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Volatility Management in Factor Investing: Evidence from the United States, Europe and Developed Markets

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Abstract

This paper examines whether volatility management enhances the risk-return profile of factor investing strategies based on the *momentum* factor and the *five-factor* model across major developed equity markets. The study uses daily and monthly data from the Kenneth R. French database for the United States, Europe, and Developed Markets, covering long samples through December 2023. Volatility-managed factor returns are constructed by scaling original factor returns by functions of their realised volatility and are then evaluated against the corresponding unmanaged series. Performance is assessed by changes in average returns, volatility, and the Sharpe ratio, comparing volatility-managed factors with their unmanaged counterparts across regions and volatility-estimation horizons. The analysis evaluates whether the effectiveness of volatility management is consistent across factors, markets and estimation windows. Results show that volatility management can materially improve risk-adjusted performance for some factors and regions, particularly for momentum and profitability, although benefits are not uniform across all factors or geographies. These findings provide updated evidence on volatility management in factor investing and offer insights into the behaviour of volatility-managed factor strategies, although implementation costs and trading frictions are not incorporated in the reported results.

Keywords: volatility management; factor investing; momentum; Fama–French five-factor model; risk-adjusted performance

1. Introduction

The importance and relevance of the present paper are directly linked to the dynamic management of volatility, which is fundamental in finance research, particularly in portfolio management and risk analysis (Barroso & Santa-Clara, 2015; Moreira & Muir, 2017).

The research seeks to address the following question: How does volatility management enhance the risk-adjusted performance of economic factors beyond the momentum factor? The study builds on Barroso and Santa-Clara (Barroso & Santa-Clara, 2015), who dynamically scale exposure to the U.S. momentum factor using its lagged realised volatility, and on Moreira and Muir (Moreira & Muir, 2017), who apply inverse-volatility scaling to factor portfolios, including the five Fama–French factors and momentum. Both approaches reduce factor exposure when realised volatility is high and increase it when realised volatility is low. The present study adopts this common inverse-volatility principle and applies it separately to momentum and each of the five Fama–French (Fama & French, 2015) factors.



Academic Editor: Thanasis Stengos

Received: 21 August 2026

Revised: 10 September 2026

Accepted: 10 September 2026

Published: 12 September 2026

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The study makes three specific contributions to the literature. First, it provides updated evidence through December 2023, covering a substantially longer evaluation period than that considered in the seminal studies by Barroso and Santa-Clara (2015), Moreira and Muir (2017) and DeMiguel et al. (2024). Second, it evaluates volatility management across three major developed equity regions, namely the United States, Europe, and Developed Markets. Third, and most importantly, it investigates whether volatility management represents a broadly applicable enhancement to factor investing, or whether its effectiveness depends on factor-specific characteristics, the market environment, and the volatility-estimation horizon.

Methodologically, adjusted monthly factor returns are obtained by scaling the original returns by a factor inversely proportional to a proxy for lagged realised variance. The scaling constant is calibrated so that the volatility of each managed factor series equals the volatility of its corresponding unmanaged series, allowing performance differences to be assessed at a comparable risk level. The procedure is implemented using two alternative estimation windows: 180 trading days, motivated by Barroso and Santa-Clara (2015), and 21 trading days, following Moreira and Muir (2017). Comparing these windows tests whether the results are robust to a slower, more stable volatility estimate and a shorter, more responsive estimate.

Accordingly, the paper also contributes to the literature in two ways. First, it provides an updated cross-regional assessment of volatility management across six major equity factors and two volatility-estimation horizons. Second, and more importantly, it examines whether volatility management represents a generalisable enhancement to factor investing, or whether its effectiveness is conditional on factor characteristics, the market environment, and the estimation horizon. By comparing *momentum* and the individual Fama–French factors across the United States, Europe, and Developed Markets, the study identifies substantial heterogeneity in outcomes, thereby more clearly establishing the boundary conditions for volatility-management benefits.

The availability of two volatility-estimation horizons (21 days and 180 days) allows for assessing whether the risk-adjusted results remain stable across windows. From an academic perspective, the research enriches the ongoing discussion on the relationship between volatility and risk management performance in economic factors, providing evidence of the robustness of volatility-management effects.

1.1. Literature Review & Theoretical Framework

Empirical finance literature has consistently shown that actively managing risk exposure through volatility monitoring can improve the performance of financial assets (Barroso & Santa-Clara, 2015; Moreira & Muir, 2017; Daniel & Moskowitz, 2016). Volatility management is grounded in the empirical observation that asset return volatility is more predictable than expected returns. Consequently, portfolio risk can be adjusted dynamically by scaling exposures inversely to recently observed volatility (Cejnek & Mair, 2021; Li & Wang, 2024). The theoretical rationale for volatility management is that return volatility exhibits greater persistence and predictability than expected returns, allowing portfolio risk to be adjusted dynamically through volatility scaling (Božović, 2024). Under this framework, portfolio exposure is adjusted inversely to estimated volatility, such that exposure is reduced when expected risk is high and increased when expected risk is low (Giese, 2024). This approach is motivated by evidence that volatility is more predictable than expected returns and that factor risk *premia* do not vary proportionally with volatility. Consequently, volatility scaling may improve risk-adjusted performance by reducing downside risk and enhancing risk-adjusted return measures (Moreira & Muir, 2017).

The research by [Moreira and Muir \(2017\)](#) introduced the concept of volatility-managed portfolios, concluding that managing asset exposure based on historical volatility, by increasing exposure during low-volatility periods and reducing it during high-volatility periods, yields superior performance relative to a traditional buy-and-hold strategy (acquiring a financial asset and holding it for a long period).

Another research paper ([Harvey et al., 2018](#)) evaluated the impact of volatility targeting across a broad set of assets and investment strategies. The authors concluded that for higher-risk assets, such as equities and credit, volatility management produced a superior Sharpe ratio, whereas for lower-risk assets, such as bonds and currencies, the effect was less pronounced. Nevertheless, across all asset classes, the strategy significantly reduced the likelihood of extreme losses, stabilised volatility, and improved the overall return distribution.

[Cejnek and Mair \(2021\)](#) addressed the same line of reasoning from a more theoretical standpoint. The authors argued that in efficient markets, investors may profit from managing volatility, demonstrating that it is possible to profit from volatility's evolution. The present paper follows this reasoning, positing that investors can indeed benefit from volatility fluctuations. [Giese \(2024\)](#) showed that volatility-targeting strategies outperform traditional buy-and-hold strategies. The author examined an equity portfolio composed of S&P 500 constituents over the period 1988–2012 (24 years). By applying volatility-targeting techniques, the author increased the portfolio's Sharpe ratio from 0.147 to 0.182, thereby enhancing its risk-adjusted performance.

Other literature ([Li & Wang, 2024](#); [Gang et al., 2018](#)) analysed volatility management in the Chinese equity market and in U.S. mutual funds, respectively. Both studies showed that, despite structural differences across markets and financial products, the volatility-management framework produced positive results, reducing risk and improving asset-performance efficiency. From a theoretical perspective, [Douady and Nayar \(2024\)](#) introduced a methodology based on the Multiscale Markowitz model, which allows risk exposure to be adjusted across multiple time horizons.

[Blitz and van Vliet \(2007\)](#) highlighted that, within a risk–return framework, low-volatility stocks tend to exhibit superior risk-adjusted returns, a phenomenon commonly referred to as the volatility effect. Along the same lines of reasoning, [Frazzini and Pedersen \(2014\)](#) reinforced this notion with their Betting-against-Beta strategy, demonstrating that low-beta assets deliver stronger relative performance. Conversely, [Green et al. \(2011\)](#) argued that assets with 'lottery-like' characteristics are favoured by speculative investors, generating systematic deviations in expected returns and contributing to anomalies in equity markets.

Momentum investing is an investment strategy that involves buying assets with strong recent performance and selling (or avoiding) those with weak recent performance, based on the assumption that price trends will persist in the short to medium-term ([Hanauer & Windmueller, 2019](#); [Batten et al., 2023](#)). The concept of *momentum* investing has its roots in behavioural finance and market psychology, emerging prominently in the 1990s. Early academic research ([Jegadeesh & Titman, 1993](#)) provided empirical evidence that stocks that had performed well in the past tended to continue performing well in the short term, while those that had performed poorly continued to underperform. This phenomenon challenged the traditional efficient market hypothesis, which posited that all available information is already reflected in asset prices. *Momentum* strategies can increase risk and volatility, particularly during market downturns ([Gulen & Petkova, 2015](#)). [Ruenzi and Weigert \(2018\)](#) argued that while *momentum* can yield high returns, it can also lead to significant losses, especially when market conditions change abruptly.

In the literature on the *momentum* factor, the work of Daniel and Moskowitz (2016) and Singh and Walia (2020) is essential for understanding the concept and its associated risks. The authors concluded that, despite the strong returns of the *momentum* strategy, it is exposed to severe and persistent drawdowns—known as momentum crashes. To mitigate these crashes, the authors applied volatility management to a sample of U.S. equities over the period 1927–2013. Their results showed a substantial increase in the risk-adjusted Sharpe ratio, from 0.197 to 0.301. The study by Barroso and Santa-Clara (2015) plays a central role in this context. The authors concluded that the *momentum* factor's volatility is highly predictable and that dynamically adjusting its exposure based on realised volatility mitigates the severe losses associated with market downturns. To reduce the risk of these sharp drawdowns, the authors applied volatility management to the *momentum* factor in the U.S. market over the period 1930–2009. Dynamic risk management nearly doubled the Sharpe ratio of the momentum factor in the United States, increasing it from 0.098 to 0.179, while simultaneously reducing associated risk and capturing higher returns.

The Fama and French five-factor model is an extension of the earlier three-factor model developed by Eugene Fama and Kenneth French in 1993. This model aims to explain stock returns by incorporating additional factors that capture various dimensions of risk (Paliienko et al., 2020). The original three factors include *market risk*, *size* (small vs. large companies), and *value* (high vs. low book-to-market ratios).

In the five-factor model, two additional factors are introduced: *profitability* and *investment*. The *profitability* factor accounts for differences in returns between firms with high and low operating profitability, while the investment factor considers returns for firms that invest conservatively versus those that invest aggressively (Cakici, 2015). By incorporating these factors, the model aims to provide a more comprehensive understanding of variations in stock returns. It is widely used in asset pricing and portfolio management, helping investors assess risk and make informed investment decisions. Overall, the five-factor model enhances the ability to explain and predict stock performance in various market conditions (Dirkx & Peter, 2020).

Existing research generally documents positive effects of volatility management on the risk-adjusted performance of several investment strategies, particularly momentum and factor portfolios. However, more recent evidence suggests that these benefits may not be universal and can depend on the underlying strategy, the volatility measure employed, market conditions and the geographical scope of the analysis. While several studies report improvements in Sharpe ratio and portfolio alphas, others (Cederburg et al., 2020; Wang & Yan, 2021; Schwarz, 2024) find that performance gains weaken in real-time implementations, vary across factors, or diminish over time. Consequently, the robustness and generalisability of volatility-management strategies remain active topics of academic debate.

This study addresses these limitations by applying a common volatility-management framework to the *momentum* factor and the Fama–French five-factor model across the United States, Europe and Developed Markets using data through 2023. Rather than focusing exclusively on whether volatility management improves performance, the analysis examines the extent to which its effectiveness varies across factors, regions, and estimation horizons.

The central contribution of the paper is therefore to identify where volatility management works and where it does not. By systematically comparing six major equity factors (MKT, SMB, HML, RMW, CMA, and MOM) across three developed-market universes and two volatility-estimation windows, the study documents substantial cross-factor and cross-region heterogeneity. These results provide evidence that volatility management is not a universally beneficial overlay and that its effectiveness depends on the structural characteristics of the underlying factor.

1.2. Research Objectives

The primary objective of this study is to determine whether volatility-managed factor portfolios achieve superior risk-adjusted performance relative to their unmanaged counterparts. The principal performance criterion adopted in this study is the change in the risk-adjusted Sharpe ratio of the managed factor relative to the unmanaged factor. The analysis does not seek to evaluate investor utility or portfolio-optimisation outcomes and therefore focuses on the comparative risk-return efficiency of the factor strategies. More specifically, the paper addresses the following research questions:

- (a) RQ1: Does volatility management improve the Sharpe ratio of factor portfolios relative to the original unmanaged factors?
- (b) RQ2: Are the effects of volatility management consistent across the momentum factor and the five Fama–French factors?
- (c) RQ3: Do the results remain stable across alternative volatility-estimation horizons (21-day and 180-day windows)?
- (d) RQ4: Are the effects of volatility management robust across different developed equity markets (United States, Europe and Developed Markets)?

The secondary objective is to determine whether the benefits of volatility management are universal or depend on factor-specific characteristics and market context.

2. Materials and Methods

The methodology follows [Moreira and Muir \(2017\)](#), including the scaling factor used by the authors, which matches the volatility of the original factor to that of the adjusted factor. In the tests conducted, a 21-day volatility-estimation window was used, following [Moreira and Muir \(2017\)](#), along with an 180-day volatility-estimation window based on the methodology proposed by [Barroso and Santa-Clara \(2015\)](#).

Accordingly, the hypothesis to be tested combines the two previously identified studies to assess volatility management performance across factors other than the *momentum* factor. Thus, the methodology applied consists of constructing adjusted factors by applying volatility management to the original factors, namely the *momentum* and the *five Fama–French* factors.

2.1. Factors and Measurement

To apply the proposed methodology, historical daily and monthly return data for the factors under analysis were collected. After data collection, the variance of the previous 180 days was computed monthly, for each factor individually. This estimation window was selected because it is considered to capture different market conditions over time, thereby providing a more representative estimate of monthly volatility.

The variance proxy was calculated as the sum of squared daily returns over the previous 180 trading days. This approach follows the realised-volatility literature, in which the aggregation of squared daily returns is commonly used as a proxy for ex-post realised variance ([Fleming et al., 2003](#)). The objective is not to estimate the population variance of returns (Equation (1)) but rather to obtain a consistent measure of recent volatility that can be used to dynamically scale factor exposure. Because the volatility-management rule depends primarily on relative changes in volatility over time rather than on the absolute magnitude of the variance estimate, this proxy provides the required information for the scaling procedure.

$$\sigma_{\{t,180\}}^2 = \sum_{\{t=1\}}^{\{180\}} R_t^2 \quad (1)$$

where $\sigma_{\{180\}}^2$ is a proxy for the variance of the last 180 days and R_t^2 daily squared returns. Consistent with the volatility-management literature, the realised-variance proxy is used as a scaling variable to rank periods by recent risk conditions rather than as a parameter to be estimated unbiasedly.

Next, the scaling factor was divided by the previously computed 180-day variance proxy (Equation (2)). The scaling factor ensures that the volatility of the adjusted return matches that of the original factor, thereby preserving comparability between the original and adjusted returns. The scaling constant was calibrated separately for each factor-region combination to ensure that the volatility of the managed factor series matched that of the corresponding unmanaged series over the sample period. Microsoft Excel Goal Seek was used solely as a numerical optimisation tool to identify the value of the scaling constant that achieved this objective. The calibration was performed using the full sample available for each factor-region combination and was intended exclusively to facilitate comparability between managed and unmanaged returns at a similar volatility level. To complete the strategy, the result of this division is multiplied by the original monthly return, thus obtaining the adjusted monthly return (Equation (2)).

$$R_t^{\{adj\}} = \frac{\mathbb{C}}{\sigma_{\{180\}}^2} \cdot R_t^{\{orig\}} \quad (2)$$

where $R_t^{\{adj\}}$ is the adjusted return of the original monthly factor, $R_t^{\{orig\}}$ the return of the original monthly factor, $\sigma_{\{180\}}^2$ a proxy for the variance of the last 180 days and $\mathbb{C}$ the scaling factor.

After completing the steps detailed above, the procedure was replicated for all available months of the factor. To enable comparison between the original factor returns and the adjusted returns, a set of evaluation metrics was used to objectively assess volatility management performance across the selected factors. The choice of metrics was based on the studies (Barroso & Santa-Clara, 2015; Moreira & Muir, 2017), incorporating several of the indicators proposed by these authors, namely:

- i. Monthly and annual returns—measure the average performance over the analysis period.
- ii. Sigma—reflects the dispersion of returns around the mean and serves as a measure of factor risk.
- iii. Sharpe Ratio—relates the factor's average monthly return to its monthly volatility. Throughout the study, Sharpe ratios are reported monthly and are used primarily for relative comparisons between managed and unmanaged factor strategies. Because annualisation multiplies all Sharpe ratios by the same constant factor, it does not affect the ranking of the strategies or the conclusions regarding relative performance improvements.
- iv. Minimum and maximum values—provide descriptive information regarding the most extreme realised monthly returns observed during the sample period. These statistics are reported for completeness but are not interpreted as formal measures of downside risk or tail-risk exposure.

The selected performance measures capture different dimensions of portfolio behaviour. Average returns evaluate profitability, volatility measures return dispersion, and the Sharpe ratio assesses risk-adjusted performance. The minimum and maximum observed returns are reported as descriptive indicators of extreme realised outcomes and are not interpreted as formal measures of downside risk.

To avoid look-ahead bias, the volatility estimate used to scale returns at month t is based exclusively on daily information available before the start of month t . Specifically, the realised-variance proxy is calculated using the previous 21 or 180 trading days ending on the last trading day of month $t - 1$, and the resulting scaling coefficient is applied to the

factor return observed during month t . No information from month t is used in computing the volatility estimate.

For the first observations of each series, volatility-managed returns are calculated only after a complete estimation window is available. Consequently, the first 21 or 180 trading days, depending on the specification, are used solely to estimate initial volatility and are excluded from the managed-return calculations.

The scaling constant c in Equation (2) is calibrated separately for each factor-region combination. Following [Moreira and Muir \(2017\)](#), c is chosen such that the ex-post volatility of the managed factor equals that of the corresponding unmanaged factor over the sample period. In Microsoft Excel, this calibration is implemented using the Goal Seek function by setting the ratio of managed-to-unmanaged volatility equal to one.

All volatility estimates were calculated sequentially over time using only information available at each decision date. Consequently, the volatility-management rule itself operates without look-ahead bias. However, the scaling constant was calibrated using the full available sample for each factor-region combination and should therefore be interpreted as an ex-post normalisation parameter rather than a purely out-of-sample estimate.

It should be noted that the scaling constant itself is not a forecasting parameter and does not determine the monthly volatility estimate used by the strategy. Its sole purpose is to ensure that the managed and unmanaged return series are compared at a similar volatility level. The time-varying volatility estimates used in portfolio scaling are always based exclusively on information available prior to the investment month. Accordingly, while the volatility forecasts are generated using only information available prior to the investment month, the overall implementation should be regarded as partially out-of-sample rather than fully out-of-sample, given the full-sample calibration of the scaling constant.

The volatility-management strategy adjusts exposure mechanically through inverse-volatility scaling. No explicit leverage constraints, caps, or exposure limits were imposed during the analysis. Consequently, periods of exceptionally low estimated volatility may generate relatively large portfolio exposures, whereas periods of high volatility lead to reduced exposure. The study focuses on the resulting factor-return performance and does not separately report the distribution of scaling coefficients, maximum exposure levels or leverage statistics. This should be considered when interpreting the practical implementation of the strategy.

2.2. Factor Definitions

Widely recognised factors in the finance literature were selected: the *momentum* factor and the *five-factor model* ([Fama & French, 2015](#)). These factors were chosen because they have been extensively examined in the literature ([Moreira & Muir, 2017](#); [Daniel & Moskowitz, 2016](#)), and substantial information is available on them.

The *momentum* factor measures the persistence of stock returns, reflecting the tendency for financial assets that have recently performed well to continue performing well in the near future. In practical terms, the factor is constructed by going long on stocks with the highest past returns, “winners,” and short on those with the lowest past returns, “losers.” Thus, a long portfolio of winner stocks and a short portfolio of loser stocks are formed, and the *momentum* factor return is calculated as the return on the winner portfolio minus the return on the loser portfolio.

The *five-factor model* (5FF) expands the traditional three-factor framework (*Market*, *Size*, and *Value*) by incorporating two additional factors: *Profitability* and *Investment*. This set of factors seeks to explain cross-sectional variations in equity returns and is currently one of the most widely used references in financial research and practice. The model includes the following factors:

- i. MKT (Market)—the difference between the market return and the risk-free rate.
- ii. SMB (Small Minus Big)—measures the return spread between small-capitalisation stocks and large-capitalisation stocks.
- iii. HML (High Minus Low)—measures the return differential between high book-to-market stocks and low book-to-market stocks.
- iv. RMW (Robust Minus Weak)—the difference between the average returns of firms with high profitability and firms with low profitability.
- v. CMA (Conservative Minus Aggressive)—the return spread between firms with conservative investment policies and those with aggressive investment policies.

The inclusion of these widely recognised and extensively studied factors in the financial literature enables the examination of their explanatory power for asset returns and the assessment of the impact of the estimation horizon on volatility management.

2.3. Geographic Markets

The analysis included evaluating factors across different geographical regions to assess the consistency of the adjusted results and identify potential differences across markets, including the United States, Europe, and Developed Markets, as approached by [Shojaei et al. \(2025\)](#). It should be noted that the Developed Markets dataset includes both the United States and European markets. Consequently, the three regional datasets are not fully independent and should be interpreted as complementary perspectives on the robustness of the results rather than as completely distinct market universes.

The decision to include the United States is motivated by its offering the longest and most comprehensive financial data series, enabling a detailed assessment across multiple economic cycles, including periods of expansion, recession, and financial crises ([Xiong et al., 2022](#); [Almansour et al., 2024](#)). The extensive availability of information enables an effective evaluation of volatility management over diverse market regimes. Europe, in turn, provides a market structure distinct from that of the United States, characterised by its own institutional features and dynamics. Analysing risk management in this region allows for testing methodological consistency across markets with different risk profiles and behaviours, ensuring that the results are not specific to a single market environment. Finally, Developed Markets were included to provide a broader perspective encompassing several mature and well-regulated economies. The analysis in this region allows the findings to be generalised across a wider economic context.

The selection of these three geographical areas ensures a balance between temporal depth, market heterogeneity, and analytical robustness, thereby enabling a comprehensive and rigorous assessment of the effectiveness of volatility management.

2.4. Data Sources and Preparation

This section presents the data sources, the sample universe, the temporal coverage, and the data-preparation procedures used to assess the impact of volatility management on (i) the *momentum* factor and (ii) the *five Fama and French* ([Fama & French, 2015](#)) factors across the United States, Europe, and Developed Markets.

Kenneth R. French (KRF) data library:

- i. Momentum Factor—Regional series provided by KRF on a daily and monthly basis.
- ii. Five Fama & French factors ([Fama & French, 2015](#))—Regional series provided by KRF on a daily and monthly basis. Includes the following factors: MKT; SMB; HML; RMW; CMA and data relating to risk-free assets (rf).

Both the daily and monthly versions of the files were used, with the sample defined as the first month with available data through 31 December 2023 (the analysis period for each

factor is presented in Table 1). It should be noted that not all analyses were conducted over the same time window, as some series contained more available observations than others.

Table 1. Data summary.

Sets	Region	Frequency	Variables	Start	End
MOM (KRF)	EUA	Daily/Monthly	MOM	3 January 1927	29 December 2023
MOM (KRF)	Europe	Daily/Monthly	MOM	1 November 1990	29 December 2023
MOM (KRF)	Developed Countries	Daily/Monthly	MOM	1 November 1990	29 December 2023
5FF (KRF)	EUA	Daily/Monthly	MKT; SMB; HML; RMW; CMA	1 July 1963	29 December 2023
5FF (KRF)	Europe	Daily/Monthly	MKT; SMB; HML; RMW; CMA	2 July 1990	29 December 2023
5FF (KRF)	Developed Countries	Daily/Monthly	MKT; SMB; HML; RMW; CMA	2 July 1990	29 December 2023

Source: Data library of Kenneth R. French.

Regarding the universe, conventions, and units, the day and month were adopted as time units: daily and monthly returns for each factor were expressed as a percentage of the day/month. Concerning the return type, the gross portfolio returns were adopted.

After extracting the data from the Kenneth R. French Data Library, the files were imported into MS Excel, where the tests were conducted. The different factors were standardised using a consistent naming convention, adopting uniform designations (MKT, SMB, HML, RMW, CMA, and MOM) and a common structural format.

Because the Kenneth R. French datasets became available at different dates across factors and regions, the effective sample period varies across tests. All analyses were conducted using the maximum available history for each factor-region combination. Accordingly, sample periods reported in the results tables should be interpreted as factor-specific and are summarised in Table 1.

2.5. Descriptive Statistics of Monthly Returns

The analysis comprises 36 primary factor-region-window comparisons, corresponding to six factors, three regional datasets, and two volatility-estimation windows. The empirical evaluation is primarily descriptive and comparative, focusing on differences in mean returns, volatility, Sharpe ratio, and extreme-return measures between unmanaged and volatility-managed factors. Given the exploratory nature of the study, the results are interpreted based on the magnitude and consistency of performance changes across factors, regions, and estimation windows rather than on formal hypothesis-testing procedures.

Table 2 presents the descriptive statistics of the monthly returns of the factors analysed in their traditional (buy-and-hold) form. Each table reports the main evaluation metrics: the mean monthly return, the standard deviation, the Sharpe ratio, and the minimum and maximum returns for each factor in each region. These indicators characterise the behaviour of the factors over the analysis period and enable a comparison between the traditional metrics and those of the adjusted factors.

All reported Sharpe ratios are calculated using monthly returns and monthly volatility and therefore represent monthly Sharpe ratios. The focus of the analysis is on the relative change between unmanaged and volatility-managed factors rather than on comparison with a specific absolute benchmark. Consequently, annualising the Sharpe ratios would not alter the direction or magnitude of the documented performance improvements in relative terms.

All documents used as the basis for the analysis were stored to ensure the integrity of the tests conducted. All data-organisation tasks and statistical calculations were performed using Microsoft Excel. Each panel (United States, Europe, and Developed Markets) includes dedicated worksheets to keep the data clear and well-structured. The developed Excel files are stored in a way that ensures the consistency of the results and guarantees full reproducibility.

Table 2. Results of descriptive statistics.

Region/Factor	Mean (%)	Volatility (%)	Sharpe Ratio (Monthly)	Min (%)	Max (%)
<i>Momentum</i>					
USA	0.61%	4.71%	0.130	−52.05%	18.20%
EUROPE	0.85%	3.91%	0.219	−26.09%	13.65%
Developed Cout.	0.56%	3.78%	0.149	−24.26%	17.73%
Model Five Factors Fama and French (2015) —USA					
MKT	0.56%	4.52%	0.124	−23.19%	16.10%
SMB	0.22%	3.04%	0.072	−15.54%	18.46%
HML	0.29%	2.99%	0.096	−13.83%	12.92%
RMW	0.28%	2.24%	0.126	−18.95%	13.05%
CMA	0.27%	2.07%	0.128	−7.06%	9.01%
Model Five Factors Fama and French (2015) —Europe					
MKT	0.54%	4.95%	0.108	−22.02%	16.8%
SMB	0.04%	2.10%	0.019	−7.33%	9.2%
HML	0.29%	2.65%	0.108	−11.30%	11.37%
RMW	0.36%	1.63%	0.219	−5.40%	7.0%
CMA	0.13%	1.83%	0.073	−7.30%	8.71%
Model Five Factors Fama and French (2015) —Developed Countries					
MKT	0.54%	4.34%	0.125	−19.51%	19.97%
SMB	0.03%	1.89%	0.016	−8.65%	8.39%
HML	0.25%	2.60%	0.096	−10.14%	9.87%
RMW	0.35%	1.49%	0.235	−5.75%	7.60%
CMA	0.21%	1.95%	0.107	−6.44%	6.01%

Source: Data library of Kenneth R. French.

3. Volatility Management Analysis (180 Days)

3.1. Momentum Factor: 180-Day Window

The return on the strategy is called the *momentum* premium, which is the return on the best-performing stocks minus the return on the worst-performing stocks. The vulnerability of this strategy lies in its significant losses during periods of high volatility, as argued by [Daniel and Moskowitz \(2016\)](#). The authors noted that although the strategy is, on average, profitable, it is exposed to large losses during sharp market rebounds. They argued that this risk can be mitigated through dynamic risk-exposure management adjusted to prevailing market conditions.

Following a similar line of reasoning, [Barroso and Santa-Clara \(2015\)](#) introduced a methodology that reduces factor exposure during periods of high volatility and increases it during periods of low volatility. The authors assumed that factor returns were relatively stable, while volatility was both variable and predictable. Their analysis, conducted through 2011, yielded strong positive results.

Considering the above, a simplified methodology was tested based on the approaches of ([Barroso & Santa-Clara, 2015](#); [Moreira & Muir, 2017](#)), extending the analysis through 2023 to validate the findings of the financial literature and assess the consistency of volatility management for the momentum factor in more recent periods.

3.2. Volatility Management in Factor Momentum (180 Days)

Table 3 presents the comparison between the original return and the adjusted return obtained through volatility management of the *momentum* factor, using a 180-day volatility-estimation window. Table 3 enables analysis and comparison of results before and after the application of dynamic risk management, thereby assessing the methodology's performance for the factor under consideration. The results reported in Table 3 are expressed monthly.

Table 3. Analysis of volatility management performance in the momentum factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1927–2023	0.61%	1.33%	4.71%	4.71%	0.130	0.283	−52.05%	−25.58%	18.20%	37.48%
Europe	1990–2023	0.85%	1.56%	3.91%	3.91%	0.219	0.400	−26.09%	−13.40%	13.65%	18.43%
Dev. Co.	1990–2023	0.56%	1.22%	3.78%	3.78%	0.149	0.323	−24.26%	−13.58%	17.73%	16.76%

Source: Own elaboration.

The results obtained by extending the simplified methodology through 2023 reinforce the conclusions presented in [Barroso and Santa-Clara \(2015\)](#), showing that dynamic risk management substantially improves the risk-adjusted return of the momentum factor across all regions analysed. Moreover, the Sharpe ratio nearly doubled across all regions, thereby confirming the effectiveness of active risk management.

In addition, an overall reduction in the minimum return was observed throughout the analysis period. These findings indicate that the volatility-managed strategy experienced less severe worst-case monthly outcomes within the sample period. However, the reported minimum returns should be interpreted as descriptive statistics rather than formal measures of downside risk. The results are consistent with the arguments presented by [Moreira and Muir \(2017\)](#) and [Daniel and Moskowitz \(2016\)](#), reinforcing the view that volatility management is associated with improved realised worst-month outcomes in the analysed sample.

Similarly, it is important to highlight that maximum returns generally increase. Thus, volatility management not only improved the risk–return profile of the assets but also enabled higher returns, except in Developed Markets. These findings strengthen the view that superior returns can be achieved with greater risk efficiency, a line of reasoning discussed by [Cejnek and Mair \(2021\)](#), who argued that in efficient markets, investors have opportunities to profit by managing volatility. Their research showed that it is possible to benefit from volatility’s evolution without forecasting investment performance.

3.3. Fama–French Five-Factor Model: 180-Day Window

Also, the simplified methodology was applied to the *Five Fama–French* factors (5FF). The objective was to assess whether volatility management improves the risk-adjusted performance of the 5FF factors, as observed for the *momentum* factor. It is important to note that a similar analysis was conducted by [Moreira and Muir \(2017\)](#). However, the volatility-management methodology employed by the authors is based on assumptions that differ from those used in the present test, with the main distinction being the volatility-estimation window.

While the methodology used in this test relies on a 180-day window, the study by [Moreira and Muir \(2017\)](#) employs a much shorter 21-day horizon. The authors’ methodological choice results in a more reactive volatility estimate, one that captures shorter fluctuations with greater sensitivity. In contrast, a longer-horizon approach (180-day) produces a more stable estimate, less affected by short-term variations.

Tables 4–8 present the comparison between the original return and the adjusted return obtained through volatility management of the 5 factors (*market, size, value, profitability* and *investment*) using a 180-day volatility-estimation window. These data enable the analysis and comparison of results before and after the application of dynamic risk management, thereby assessing the methodology’s performance across the five factors.

Table 4. Analysis of volatility management performance in the *market* factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.56%	0.43%	4.52%	4.52%	0.124	0.096	−23.19%	−30.43%	16.10%	16.96%
Europe	1990–2023	0.54%	0.64%	4.95%	4.95%	0.108	0.129	−22.02%	−22.14%	16.62%	16.85%
Dev. Co.	1990–2023	0.54%	0.59%	4.34%	4.34%	0.125	0.136	−19.51%	−16.22%	13.34%	19.97%

Source: Own elaboration.

Table 5. Analysis of volatility management performance in the *size* factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.22%	0.15%	3.04%	3.04%	0.072	0.050	−15.54%	−20.46%	18.46%	18.38%
Europe	1990–2023	0.04%	−0.06%	2.10%	2.10%	0.019	−0.031	−7.33%	−9.19%	8.83%	11.21%
Dev. Co.	1990–2023	0.03%	−0.03%	1.89%	1.89%	0.016	−0.014	−8.65%	−8.16%	8.37%	8.39%

Source: Own elaboration.

Table 6. Analysis of volatility management performance in the *value* factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.29%	0.24%	2.99%	2.99%	0.096	0.079	−13.83%	−13.13%	12.92%	15.78%
Europe	1990–2023	0.29%	0.30%	2.65%	2.65%	0.108	0.114	−11.30%	−10.52%	12.09%	11.37%
Dev. Co.	1990–2023	0.25%	0.30%	2.60%	2.60%	0.096	0.114	−10.14%	−11.03%	12.24%	9.87%

Source: Own elaboration.

Table 7. Analysis of volatility management performance in the *profitability* factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.29%	0.33%	2.24%	2.24%	0.126	0.146	−18.95%	−7.60%	13.05%	10.20%
Europe	1990–2023	0.36%	0.48%	1.63%	1.63%	0.219	0.298	−5.40%	−4.62%	6.40%	7.01%
Dev. Co.	1990–2023	0.35%	0.38%	1.49%	1.49%	0.235	0.256	−5.75%	−4.72%	6.20%	7.60%

Source: Own elaboration.

Table 8. Analysis of volatility management performance in the *investment* factor (180 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.27%	0.25%	2.07%	2.07%	0.128	0.121	−7.06%	−5.48%	9.01%	9.94%
Europe	1990–2023	0.13%	−0.05%	1.83%	1.83%	0.073	−0.030	−7.30%	−9.32%	8.77%	8.71%
Dev. Co.	1990–2023	0.21%	0.06%	1.95%	1.95%	0.107	0.029	−6.64%	−7.89%	9.57%	6.01%

Source: Own elaboration.

Among the 5 factors analysed, *profitability* (Table 7) exhibited the strongest performance, showing improvements in Sharpe ratio across all regions (U.S.: 0.126–0.146; Europe: 0.219–0.298; Developed Markets: 0.235–0.256). This suggests that the factor displays favourable sensitivity to dynamic volatility management, enabling greater efficiency and sustainability in its risk–return profile. Overall, the strategy reduced risk while capturing higher gains relative to the original factor.

In contrast, applying volatility management to *market* and *value* factors (Tables 4 and 6) produced inconsistent effects, highlighting the methodology's limitations when applied outside the momentum-type context. Both factors recorded modest improvements in certain regions, though these gains were neither substantial nor consistent. In several cases, volatility adjustment even worsened performance. For the *market* factor, improvements in the risk–return relationship were observed in Europe and Developed Markets (0.108–0.129; 0.125–0.136, respectively), while results deteriorated in the United States (0.124–0.096). These patterns show a lack of consistency across regions. The *value* factor followed a similar trajectory: the Sharpe ratio declined in the United States (0.096–0.079) but increased in Europe and Developed Markets (0.108–0.114; 0.096–0.114, respectively). This behaviour suggests that the methodology adopted by (Barroso & Santa-Clara, 2015; Moreira & Muir, 2017) faces challenges in capturing meaningful, persistent gains for factors whose volatility is less predictable over time. In short, the simplified approach appears limited and inconsistent when applied to MKT and HML, highlighting the need for selective application.

Finally, the *size* and *investment* factors (Tables 5 and 8) showed a clear deterioration in performance after volatility management. For the *size* factor, in Europe and Developed Markets, the Sharpe ratio turned negative under volatility adjustment (0.019 to –0.031; 0.016 to –0.014, respectively). The *investment* factor showed declines in the Sharpe ratio across all regions, suggesting that the methodology may introduce additional instability and reduce the efficiency of the adjusted factor relative to its original version.

Based on these results, using a 180-day volatility-estimation window, it can be concluded that the strategy does not consistently improve returns or risk–return relationships for the *Fama–French five* factors, unlike for the *momentum* and *profitability* factors. The effects of volatility management proved heterogeneous, with increases and decreases appearing in specific regions. The only exception was *profitability*, which improved consistently across all regions. Taken together, the variations in Sharpe ratio across factors and regions indicate that the volatility-management methodology used does not yield systematic improvements but instead reflects the underlying structural characteristics of each factor and the regional markets under analysis.

4. Volatility Management Analysis: 21-Day Window

This chapter analysed a 21-day volatility-estimation window. This adjustment aims to achieve a more robust analysis, enabling a more rigorous assessment of the research question: whether volatility management improves the performance of factors other than momentum. Accordingly, it is pertinent to compare the results obtained in this section with those presented by Moreira and Muir (2017), who examined volatility management for the *momentum* factor and the *five Fama and French* (Fama & French, 2015) factors up to 2015, whereas the present analysis extends to 2023.

In Moreira and Muir (2017), the authors used the concept of alpha (α) to evaluate the performance of the factors analysed. Moreira and Muir (2017) evaluate volatility-managed portfolios using factor-model alphas obtained from time-series regressions. Alpha measures abnormal risk-adjusted performance relative to an asset-pricing benchmark and therefore differs conceptually from the Sharpe ratio adopted in the present study. Consequently, the results reported below are discussed qualitatively in relation to the findings of Moreira and Muir (2017), rather than compared directly on a numerical basis.

4.1. Momentum Factor

Table 9 presents a comparison between the original return and the adjusted return obtained through volatility management of the *momentum* factor, using a 21-day volatility-estimation window, allowing analysis and comparison of results before and after dynamic

risk management and thereby assessing the performance of the methodology for the factor under examination.

Table 9. Analysis of volatility management performance in the momentum factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1927–2023	0.61%	1.24%	4.71%	4.71%	0.130	0.264	−52.05%	−40.11%	18.20%	36.35%
Europe	1990–2023	0.85%	1.68%	3.91%	3.91%	0.219	0.429	−26.09%	−14.64%	13.65%	23.52%
Dev. Co.	1990–2023	0.56%	1.23%	3.78%	3.78%	0.149	0.326	−24.26%	−13.68%	17.73%	23.33%

Source: Own elaboration.

There is a substantial increase in the Sharpe ratio across all regions. In the United States, it rises from 0.130 to 0.264; in Europe, from 0.219 to 0.429; and in Developed Markets, from 0.149 to 0.326. These results demonstrate that adjusting the factor to account for risk consistently improves the risk–return trade-off, reinforcing the methodology’s effectiveness across different regions.

A pronounced reduction in monthly losses is also observed in all regions. In the United States, for example, the minimum return improved from −52.05% to −40.11%, while maximum returns increased from 18.20% to 37.48%. This indicates that volatility management does not eliminate risk but makes it more controlled and efficient, reducing extreme losses without constraining the potential for high gains. Part of these larger positive outcomes may reflect periods of increased exposure generated by the volatility-management rule during low-volatility environments.

Overall, mean returns increased from 0.56 to 0.85% and to 1.23–1.68%, while volatility remained at comparable levels. Consequently, the Sharpe ratio nearly doubles, reflecting a more favourable risk–return profile and greater stability in performance across the contexts examined.

In conclusion, both the 21-day and 180-day volatility-estimation windows yield broadly similar results for adjusted returns and Sharpe ratio. The key distinction lies in the 180-day estimation window, which offers greater stability, particularly in the United States, while the 21-day estimation window is more reactive, especially in Europe. Thus, the choice between horizons does not materially alter overall performance but does influence the degree of risk exposure. The findings of this test are consistent with those reported by [Moreira and Muir \(2017\)](#). As noted, their study focused on the United States over the period 1926–2015, using a methodology comparable to that applied here. [Moreira and Muir \(2017\)](#) reported strong evidence in favour of volatility management for the momentum factor using alpha-based measures. Although the performance metric used in the present study is different, the substantial improvement observed in the Sharpe ratio is qualitatively consistent with their conclusion that volatility management enhances the risk-adjusted performance of momentum strategies.

4.2. Fama and French’s Five-Factor Model (21 Days)

The methodology used in this test relies on a 21-day window, following the time frame applied by [Moreira and Muir \(2017\)](#). The authors’ methodological choice results in a more reactive volatility estimate, one that captures short-term fluctuations with greater sensitivity. Tables 10–14 present a comparison between the original return and the adjusted return obtained through volatility management of the 5 factors (market, size, value, profitability, and investment) using a 21-day volatility-estimation window. This data enables analysis and comparison of results before and after the application of dynamic risk management, thereby assessing the methodology’s performance across the five factors.

Table 10. Analysis of volatility management performance in the *market* factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.56%	0.55%	4.52%	4.52%	0.124	0.123	−23.19%	−25.26%	16.10%	25.41%
Europe	1990–2023	0.54%	0.72%	4.95%	4.95%	0.108	0.146	−22.02%	−20.52%	16.62%	18.60%
Dev. Co.	1990–2023	0.54%	0.48%	4.34%	4.34%	0.125	0.111	−19.51%	−23.48%	13.34%	21.78%

Source: Own elaboration.

Table 11. Analysis of volatility management performance in the *size* factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.22%	0.13%	3.04%	3.04%	0.072	0.043	−15.54%	−21.26%	18.46%	19.65%
Europe	1990–2023	0.04%	0.19%	2.10%	2.10%	0.019	0.090	−7.33%	−7.25%	8.83%	9.80%
Dev. Co.	1990–2023	0.03%	0.06%	1.89%	1.89%	0.016	0.030	−8.65%	−6.34%	8.37%	13.84%

Source: Own elaboration.

Table 12. Analysis of volatility management performance in the *value* factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.29%	0.28%	2.99%	2.99%	0.096	0.092	−13.83%	−21.96%	12.92%	18.30%
Europe	1990–2023	0.29%	0.34%	2.65%	2.65%	0.108	0.128	−11.30%	−15.43%	12.09%	11.62%
Dev. Co.	1990–2023	0.23%	0.31%	2.59%	2.59%	0.090	0.118	−10.14%	−9.54%	13.34%	14.58%

Source: Own elaboration.

Table 13. Analysis of volatility management performance in the *profitability* factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.28%	0.36%	2.24%	2.24%	0.126	0.163	−18.95%	−10.80%	13.05%	16.36%
Europe	1990–2023	0.36%	0.37%	1.63%	1.63%	0.219	0.226	−5.40%	−7.02%	6.40%	7.13%
Dev. Co.	1990–2023	0.35%	0.37%	1.49%	1.49%	0.235	0.252	−5.75%	−6.61%	6.20%	7.39%

Source: Own elaboration.

Table 14. Analysis of volatility management performance in the *investment* factor (21 days).

Region	Time Window	Avg. Return (Orig.)	Avg. Return (Adjus.)	Volatility (Orig.)	Volatility (Adjus.)	Sharpe Ratio (Monthly Orig.)	Sharpe Ratio (Monthly Adjus.)	Min (Orig.)	Min (Adjus.)	Máx (Orig.)	Máx (Adjus.)
USA	1963–2023	0.27%	0.20%	2.07%	2.07%	0.128	0.098	−7.06%	−7.01%	9.01%	14.21%
Europe	1990–2023	0.13%	0.03%	1.83%	1.83%	0.073	0.019	−7.30%	−9.06%	8.77%	10.55%
Dev. Co.	1990–2023	0.21%	0.15%	1.95%	1.95%	0.107	0.078	−6.44%	−6.33%	9.57%	8.61%

Source: Own elaboration.

Regarding the marketing factor (Table 10), risk management effectiveness is not uniform and varies across regions. In Europe, the adjustment results in a modest improvement in the Sharpe ratio, suggesting more efficient volatility management. In contrast, in the United States and Developed Markets, the results show slight reductions in performance relative to the original buy-and-hold strategy, indicating that the factor's response to volatility management is highly dependent on the market context. Thus, for the *market* factor,

dynamic risk management exhibits an asymmetric and inconsistent impact, only partially reinforcing the factor's stability in certain regions.

Moreira and Muir (2017) reported positive alpha estimates for the market factor. While alpha and Sharpe ratio are not directly comparable measures, the present results do not provide similarly strong evidence in favour of volatility management for the U.S. market factor during the extended sample period. As shown in Table 10, however, the U.S. risk–return relationship in the present analysis shows a slight deterioration relative to the original factor (from 0.124 to 0.123). The main difference between the authors' results and those of the present test lies in the time period considered: the authors analysed the period from 1926 to 2015. This change in the temporal window suggests that the *market* factor does not consistently respond positively to volatility management, reinforcing the notion that shifts in the analysis period may lead to a degradation of results.

Concerning the *size* factor (Table 11), the volatility management applied does not exhibit a uniform or consistent impact across regions. In some markets, such as Europe, volatility management contributes positively to performance, whereas in the United States, the results deteriorate noticeably. This indicates that the adjustment's effect depends heavily on market conditions and the factor's cyclical nature.

Moreira and Muir (2017) reported weak evidence for volatility management in the size factor. Although the performance measures differ, the present results similarly suggest that volatility management does not consistently improve the performance of this factor. Although the time period analysed by the authors (1926–2015) differs from that considered in the present test, the factor continues to show an inability to generate positive outcomes in the U.S. market, suggesting that volatility management does not add value to the factor.

Analysing the *value* factor (Table 12), the results do not follow a uniform pattern, indicating that the effect of volatility management on HML depends heavily on market conditions and the timing of its application. Regarding the findings of Moreira and Muir (2017), the authors reported an annualised alpha of 1.97%, which they interpreted as evidence of a modest improvement in performance. This value indicates that the volatility-managed factor performed slightly better than the original, although the improvement was modest. The positive alpha is consistent with a small improvement in the risk–return efficiency of the volatility-managed strategy relative to the original factor, but the effect is limited and sensitive to the analysis period.

The period analysed by Moreira and Muir (2017) spanned 1926–2015, whereas the period used here (1963–2023) differs. Such a difference may reflect structural changes in the U.S. market, potentially explaining the reduction in the *value* factor's Sharpe ratio observed here (from 0.096 to 0.092).

Overall, the results indicate that the HML factor does not respond meaningfully to volatility management, with outcomes being highly sensitive to the temporal window considered. Thus, the evidence does not support a consistent pattern of improvements in volatility management for the *value* factor.

Regarding the *profitability* factor (Table 13), the results obtained are consistent with those presented by Moreira and Muir (2017). Moreira and Muir (2017) found favourable evidence for volatility management in the profitability factor. Although the present study relies on the Sharpe ratio rather than alpha estimates, the results point in the same direction, with profitability emerging as the most consistently successful factor outside momentum. The consistency between both results—which extends the analysis period to 2023—suggests that the factor exhibits a structure conducive to dynamic risk management, potentially allowing investors to benefit from volatility fluctuations to enhance the risk–return trade-off.

Finally, regarding the *investment* factor (Table 14), the results suggest that the volatility-management approach employed is ineffective at reducing risk and, in fact, detrimental, as it led to a decline in the factor's average returns.

With respect to the findings of Moreira and Muir (2017), the authors analysed this factor over the period 1963–2015, thereby providing a suitable basis for comparison. In their study, the investment factor exhibited an annualised alpha of 0.38%, which is economically small and indicates that volatility management did not generate meaningful improvements in risk-adjusted performance. The results presented in Table 13 are consistent with those reported by Moreira and Muir (2017), and extending the analysis period to 2023 even suggests that the adjusted results may have deteriorated further.

5. Discussion

The evidence indicates that volatility management is factor- and region-dependent rather than universally beneficial. *Momentum* exhibits the most robust improvements across both estimation windows and all regions, while *profitability* is the only Fama–French factor with consistently positive risk-adjusted outcomes. *Market* and *value* effects are mixed, and *investment* generally deteriorates after adjustment. The contrast between the 21-day and 180-day windows further suggests that responsiveness and stability are trade-offs: shorter windows respond more rapidly to changing conditions, whereas longer windows smooth short-term fluctuations. These results support a selective, factor-specific application of volatility management and caution against treating volatility targeting as a uniform overlay across factor portfolios. These conclusions are based on descriptive comparisons of returns, volatility and Sharpe ratio across factors, regions and estimation horizons. Accordingly, the reported differences should be interpreted as indicative patterns rather than as formally established statistical relationships.

The regional comparisons should nevertheless be interpreted with caution because the Developed Markets dataset partially overlaps with the United States and European datasets. Therefore, consistency across these samples should not be viewed as evidence from three fully independent market universes but rather as an indication that similar patterns are observed across nested developed-market datasets.

The observed cross-factor heterogeneity is economically plausible. Volatility management is expected to be most effective when factor volatility is persistent and predictable. The *momentum* factor appears particularly well-suited to volatility scaling because it is characterised by episodic crashes and substantial volatility fluctuations. In contrast, size and investment factors may exhibit weaker volatility persistence and a less stable relationship between volatility and expected returns, reducing the potential benefits of volatility management. Profitability occupies an intermediate position and appears to benefit more consistently from volatility scaling. These findings suggest that the effectiveness of volatility management depends on factor-specific characteristics rather than representing a universally applicable enhancement across all equity factors. Regional differences may also help explain the variation in results. The United States, Europe and Developed Markets differ in terms of market composition, sector concentration, investor behaviour and economic conditions. As a result, the volatility dynamics of individual factors may differ across regions, influencing the effectiveness of volatility scaling. The results therefore suggest that factor performance under volatility management depends not only on the characteristics of the factor itself but also on the broader market environment in which it is applied.

An important implication of these findings is that volatility management should not be viewed as a universally effective overlay for factor investing. While earlier studies primarily focused on documenting performance improvements, the present results help identify the conditions under which volatility management is most effective. Specifically, the

evidence suggests that the success of volatility scaling depends on whether a factor exhibits sufficiently predictable volatility dynamics and whether such predictability translates into economically meaningful improvements in risk-adjusted returns. This contributes to the literature by shifting attention from whether volatility management works in general to where and for which factors it works.

The comparison between the 21-day and 180-day estimation windows highlights the trade-off between responsiveness and stability. Shorter estimation windows react more quickly to changing market conditions and therefore adjust factor exposure more aggressively. Longer windows provide smoother volatility estimates and may reduce the influence of short-term market noise. The results suggest that neither approach is uniformly superior, with effectiveness depending on both factor characteristics and prevailing market conditions.

A practical implication of this trade-off is that shorter volatility-estimation windows may require more frequent portfolio adjustments than longer-horizon approaches. Although implementation costs were not analysed in the present study, higher rebalancing frequency may increase transaction costs and portfolio turnover, potentially reducing the realised benefits of volatility management. Consequently, the performance differences reported in this paper should be interpreted as gross results obtained before implementation expenses. The extent to which the documented improvements would persist after accounting for trading costs cannot be determined from the present analysis and therefore remains an open empirical question.

6. Conclusions

The results, although heterogeneous, allow the initial research question to be addressed: To what extent does volatility management improve the risk-adjusted performance of economic factors beyond *momentum*? The conclusions should be interpreted within the descriptive framework adopted in this study. The analysis focuses on the economic magnitude and consistency of performance differences rather than on formal statistical tests of significance.

The results extend the sample to 2023 and incorporate robustness elements, namely two volatility-estimation windows (21 and 180 days) and a cross-regional approach (United States, Europe, and Developed Markets), confirming and reinforcing prior evidence, particularly the conclusions of Barroso and Santa-Clara (2015) and Moreira and Muir (2017). The presented results show that the *momentum* factor exhibited the most pronounced improvements in the United States, with Sharpe ratio increases of 118% (180-day window) and 103% (21-day window), and in Developed Markets, with increases of 117% (180-day window) and 119% (21-day window). These results, under both the shorter and the longer estimation horizons, support the findings of Barroso and Santa-Clara (180-day volatility-estimation window) and Moreira and Muir (21-day volatility-estimation window), who documented an approximate doubling of the Sharpe ratio for the adjusted factor.

After examining the influence of volatility management on the *momentum* factor, the analysis was extended to the economic factors in the Fama and French (Fama & French, 2015) model by assessing the effect of volatility management using a 180-day estimation window, a horizon for which there are no directly comparable published results for these factors. Volatility management produced heterogeneous effects across the 5FF. The *profitability* factor stood out as the only factor with consistent improvements in the risk–return profile across all regions and estimation horizons, for example, increases in the Sharpe ratio from 0.126 to 0.146 in the United States and from 0.219 to 0.298 in Europe. *Market* and *value* displayed mixed outcomes in the adjusted Sharpe ratio: localised gains in Europe (0.108–0.129 and 0.108–0.114, respectively) but declines in the United States (0.124–0.096 and 0.096–0.079,

respectively), indicating a lack of consistency. By contrast, size and investment factors showed a consistent deterioration in performance across all regions. It is possible to conclude that the 180-day approach has a heterogeneous impact on the 5FF and does not consistently enhance the risk–return relationship, suggesting that effectiveness is contingent on the structural characteristics of each factor and region.

Using a 21-day estimation window likewise yielded heterogeneous behaviour, sensitive to market conditions, mirroring the 180-day results. The *profitability* factor was the only factor with consistently positive adjusted outcomes, notably a 29% increase in the adjusted Sharpe ratio relative to the original. *Market* and *value* again showed mixed results, with modest improvements in Europe and deteriorations in the United States. The *investment* factor continued to underperform on an adjusted basis, at times exposing it to higher risk; in Europe, the adjusted Sharpe ratio worsened by 74% relative to the original. Finally, the *size* factor with a 21-day window performed better, with substantial increases in the adjusted Sharpe ratio of 374% in Europe and 88% in Developed Markets.

The U.S. results are broadly consistent with those of [Moreira and Muir \(2017\)](#), though with some regional and temporal divergences. The *profitability* factor behaves as expected, delivering consistent, sustainable gains aligned with the authors' findings. *Size* and *investment* factors show unfavourable results, broadly consistent with the limited economic benefits reported in their study. The *value* factor exhibits a marginal, period-dependent impact, with only limited economic relevance. Only the *market* factor diverges, registering deterioration in contrast to the improvement observed by [Moreira and Muir \(2017\)](#), suggesting that the change in the analysis period may account for the decline.

The findings should also be interpreted within a frictionless implementation framework. Because transaction costs, portfolio turnover, bid–ask spreads and market–impact effects are not incorporated into the analysis, the reported improvements in risk-adjusted performance should not be interpreted as estimates of net investor returns. In the absence of a transaction-cost sensitivity analysis, the extent to which these gains would persist after implementation costs remains uncertain.

Beyond extending the sample period and geographic scope, the study contributes to the literature by documenting that volatility management is not a universally beneficial factor-investing technique. The results reveal systematic cross-factor and cross-region heterogeneity, indicating that the effectiveness of volatility scaling depends on the structural characteristics of the underlying factor rather than on the mechanical application of an inverse-volatility rule. This finding helps reconcile conflicting evidence reported in the literature and provides a more nuanced understanding of when volatility management is likely to add value.

In conclusion, and in response to the research question, the results reinforce the existing literature on the *momentum* factor. However, for the remaining factors under examination, the outcomes are inconsistent and heterogeneous; therefore, it is not possible to assert that volatility management improves the performance of economic factors other than *momentum*.

7. Limitations and Future Research

The study's findings on the effectiveness of volatility management are largely confined to the *momentum* and *profitability* factors, with inconsistent or even adverse results observed for the other *Fama–French* factors across different regions. This suggests that the benefits of volatility targeting are not universally applicable and may depend heavily on factor-specific characteristics and predictable volatility patterns, limiting the broader applicability of the proposed methodology. Also, the study relies on idealised, frictionless factor–return data and does not account for real-world implementation costs such as transaction fees,

bid-ask spreads, portfolio turnover, market impact or financing costs associated with dynamic portfolio adjustment. This limitation may be particularly relevant for the 21-day volatility-estimation window, which is likely to require more frequent rebalancing than the 180-day specification. Consequently, the reported results should be interpreted as gross performance measures that may overstate the returns achievable in practical investment settings. Additionally, the analysis is limited to developed equity markets and a narrow set of factors, restricting the external validity and applicability of the findings to broader asset classes or less developed markets. The Sharpe ratios reported in the study are presented monthly. Although this choice does not affect the relative comparison between managed and unmanaged strategies, future research may present annualised metrics to facilitate direct comparison with other studies in the literature. No sensitivity analysis was conducted to assess the impact of alternative assumptions regarding transaction costs, portfolio turnover or market impact. Consequently, the study cannot determine the level of implementation costs that would materially reduce or eliminate the observed performance improvements.

An additional limitation is that the study does not report the distribution of scaling coefficients, leverage levels, maximum portfolio exposure or peak scaling weights generated by the volatility-management rule. Because no leverage constraints or exposure caps were imposed, the strategy may at times generate substantial variation in factor exposure as estimated volatility changes. Although the volatility of managed and unmanaged series is matched through the calibration procedure, the absence of reported leverage statistics limits the assessment of practical implementation risk. Future research could examine leverage dynamics, exposure distributions, turnover characteristics and exposure limits in greater detail. Although the volatility of managed and unmanaged factor series is matched through the calibration procedure, exposure can vary over time as a function of estimated volatility. Future research could examine leverage dynamics, turnover characteristics and exposure limits in greater detail.

A further limitation is that the analysis focuses on descriptive performance comparisons and does not formally test statistical significance through confidence intervals, p-values, or multiple-testing adjustments. Future research could extend the framework by incorporating formal inferential procedures to assess the statistical robustness of the observed performance differences.

While this study provides valuable insights into the role of volatility management in enhancing the risk–return profile of factor investing strategies, several avenues remain open for future exploration. First, subsequent research could incorporate real-world implementation costs, such as transaction fees, bid–ask spreads, and market impact (Barroso & Detzel, 2021), to assess the net performance of volatility-managed strategies under realistic trading conditions. This would provide a more accurate picture of their practical viability, particularly for high-turnover factors like *momentum*.

Second, expanding the analysis to include a broader range of asset classes (e.g., fixed income, commodities, or currencies) and geographic regions, especially emerging and frontier markets, could test the robustness and generalisability of the findings. Additionally, future studies might explore alternative volatility-estimation techniques, such as adaptive or regime-switching models, to determine whether more dynamic approaches can improve the consistency of volatility management across different factors. Finally, investigating the interaction between volatility management and other portfolio construction techniques, such as factor timing, machine learning-based allocation, or risk-parity frameworks, could yield further insights into how best to integrate volatility targeting within modern investment strategies.

Author Contributions: Conceptualization, N.J.P.R., R.J.P.C. and F.S.; methodology, N.J.P.R. and R.J.P.C.; formal analysis, R.J.P.C.; investigation, N.J.P.R. and R.J.P.C.; writing—original draft prepara-

tion, N.J.P.R. and R.J.P.C.; writing—review and editing, N.J.P.R. and F.S.; supervision, N.J.P.R. and F.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by national funds through FCT—Fundação para a Ciência e a Tecnologia, I.P., under Programme Contract UID/05105/2025, <https://sciproj.ptcris.pt/177079UID> (accessed on 9 September 2026).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data analysed in this study are publicly available from the Kenneth R. French Data Library. The analytical workbooks may be made available by the corresponding author upon reasonable request.

Acknowledgments: During the preparation of this manuscript, the authors used Microsoft Copilot365 version 2608 to assist with data organisation, summarisation and manuscript formatting. The authors reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

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