MOM stocks. However, this monotonicity disappears for the High MOM (Winner) stocks.

The conditional alphas we observe in Tables 3, 4 and 6 are therefore distinct: momentum volatility scaling adds value by timing the *aggregate* risk of the strategy, whereas high idiosyncratic volatility serves as a limit to arbitrage (preventing mispricings from being quickly corrected) that widens the cross-sectional spread between Winners and Losers. The fact that significant momentum profits persist and indeed strengthen within high-IVOL regimes confirms that momentum and IVOL are distinct phenomena, and that the volatility timing mechanism operates independently of the low-IVOL anomaly.

Table 8: Spanning regressions for the volatility-managed Winner and Loser portfolios and MOM with controls for the time-series momentum and liquidity risk.

This table shows the results of regressing the excess returns of Winner $^\sigma$ and Loser $^\sigma$ portfolios, and returns of MOM $^\sigma$, on their unmanaged counterparts, controlling for the time-series momentum factor of Moskowitz et al. (2012) (TSMOM, Panel A) and traded liquidity factor of Pástor and Stambaugh (2003) (TLiq, Panel B). The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). MOM is the difference in Winner and Loser returns (see Eq. 3). The row “Unmanaged” reports regression coefficients corresponding to Winner, Loser and MOM regressors, respectively. The sample period is January 1980 to October 2025 in Panel A and January 1968 to December 2024 in Panel B. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). We also report the R^2 and the root mean square error (RMSE). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Panel A: Time-series momentum			
	Winner $^\sigma$	Loser $^\sigma$	MOM $^\sigma$
Intercept	0.23** (0.11)	−0.40** (0.20)	0.56*** (0.12)
Unmanaged	0.83*** (0.06)	0.72*** (0.07)	0.79*** (0.07)
TSMOM	0.07 (0.07)	0.30*** (0.08)	0.11*** (0.02)
R^2	0.80	0.71	0.68
RMSE	2.36	3.78	2.53
Panel B: Liquidity risk			
	Winner $^\sigma$	Loser $^\sigma$	MOM $^\sigma$
Intercept	0.29*** (0.10)	−0.06 (0.17)	0.67*** (0.13)
Unmanaged	0.90*** (0.03)	0.88*** (0.07)	0.81*** (0.08)
TLiq	−0.13*** (0.04)	−0.18*** (0.06)	0.01 (0.03)
R^2	0.81	0.69	0.66
RMSE	2.32	3.90	2.59

Table 9: Abnormal returns of MOM in periods of high- and low- own-factor volatility and sentiment.

This table assigns months to one of four regimes based on whether prior-month [Baker and Wurgler \(2007\)](#) sentiment index and realized momentum volatility are above or below their median value and presents alphas (in percent per month) obtained by regressing the unmanaged momentum returns on five factors of [Fama and French \(2015\)](#) in each of the four regimes. Regression slopes and intercepts are estimated separately in each regime. The sample period is July 1965 to December 2023. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Sentiment	Momentum volatility			
	Low	High	Low – High	Average
Low	1.14*** (0.20)	0.30 (0.41)	0.84* (0.46)	0.72*** (0.23)
High	0.79*** (0.24)	0.11 (0.41)	0.69 (0.48)	0.45* (0.24)
High – Low	−0.35 (0.31)	−0.19 (0.58)	1.03* (0.59)	−0.27 (0.33)
Average	0.97*** (0.16)	0.20 (0.29)	0.76** (0.33)	

Table 10: Abnormal returns and Sharpe ratios of double-sorted portfolios on MOM and IVOL. Panel A presents alphas (in percent per month) obtained by regressing the monthly excess returns of nine portfolios formed from a double sort on momentum (MOM) and idiosyncratic volatility (IVOL) on five factors of [Fama and French \(2015\)](#). Panel B presents the annualized Sharpe ratios for these portfolios. At the beginning of each month, stocks are independently sorted into three groups (Low, Medium, High) based on their momentum (cumulative return from $t - 12$ to $t - 2$) and three groups based on their idiosyncratic volatility (standard deviation of residuals from a rolling 60-month FF5 regression). The group breakpoints are the 30th and the 70th NYSE percentiles. The resulting nine portfolios are the intersections of these groups. The sample period is July 1963 to December 2024. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Panel A: Abnormal returns (%)			
MOM sort			
IVOL sort	Low	Medium	High
Low	−0.16 (0.14)	−0.14*** (0.06)	0.06 (0.08)
Medium	−0.47*** (0.14)	−0.12** (0.06)	0.32*** (0.09)
High	−0.57*** (0.15)	−0.14 (0.10)	0.53*** (0.12)
Panel B: Sharpe ratios			
MOM sort			
IVOL sort	Low	Medium	High
Low	0.36	0.45	0.54
Medium	0.16	0.41	0.63
High	0.04	0.22	0.50

5.2 Implementation and constraints

A key concern for any factor strategy, particularly one with dynamic rebalancing, is whether its profits survive realistic transaction costs. [Lesmond, Schill, and Zhou \(2004\)](#) argue that standard momentum profits may be illusory once accounting for bid-ask spreads and trading commissions, especially given the high turnover and illiquidity often associated with the Loser leg. [Patton and Weller \(2020\)](#) find that typical mutual funds earn no returns to momentum after accounting for implementation costs. Table 11 investigates the after-cost alphas for the volatility-managed Winner, Loser and combined momentum portfolios across three transaction cost scenarios: 10 bp, 25 bp, and 50 bp. The 10 bp cost, as discussed by [Frazzini, Israel, and Moskowitz \(2012\)](#), is appropriate for sophisticated institutional investors with minimal liquidity demands. The 25 bp and 50 bp costs, reported by [Barroso and Detzel \(2021\)](#), [Hasbrouck \(2009\)](#) and [Novy-Marx and Velikov \(2016\)](#), are more representative of the expenses faced by strategies with higher liquidity demands.

The results firmly demonstrate the robustness of volatility-managed momentum and its driving mechanisms. For the Winner portfolio, the alpha remains significant across all cost levels, ranging from 0.32% at 10 bp to 0.14% at 50 bp. Its break-even transaction cost of 82.75 bp is substantially higher than the 50 bp scenario, indicating ample survival margins. The Loser portfolio, consistent with our previous findings, shows no significant positive alpha even before costs, and quickly becomes a drag on performance. Its break-even cost of 8.24 bp is very low, highlighting its extreme sensitivity to trading expenses. Crucially, the combined momentum portfolio exhibits remarkable resilience. Its alpha remains highly significant and positive, ranging from 0.50% at 10 bp down to 0.31% at 50 bp. The break-even transaction cost for the managed momentum factor is 115.39 bp, far exceeding the cost scenarios tested. This evidence strongly refutes the critique that volatility-managed momentum profits are eroded by trading costs, confirming that the underlying alpha is

robust and implementable.

Table 11: After-cost alphas for the volatility-managed Winner and Loser portfolios and MOM. This table shows the spanning regressions alphas obtained by regressing the excess returns of Winner $^\sigma$ and Loser $^\sigma$ portfolios, and returns of MOM $^\sigma$, on their unmanaged counterparts, after accounting for transaction costs. We consider three levels of transaction costs: 10 bp, 25 bp and 50 bp. Break-even costs are the implied transaction costs (in basis points) required to drive the alphas to zero. The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). MOM is the difference in Winner and Loser returns (see Eq. 3). Winner $^\sigma$ and Loser $^\sigma$ are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). MOM $^\sigma$ scales MOM each month by its realized volatility estimated over the previous month (see Eq. 4). The sample period is January 1927 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Transaction costs	Winner $^\sigma$	Loser $^\sigma$	MOM $^\sigma$
10 bp	0.32*** (0.09)	−0.01 (0.14)	0.50*** (0.11)
25 bp	0.25*** (0.09)	−0.08 (0.14)	0.43*** (0.11)
50 bp	0.14* (0.09)	−0.21 (0.14)	0.31*** (0.11)
Break-even cost (bp)	82.75	8.24	115.39

Another prominent critique of volatility-managed strategies, articulated by Boguth, Carlson, Fisher, and Simutin (2011), suggests that the superior performance of such portfolios may be spurious, primarily driven by taking extreme leverage during periods of exceptionally low volatility. If abnormal returns rely on leverage ratios that are practically unfeasible for institutional investors (e.g., exceeding 2.0x or 3.0x), the strategy’s theoretical benefits would hold little practical value. To address this concern, Table 12 reports spanning regressions of the volatility-managed Winner, Loser, and momentum portfolios where the weight of the unmanaged leg is strictly capped at 2.0 (100% leverage), 1.5 (50% lever-

Table 12: Spanning regressions alphas for the volatility-managed Winner and Loser portfolios and MOM with leverage constraints.

This table shows the spanning regressions alphas obtained by regressing the excess returns of Winner $^\sigma$ and Loser $^\sigma$ portfolios, and returns of MOM $^\sigma$, on their unmanaged counterparts with restricted exposure. We restrict the unmanaged exposure below 2.0 (i.e., maximum 100% leverage), below 1.5 (i.e., maximum 50% leverage) and below 1.0 (i.e., no leverage). The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). MOM is the difference in Winner and Loser returns (see Eq. 3). Winner $^\sigma$ and Loser $^\sigma$ are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). MOM $^\sigma$ scales MOM each month by its realized volatility estimated over the previous month (see Eq. 4). The sample period is January 1927 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Exposure restriction	Winner $^\sigma$	Loser $^\sigma$	MOM $^\sigma$
Max. 100% leverage	0.30*** (0.08)	0.04 (0.12)	0.57*** (0.09)
Max. 50% leverage	0.23*** (0.07)	0.03 (0.10)	0.43*** (0.08)
No leverage	0.10** (0.05)	0.00 (0.06)	0.25*** (0.06)

age) and 1.0 (no leverage). The results clearly demonstrate that extreme leverage does not drive the strategy’s performance and its mechanisms. For relatively relaxed weight caps of 2.0, the Winner alpha reaches 0.30%, the Loser alpha is 0.04%, and the momentum alpha is 0.57%, approaching their unconstrained values reported in Tables 6 and 2. As the weight cap is tightened to 1.5, a constraint feasible for many quantitative funds, the Winner alpha drops to 0.23% per month, while the momentum alpha decreases to 0.43%. However, both remain highly significant. Even under the strictest constraint (no leverage), the managed Winner portfolio generates a statistically significant alpha of 0.10% per month, and the combined momentum factor yields a robust 0.25% monthly alpha. The Loser portfolio yields no significant alpha across any leverage regime. These findings confirm that the

timing benefit is structural: the strategy correctly identifies high-return states, and while leverage amplifies gains, the alpha persists even when borrowing is entirely restricted.

5.3 International evidence

The exceptional performance of volatility-managed momentum in the U.S. raises the question of whether its underlying drivers are universal. Testing the strategy across diverse economic environments is essential not merely to validate its profitability, but to determine if the asymmetric sensitivity of the Winner leg is a fundamental feature of momentum or a U.S.-specific artifact. International markets, particularly Japan, offer a unique laboratory for this investigation, as conventional momentum strategies have historically failed there ([Asness et al., 2013](#)). Extending our analysis internationally allows us to examine whether the volatility-timing mechanism can isolate conditional alpha in other markets, or if the benefits of asymmetric conditioning are geographically constrained.

Table 13 presents descriptive statistics for the unmanaged and volatility-managed Winner, Loser, and momentum portfolios across Europe (Panel A), Asia-Pacific excluding Japan (Panel B), and Japan (Panel C). Consistent with our U.S. findings, the volatility-managed strategies in Europe and Asia-Pacific demonstrate substantial improvements. For MOM, both regions show significant performance improvements. For example, the mean return in Europe increases from 0.90% to 1.72% per month, and the annualized Sharpe ratio rises from 0.23 to 0.45. Volatility scaling also effectively reduces negative skewness and kurtosis across these two regions, transforming the risk profile of MOM. The Winner portfolio in both regions similarly benefits from volatility management, with significantly higher Sharpe ratios. The Loser portfolio, while experiencing improved higher-moment statistics, does not show a statistically significant change in its Sharpe ratio.

Table 13: Performance of international Winner, Loser and MOM portfolios and their volatility-managed counterparts.

This table shows descriptive statistics for portfolios obtained by sorting stocks on their prior returns, as described in Section 2, for Europe (Panel A), Asia-Pacific excluding Japan (Panel B) and Japan (Panel C). The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). MOM is the difference in Winner and Loser returns (see Eq. 3). Winner $^\sigma$ and Loser $^\sigma$ are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). MOM $^\sigma$ scales MOM each month by its realized volatility estimated over the previous month (see Eq. 4). The statistics are: mean excess return (Mean), standard deviation (SD), skewness (Skew), excess kurtosis (Kurt), and the annualized Sharpe ratio (SR). The sample period is November 1990 to October 2025. The bracket reports the studentized difference in Sharpe ratios between managed and unmanaged portfolios obtained from the bootstrap method of Ledoit and Wolf (2008).

Panel A: Europe					
	Mean (%)	SD (%)	Skew	Kurt	SR
Winner	1.06	4.78	−0.60	1.32	0.22
Winner $^\sigma$	1.35	4.78	−0.17	1.31	0.28
					[2.17]
Loser	0.16	6.23	0.14	4.59	0.03
Loser $^\sigma$	0.16	6.23	−0.23	0.61	0.02
					[−0.03]
MOM	0.90	3.85	−1.42	8.99	0.23
MOM $^\sigma$	1.72	3.85	0.45	1.29	0.45
					[5.78]
Panel B: Asia-Pacific					
	Mean (%)	SD (%)	Skew	Kurt	SR
Winner	1.22	6.14	−0.85	3.03	0.20
Winner $^\sigma$	1.72	6.14	0.09	1.60	0.28
					[2.78]
Loser	0.36	7.05	0.77	6.72	0.05
Loser $^\sigma$	0.30	7.05	−0.05	1.99	0.04
					[−0.29]
MOM	0.86	4.23	−2.86	19.96	0.20
MOM $^\sigma$	1.48	4.23	−0.10	2.95	0.35
					[3.32]

Panel C: Japan					
	Mean (%)	SD (%)	Skew	Kurt	SR
Winner	0.30	5.41	0.08	0.80	0.06
Winner $^{\sigma}$	0.25	5.41	-0.23	1.02	0.05 [-0.47]
Loser	0.19	6.31	0.54	2.08	0.03
Loser $^{\sigma}$	-0.07	6.31	-0.20	1.15	-0.01 [-1.88]
MOM	0.11	4.06	-0.44	3.55	0.03
MOM $^{\sigma}$	0.15	4.06	-2.60	21.14	0.04 [0.34]

Table 14 further reinforces these findings through spanning regressions. In Europe and the Asia-Pacific, the volatility-managed Winner and MOM portfolios yield large, statistically significant alphas. These results confirm that the unmanaged counterparts cannot fully explain the returns of their volatility-managed versions, mirroring the effectiveness observed in the U.S.

However, Japan presents a stark contrast. Table 13, Panel C, shows that the unmanaged MOM factor in Japan has a very low and insignificant Sharpe ratio (0.027). Volatility management, while marginally increasing the mean return, fails to produce a statistically significant improvement in the risk-adjusted performance in this market. This lack of improvement is further corroborated by Table 14, where the spanning alpha of 0.07% for MOM $^{\sigma}$ is statistically insignificant. Unlike other regions, simple volatility management of the aggregate momentum factor does not resurrect its performance in Japan. The Winner and Loser legs in Japan also fail to show significant benefits from volatility management, having insignificant differences between their managed and unmanaged Sharpe ratios.

To investigate the universality of the conditional drivers, we examine the abnormal returns of the unmanaged factor across volatility states in each region. Table 15 dissects

Table 14: Spanning regressions alphas for the international volatility-managed Winner and Loser portfolios and MOM.

This table shows the spanning regressions alphas obtained by regressing obtained by regressing the excess returns of Winner $^\sigma$ and Loser $^\sigma$ portfolios, and returns of MOM $^\sigma$, on their unmanaged counterparts with restricted exposure, for Europe, Asia-Pacific (excluding Japan) and Japan. The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). MOM is the difference in Winner and Loser returns (see Eq. 3). Winner $^\sigma$ and Loser $^\sigma$ are obtained by scaling the respective portfolio each month by its own realized volatility estimated over the previous month (see Eqs. 6 and 7). MOM $^\sigma$ scales MOM each month by its realized volatility estimated over the previous month (see Eq. 4). The sample period is November 1990 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Region	Winner $^\sigma$	Loser $^\sigma$	MOM $^\sigma$
Europe	0.40*** (0.12)	0.02 (0.17)	1.01*** (0.14)
Asia-Pacific	0.64*** (0.17)	0.00 (0.19)	0.78*** (0.19)
Japan	-0.03 (0.09)	-0.24* (0.13)	0.07 (0.13)

the FF5 alphas of unmanaged MOM in four market- and momentum-volatility regimes. In Europe and the Asia-Pacific, the pattern essentially replicates the U.S. findings. The momentum factor continues to exhibit a sweet-spot behavior, with alpha highest during low-momentum volatility episodes. The interaction effect is very pronounced in the Asia-Pacific region, where the LH alpha is 1.59% per month.

Japan again deviates from this pattern. Table 15, Panel C, shows that MOM alphas are generally low and statistically insignificant across all four volatility regimes. The observed interaction benefits do not materialize, nor are there statistically significant differences across any of the volatility states. The fundamental conditional predictability of MOM returns, which volatility timing seeks to exploit, is absent in Japan.

Table 15: Abnormal returns of international MOM in periods of high- and low- own-factor and market volatility.

This table assigns months to one of four regimes based on whether prior-month realized market volatility and realized momentum volatility are above or below their median value and presents alphas (in percent per month) obtained by regressing the unmanaged momentum returns on five factors of [Fama and French \(2015\)](#) in each of the four regimes. Regression slopes and intercepts are estimated separately in each regime, for Europe (Panel A), Asia-Pacific excluding Japan (Panel B) and Japan (Panel C). The sample period is November 1990 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Panel A: Europe				
	Momentum volatility			
Market volatility	Low	High	Low – High	Average
Low	1.37*** (0.15)	1.78*** (0.44)	−0.40 (0.47)	1.49*** (0.20)
High	1.21*** (0.33)	0.09 (0.34)	1.12** (0.47)	0.24 (0.29)
High – Low	−0.16 (0.36)	−1.69*** (0.56)	1.52** (0.66)	−1.25*** (0.35)
Average	1.39*** (0.14)	0.49* (0.29)	0.90*** (0.32)	
Panel B: Asia-Pacific				
	Momentum volatility			
Market volatility	Low	High	Low – High	Average
Low	1.14*** (0.24)	2.03*** (0.56)	−0.90 (0.60)	1.54*** (0.24)
High	1.59*** (0.39)	0.09 (0.46)	1.50** (0.60)	0.60* (0.33)
High – Low	0.45 (0.46)	−1.95*** (0.72)	−2.40*** (0.85)	−0.94** (0.41)
Average	1.43*** (0.25)	0.88** (0.34)	0.55 (0.42)	
Panel C: Japan				
	Momentum volatility			

Market volatility	Low	High	Low – High	Average
Low	0.16 (0.19)	0.74** (0.36)	−0.58 (0.40)	0.45** (0.20)
High	0.01 (0.41)	0.20 (0.47)	−0.19 (0.62)	0.08 (0.34)
High – Low	−0.15 (0.45)	−0.54 (0.59)	−0.39 (0.74)	−0.37 (0.40)
Average	0.06 (0.22)	0.36 (0.34)	−0.30 (0.41)	

Table 16 provides further insight by examining the conditional alphas of the unmanaged Winner and Loser portfolios based solely on momentum volatility (Eq. 5). In Europe, the Winner portfolio generates a highly significant 0.70% alpha in low-volatility states, but only 0.23% in high-volatility states. This difference of 0.47% is highly significant, confirming the conditional asymmetry observed in the U.S. Similarly, Loser alphas are significantly more negative in low-volatility states, contributing to the offensive mechanism. The Asia-Pacific region also shows a higher Winner alpha in low (0.70%) vs. high (0.54%) momentum volatility states, although the difference (0.16%) is not statistically significant.

In Japan, the conditional asymmetry documented elsewhere is absent. Table 16, Panel C, shows that Winner alphas are statistically insignificant in both low (0.04%) and high (0.17%) momentum volatility states. The difference is also insignificant. Similarly, Loser alphas remain insignificant in both regimes. This absence of conditional alpha and its sensitivity to momentum volatility in Japan fundamentally explains why volatility-managed MOM (Table 13) does not lead to significant performance improvements in this market. In Japan, volatility timing cannot resurrect momentum because the underlying conditional alpha that the strategy aims to exploit simply does not exist.

Table 16: Abnormal returns of the international Winner and Loser portfolios in periods of high- and low- momentum volatility.

This table presents alphas (in percent per month) obtained by regressing the unmanaged Winner and Loser portfolio excess returns on five factors of [Fama and French \(2015\)](#) over the subsample period of months with below-median lagged volatility (Low), the subsample period with above-median volatility (High), and the corresponding differences, for Europe (Panel A), Asia-Pacific excluding Japan (Panel B) and Japan (Panel C). The “Winner” stocks correspond to the top 30 percent of performers (i.e., high momentum) and the “Loser” stocks correspond to the bottom 30 percent of performers (i.e., low momentum). The sample period is November 1990 to October 2025. The numbers in parentheses are heteroskedasticity-consistent standard errors of [White \(1980\)](#). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

Panel A: Europe			
	Low	High	Low – High
Winner	0.70*** (0.08)	0.23* (0.13)	0.47*** (0.15)
Loser	−0.69*** (0.07)	−0.26 (0.16)	−0.43** (0.18)
Panel B: Asia-Pacific			
	Low	High	Low – High
Winner	0.70*** (0.13)	0.54*** (0.16)	0.16 (0.21)
Loser	−0.73*** (0.13)	−0.34 (0.21)	−0.39 (0.24)
Panel C: Japan			
	Low	High	High – Low
Winner	0.04 (0.11)	0.17 (0.17)	−0.13 (0.20)
Loser	−0.01 (0.12)	−0.18 (0.19)	0.17 (0.22)

6 Conclusion

This paper re-examines the momentum anomaly through the lens of conditional volatility, presenting a novel perspective on its drivers and implementability. Our main findings reveal a nuanced and robust mechanism underlying momentum’s performance. We demonstrate that the strategy’s abnormal returns and Sharpe ratio increase significantly following months when the realized volatility is below the median. The performance drastically reduced in high-volatility states.

We highlight a crucial asymmetry in the conditional performance of momentum. While the Loser portfolio’s alpha remains consistently negative across various volatility regimes, the Winner portfolio’s alpha nearly triples in the low-volatility state compared to the high-volatility state. The significance of this asymmetry becomes even more pronounced in periods following high market volatility, where the difference in momentum’s abnormal returns between low- and high-volatility states is largest. Standard asset pricing models consistently fail to explain this asymmetry.

Our results are robust against several alternative explanations. We find that the observed conditional alpha is not merely a proxy for broader investor sentiment, nor does it solely reflect periods of high investor confidence or overreaction. Our findings also confirm that the conditional performance is not just a hidden manifestation of trend-following effects (captured by the time-series momentum) nor does it primarily compensate for liquidity risk. Moreover, the effect is distinct from the low-volatility anomaly, as high idiosyncratic volatility actually amplifies momentum profits.

Academically, our results deepen the volatility puzzle by demonstrating that momentum’s significant alpha is concentrated exclusively in low-volatility states, contrary to the standard intertemporal risk-return trade-off. These low-risk environments create a “sweet spot” where momentum yields high returns with low factor exposure. Our analysis un-

equivocally shows that the volatility-managed momentum strategy works by exploiting this time-varying risk premium of Winners in calm markets, rather than solely hedging the crash risk of rebounding Losers in post-distress markets.

From a practical perspective, our paper offers clear guidance for portfolio management. Momentum strategies should be aggressive in low-volatility regimes and defensive in high-volatility regimes to maximize alpha capture. Volatility timing should effectively down-weight the momentum portfolio when Winners stop generating abnormal returns, not just when Losers become risky. This approach delivers alpha that survives realistic trading costs and is robust to various leverage constraints, showing that outperformance is not an artifact of extreme borrowing. International evidence from Europe and Asia-Pacific confirms the identical asymmetric pattern observed in the U.S. Thus, volatility timing driven by the outperformance of Winner stocks following low-volatility periods appears to be a universal mechanism. However, it does not hold for Japan, where the underlying conditional alpha appears absent, consistent with the long-documented general failure of unmanaged momentum in that market.

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