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APPLICATION OF VOLATILITY-MANAGED PORTFOLIOS IN THE CONTEXT OF A VOLATILITY INDEX

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Abstract

This paper studies the volatility-managed portfolios of Moreira and Muir (2017) and analyses whether the volatility-management trading strategy provides a large utility gain for mean-variance investors for the CBOE Volatility Index (VIX) across multiple equity factors. Upon direct comparison, we document that the volatility-managed scaled factor earns higher returns compared to its original unscaled counterpart. The results from our in-sample spanning regression supports the above findings indicating that volatility-managed factors outperform the original factor by extending the mean-variance frontier even after controlling for additional factors. This result is significant in particular with the volatility-managed momentum factor. The ex-post optimization parameters also suggest a positive Sharpe ratio and CER percent (Certainty Equivalent Return) across equity factors.

Keywords: *Volatility managed portfolio, Volatility index, Momentum, risk, return, mean-variance, Fama-French factor, alpha,* Appraisal Ratio

JEL Codes: *G10, G11, G12*

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INTRODUCTION

The relationship between return and risk is crucial in modern finance (Janani *et. al.*, 2022). While traditional finance often suggests that high risk could yield high returns, evidence from the world equity markets present a different relationship (Saraf and Kayal, 2023). Many investors believe that there exists a negative correlation between returns and volatility. This relationship results in the tendency to produce negative equity returns when volatility is high. Optimal portfolio choice trades off these risks with a potential of returns (Ang, 2014). Similarly, while past volatility predicts near-term future volatility, past returns fail to predict future returns. As a result, there have been multiple studies with respect to strategic trading among investors for better asset management. Many factor strategies (market, size, value etc.) have the potential to beat the market. In particular, momentum (Jegaeesh and Titman, 1993; Barroso and Santa-Clara, 2015) and betting-against-beta (Barroso and Maio, 2016) provide strong empirical performances across multiple trading strategies. To determine the right factor for efficient asset management, it is pertinent to ask how effective can rational investors weather hard times relative to an average investor. Answering this question could assist investors to reap long-run factor premium by embracing risk that loses money during bad times but makes up for it the rest of the time with high rewards (Ang, 2014).

Managed portfolios show more potential for diversification as supposed to the market portfolio. While evaluating the performance of such portfolios, studies suggest stripping those areas of performance that were achieved through simple strategies (Hanke *et. al.*, 2019). Risk-scaling strategies adjust the risk exposure towards an underlying portfolio scale down exposure when volatility is high and takes a more aggressive position when volatility is low. The weak correlation between future returns and volatility is largely responsible for the benefits investors receive from managed strategies (Kim, 2021).

Several recent studies show that volatility-managed trading strategies increase utility of investors by producing significant and positive alphas (Moreira and Muir, 2017; Cederburg *et. al.*, 2020; Barroso and Santa Clara, 2015). Volatility-managed trading strategies constructed by Moreira and Muir (2017) are based on the previous month's returns that can decrease portfolio risk exposure when variance is high. These strategies are typically characterized by taking conservative positions in the underlying factors when volatility was high and more aggressively levered positions when volatility was recently low (Wang and Yan, 2021). This is counter to most theories that suggest investors' willingness to take risks at periods of high market volatility must be high. Volatility-management reduce risk during volatile times when the convention is to increase risk-taking or hold it constant. There exists a spillover of volatility where portfolios that are volatile in the previous months are likely to be volatile in the current month, but this relationship is not significant with respect to returns. As a result, in the short run, variance is highly forecastable while returns are only weakly related. Consequently, mean-variance investors try to time volatility based on short time horizons by taking more risk when volatility is low. As a result, there is a 65 percent increase in utility for an investor investing only in the market portfolio through volatility timing (Moreira and Muir, 2017). However, Cederburg *et. al.* (2020) extend the study of Moreira and Muir (2017) and assess the real-time implications of volatility management with a total of 103 equity trading strategies. They report positive spanning regression alphas for volatility-managed portfolios from the in-sample test which extends the mean-variance frontier. In order to understand if rational investors can capture economic gains from these resulting alphas, an out-of-sample test is estimated based on the combinations of the original and the volatility-managed factors. The out-of-sample test confirms that this particular trading strategy does not improve real-time performance except in the case of the momentum strategy. Investors are however required to combine the original and volatility-managed portfolios using ex-post optimal weights (Cederburg *et. al.*, 2020; Kang and Kwong, 2021; Barroso and Santa-Clara, 2015).

They also appreciate the success of the volatility management strategies of Moreira and Muir (2017) and the attention from investors towards the real-time implications by referring to the press in the Financial Times on the 9th of March, 2016 (See Footnote 2 of Cederburg *et. al.*, (2020)).

This work aims to extend the literature on volatility management in the CBOE Volatility Index (VIX) and analyse whether the trading strategy proposed by Moreira and Muir (2017) can in fact lead to large utility gains for mean-variance investors. As the VIX measures the level of stress in the stock market, many investors time their investments based on the movement of VIX. For this, we examine the volatility management of market (MKT), size (SMB) and value (HML) factors from the Fama and French (1993) three-factor model, profitability (RMW), investment (CMA) and momentum (MOM) from the Fama and French (2015) five-factor model, profitability (ROE) and investment (IA) factors from Hou *et. al.* (2015) and betting-against beta factor (BAB) of Frazzini and Pedersen (2015). We document the direct comparison between the original and the volatility-managed factor (Table 1). Consistent with past studies (Cederburg *et. al.*, 2020; Kang and Kwong, 2021), our results indicate that the volatility-managed factors outperform the original factors and provide utility gains by extending the mean-variance frontier.

We follow Moreira and Muir (2017) and construct the in-sample spanning regression (Table 2) between the original (unscaled) and the volatility-managed (scaled) factor across the nine equity factors analysed by Cederburg *et. al.* (2020). We analyse if volatility management significantly extends the mean-variance frontier and provides utility gains. Upon comparing the original and the volatility-managed factor, we document that the volatility-managed MOM, BAB and ROE factors show a significant positive difference by outperforming the original factor. We confirm the positive spanning regression alphas for the volatility-managed portfolios as reported by Moreira and Muir (2017). Our In-sample test result suggests that the MKT and MOM factors generate improvement from volatility management. The volatility-managed MOM factor in particular reports significant alpha and Appraisal Ratio. This result of MOM strategies showing significant benefits by applying volatility-management was also reported by Cederburg *et. al.* (2020).

The volatility-management strategies constructed based on Moreira and Muir (2017) are possible in real-time, the spanning regression however is not. This is largely due to the fact that optimal weighing of the volatility-managed and original factor depends on the in-sample returns moments, the required strategy, however, is not known prior to the end of the sample. To address the above issue, we follow the standard approach and construct ex-post optimization parameters for the mean-variance investor (Cederburg *et. al.*, 2020). The optimization parameters have no fixed range for the relative weights of the volatility-managed factors and the ex-post optimal weights. This is consistent with Cederburg *et. al.* (2020) and Kang and Kwong (2021) suggesting that no fixed trading rule is available for equity factors. We also report positive Sharpe ratio and CER percent combination strategies across the equity factors analysed. Additional control for the Fama and French (1993) three-factor model provides robustness to the study.

This paper proceeds as follows – next we review the existing literature on volatility-managed portfolios. Then we introduce the data used in our study and the construction of the volatility-managed portfolio. Afterward we report the Empirical Results and in last, we provide the concluding remarks.

REVIEW OF LITERATURE

The economic literature on the volatility-managed portfolio is thin. The seminal paper on volatility-management scales monthly returns by the inverse of their previous month's realized variance. This strategy provides positive alpha across multiple asset pricing factors (market, value, size, momentum) which implies large utility gains for mean-variance investors. Volatility-management trading strategies are also considered systematically beneficial for investors and also have real-time implications (Moreira and Muir, 2017). Based on the empirical success of volatility management reported by Moreira and Muir (2017), several studies (Cederburg *et. al.*, 2020; Kang and Kwong, 2021; Barroso and Detzel, 2018; DeMiguel *et. al.*, 2021; Waholm, 2019) extend the literature. These studies might lead to the impression that volatility-management could only provide large utility gains theoretically, but there are important real-time implications of volatility-management trading strategies for investors.

Although recent studies show strong evidence of in-sample benefits of volatility management of popular trading strategies based on the positive alphas of the spanning regression, it requires investors to take a combination of the volatility-managed and original factor using the ex-post optimal weights of the portfolio. This largely constitutes the reason why volatility-managed trading strategies are not implementable in real-time (Cederburg *et. al.*, 2020; Kang and Kwong, 2021). The spanning regression estimated does not evaluate the future performance of volatility-managed factors against the original factor. Therefore, Cederburg *et. al.* (2020) insist that structural breaks are the cause of the weak out-of-sample performance of combination strategies. These results were further supported by the in-sample test of Kang and Kwong (2021) on the commodity futures market suggesting that volatility management provides utility gains, particularly in the 12-month market and momentum portfolios. The out-of-sample test, however, fails to provide a better volatility-managed Sharpe ratio as compared to the original counterpart. As a result, the in-sample test is not applicable for real-time investors in the commodity futures market. In order to increase the validity of Moreira and Muir (2017), Waholm (2019) implemented volatility management in the Norwegian market. Most of the alphas are positive and significant (other than the value factor) with the volatility managed market factor generating an alpha of 4.49 implying substantial utility gains. In order to avoid skewness in the results, optimal mean-variance portfolios were created and tested against Fama and French (1993) three-factor model which also provided positive and significant alphas.

Contrary to Moreira and Muir (2017), Several studies differ in analysing volatility management. The benefits to investors occur as volatility is persistent from month to month and is weekly related to future returns. As a result, contrary to rational models, the price of risk declines at times of high volatility. This included sorting stocks on the basis of low, medium and high Limits to Arbitrage (LTA) in order to compare the volatility management across these groups. As a result, abnormal returns are significant when arbitrage is fairly easy and market liquidity is high. The economic benefits of volatility management are largely significant only in low LTA stocks (Barroso and Detzel, 2018). While previous literature on volatility management focuses on total volatility, Wang and Yan (2021) take into account the nine-equity factors assessed by Cederburg *et. al.* (2020) and construct downside volatility-managed strategies based on unconditional average returns. When compared to the spanning regression of Moreira and Muir (2017), the downside volatility-management reports significantly high alphas for six out of the eight factors assessed. It is also reported that adding the downside volatility-management factor to the combination strategy of Moreira and Muir (2017), further increases the Sharpe ratio. The conditional multifactor portfolio of DeMiguel *et. al.* (2021) which uses the market volatility as the conditional variable significantly outperforms the unconditional portfolio in terms of the Sharpe ratio. While the works of Moreira and Muir (2017) and Cederburg *et. al.* (2020) the original and the volatility-managed portfolio or a multiple factor portfolio where the weights are constant with volatility, the conditional multifactor portfolio on contrary allows the weights on the individual factors to be dynamic with market volatility.

The Momentum factor in general is special when looking at factor investing. Despite the fact that momentum offers the highest Sharpe ratios across multiple asset pricing factors, these high returns fail to compensate for the risk investors take. In fact, there exists a negative correlation between the market and momentum. Managing such risk could translate into substantial economic gains and an improved Sharpe ratio. As a result, Barroso and Santa Clara (2015) develop a technique to scale long-short portfolios of the previous six months by their realized volatility in order to manage the risk spill over from the momentum strategy. Results suggested an increase in the Sharpe ratio from 0.53 for the unscaled momentum to 0.97 for the scaled version and a reduction in cash risk for the scaled momentum. In general, high volatility causes a negative return for the momentum factor. In order to understand the impact of such crashes, Daniel and Moskowitz (2016) suggest crashes occur when the markets have fallen and the ex-ante measures of volatility are significantly high. This is typical because of the weak performance of the momentum factor when assets are either overpriced or under-priced.

The VIX measures expected volatility instead of realized volatility. An increase (decrease) in expected return will cause the investors to demand a higher (lower) rate of return from the stock. This accounts for the reason for the spike in the VIX when markets are unstable. Despite these arguments, a question that arises is how well does the VIX perform? To answer this question, Whaley (2009) performs an experiment where the level of VIX was recorded at the beginning of each month of their sample period along with its expected ranges. Upon computing the return of the S and P 500 index and identifying when returns fell outside the range of the specified sample period, results suggested that VIX is a good predictor of expected stock index moments. While a significant number of literatures empirically show that volatility is weakly correlated to future returns (Ang, 2014; Kim, 2021; Barroso and Detzel, 2018), the aggregate market volatility (VIX) also plays a role in further explaining this relationship. In essence, an increase (decrease) in VIX tends to be followed by a negative (positive) relationship between future returns and idiosyncratic volatility (Qadan *et. al.*, 2018). In order to study the relationship between the VIX and stock market returns, Wang (2019) constructs different sizes of the VIX and stock returns of the G20. The in-sample result shows that VIX and a large component cause high volatility in the stock market. Larger the size of the VIX, the better the accuracy of the forecast of VIX. The VIX remains as a reliable tool for real-time investors to build strategies. For instance, investors typically de-leverage their position in order to reduce the impact of stock-loss when volatility increases.

DATA AND METHODOLOGY

In this section, we introduce the data used in the study and explain the construction of the volatility-managed portfolios.

Data Description

We consider the equity factors analyzed by Cederburg *et. al.* (2020) by collecting monthly data in order to examine the volatility management of market (MKT), size (SMB) and value (HML) factors from the Fama and French (1993) three-factor model, profitability (RMW), investment (CMA) and momentum (MOM) from the Fama and French (2015) five-factor model, profitability (ROE) and investment (IA) factors from Hou *et. al.* (2015) and betting-against beta factor (BAB) of Frazzini and Pedersen (2015). Additionally, we also collect monthly data on the CBOE Volatility Index (VIX). The time period of the study is between January 1990 and March 2022 which covers periods of economic instability as well. We summarize our findings of the volatility-managed (scaled) and original (unscaled) factors in Table 1.

Construction of Volatility-Managed Portfolios

There exist several studies that use different methodologies in the construction of the volatility-managed portfolios (See Footnote 7 of Cederburg *et. al.*, (2020)). We construct the volatility–managed portfolios based on Moreira and Muir (2017) which is given by –

$$f_{\sigma,t} = \frac{c^*}{\dot{\sigma}_{t-1}^2} f_t \tag{1}$$

Where c* is a constant such that the variance of $f_{\sigma,t}$ and f_t are the same, $\dot{\sigma}_{t-1}^2$ is the expected market volatility for month t-1. This expected market volatility in constructing the volatility-managed portfolio is different from that considered by Cederburg *et. al.* (2020).

The scaling factor S_t that is defined as $c^*/\dot{\sigma}_{t-1}^2$. When we plot S_t plotted across time t, we find how much we leverage our payoff in order to invest in the volatility-managed portfolios at month t-1 (Moreira and Muir, 2017).

EMPIRICAL RESULTS

Direct Comparison

Recent studies have shown volatility management strategies significantly outperform the unmanaged counterpart (Cederburg *et. al.*, 2020; Kang and Kwong, 2021). Specifically, with the MOM factor, Barroso and Santa-Clara (2015) compares the Sharpe ratios of scaled and unscaled versions. Similar results with the volatility-managed MOM factor were also reported by Cederburg *et. al.* (2020) and Kang and Kwong (2021). We follow Cederburg *et. al.* (2020) and focus on the direct comparison in terms of performance between the volatility-managed (scaled) factor and the original (unscaled) factor.

We present our findings of the direct comparison in Table 1. Panel A provides the Mean, Standard deviation and Sharpe ratio of the original factor and Panel B provides for the volatility-managed factors. It is to be noted that the standard deviation of the scaled and unscaled factors is the same by construction. Both the scaled and unscaled factors provide positive average returns across all the equity factors. The scaled factor however earns a higher return upon comparision with its unscaled counterpart across eight equity factors assessed. The unscaled factor provides a higher average return only in the case of SMB. Panel C provides the difference in the Sharpe ratio between the volatility-managed (scaled) and original (unscaled) factor. The Sharpe ratio difference remains positive across all factors except in the case of SMB and IA. We also report that the volatility-managed MOM, BAB and ROE factors show a significant positive difference by outperforming the original factor by 2.34 percent, 2.813 percent and 2.267 percent respectively per year. Consistent with previous literature, our findings specify the advantage of volatility-management of MOM (Jegaeesh and Titman, 1993; Barroso and Santa-Clara, 2015) and BAB (Barroso and Maio, 2016). It is to be noted that the volatility-managed Sharpe ratio of MOM exceeds that of the MKT, SMB and HML of the Fama and French (1993) three-factor model. We also observe that our findings in the direct comparision are consistent with Cederburg *et. al.* (2020) and Barroso and Santa-Clara (2015).

Panel D provides the properties of the volatility-managed (scaled) factor. When constructing the volatility-management trading strategy, we use the expected market volatility. As a result, the correlation coefficient between the volatility-managed and the original factors is stronger than that reported by Cederburg *et. al.* (2020). The distribution of scaled factor's implied weights on its unscaled counterpart shows differences from that reported by Cederburg *et. al.* (2020). Our results show that the median position (p_{50}) tends to be slightly greater than one, ranging between 1.051 and 1.227 and the 99th percentile (p_{99}) ranges between 1.774 and 2.075. This difference in the results of the 99th percentile reported by Cederburg *et. al.* (2020) implies that volatility management for the CBOE VIX takes smaller leverage even in extreme cases. These differences in the distribution of weights suggest that volatility management does not change the exposure to the original factor largely over time.

Table 1: Volatility-Managed (scaled) and Original (unscaled) Factors

	MKT	SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
Panel A: Original factors									
Mean	8.874	1.301	1.615	32.219	4.372	2.640	5.568	2.234	9.967
SD	4.301	3.166	3.218	2.299	2.631	2.075	2.930	2.063	2.706
SR	0.167	0.026	0.035	1.158	0.129	0.097	0.156	0.080	0.299
Panel B: Volatility-managed factors									
Mean	10.019	0.616	2.852	34.559	4.907	2.622	7.835	2.229	12.780
SD	4.301	3.166	3.218	2.299	2.631	2.075	2.930	2.063	2.706
SR	0.189	0.009	0.067	1.243	0.146	0.098	0.223	0.079	0.386
Panel C: Sharpe ratio difference									
Diff	0.022	-0.017	0.032	0.084	0.016	0.001	0.066	-0.001	0.086
Panel D: Properties of volatility-managed factors									
Corr	0.928	0.954	0.945	0.862	0.962	0.954	0.941	0.949	0.933
$p_{01}(c^*/\dot{\sigma}_{t-1}^2)$	0.465	0.429	0.433	0.459	0.436	0.406	0.455	0.399	0.389
$p_{50}(c^*/\dot{\sigma}_{t-1}^2)$	1.227	1.106	1.117	1.206	1.176	1.094	1.225	1.075	1.051
$p_{99}(c^*/\dot{\sigma}_{t-1}^2)$	2.028	1.858	1.877	1.994	1.981	1.844	2.075	1.821	1.774

Note: The above table provides a direct comparison between the volatility-managed (scaled) and the original (unscaled) factor. Panel A and B compares the mean, standard deviation (SD) and the annualized Sharpe ratio (SR) of the unscaled and scaled factors respectively. Panel C compares the difference in Sharpe ratio (SR) between the scaled and unscaled factors. Panel D shows the correlation coefficient (Corr) between the scaled and unscaled factor along with the percentiles (1^{st}, 50^{th} and 99^{th}) of the time series distribution of the implied weights of the scaled factor on the unscaled counterpart.

Optimal Portfolio

Moreira and Muir (2017) empirically show that the volatility-management trading strategies are more valuable when combined with the original factor as supposed to a stand-alone portfolio. We construct the spanning regression and combination strategies between the original and the volatility-managed factor and report the results of the in-sample test.

Spanning Regression and Combination Strategies

Moreira and Muir (2017) suggest that volatility management is more valuable when combined with the original portfolio. Both Moreira and Muir (2017) and Cederburg *et. al.* (2020) show that volatility-management trading strategies increase the Sharpe ratio of eight popular equity strategies (Kang and Kwong, 2021). The findings presented by Moreira and Muir (2017) are particularly interesting since they show that the volatility-management is not restricted to a particular strategy. In order to show the success of such trading strategies, Moreira and Muir (2017) estimate the spanning regression. They evaluate the performance of the volatility-managed factors by estimating time-series regression of the form-

$$f_{\sigma,t} = \alpha + \beta f_t + \varepsilon_t \tag{2}$$

The spanning regression focuses on the α is estimated to be positive and statistically significant across multiple asset pricing factors (Moreira and Muir, 2017; Cederburg *et. al.*, 2020). A positive intercept suggests that the volatility-managed factor outperforms its original counterpart. It is also the optimal ex-post combination of the volatility-managed and original portfolio. As a result, investors' mean-variance frontier expands by taking a combination of the scaled and unscaled factors. An increase in the Sharpe ratio and utility gains can also be obtained by taking the combination as supposed to volatility-managed portfolio alone. (Cederburg *et. al.*, 2020; Kang and Kwong, 2021).

The vector for the ex-post optimal weights on volatility-managed (x_σ^*) and original factor (x^*) of investors is given by –

$$a = \begin{bmatrix} x_\sigma^* \\ x^* \end{bmatrix} = \frac{1}{\gamma} \hat{\Sigma}^{-1} \hat{\mu} \tag{3}$$

Where $\hat{\mu}$ is the excess return vector, $\hat{\Sigma}$ is the variance-covariance matrix and γ is the risk aversion parameter. Mean-variance investors invest in the combination of the volatility-managed (scaled) and its unscaled counterpart and as a result have to be the optimal weight of distribution between the two which is given by –

$$\begin{bmatrix} w_\sigma^* \\ w^* \end{bmatrix} = \frac{\hat{\Sigma}^{-1} \hat{\mu}}{|1_2^T \hat{\Sigma}^{-1} \widehat{\mu}|} \tag{4}$$

Where 1_2 is a 2 x 1 unit vector. The risk aversion is mainly responsible for the weight investors assign to the original and volatility-managed assets. Expanding on this, the optimal allocation of volatility-managed factors can be defined as –

$$x_\sigma^* = \frac{\hat{\alpha}}{\gamma\, \dot{\sigma}_f^2 (1 - \hat{p}^2)} \tag{5}$$

Where $\hat{\alpha}$ is the spanning regression intercept, $\dot{\sigma}_f^2$ is the unconditional variance of the original unscaled factor and $\hat{p}$ is the correlation coefficient between the volatility-managed (scaled) and original (unscaled) factor. It is important to note that volatility-managed factors report positive weights only when there exists a positive spanning regression alpha. Upon combining the above equations with the volatility-managed factor (Eq 1), the dynamic investment rule can be defined as –

$$y_t^* = x_\sigma^* \left(\frac{c^*}{\dot{\sigma}_{t-1}^2} \right) + x^* \tag{6}$$

Where y_t^* is the position on the original factor at month t. Investors allocate weights to the volatility-managed (scaled) factor (x_σ^*) and the original (unscaled) factor (x^*) (Cederburg *et. al.*, 2020).

In-Sample Test

We report the results from the spanning regression of Moreira and Muir (2017) for the nine equity factors analysed in Table 2. Panel A estimates the result of the regression of volatility-managed (scaled) factors on the original (unscaled) counterpart. Consistent with past literature, we report that volatility management generates positive alpha relative to its unscaled counterpart for eight of the nine equity factors. The volatility-managed MKT, HML, MOM, ROE and BAB provide positive and statistically significant alphas with the highest being reported by MOM (Moreira and Muir, 2017; Cederburg *et. al.*, 2020). These results are similar to our findings from the direct comparison reported in Table 1. We report the Appraisal Ratio (AR) which measures how much volatility management extends the slope of the mean-variance frontier. We find that the volatility-managed MOM factor generates a higher Sharpe ratio as compared to the original MOM. The alpha and the AR of the volatility-managed MOM factor are reported as 6.947 percent with the t-statistics at 6.272 and 1.718 respectively suggesting potentially large utility gains for mean-variance investors. We also find that the volatility-managed MKT presents positive α but the value is smaller compared to MOM at 1.779 percent with t-statistics of 1.737. As a result, we confirm the in-sample success of volatility management consistent with the literature (Moreira and Muir, 2017; Cederburg *et. al.*, 2020; Kang and Kwong, 2021).

Panel B specifies the ex-post optimization parameters as defined in Equations (3) and (5). We report the scaling parameter (c^*) of the volatility-managed (scaled) portfolios. The optimal MOM portfolio requires relative weights of 81.4 percent and 18.6 percent in the volatility-managed and original factors respectively. Motivated by Kang and Kwong (2021), the sign observed in the spanning regression alpha is consistent with the signs of the optimal relative weights. The relative weights of the volatility-managed factors range between -10 percent and 95 percent implying that there exists no fixed trading rule across the equity factors. We can also extend this argument to the ex-post optimal weights of volatility-managed (x_σ^*) and original factor (x^*) which ranges between 12.2 percent and 109.4 percent (Cederburg *et. al.*, 2020; Kang and Kwong, 2021).

Panel C documents that the Sharpe ratio of combination strategies is greater than that of the original strategy with the highest difference of 1.263 being observed in the MOM factor. The IA factor also reports a fairly high difference in Sharpe ratio of 0.099. Based on the risk-aversion parameter set, we report the positive difference in the CER percent across all the nine equity factors analysed. The CER percent for the volatility-managed MOM factor is the highest at 8.116 percent compared to the original counterpart of 6.230 percent.

Table 2: Spanning Regression and In-Sample Test

	MKT	SMB	HML	MOM	RMW	CMA	ROE	IA	BAB
Panel A: Spanning regression									
α	1.779 (1.737)	-0.630 (-1.089)	1.325 (2.088)	6.947 (6.272)	0.695 (1.566)	0.102 (0.267)	2.591 (4.364)	0.107 (0.270)	3.472 (5.587)
β	11.141	11.497	11.343	10.349	11.557	11.544	11.299	11.396	11.206
R^2	0.861	0.911	0.894	0.743	0.925	0.911	0.886	0.901	0.871
AR	0.320	-0.192	0.427	1.718	0.278	0.047	0.782	0.423	1.033
Panel B: Ex-post optimization parameters									
c^*	21.130	19.365	19.556	20.782	20.588	19.020	21.556	18.920	18.430
$x_\sigma^* + x^*$	0.530	0.122	0.261	1.884	0.802	0.589	0.692	0.404	1.094
Relative weights									
w_σ^*	0.679	-0.105	0.368	0.814	0.569	0.081	0.953	0.423	0.504
w^*	0.321	1.105	0.632	0.186	0.431	0.919	0.047	0.577	0.496
Panel C: Portfolio performance									
Sharpe ratio									
Original	0.167	0.026	0.035	1.158	0.129	0.097	0.156	0.080	0.299
Combination	0.376	0.055	0.122	2.421	0.295	0.215	0.399	0.179	0.705
Difference	0.209	0.029	0.087	1.263	0.166	0.118	0.243	0.099	0.404
CER (percent)									
Original	1.496	1.027	1.661	6.230	2.409	2.531	2.764	2.399	2.441
Combination	2.635	1.204	1.906	8.116	2.751	2.906	2.462	2.761	2.749
Difference	1.139	0.177	0.245	1.885	0.342	0.375	0.302	0.362	0.308
Panel D: Additional control for Fama and French (1993) three factor model									
α	2.048 (2.016)	-0.469 (-0.798)	1.734 (2.636)	34.480 (23.634)	6.123 (4.579)	3.092 (3.200)	9.915 (6.451)	2.787 (2.838)	13.745 (8.293)
R^2	0.864	0.911	0.895	0.742	0.333	0.446	0.243	0.418	0.032
AR	0.373	-0.143	0.480	4.309	0.821	0.573	1.161	0.511	1.490

Note: The above table reports the in-sample results of volatility-management. Panel A presents the results of the spanning regression of the volatility-managed (scaled) factor on the original (unscaled) factor. The number in the parenthesis are the t-statistics for the respective regressions. We also compute the adjusted R^2 and the Appraisal Ratio (AR). The results of the ex-post optimization are presented in Panel B. This includes the scaling parameter (c^*), the ex-post optimal weights of the volatility-managed and original factor ($x_\sigma^* + x^*$) and the ex-post optimal relative weights of the scaled (w_σ^*) and unscaled (w^*). Panel C reports the Sharpe Ratio and the Certainty Equivalent Return (CER percent). The original strategy consists of the ex-post optimal combination of original factor and risk-free asset while the combination strategy consists of the ex-post optimal combination of original factor, volatility-managed factor and risk-free asset. Consistent with Cederburg *et. al.* (2020), we set the risk aversion parameter $\gamma = 5$. Panel D adds the Fama and French (1993) three-factors as additional controls for the spanning regression.

We perform a robustness check by controlling for the Fama and French (1993) three factor model and report our findings in Panel D of Table 1. Similar to the results reported in Panel A, the spanning regression alphas are positive across eight of the nine equity factors analyzed except in the case with the SMB factor. The main results of our in-sample test is that volatility-management trading strategies can provide utility gains by extending the mean-variance frontier for the in-sample portfolio (Moreira and Muir, 2017; Cederburg *et. al.*, 2020; Kang and Kwong, 2021).

CONCLUSION

This work investigates volatility-management across multiple equity factors. We construct volatility-managed portfolios of Moreira and Muir (2017) based on previous month's expected volatility and extend the literature of such trading strategies on the COBE Volatility Index (VIX). The direct comparison between the volatility-managed (scaled) and original (unscaled) factor suggest that volatility-management trading strategies outperform its original counterpart in eight of the nine equity strategies assessed. In particular, the Sharpe ratio of the volatility-managed MOM outperforms that of MKT, SMB and HML. This is consistent with previous literature (Moreira and Muir, 2017; Cederburg *et. al.*, 2020).

In addition to this, we perform the in-sample spanning regression and report that volatility-management trading strategies provide utility-gains to mean-variance investors by extending the mean-variance frontier. We observe that the volatility-managed MOM factor provides significant alpha and Sharpe ratio consistent with Cederburg *et. al.* (2020). The ex-post optimization parameters suggest no fixed trading rules across the equity factors analysed. We also document positive difference between the combination and original strategies of SR and CER percent. Despite such strong performance of volatility-management in-sample, many studies (Cederburg *et. al.*, 2020; Kang and Kwong, 2021) question the real-time performance of volatility-management trading strategies and report poor out-of-sample performances.

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