VIX-managed portfolios

Miloš Božović*

University of Belgrade, Faculty of Economics and Business

Abstract

We propose a simple portfolio management strategy that gauges the leverage based on the observed implied volatility index (VIX). The strategy involves taking less risk when the cumulative previous-month VIX is high and more when it is low. We show that the strategy yields more stable weights and thus requires less rebalancing than comparable strategies based on realized volatility. As a result, it produces substantially higher spanning regression alphas when transaction costs are taken into account. We document this for ten equity factors, six classes of mean-variance efficient portfolios and 176 anomaly portfolios. We argue that the superior performance of the VIX-based strategy is driven by its ability to time volatility and tail risk simultaneously, resulting from the forward-looking nature of the information entailed in the index and the higher-order return moments embedded in the implied volatility smile.

Keywords: implied volatility; downside variance; transaction costs; volatility timing; tail risk

JEL classification: G11, G12

*Email: `milos.bozovic@ekof.bg.ac.rs`

1 Introduction

Short-term predictability of returns is elusive, but volatility is highly persistent. Simple portfolio management strategies that involve scaling the original exposures inversely by some measure of current risk improve the risk-adjusted performance for investors (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Moreira and Muir, 2017; Liu et al., 2019; Cederburg et al., 2020; Eisdorfer and Misirli, 2020; Barroso and Detzel, 2021; Wang and Yan, 2021). This straightforward approach has recently gained considerable traction among researchers.

Moreira and Muir (2017) show that investors can increase Sharpe ratios by scaling with realized variance. However, such a strategy may underperform out of the sample (Cederburg et al., 2020) or in the presence of realistic transaction costs (Barroso and Detzel, 2021). Some authors suggest that partial second moments contain valuable information about future volatility and returns (Barndorff-Nielsen et al., 2010; Feunou et al., 2011; Patton and Sheppard, 2015; Bollerslev et al., 2020; Atilgan et al., 2020). Wang and Yan (2021) show that portfolios scaled by downside volatility improve the risk-adjusted performance of strategies scaled by total volatility. Others explore the possibility of controlling for higher-order moments, such as conditional skewness (Bianchi et al., 2022) or a combination of skewness and downside volatility (Fernandes and Batista, 2023). Aside from (partial) return moments, additional signals have been used to create analogous timing strategies. These include variables derived from the principal components of a large set of equity factors (Haddad et al., 2020) or various macroeconomic indicators (Bass et al., 2017; Amenc et al., 2019; Bender et al., 2019; Gómez-Cram, 2022).

The unifying feature of these volatility timing strategies is that they rely on current but backward-looking risk measures. In this paper, we exploit the potential of implied volatility to capture risk. In particular, we use the Chicago Board Options Exchange's implied volatility index (VIX), which measures market expectation of stock return volatility implied from the supply and demand of S&P500 index options over the next 30 calendar days. Several reasons motivated this choice. In contrast to realized volatility, implied volatility is a forward-looking risk metric inferred from the trading activity of sophisticated option investors. VIX-based trading strategies are commonly used in practice for hedging, speculation and market timing (Nagel, 2012). VIX is a widely accepted measure of market sentiment (Whaley, 2000, 2009; Kaplanski and Levy, 2010; Da et al., 2014). It moves along with the business cycles, spiking in recessions and remaining relatively low during the anecdotal bubble periods in the US market (see Figure 1). VIX has predictive power for future returns of diversified portfolios and market indices (Giot, 2005; Banerjee et al., 2007; Chow et al., 2020). It is negatively correlated with contemporaneous returns and positively correlated with long-term future returns (Bekaert and Hoerova, 2014). Monthly adjustments to the S&P500 exposure in an equity/cash portfolio based on the prior month-end VIX quote not only smooth out the level of market risk over time but also produce a higher realized Sharpe ratio (Clarke et al., 2020). Holding sentiment-prone stocks when VIX is low and sentiment-immune stocks when VIX is high generates significantly higher excess returns than the benchmark long-short portfolios that do not condition on VIX (Ding et al., 2021). Finally, VIX has predictive power for higher-order moments and helps capture tail risk (Kelly and Jiang, 2014; Park, 2015; Wang and Yen, 2018; Li et al., 2023).

We propose a simple portfolio management strategy that gauges the leverage by scaling the original exposure with implied volatility. The strategy involves taking less risk when the squared sum of daily levels of VIX over the past month is high and vice-versa. We assess the performance of managed portfolio strategies compared to the original exposures using spanning regressions à la Moreira and Muir (2017) and directly compare their Sharpe ratios. Our test assets involve ten equity factors, six classes of mean-variance efficient portfolios

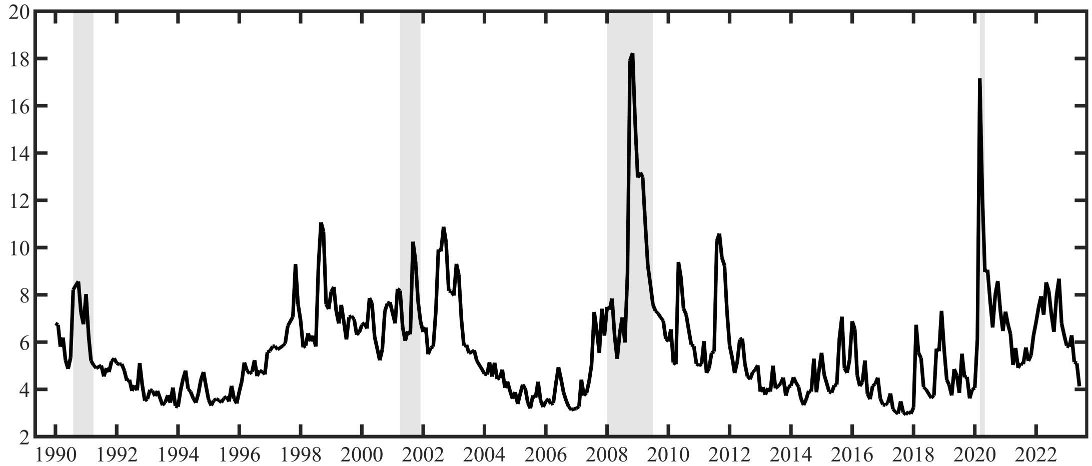

Figure 1: VIX and the business cycles. The figure shows the annualized previous-month VIX, in percent, calculated by aggregating the daily data between January 2, 1990, and June 20, 2023. The shaded bars indicate NBER recessions.

and 176 anomaly portfolios. We compare the VIX-based strategy with the analogous one that uses realized volatility (RV). Motivated by the success of downside risk measures suggested by Wang and Yan (2021), we also use the VIX and RV strategies with partial second moments, resulting in four competing strategies.

We show that VIX-based strategies provide a potential for investors' utility gains by timing both volatility and kurtosis. The former comes from the forward-looking nature of the information entailed in the implied volatility, and the latter from the short-term implied volatility smiles. Without trading frictions, VIX strategies display a better performance in spanning regressions than those based on realized (downside) volatility but fare only marginally better in terms of the Sharpe ratio improvements. However, VIX-based strategies produce more stable weights when we include transaction costs, leading to less intensive portfolio rebalancing than analogous RV-based strategies. The stability of weights likely originates from improved kurtosis timing, as it anticipates large return swings better. As a result, VIX-managed portfolios produce markedly higher after-cost alphas than RV counterparts.

This paper contributes to the growing literature on volatility-managed portfolios in several ways. First, to the best of our knowledge, this is the first study in which a universal volatility timing strategy is entirely built on an implied rather than realized volatility metric. Second, it introduces a simple way to scale with downside risk while relying on VIX. Third, the proposed strategies are implementable in real time, as they alleviate the problem of look-ahead bias in the scaling coefficients pointed out by Cederburg et al. (2020), which we achieve through dynamic scaling. We also test our strategies against dynamically efficient portfolios. Fourth, the paper critically assesses the robustness of the VIX-based management strategies to transaction costs. VIX-managed portfolios exhibit stability of weights over time and require less leverage than comparable RV strategies, which is crucial for any real-time strategy aimed to produce a significant net profit. Fifth, VIX strategies simultaneously provide a natural market-based mechanism for timing volatility *and* tail risk.

The remainder of the paper is organized as follows. In Section 2, we describe the data and the methodology used for the construction of VIX-managed portfolios. In Section 3, we present the empirical results. Section 4 concludes.

2 Data and methodology

2.1 Data

Our portfolio management strategy is based on 8,431 daily observations of the CBOE implied volatility index (VIX) between January 2, 1990, and April 30, 2023. In addition, we use the returns on the underlying S&P500 index over the same observation period.

Both series are available from Refinitiv.

We use two groups of test assets. The first consists of ten equity factors used by Moreira and Muir (2017) and Wang and Yan (2021): the market (MKT), size (SMB), and value (HML) factors from Fama and French (1993), the profitability (RMW) and investment (CMA) factors from Fama and French (2015), the momentum (MOM) factor from Carhart (1997), the investment (IA) and profitability (ROE) factors from Hou et al. (2014), the expected growth (EG) factor from Hou et al. (2020) and the betting-against-beta factor (BAB) from Frazzini and Pedersen (2014). Data on MKT, SMB, HML, RMW, CMA and MOM are from Kenneth French's website. Data on IA, ROE and EG are from Hou-Xue-Zhang *q*-factors data library. Data on BAB are from Andrea Frazzini's website. We use daily and monthly data covering the same period as our VIX series, i.e., between January 1990 and April 2023.

The ten equity factors represent a set of proxies for actual sources of non-diversifiable risk. As such, they are valuable benchmarks in asset pricing models. However, these factors cannot adequately capture many anomalies (see, for instance, Kozak et al., 2020). Therefore, we use another group of test assets consisting of a comprehensive panel of anomaly portfolios from Chen and Zimmermann (2022). The data on 207 anomaly portfolios are available from the Open Source Asset Pricing website. The sample period varies across the portfolios from June 1926 to December 2021. This approach is similar to Cederburg et al. (2020) and Wang and Yan (2021), who use 94 anomaly portfolios. As with the ten equity factors, we use daily and monthly data that continuously overlap with the respective VIX series. The resulting sample contains 176 surviving portfolios.

2.2 Portfolio formation

We form the managed portfolios by changing the risk exposure to the original buy-and-hold portfolio based on variations in some measure of conditional variance. Specifically, for each month t, the next-month excess return on the managed portfolio, f_{t+1}^{σ}, is constructed as:

$$f_{t+1}^{\sigma} = w_t f_{t+1}, \tag{1}$$

where f_t is the original excess return of the portfolio. The weight

$$w_t = \frac{c_t}{\widehat{\sigma}_t^2} \tag{2}$$

varies reciprocally to the original portfolio's conditional variance proxy $\widehat{\sigma}_t^2$. Intuitively, if our risk measure increases in the current month t, we will decrease the exposure to our portfolio for the next month $t+1$, and vice-versa. Since we work with excess returns, the weights are unconstrained unless we impose leverage restrictions, such as those considered by Moreira and Muir (2017).

The scaling coefficient c_t is chosen such that the managed and the original portfolio have the same sample standard deviation calculated using only the information available at time t, i.e.,

$$\sum_{s=1}^{t} \left(f_s^{\sigma} - \overline{f^{\sigma}} \right)^2 = \sum_{s=1}^{t} \left(f_s - \overline{f} \right)^2, \tag{3}$$

where $\overline{f^{\sigma}}$ and $\overline{f}$ are the average excess returns calculated using the managed and unmanaged series that end in month t. We use the scaling condition (3) iteratively to obtain the scaling constant c_t for each month $t = t_{\min}+1, t_{\min}+2, \ldots, T$, where T is the length of the monthly series. We use $t_{\min} = 36$, i.e., burn in the first 36 months, to allow for enough observations to calculate the sample standard deviation. This type of scaling avoids the issue pointed out by Cederburg et al. (2020) of using ex-post optimal weights, which are not available to investors in real-time. The issue was raised since many prior studies scaled the excess returns by a constant obtained by fixing the full-sample unconditional variances of managed and optimal portfolios.

We construct four managed portfolios for each original portfolio we consider, using Equation (1) based on different proxies for the conditional variance $\widehat{\sigma}_t^2$. We use the following proxies:

1. Implied volatility (**"VIX-managed strategy"**), where

$$\widehat{\sigma}_t^2 = \frac{1}{12} \sum_{d \in t} \mathrm{VIX}_d^2, \tag{4}$$

   and VIX_d is the observed value of the CBOE implied volatility index on day d in month t. Given that the VIX data are annualized, but the excess returns are monthly, the 1/12 fraction in front of the sum in Equation (4) reconciles the scaling.

2. Implied volatility that captures downside risk (**"Downside VIX-managed strategy"**), in which

$$\widehat{\sigma}_t^2 = \frac{1}{12} \sum_{d \in t} \mathrm{VIX}_d^2 \; \mathbb{1}_{(\mathrm{SPX}_d < 0)}, \tag{5}$$

   where $\mathbb{1}_{(\cdot)}$ is the indicator function and SPX_d is the observed daily excess return on the S&P500 market index on day d in month t.

3. Realized volatility (**"RV-managed strategy"**), in which

$$\widehat{\sigma}_t^2 = \sum_{d \in t} \left(f_d - \overline{f}_t \right)^2, \tag{6}$$

where f_d is the observed return on the original portfolio on day d in month t, and

$$\overline{f}_t = \frac{1}{N_t} \sum_{d \in t} f_d$$

is the average of daily returns in month t in which there were N_t trading days.

4. Realized volatility that captures downside risk (**"Downside RV-managed strategy"**), where

$$\widehat{\sigma}_t^2 = \sum_{d \in t} \left(f_d - \overline{f}_t \right)^2 \mathbb{1}_{(f_d < 0)}. \tag{7}$$

If there are no negative daily excess returns in month t, we use the ordinary realized volatility for that month instead.

In strategies 1 and 2, we use VIX and the S&P500 index as the underlying asset, irrespective of the test portfolio. In contrast, in strategies 3 and 4, we calculate the realized (semi)variance using returns on the test portfolio. We do this for practical reasons, simplifying the implied-volatility-based strategies as much as possible. An obvious—albeit more tedious—alternative is to use the implied volatility of each asset in the test portfolio. However, this introduces the issue of insufficient trading liquidity of many option contracts and complicates the implementation immensely. Our rationale here is that by relying on VIX as a general measure of market sentiment, we should be able to capture the general highs and lows of any diversified portfolio.

2.3 Performance evaluation

We follow the approach of Moreira and Muir (2017) and run a time-series regression of the managed portfolio excess returns on their original counterparts:

$$f_t^{\sigma} = \alpha + \beta f_t + \varepsilon_t. \tag{8}$$

This regression is used to evaluate the performance of the managed portfolios. A significant positive intercept α indicates that volatility timing improves the risk-return relationship of the managed portfolio over the original buy-and-hold strategy. By using each conditional variance proxy defined by Equations (4)–(7) to obtain the managed portfolio excess return f_t^{σ}, we can compare the embedded strategies' ability to expand the mean-variance frontier.

We estimate the coefficients of the spanning regression given by Equation (8) for a broad set of test assets that represent mimicking portfolios to genuine systemic sources of risk or otherwise contribute to capturing economy-wide shocks. As described in Subsection 2.1, we use ten equity factors and 176 anomaly portfolios as individual test assets. However, Moreira and Muir (2017) argue that a single-factor volatility timing strategy may not necessarily improve the performance relative to the best buy-and-hold strategy for an investor with access to multiple factors. A more expansive investment universe for investors with different levels of sophistication can be achieved by extending the analysis to a multifactor setting, where the investors can time risk and gauge the leverage of a mean-variance efficient (MVE) portfolio. DeMiguel et al. (2021) show that volatility management of the multifactor portfolio weights outperforms the original multifactor portfolio, net of transaction costs, regardless of whether sentiment is high or low.

The original MVE portfolio excess return is simply a linear combination of factor excess returns $\mathbf{F}_{t+1}$:

$$f_{t+1}^{MVE} = \mathbf{b}_t' \mathbf{F}_{t+1}. \tag{9}$$

In Equation (9), $\mathbf{b}_t$ s the vector of in-sample Sharpe ratio-maximizing factor weights:

$$\mathbf{b}_t \propto \mathbf{V}_t^{-1} \boldsymbol{\mu}_t, \tag{10}$$

defined up to a scalar constant, where $\mathbf{V}_t$ and $\boldsymbol{\mu}_t$ are the sample covariance matrix and the sample mean for the set of factor excess returns using only their history available at time t. This MVE portfolio construction is dynamic and free from any look-ahead bias. It differs from the one with static weights that Moreira and Muir (2017) applied. In addition to the market excess return (MKT), we build six universes of factors, using the Fama and French (1993) three factors (FF3), the FF3 augmented by the Carhart (1997) momentum factor (MOM), the Fama and French (2015) five factors (FF5), the FF3 augmented by MOM, the Hou et al. (2014, 2020) three factors (HXZ), and the HXZ augmented by MOM. This set of factor universes represents a combination of the ones considered by Moreira and Muir (2017), Wang and Yan (2021) and Fernandes and Batista (2023).

We next construct the managed MVE portfolio excess return in analogy to Equation (1):

$$f_{t+1}^{MVE,\sigma} = w_t f_{t+1}^{MVE}, \tag{11}$$

applying the same principles for calculating the weight w_t and the scaling parameter as in the single-factor case. Finally, the spanning regression for the MVE portfolio is simply

$$f_t^{MVE,\sigma} = \alpha + \beta f_t^{MVE} + \varepsilon_t. \tag{12}$$

We assess the significance of each of the spanning regression intercepts α via the usual t-statistics, using the heteroskedasticity-consistent standard errors of Huber (1967) and White (1980). Given that the scaling condition is determined by Equation (3), the coefficient c_t for each management strategy will change over time, and the unconditional variances will not be the same for the managed and the original portfolios. Therefore, assessing the performance of strategies based on alphas alone is insufficient to infer conclusions about the relationship between their Sharpe ratios. We compare the Sharpe ratios of managed and original strategy, respectively, by calculating their difference:

$$\Delta = SR^{\sigma} - SR. \tag{13}$$

We test the statistical significance of this difference using the procedure of Wright et al. (2012). This test is more general than others commonly applied throughout the literature, as it allows testing for equality of multiple Sharpe ratios and only assumes that the excess returns are stationary and ergodic. It is not limited to pairwise tests, nor does it assume that returns have to be normally distributed (Jobson and Korkie, 1981; Memmel, 2003), it does not require a bootstrap procedure (Ledoit and Wolf, 2008), and the condition that the returns are independent and identically distributed is not necessary (Leung and Wong, 2008).

3 Results

3.1 Baseline results

Table 1 shows the results of spanning regressions for the ten equity factors. Across all four managed strategies (panels A through D), the alphas are positive and significant at a 5% level for MKT, MOM, ROE, EG and BAB factors.[1] MKT, MOM, ROE and BAB were also highly significant for the RV-managed strategy of Moreira and Muir (2017) and downside volatility-managed strategy of Wang and Yan (2021), while the EG was highly significant for similar strategies considered in Fernandes and Batista (2023). We do not find significant alphas for SMB, HML, RMW, CMA and IA, which may originate from a shorter

[1]For expositional brevity, we only show the results for univariate spanning regressions. The results obtained when controlling for Fama and French (1993) three factors, Carhart (1997) four factors and Fama and French (2015) five factors are available upon request. They do not provide any substantial qualitative changes to the results obtained in the univariate case. We treat the multivariate case through MVE portfolios (Tables 3 and 4), allowing a broader set of factors to be exploited more naturally.

sample used in this paper. Thus, all managed strategies show promising profit potential for at least five factors relative to their unmanaged versions. There is a subtle difference between the strategies, however. When alphas are significant, they exhibit slightly higher numerical values for VIX- and downside VIX-managed portfolios than their corresponding RV counterparts. Irrespective of the significance of the intercepts, strategies that exploit VIX also provide a better fit in the spanning regressions, having markedly higher R^2s and lower root mean squared errors (RMSE). The combination of higher alphas and lower RMSE translates to higher annualized appraisal ratios of these strategies compared to the RV-based ones for MKT and BAB. We should expect the most considerable improvement in the Sharpe ratios for these two factors (cf. Table 2).

Figure 2 provides further intuition for the results in Table 1. Following our VIX-based management strategy, we sort time-series returns on five Fama-French factors (MKT, SMB, HML, RMW and CMA) and momentum (MOM). The sorts are based on the previous month's VIX, calculated from the daily VIX levels using Equation (4). They are then used to sort the following month's daily returns on each factor. We group them into quintiles, from months in which VIX was in the lowest historical fifth to months in which it was in the highest fifth of its values. The figure shows each factor's annualized average and standard deviation of next-month returns.

Unlike lagged realized volatility (Moreira and Muir, 2017), the lagged VIX is inversely related to the average return on the market portfolio (MKT), consistently with the findings of Bekaert and Hoerova (2014). On the other hand, sorting on lagged VIX displays no visible relationship with the average returns on the remaining five factors. However, for all factors, there is a strong relationship between lagged VIX and current volatility: high implied volatility of the S&P500 in the previous month is associated with high factor volatility. Therefore, VIX can be used for the volatility timing of any of the Fama-French factors and momentum, and in addition, it can time the return of the market portfolio.

Table 1: Spanning regressions for the ten equity factors. This table shows results from univariate spanning regressions, given by $f_t^\sigma = \alpha + \beta f_t + \varepsilon_t$, where f_t^σ is the monthly return for the managed factor, and f_t is the monthly return for the original factor. The managed strategies are based on implied volatility and realized volatility (RV). Panels A through D report the results for the managed strategy based on VIX, downside VIX, RV and realized downside RV, respectively. The reported alphas are in annualized percentage terms. The appraisal ratio is $\alpha/\sigma_\varepsilon$, where σ_ε is the root mean square error (RMSE). The sample period for all regressions is between 1990-01 and 2023-04. MKT, SMB and HML are from Fama and French (1993), RMW and CMA are from Fama and French (2015), MOM is from Carhart (1997), IA, ROE and EG are from Hou et al. (2014, 2020) and BAB is from Frazzini and Pedersen (2014). Numbers in parentheses are heteroskedasticity-consistent standard errors of Huber (1967) and White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	SMB	HML	RMW	CMA	MOM	IA	ROE	EG	BAB
Panel A: VIX-managed strategy										
Alpha (α)	3.07**	−1.04	0.23	0.77	−0.06	3.18***	0.27	2.44***	1.59***	6.69***
	(1.44)	(0.84)	(0.80)	(0.69)	(0.57)	(1.19)	(0.59)	(0.79)	(0.57)	(1.06)
R^2	0.64	0.70	0.70	0.73	0.68	0.60	0.67	0.67	0.68	0.68
RMSE	33.19	21.91	20.33	17.07	14.93	35.87	15.48	18.54	15.03	22.65
Appraisal ratio	0.32	−0.16	0.04	0.16	−0.01	0.31	0.06	0.46	0.37	1.02
Panel B: Downside VIX-managed strategy										
Alpha (α)	3.39***	−0.16	0.37	0.38	0.18	3.90***	0.33	2.05***	1.50***	7.86***
	(1.27)	(0.88)	(0.81)	(0.70)	(0.61)	(1.26)	(0.59)	(0.78)	(0.55)	(1.11)
R^2	0.56	0.64	0.58	0.60	0.58	0.52	0.58	0.56	0.54	0.58
RMSE	32.22	23.53	24.74	22.37	17.56	39.33	17.64	22.04	17.32	27.17
Appraisal ratio	0.36	−0.02	0.05	0.06	0.04	0.34	0.06	0.32	0.30	1.00
Panel C: RV-managed strategy										
Alpha (α)	3.13***	−0.03	0.68	0.78	−0.19	2.60***	0.45	2.43***	1.26**	6.51
	(1.14)	(0.67)	(0.85)	(0.58)	(0.66)	(0.83)	(0.74)	(0.66)	(0.53)	(1.07)
R^2	0.35	0.57	0.27	0.34	0.42	0.30	0.37	0.33	0.48	0.24
RMSE	38.53	25.81	34.08	17.23	17.45	27.30	21.69	20.43	14.32	41.38
Appraisal ratio	0.28	−0.00	0.07	0.16	−0.04	0.33	0.07	0.41	0.30	0.54
Panel D: Downside RV-managed strategy										
Alpha (α)	2.41**	−0.36	0.53	0.74	−0.32	2.09***	0.48	2.40***	1.25**	6.45***
	(0.94)	(0.66)	(0.78)	(0.55)	(0.68)	(0.72)	(0.78)	(0.63)	(0.50)	(1.05)
R^2	0.31	0.55	0.29	0.32	0.41	0.27	0.37	0.32	0.46	0.23
RMSE	36.45	25.97	30.53	16.32	16.76	25.71	21.68	19.31	13.93	39.73
Appraisal ratio	0.23	−0.05	0.06	0.16	−0.07	0.28	0.08	0.43	0.31	0.56

Figure 3 plots the cumulative nominal returns to the VIX-managed and RV-managed market factor compared to a buy-and-hold strategy from January 1993 to April 2023. We track a dollar invested in each of the three strategies at the beginning of the sample. VIX- and RV-based strategies provide more steady gains than the buy-and-hold approach. These gains are a direct consequence of their spanning regression alphas being both above 3% per year (see Table 1). They also behave more smoothly in recessions, avoiding substantial losses in high-volatility episodes. The top three monthly losses of the market portfolio in our sample happened in July 1998 (investors reflecting on poor corporate earnings reports), September 2008 (bankruptcy of Lehman Brothers) and February 2020 (COVID-19 pandemic). At the same time, the top three losses for the VIX-managed portfolio occurred in September 2018, April 2019 and January 2020, while the top three losses for the RV-managed portfolio happened in June 1996, September 2018 and April 2019. Volatility-timing strategies take more risk in periods of low volatility in the market (in our sample, these are 1993–1997, 2004–2007 and 2013–2019, cf. Figure 1), and this is when they typically suffer biggest losses. They are also conservative when the market is very volatile – precisely when the buy-and-hold strategy loses most of the investment. However, the VIX-managed portfolio accumulates to \$14.29 at the end of the sample, compared to \$8.63 for the buy-and-hold strategy. In contrast, a dollar invested in the RV-managed portfolio would be worth \$8.66 in April 2023, a mere three cents above the buy-and-hold strategy.

Table 2 compares the annualized Sharpe ratios of the managed factor returns with those of the original ones for the ten equity factors. The first row of the table shows the Sharpe ratios for the original factors. At the same time, the lower panel displays the Sharpe ratio differences (Δ) between the managed and the original factor returns. The statistical significance of the differences in Sharpe ratios is measured by Wright et al. (2012) test

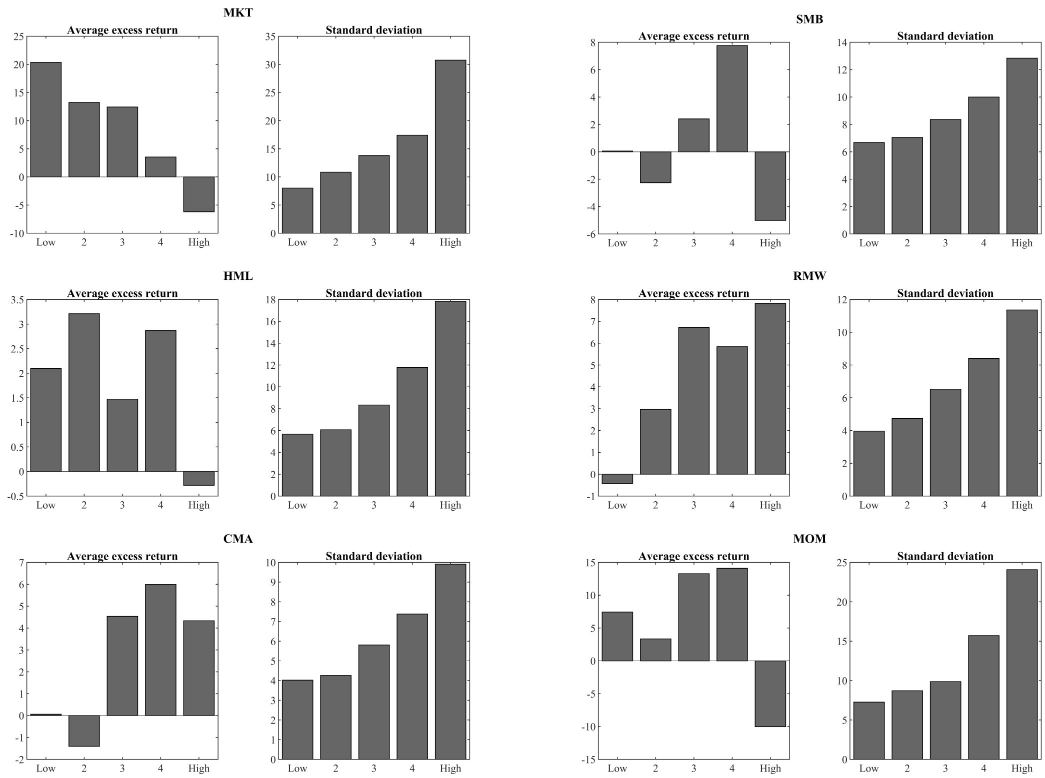

Figure 2: VIX-based return and volatility timing. This figure represents time-series sorts based on the previous month's VIX for five Fama-French factors (MKT, SMB, HML, RMW and CMA) and momentum (MOM). The time series of the previous month's VIX was constructed by aggregating the daily data between January 2, 1990, and April 28, 2023, and used to sort the following month's daily returns. We use five buckets, where the "Low/High" shows the properties of cumulative daily returns over the month in which VIX was in the lowest/highest fifth of its values. We show each factor's annualized average and standard deviation of next-month returns.

statistics, reported in the brackets.[2] We see statistically significant improvements in MOM, ROA and BAB factors for all managed strategies. The MOM Sharpe ratio improvement is more than doubled across all strategies, adding between 0.36 and 0.42 on top of the original 0.28. This result is consistent with Barroso and Santa-Clara (2015), who demonstrated that

[2] Under the null hypothesis that $\Delta = 0$, the Wright et al. (2012) test statistic is asymptotically χ^2_1. If we test the equality of k different Sharpe ratios, the test statistic converges in distribution to χ^2_k.

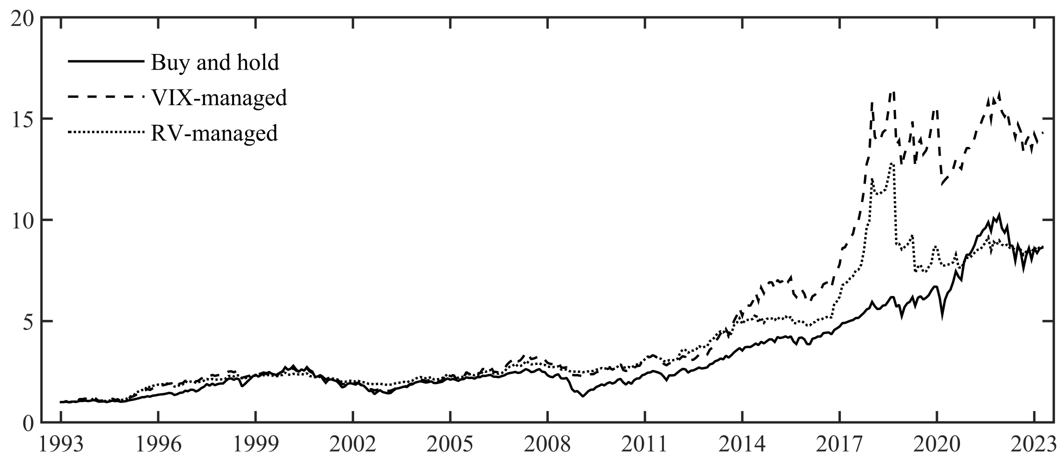

Figure 3: Cumulative returns on the VIX-managed market portfolio. The figure shows the cumulative returns on a buy-and-hold strategy versus VIX-managed and RV-managed strategies for the market portfolio from 1993-01 to 2023-04.

strategies that rely on timing momentum have exceptional performance. MOM and BAB Sharpe ratios are also improved in the realized (semi)volatility strategies of Fernandes and Batista (2023).

Except for CMA and ROE, the Wright et al. (2012) test statistics relying on implied volatility scaling are higher than the ones based on realized volatility. The downside VIX strategy exactly doubles the original Sharpe ratio of 0.67 for BAB. The VIX-based scaling is improving the Sharpe ratios of MKT and EG more than any other management strategy, adding 0.10 and 0.13, respectively,[3] albeit these differences are not statistically significant.

We now turn to the multivariate setting. Table 3 shows the results of spanning regressions for the MVE portfolios, given by Equation (12). The alphas are all positive and, except for the Fama and French (1993) three-factor model, highly significant. The VIX-managed or the downside VIX-managed efficient portfolios produce notably higher

[3]This is consistent with Clarke et al. (2020), who find that the improvement in Sharpe ratio from a static 50:50 exposure to cash and the S&P500 portfolio to a dynamic strategy that varies the market exposure based on the inverse of the prior month-end VIX quote, is around 0.09.

alphas than the (downside) RV-based strategies. The improvement from RV-managed to VIX-managed alphas ranges between 20 basis points for the Hou et al. (2014, 2020) three factors (HXZ) and 40 basis points for the Carhart (1997) four factors (FF3 + MOM). The corresponding increments for the downside strategies in the identical factor universes are 15 and 125 basis points.

Similar to the results of the univariate spanning regressions (Table 1), the quality of fit is also better for implied than realized volatility-based strategies, having generally higher values of R^2 and lower values of RMSE. Appraisal ratios also tend to be the highest for downside VIX-managed MVE portfolios. Except for the Fama and French (1993) three-factor model, they are all economically large and range from 0.27 to 0.53. In contrast, the highest appraisal ratio for an RV-managed strategy is 0.46, obtained for the Fama and French (2015) five factors augmented by momentum (FF5 + MOM).

The improvement in Sharpe ratios between managed and unmanaged MVE portfolios is slight. Being already efficient, the original annualized Sharpe ratios, shown in the first row of Table 4, are quite large, ranging between 0.54 and 0.98. The improvement introduced by volatility timing is statistically significant only for the Carhart (1997) four factors (FF3 + MOM), likely as a result of the ability to avoid momentum crashes described by Barroso and Santa-Clara (2015). As in the univariate case (Table 2), the Wright et al. (2012) statistic is typically the highest for VIX-managed MVE portfolios, dominating all other strategies in six out of seven universes considered.

Note that the Sharpe ratios of the original and the managed MVE portfolios are directly comparable since the optimal weights for both categories are constructed in the sample. Hence, they do not suffer from the understatement/overstatement issue as in Moreira and Muir (2017).

Table 2: Sharpe ratios for the ten equity factors. This table compares the annualized Sharpe ratios of the managed factor returns with those of the original ones. The managed strategies are based on implied volatility and realized volatility (RV). The first row shows the Sharpe ratios for the ten original factors. The lower panel of the table displays the Sharpe ratio differences (Δ) between the managed and the original factor returns. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period is between 1990-01 and 2023-04. MKT, SMB and HML are from Fama and French (1993), RMW and CMA are from Fama and French (2015), MOM is from Carhart (1997), IA, ROE and EG are from Hou et al. (2014, 2020) and BAB is from Frazzini and Pedersen (2014). Numbers in brackets are the test statistics of Wright et al. (2012) for the differences in Sharpe ratios. The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	SMB	HML	RMW	CMA	MOM	IA	ROE	EG	BAB
Original Sharpe	0.54	0.09	0.15	0.46	0.42	0.28	0.43	0.48	0.93	0.67
Sharpe ratio differences (Δ)										
VIX	0.10	−0.13	0.04	0.05	−0.14	0.36***	−0.16	0.27**	0.13	0.61***
	[0.62]	[1.48]	[0.18]	[0.22]	[1.66]	[7.78]	[2.04]	[4.49]	[1.24]	[28.47]
Downside VIX	0.08	−0.10	0.07	0.00	−0.14	0.36***	−0.15	0.19	0.02	0.67***
	[0.29]	[0.75]	[0.31]	[0.00]	[1.09]	[6.91]	[1.33]	[1.69]	[0.01]	[27.08]
RV	0.05	−0.06	0.02	−0.02	−0.23	0.42**	−0.12	0.45***	−0.01	0.54***
	[0.07]	[0.26]	[0.01]	[0.01]	[2.26]	[5.85]	[0.59]	[7.40]	[0.01]	[10.51]
Downside RV	0.04	−0.09	0.03	−0.04	−0.22	0.40**	−0.11	0.43**	−0.03	0.56***
	[0.04]	[0.48]	[0.03]	[0.05]	[2.03]	[5.41]	[0.50]	[6.41]	[0.05]	[10.82]

Table 3: Spanning regressions for mean-variance efficient (MVE) portfolios. The MVE portfolios are formed using various combinations of equity factors. These underlying factors can be considered the relevant investment universe for various levels of investors' sophistication. The spanning regressions are given by $f_t^{MVE,\sigma} = \alpha + \beta f_t^{MVE} + \varepsilon_t$, where $f_t^{MVE,\sigma}$ is the monthly return for managed MVE portfolio, and f_t^{MVE} is the monthly return for the original MVE portfolio. The managed strategies are based on implied volatility and realized volatility (RV). Panels A through D report the results for the managed strategy based on VIX, downside VIX, RV and realized downside RV, respectively. The appraisal ratio is $\alpha/\sigma_\varepsilon$, where σ_ε is the root mean square error (RMSE). The sample period for all regressions is between 1990-01 and 2023-04. The factors considered are the market excess return (MKT), the Fama and French (1993) three factors (FF3), the Carhart (1997) momentum factor (MOM), the Fama and French (2015) five factors (FF5), and the Hou et al. (2014, 2020) three factors (HXZ). Numbers in parentheses are heteroskedasticity-consistent standard errors of Huber (1967) and White (1980). The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	FF3	FF3+MOM	FF5	FF5+MOM	HXZ	HXZ+MOM
Panel A: VIX-managed strategy							
Alpha (α)	3.07**	0.56	1.67***	0.61*	0.99***	1.44***	1.43***
	(1.44)	(0.54)	(0.50)	(0.32)	(0.31)	(0.53)	(0.52)
R^2	0.64	0.64	0.61	0.69	0.68	0.68	0.67
RMSE	33.19	15.02	12.75	8.47	7.98	13.85	13.79
Appraisal ratio	0.32	0.13	0.45	0.25	0.43	0.36	0.36
Panel B: Downside VIX-managed strategy							
Alpha (α)	3.39***	0.87*	2.24***	0.80**	1.20***	1.29**	1.27***
	(1.27)	(0.53)	(0.54)	(0.35)	(0.36)	(0.53)	(0.51)
R^2	0.56	0.54	0.53	0.58	0.59	0.53	0.53
RMSE	32.22	16.85	14.58	10.18	9.47	16.61	16.40
Appraisal ratio	0.36	0.18	0.53	0.27	0.44	0.27	0.27
Panel C: RV-managed strategy							
Alpha (α)	3.13***	0.25	1.27***	0.57***	0.73***	1.24***	1.20***
	(1.14)	(0.22)	(0.39)	(0.19)	(0.20)	(0.43)	(0.45)
R^2	0.35	0.44	0.42	0.41	0.35	0.46	0.46
RMSE	38.53	7.21	10.81	5.52	5.55	11.62	12.21
Appraisal ratio	0.28	0.12	0.41	0.36	0.46	0.37	0.34
Panel D: Downside RV-managed strategy							
Alpha (α)	2.41**	0.12	0.99***	0.54***	0.73***	1.14***	1.08***
	(0.94)	(0.16)	(0.32)	(0.18)	(0.19)	(0.41)	(0.42)
R^2	0.31	0.42	0.41	0.39	0.32	0.44	0.44
RMSE	36.45	5.78	8.91	5.39	5.57	11.30	11.83
Appraisal ratio	0.23	0.07	0.38	0.35	0.45	0.35	0.32

Table 4: Sharpe ratios for mean-variance efficient (MVE) portfolios. The MVE portfolios are formed using various combinations of equity factors. These underlying factors can be considered the relevant investment universe for various levels of investors' sophistication. This table compares the annualized Sharpe ratios of the managed MVE portfolio returns with those of the original MVE portfolio returns. The managed strategies are based on implied volatility and realized volatility (RV). The first row shows the Sharpe ratios for the original MVE portfolios. The lower panel of the table displays the Sharpe ratio differences (Δ) between the managed and the original MVE portfolio returns. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period is between 1990-01 and 2023-04. The factors considered are the market excess return (MKT), the Fama and French (1993) three factors (FF3), the Carhart (1997) momentum factor (MOM), the Fama and French (2015) five factors (FF5), and the Hou et al. (2014, 2020) three factors (HXZ). Numbers in brackets are the test statistics of Wright et al. (2012) for the differences in Sharpe ratios. The asterisks indicate the usual significance levels: *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	FF3	FF3+MOM	FF5	FF5+MOM	HXZ	HXZ+MOM
Original Sharpe	0.54	0.56	0.63	0.94	0.98	0.97	0.98
Sharpe ratio differences (Δ)							
VIX	0.10	0.00	0.33**	−0.10	0.10	0.11	0.11
	[0.62]	[0.00]	[5.72]	[0.71]	[0.65]	[0.88]	[0.88]
Downside VIX	0.08	0.02	0.34**	−0.11	0.10	−0.02	−0.01
	[0.29]	[0.02]	[4.59]	[0.75]	[0.55]	[0.01]	[0.01]
RV	0.05	0.02	0.34**	−0.03	0.13	0.04	0.03
	[0.07]	[0.02]	[4.22]	[0.04]	[0.53]	[0.06]	[0.03]
Downside RV	0.04	−0.02	0.37**	−0.04	0.10	0.00	0.00
	[0.03]	[0.02]	[5.24]	[0.09]	[0.34]	[0.00]	[0.00]

Table 5 presents spanning regression alphas and Sharpe ratio differences (Δ) for the 176 anomaly portfolios. We show the number of positive, negative and significant alphas and differences using the 5% significance levels. We find that between 65 and 73 percent of the anomalies exhibit positive spanning regression alphas, depending on the applied strategy. The results on this broader sample are consistent with those for the ten equity factors and seven MVE portfolios: VIX-managed and downside VIX-managed anomaly portfolios tend to outperform the original counterparts more often than the RV and downside RV strategies. They produce 47 and 42 alphas statistically significant at the 5% level, compared to 38 and 41 for the two RV methods. Only six VIX-managed portfolio alphas (around three percent) are negative and significant. The downside RV strategy generates a negative alpha on 48 occasions and a significant and negative alpha in only one case.

The results for Sharpe ratio differences are less convincing: the instances with positive and negative differences are comparable for all four strategies, and the number of positive differences that are significant at the 5% level ranges between 16 and 21. Therefore, volatility timing may not be as effective for anomaly portfolios as for the individual factors regarding the risk-return tradeoff, irrespective of the applied strategy. However, the most apparent asymmetry between the differences is for the downside VIX strategy, with 16 significant positive and five significant negative deltas.

Table 5: Spanning regression alphas and Sharpe ratio differences for the 176 anomaly portfolios. The left column of this table reports the results from univariate spanning regressions of managed portfolio returns on the corresponding original portfolio returns. It shows the number of alphas that are positive and negative. The numbers in brackets show how many alphas are significant at the 5% level. Statistical significance of the alpha estimates is based on heteroskedasticity-consistent standard errors of Huber (1967) and White (1980). The spanning regressions are given by $f_t^\sigma = \alpha + \beta f_t + \varepsilon_t$, where f_t^σ is the monthly return for the managed portfolio and f_t is the monthly return for the original portfolio. The right column displays the corresponding results for Sharpe ratio differences (Δ) between the managed and the original portfolio returns. It counts the instances in which such differences are positive and negative. The numbers in brackets show how many differences are significant at the 5% level. The statistical significance of the Δ estimates is based on Wright et al. (2012) test for the differences in Sharpe ratios. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period is between 1990-01 and 2023-04. All anomaly portfolios are from Chen and Zimmermann (2022).

	Alpha (α)		Sharpe ratio difference (Δ)	
	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	$\Delta > 0$ [Signif.]	$\Delta < 0$ [Signif.]
VIX	114 [47]	62 [6]	91 [16]	85 [18]
Downside VIX	124 [42]	52 [4]	88 [16]	88 [5]
RV	127 [38]	49 [2]	91 [21]	85 [18]
Downside RV	128 [41]	48 [1]	91 [19]	85 [18]

3.2 Transaction costs

Timing strategies typically involve frequent trades. This aspect is a challenging one for their implementation in practice. If they are to provide economically significant profits to investors, the spanning regression alphas of managed portfolios should survive transaction costs. Here, we adopt the approach of Wang and Yan (2021), who extend Moreira and Muir (2017) and consider a set of stylized trading costs of 1, 10, 14, 25 and 50 basis points. The cost of 1 bp comes from Fleming et al. (2003) and is probably too tiny for more complex portfolios such as MVE or anomaly portfolios that are difficult to mimic with passive strategies. The costs of 10 and 14 bp are from Frazzini et al. (2012), the latter representing an addition of 4 bp to account for high volatility episodes. They are more appropriate for sophisticated institutional investors who avoid high liquidity demands. The costs of 25 and 50 bp originate from Hasbrouck (2009), Novy-Marx and Velikov (2016) and Barroso and Detzel (2021), and are considered more representative of liquidity-demanding equity strategies.

Table 6 reports the results of the spanning regressions for the ten equity factors before and after accounting for transaction costs. For each factor and trading strategy, we first illustrate the managed factor's stability by showing the average absolute change in monthly weights. The VIX-managed strategy is by far the most stable, with the average $|\Delta w_t|$ between 0.24 and 0.29, followed by the downside VIX, where these values range from 0.43 to 0.57. The VIX-based values are considerably below the average absolute weight changes for the RV-managed factors (between 0.48 and 0.63) and the downside RV-managed factors (between 0.45 and 0.66). Thus, to implement the VIX-managed strategy, we typically have to buy or sell around a quarter of our exposure per month, while running an RV-managed portfolio may require trading as much as half or even two-thirds of our holdings every month.

The difference in stability immediately translates to heterogeneous sensitivity to transaction costs. Indeed, the spanning regression alphas that were statistically significant before applying the transaction costs remain so across several cost levels for VIX and downside VIX strategies. At the cost level of 25 bp, the VIX-managed MKT factor alpha is statistically significant at the 10% level, while the MOM and EG alphas are statistically significant at the 5% level. The MKT and MOM after-cost alphas also have economically significant values of 2.23% and 2.30% per annum. The alphas for ROE and BAB are highly significant even for the cost of 50 bp, with annualized values of 1.49% and 4.56%, respectively.

In contrast, for RV and downside RV strategies, the after-cost alphas fall more rapidly: at 25 bp, the alpha for MKT, MOM, ROE, EG and BAB ceases to be statistically significant. The RV-managed MKT alpha at this cost is 1.23%, an entire percentage point below the corresponding value for the VIX-managed strategy. The RV-managed MOM factor alpha is only 0.29% – more than two percentage points below the VIX-based counterpart. The momentum alpha is already insignificant at the 5% level for the cost of 14 bp. At 50 bp, the after-cost alphas for the RV-managed MOM, ROE and BAB factors become significantly *negative*. The same effect happens for the downside RV-managed MOM and BAB factors.

Where applicable, we report the break-even cost for each factor and strategy, which is the implied transaction cost required to drive the alphas to zero.[4] For the factors with significant frictionless alphas (MKT, MOM, ROE, EG and BAB), we observe a sharp decline in break-even costs from panel A to panel D, indicating that the VIX-managed strategies are more robust to transaction costs than their (downside) RV-based counterparts. For example, the break-even costs for the VIX-managed MKT and MOM factors are 91 bp. In comparison, the RV-managed strategy for the same factors becomes already unprofitable

[4]The break-even cost cannot be assessed if all the point estimates of before- and after-cost alphas are negative, even if they are statistically insignificant.

at 41 and 28 bp, respectively. For ROE and BAB, the difference is even more extreme: the RV strategy breaks at 30 and 29 bp, while VIX-based alphas persist until the costs reach 128 and 157 bp, respectively.

Table 6: This table reports spanning regressions alphas for the ten equity factors after accounting for transaction costs. The managed strategies are based on implied volatility and realized volatility (RV). Panels A through D report the results for the managed strategy based on VIX, downside VIX, RV and realized downside RV, respectively. Average $|\Delta w_t|$ is the average absolute change in monthly weights. The reported alphas are in annualized percentage terms. We consider five levels of transaction costs: 1 bp, 10 bp, 14 bp, 25 bp and 50 bp. We also report zero-cost alphas for comparison. Break-even costs are the implied transaction costs (in basis points) required to drive the alphas to zero, where applicable. The sample period for all regressions is between 1990-01 and 2023-04. MKT, SMB and HML are from Fama and French (1993), RMW and CMA are from Fama and French (2015), MOM is from Carhart (1997), IA, ROE and EG are from Hou et al. (2014, 2020) and BAB is from Frazzini and Pedersen (2014). The asterisks indicate the usual significance levels under heteroskedasticity-consistent standard errors of Huber (1967) and White (1980): *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	SMB	HML	RMW	CMA	MOM	IA	ROE	EG	BAB
Panel A: VIX-managed strategy										
Average $\lvert\Delta w_t\rvert$	0.27	0.25	0.24	0.27	0.25	0.29	0.24	0.27	0.24	0.26
Transaction costs	After-cost alpha (α)									
0 bp	3.07**	−1.04	0.23	0.77	−0.06	3.18***	0.27	2.44***	1.59***	6.69***
1 bp	3.03**	−1.05	0.22	0.76	−0.07	3.14***	0.26	2.42***	1.57***	6.65***
10 bp	2.73**	−1.09*	0.19	0.68	−0.10	2.83***	0.24	2.25***	1.35***	6.26***
14 bp	2.60**	−1.11*	0.18	0.65	−0.11	2.69**	0.23	2.17***	1.25**	6.09***
25 bp	2.23*	−1.17*	0.14	0.56	−0.15	2.30**	0.19	1.96***	0.98**	5.62***
50 bp	1.39	−1.30*	0.06	0.34	−0.23	1.42	0.12	1.49**	0.37	4.56***
Break-even cost (bp)	91		68	90		91	89	128	65	157
Panel B: Downside VIX-managed strategy										
Average $\lvert\Delta w_t\rvert$	0.47	0.48	0.47	0.55	0.48	0.57	0.46	0.52	0.43	0.54
Transaction costs	After-cost alpha (α)									
0 bp	3.39***	−0.16	0.37	0.38	0.18	3.90***	0.33	2.05***	1.50***	7.86***
1 bp	3.34***	−0.17	0.37	0.36	0.18	3.81***	0.32	2.02***	1.47***	7.73***
10 bp	2.86**	−0.20	0.37	0.21	0.15	2.99***	0.30	1.70**	1.15**	6.59***
14 bp	2.64**	−0.21	0.37	0.14	0.13	2.62**	0.29	1.56**	1.00**	6.08***
25 bp	2.05*	−0.25	0.36	−0.05	0.10	1.62*	0.26	1.17*	0.61	4.69***
50 bp	0.72	−0.34	0.35	−0.48	0.02	−0.66	0.19	0.29	−0.28	1.53*
Break-even cost (bp)	63		698	22	55	43	123	58	42	62

Panel C: RV-managed strategy										
Average $\lvert\Delta w_t\rvert$	0.62	0.50	0.51	0.48	0.55	0.50	0.60	0.53	0.48	0.63
Transaction costs	After-cost alpha (α)									
0 bp	3.13***	−0.03	0.68	0.78	−0.19	2.60***	0.45	2.43***	1.26**	6.51***
1 bp	3.06***	−0.04	0.67	0.76*	−0.20	2.51***	0.43	2.35***	1.24**	6.28***
10 bp	2.37**	−0.11	0.63	0.64	−0.21	1.68**	0.22	1.62***	1.01**	4.25***
14 bp	2.07**	−0.15	0.61	0.59	−0.22	1.31*	0.13	1.29**	0.91**	3.34***
25 bp	1.23	−0.25	0.55	0.44	−0.24	0.29	−0.13	0.40	0.64	0.86
50 bp	−0.67	−0.47	0.43	0.11	−0.28	−2.03***	−0.71	−1.64***	0.02	−4.79***
Break-even cost (bp)	41		137	58		28	19	30	51	29
Panel D: Downside RV-managed strategy										
Average $\lvert\Delta w_t\rvert$	0.62	0.52	0.50	0.45	0.56	0.53	0.63	0.52	0.49	0.66
Transaction costs	After-cost alpha (α)									
0 bp	2.41**	−0.36	0.53	0.74	−0.32	2.09***	0.48	2.40***	1.25**	6.45***
1 bp	2.34***	−0.36	0.51	0.74*	−0.32	1.98***	0.48	2.35***	1.23***	6.23***
10 bp	1.71**	−0.40	0.39	0.66	−0.33	1.04*	0.45	1.85***	0.99**	4.24***
14 bp	1.43*	−0.42	0.34	0.62	−0.33	0.62	0.43	1.63***	0.88**	3.36***
25 bp	0.67	−0.47	0.19	0.52	−0.34	−0.54	0.39	1.03*	0.59	0.93
50 bp	−1.08	−0.58	−0.15	0.30	−0.37	−3.16***	0.30	−0.34	−0.06	−4.59***
Break-even cost (bp)	35		39	83		20	134	44	48	29

Figure 4 illustrates the wedge driven by transaction costs. It plots the cumulative nominal returns to the VIX-managed and RV-managed market factor compared to a buy-and-hold strategy from January 1993 to April 2023 under transaction costs of 25 basis points. As in Figure 3, we track a dollar invested in each of the three strategies at the beginning of the sample. The difference of 100 bp in after-cost alphas of VIX-managed and RV-managed strategy is visible, as the former remains persistently above the buy-and-hold value. At the same time, the latter cannot beat the market. The VIX-managed portfolio would be worth $11.70 at the end of the sample, while the RV-managed portfolio would end up at $5.68 in April 2023, almost three dollars below the buy-and-hold strategy. Such poor performance is a direct consequence of more frequent trading: the RV-managed portfolio, on average, changes its relative exposure to the market more than twice as often as the

VIX-managed portfolio (cf. Table 6), so higher trading costs evaporate any profit made by its ability to time the volatility.

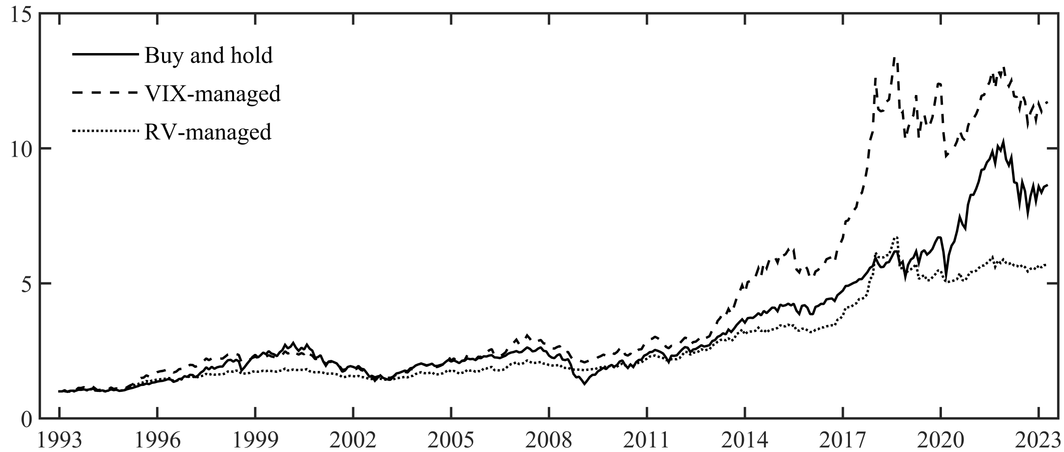

Figure 4: Cumulative returns on the VIX-managed market return with transaction costs. The figure shows the cumulative returns on a buy-and-hold strategy versus VIX-managed and RV-managed strategies for the market portfolio from 1993-01 to 2023-04 under transaction costs of 25 basis points.

The transaction costs similarly affect spanning regression alphas for the managed MVE portfolios. We can observe this from Table 7. Apart from the market portfolio, the tendency of after-cost alphas for strategies that rely on realized volatility to decline more abruptly with trading costs than the implied volatility strategies is also apparent for FF3+MOM, FF5+MOM, HXZ and HXZ+MOM factor universes. They are more robust to trading frictions: the break-even costs required to set the alphas to zero are also the highest for the VIX strategy in these universes.

For example, at 25 bp, the VIX-managed MVE portfolio has after-cost alphas of 1.31% if constructed from FF3+MOM and 0.73% if constructed from FF5+MOM. Both alphas are statistically significant at the 5% level. The corresponding values for the RV-managed portfolios are 0.53% and 0.40%, and only the latter is significant at the 5% level. If we increase the cost to 50 bp, the VIX-managed alphas drop to 0.96% and 0.48%, respectively, the former remaining significant at the 5% level and the latter at the 10% level. The point estimates of the analogous alphas for the RV-based strategy are now −0.21% and 0.07%, and neither is statistically significant. The break-even costs for the FF3+MOM universe are 117 bp for the VIX strategy, 65 bp for the downside VIX strategy, 43 bp for the RV strategy and 47 bp for the downside RV strategy. The corresponding costs for the FF5+MOM are 97 bp, double the value for any other strategy. The exceptions are the FF5 universe, where after-cost alphas fare comparably across the strategies, and the FF3 universe, where most alphas are insignificant.

Again, these results originate from very disparate stability of weights across the four strategies. The VIX-managed strategy has average absolute changes between 0.23 and 0.27. Thus, investors will benefit from this strategy even under tight leverage constraints.[5] These values range between 0.47 and 0.52 for the downside VIX-managed strategy. In contrast, the average absolute changes for the RV-managed strategy are between 0.21 and 0.62, while for the downside RV-managed strategy, they span from 0.17 to 0.62.

The same can be observed for the 176 anomaly portfolios in Table 8. The cross-sectional mean of time-averaged absolute changes in monthly weights for the VIX-managed portfolios is 0.25. One must almost double the trades to implement the downside VIX strategy. On the other hand, the average change in weights required to maintain the RV-managed and downside RV-managed strategies is around two-thirds. Again, the difference in weight stability translates directly to the sensitivity of these strategies to transaction costs. We can also see this directly from Table 9, which reports the results of spanning regressions for the anomaly portfolios after accounting for transaction costs. For VIX and downside VIX strategies, the number of positive and significant alphas across the anomaly portfolios

[5] We verified this for the leverage constraints $w_t < 1.5$ (i.e., a maximum of 50% leverage) and $w_t < 1$ (i.e., no leverage), which is the same set of constraints considered by Moreira and Muir (2017).

remains stable with transaction costs (or even slightly increases), ranging between 47 and 56. At the same time, the number of positive and significant alphas for the RV strategy decreases from 38 to 36 and for the downside RV strategy from 41 to 27.

The regression statistics mirror the effect of transaction costs. Within the same strategy, the cross-sectional average of positive alphas and average RMSE decrease while the average R^2 increases. Across the strategies, the VIX-managed portfolios tend to perform the best in all these parameters. Their average positive alphas decrease by 35 bp when costs go from zero to 50 bp, down to 1.74% per year. The same statistic drops by 95 bp and 94 bp for RV and downside RV strategies, resulting in after-cost alphas that are below 1%. The average appraisal ratios are comparable within and across the strategies until transaction costs reach 50 bp. Then, VIX and downside VIX remain stable, while RV and downside RV fall to 0.10 and 0.08.

Table 7: This table reports spanning regressions alphas for mean-variance efficient (MVE) portfolios after accounting for transaction costs. The MVE portfolios are formed using various combinations of equity factors. The managed strategies are based on implied volatility and realized volatility (RV). Panels A through D report the results for the managed strategy based on VIX, downside VIX, RV and realized downside RV, respectively. Average $|\Delta w_t|$ is the average absolute change in monthly weights. The reported alphas are in annualized percentage terms. We consider five levels of transaction costs: 1 bp, 10 bp, 14 bp, 25 bp and 50 bp. We also report zero-cost alphas for comparison. Break-even costs are the implied transaction costs (in basis points) required to drive the alphas to zero. The sample period for all regressions is between 1990-01 and 2023-04. The factors considered are the market excess return (MKT), the Fama and French (1993) three factors (FF3), the Carhart (1997) momentum factor (MOM), the Fama and French (2015) five factors (FF5), and the Hou et al. (2014, 2020) three factors (HXZ). The asterisks indicate the usual significance levels under heteroskedasticity-consistent standard errors of Huber (1967) and White (1980): *** for significance at 1%; ** for significance at 5%; * for significance at 10%.

	MKT	FF3	FF3+MOM	FF5	FF5+MOM	HXZ	HXZ+MOM
Panel A: VIX-managed strategy							
Average $\lvert\Delta w_t\rvert$	0.27	0.23	0.24	0.26	0.26	0.25	0.25
Transaction costs				After-cost alpha (α)			
0 bp	3.07**	0.56	1.67***	0.61*	0.99***	1.44***	1.43***
1 bp	3.03**	0.55	1.65***	0.61**	0.97***	1.42***	1.41***
10 bp	2.73**	0.46	1.53***	0.54**	0.88***	1.20**	1.19**
14 bp	2.60**	0.42	1.47***	0.51*	0.84***	1.10**	1.09**
25 bp	2.23*	0.31	1.31**	0.43*	0.73***	0.83*	0.83*
50 bp	1.39	0.07	0.96**	0.25	0.48*	0.21	0.22
Break-even cost (bp)	91	57	117	84	97	59	59
Panel B: Downside VIX-managed strategy							
Average $\lvert\Delta w_t\rvert$	0.47	0.45	0.47	0.52	0.54	0.47	0.47
Transaction costs				After-cost alpha (α)			
0 bp	3.39***	0.87*	2.24***	0.80**	1.20***	1.29**	1.27**
1 bp	3.34***	0.85**	2.21***	0.79**	1.18***	1.26***	1.23***
10 bp	2.86**	0.69*	1.90***	0.68**	0.97***	0.93**	0.91**
14 bp	2.64**	0.61	1.76***	0.63**	0.88***	0.79*	0.76*
25 bp	2.05*	0.42	1.39***	0.50*	0.63**	0.39	0.37
50 bp	0.72	−0.04	0.53	0.20	0.06	−0.51	−0.53
Break-even cost (bp)	63	48	65	67	53	36	35
Panel C: RV-managed strategy							
Average $\lvert\Delta w_t\rvert$	0.62	0.21	0.45	0.32	0.36	0.42	0.44
Transaction costs				After-cost alpha (α)			
0 bp	3.13***	0.25	1.27***	0.57***	0.73***	1.24***	1.20***
1 bp	3.06***	0.25	1.24***	0.56***	0.72***	1.21***	1.17***

10 bp	2.37**	0.21	0.97***	0.50***	0.60***	1.01**	0.93**
14 bp	2.07**	0.19	0.86**	0.48***	0.55***	0.92*	0.82**
25 bp	1.23	0.15	0.53*	0.40**	0.40**	0.68	0.53
50 bp	−0.67	0.04	−0.21	0.24	0.07	0.11	−0.14
Break-even cost (bp)	41	60	43	85	55	55	45
Panel D: Downside RV-managed strategy							
Average $\lvert\Delta w_t\rvert$	0.62	0.17	0.42	0.35	0.39	0.44	0.46
Transaction costs	After-cost alpha (α)						
0 bp	2.41**	0.12	0.99***	0.54***	0.73***	1.14***	1.08**
1 bp	2.34***	0.11	0.97***	0.53***	0.71***	1.12***	1.06***
10 bp	1.71**	0.07	0.78***	0.45***	0.56***	0.90**	0.81**
14 bp	1.43*	0.05	0.69**	0.41**	0.49***	0.80**	0.69*
25 bp	0.67	0.00	0.46*	0.31**	0.31*	0.54*	0.39
50 bp	−1.08	−0.11	−0.07	0.07	−0.11	−0.06	−0.31
Break-even cost (bp)	35	26	47	58	43	48	39

Table 8: Stability of scaling weights for the 176 anomaly portfolios. The table displays the average absolute change in monthly weights, $|\Delta w_t|$, for the managed portfolios. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period is between 1990-01 and 2023-04. All anomaly portfolios are from Chen and Zimmermann (2022).

	Average $\lvert\Delta w_t\rvert$
VIX	0.25
Downside VIX	0.49
RV	0.66
Downside RV	0.65

Table 9: Spanning regressions for the 176 anomaly portfolios after accounting for transaction costs. The left column of this table reports the results from univariate spanning regressions of managed portfolio returns on the corresponding original portfolio returns. It shows the number of alphas that are positive and negative. The numbers in brackets count the alphas significant at the 5% level. The statistical significance of the alpha estimates is based on heteroskedasticity-consistent standard errors of Huber (1967) and White (1980). The right column displays the cross-sectional average of positive alphas, average R^2, average root mean squared error (RMSE) and the average appraisal ratio, $\alpha/\sigma_\varepsilon$, where σ_ε is the RMSE. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. We consider five levels of transaction costs: 1 bp, 10 bp, 14 bp, 25 bp and 50 bp. We also report zero-cost results for comparison. The sample period is between 1990-01 and 2023-04. All anomaly portfolios are from Chen and Zimmermann (2022).

	After-cost alpha (α)		Regression statistics			
Panel A: VIX-managed strategy						
Transaction costs	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	Avg. $\alpha > 0$	Avg. R^2	Avg. RMSE	Avg. app. ratio
0 bp	114 [47]	62 [6]	2.09	0.66	26.71	0.11
1 bp	114 [47]	62 [6]	2.08	0.66	26.60	0.12
10 bp	117 [47]	59 [6]	1.98	0.68	25.58	0.12
14 bp	118 [47]	58 [6]	1.94	0.70	25.14	0.12
25 bp	115 [51]	61 [6]	1.92	0.72	23.99	0.12
50 bp	116 [56]	60 [5]	1.74	0.77	21.68	0.13
Panel B: Downside VIX-managed strategy						
Transaction costs	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	Avg. $\alpha > 0$	Avg. R^2	Avg. RMSE	Avg. app. ratio
0 bp	124 [47]	62 [6]	1.79	0.58	30.34	0.11
1 bp	123 [42]	53 [4]	1.79	0.59	29.98	0.11
10 bp	126 [44]	50 [4]	1.66	0.67	26.83	0.12
14 bp	127 [43]	49 [4]	1.57	0.70	25.54	0.12
25 bp	131 [43]	45 [1]	1.37	0.77	22.44	0.12
50 bp	131 [50]	45 [5]	1.22	0.83	19.52	0.12
Panel C: RV-managed strategy						
Transaction costs	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	Avg. $\alpha > 0$	Avg. R^2	Avg. RMSE	Avg. app. ratio
0 bp	127 [38]	49 [2]	1.94	0.47	35.34	0.12
1 bp	128 [38]	48 [2]	1.90	0.49	34.72	0.12
10 bp	127 [38]	49 [2]	1.75	0.62	29.78	0.13
14 bp	129 [40]	47 [2]	1.64	0.66	28.06	0.13
25 bp	133 [37]	43 [1]	1.37	0.73	25.39	0.13
50 bp	141 [36]	35 [1]	0.99	0.59	30.41	0.10
Panel D: Downside RV-managed strategy						
Transaction costs	$\alpha > 0$ [Signif.]	$\alpha < 0$ [Signif.]	Avg. $\alpha > 0$	Avg. R^2	Avg. RMSE	Avg. app. ratio
0 bp	128 [41]	48 [1]	1.81	0.46	33.42	0.12

1 bp	128 [41]	48 [1]	1.79	0.48	32.82	0.12
10 bp	130 [41]	46 [1]	1.61	0.61	28.04	0.12
14 bp	131 [42]	45 [1]	1.52	0.65	26.43	0.12
25 bp	131 [36]	45 [2]	1.32	0.71	24.17	0.12
50 bp	136 [27]	40 [3]	0.87	0.53	29.52	0.08

3.3 Timing skewness and kurtosis

VIX-managed portfolios lead to higher after-cost alphas than other strategies. This robustness to transaction costs directly results from a smoother weight variation. The likely origin of the relative weight stability compared to the other three strategies is the ability of the VIX strategy to time kurtosis. A strategy that can predict extreme variations in next-month returns better than its counterparts has more potential to create anticipatory adjustments to these variations. As an implied volatility index, VIX embeds the market expectations of extreme returns by incorporating deep in- and out-of-the-money options prices. The ability of VIX to capture tail risk was previously documented by many authors, including Kelly and Jiang (2014), Park (2015), Wang and Yen (2018) and Li et al. (2023).

Figure 5 provides a way to visualize this property. We create time-series sorts based on VIX and RV for the market portfolio. The VIX sorts are calculated from the daily VIX levels over the previous month using Equation (4). The RV sorts are calculated from the previous month's daily returns on the market portfolio using Equation (6). They are then exploited to sort the following month's daily returns on the market portfolio, which are grouped into quintiles, from months in which VIX and RV were in the lowest fifth to months in which they were in the highest fifth of their respective values. The figure shows the skewness and kurtosis of next-month returns for the VIX-managed market portfolio (top panel) and the RV-managed market portfolio (bottom panel).

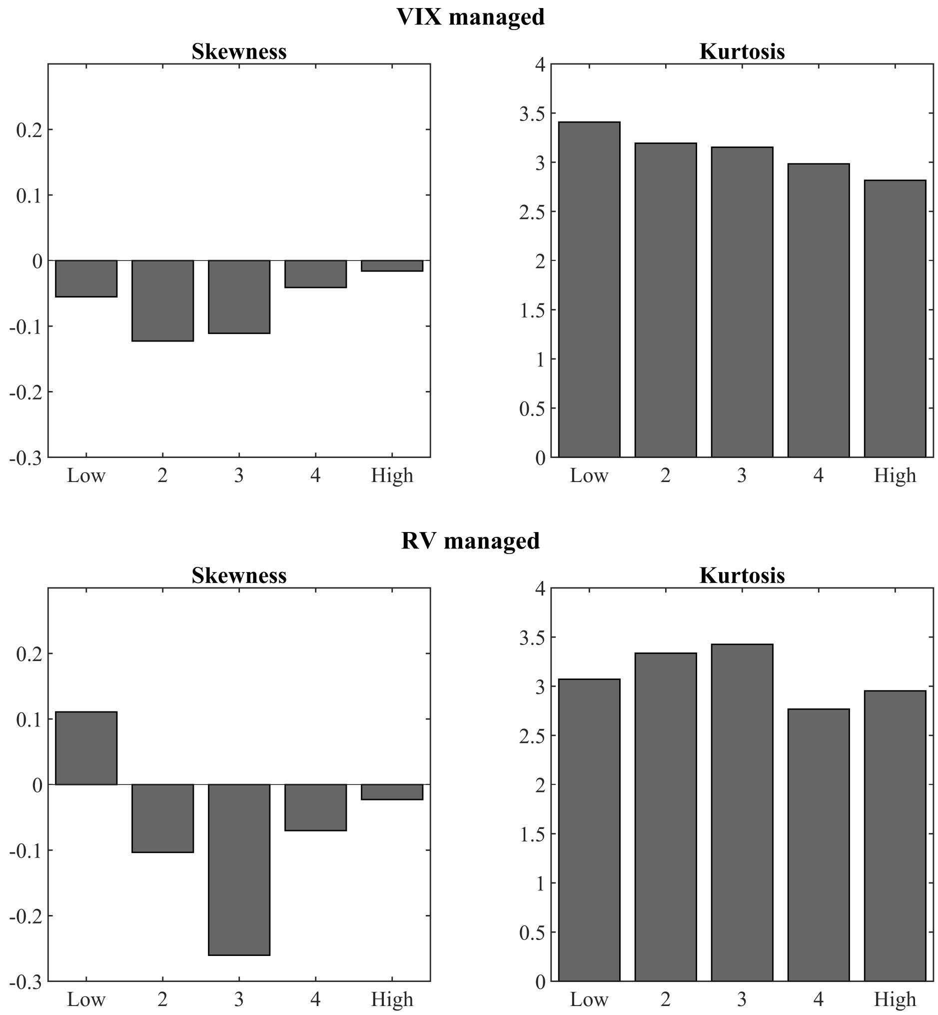

Figure 5: Timing of skewness and kurtosis. This figure represents time-series sorts based on the previous month's VIX and realized volatility (RV) for the market portfolio. The previous month's VIX and RV time series were calculated by aggregating the daily data between January 2, 1990, and April 28, 2023, and used to sort the following month's daily returns. We use five buckets, where the "Low/High" shows the properties of cumulative daily returns over the month in which VIX and RV were in the lowest/highest fifth of their values. For VIX and RV-managed portfolios, we show the skewness and kurtosis of next-month returns.

Table 10: Skewness and kurtosis for the ten equity factors. This table reports sample skewness (top panel) and kurtosis (bottom panel) for original and managed factor returns. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period for all regressions is between 1990-01 and 2023-04. MKT, SMB and HML are from Fama and French (1993), RMW and CMA are from Fama and French (2015), MOM is from Carhart (1997), IA, ROE and EG are from Hou et al. (2014, 2020) and BAB is from Frazzini and Pedersen (2014).

	MKT	SMB	HML	RMW	CMA	MOM	IA	ROE	EG	BAB
					Skewness					
Original	−0.61	0.64	0.18	−0.36	0.55	−1.46	0.61	−0.85	0.20	−0.35
VIX	−0.44	0.27	0.20	0.38	0.01	0.47	−0.13	0.10	0.51	0.30
Downside VIX	−0.57	0.11	−0.18	0.73	−0.34	0.78	−0.38	0.06	0.56	0.56
RV	−1.11	0.00	−1.85	−0.51	−0.12	1.36	−0.06	1.50	−0.01	2.70
Downside RV	−1.06	0.02	−0.47	−0.77	−0.10	1.85	−0.22	1.42	0.15	2.31
					Kurtosis					
Original	4.11	10.26	5.38	12.20	4.64	12.75	4.93	8.09	6.73	6.26
VIX	4.38	5.32	4.75	5.63	5.05	5.26	4.87	4.98	5.28	3.82
Downside VIX	4.97	5.05	6.58	9.97	7.45	6.69	6.32	8.75	8.63	4.35
RV	17.75	6.27	29.32	8.27	4.97	10.43	7.59	9.11	5.15	18.98
Downside RV	19.08	6.36	19.59	11.07	5.09	12.90	7.25	8.92	5.72	14.86

Neither the lagged VIX nor the lagged RV has any relationship with the skewness. The RV also does not appear to be related to the next-month kurtosis. However, the lagged VIX shows a mild but noticeable declining pattern: low implied volatility in the current month increases the probability of extreme returns over the next month. Conversely, the months when implied volatility is relatively high are most likely followed by months with fewer tail events. Therefore, VIX can successfully time the market portfolio's return, volatility and kurtosis.

Table 10 extends the skewness and kurtosis timing analysis to all ten equity factors. It compares sample skewness (top panel) and kurtosis (bottom panel) for the original and managed factor returns across the four strategies. A strategy that times any of these two moments well will be able to reduce the excess value of the original moment. We see mixed evidence for skewness timing, although the VIX-based strategy fares better than the other three for MKT, MOM, ROE and BAB. Recall that these factors exhibit statistically significant before- and after-cost alphas. For kurtosis timing, the results are relatively straightforward: either VIX or downside VIX notably outperforms both RV and downside RV strategies by a visible margin. For MKT, HML, MOM and BAB, the ability of the (downside) RV strategy to time the factor volatility comes at the expense of a complete failure to time their tail risk: the kurtosis of the managed factors is in double digits. Not surprisingly, MKT and BAB have the highest average absolute variation of weights in Table 6. On the other hand, VIX-managed factors offer a significantly better tradeoff, with kurtosis ranging between 3.82 and 5.63.

The ability of VIX to time the tail risk and (to some extent) return asymmetries also propagates from individual factors to portfolios. Table 11 reports the sample skewness and kurtosis for MVE portfolios. VIX is relatively successful in reducing the excess skewness of the efficient portfolios from the Fama-French universe, both with and without momentum. However, it performs relatively poorly with the HXZ factors. On the other hand, the kurtosis timing ability is quite strong: the VIX-managed portfolio kurtosis ranges from 4.36 to 6.87. The RV and downside RV strategy performs better than it did for individual factors. They still produce kurtosis values consistently above those for VIX on a portfolio-by-portfolio basis.

The same is true for the anomaly portfolios. Table 12 shows cross-sectional averages of sample skewness and kurtosis for each of the 176 sample portfolios. We observe clear monotonicity from VIX-managed to downside RV-managed portfolios in skewness and kurtosis. The VIX-managed portfolio skewness is only 0.11 on average, while their average kurtosis is 6.10, close to some efficient portfolios in Table 11. The RV and downside RV strategy holds relatively well regarding skewness timing but still have comparably higher average values than VIX (0.35 and 0.48). Their ability to time the tail risk is much worse:

the average kurtosis values are 9.75 and 10.77.

Table 11: Skewness and kurtosis for mean-variance efficient (MVE) portfolios. This table reports sample skewness (top panel) and kurtosis (bottom panel) for original and managed MVE portfolios. The MVE portfolios are formed using various combinations of equity factors. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period for all regressions is between 1990-01 and 2023-04. The factors considered are the market excess return (MKT), the Fama and French (1993) three factors (FF3), the Carhart (1997) momentum factor (MOM), the Fama and French (2015) five factors (FF5), and the Hou et al. (2014, 2020) three factors (HXZ).

	MKT	FF3	FF3+MOM	FF5	FF5+MOM	HXZ	HXZ+MOM
				Skewness			
Original	−0.61	−0.86	−0.91	0.52	0.39	0.48	0.30
VIX	−0.44	−0.37	0.15	0.02	0.24	0.55	0.53
Downside VIX	−0.57	−0.58	0.18	0.20	0.56	0.53	0.53
RV	−1.11	0.40	0.70	0.32	0.46	−0.05	−0.08
Downside RV	−1.06	0.83	0.79	0.50	0.56	0.10	0.06
				Kurtosis			
Original	4.11	7.32	8.86	5.11	7.47	7.33	7.08
VIX	4.38	6.87	4.36	5.18	5.22	5.18	5.32
Downside VIX	4.97	6.26	5.79	6.66	5.98	8.25	8.53
RV	17.75	7.36	6.31	7.65	7.03	5.31	5.38
Downside RV	19.08	9.65	6.00	9.26	9.26	6.32	6.21

Table 12: Skewness and kurtosis for 176 anomaly portfolios. This table reports the average sample skewness and kurtosis for original and managed anomaly portfolios. The managed strategies are based on VIX, downside VIX, RV and realized downside RV, respectively. The sample period for all regressions is between 1990-01 and 2023-04. All anomaly portfolios are from Chen and Zimmermann (2022).

	Avg. skewness	Avg. kurtosis
Original	0.07	9.09
VIX	0.11	6.10
Downside VIX	0.24	7.48
RV	0.35	9.75
Downside RV	0.48	10.77

4 Conclusion

We build on the recent literature on volatility-managed portfolios and explore the possibility of scaling with implied instead of realized volatility. The scaling is based on the CBOE implied volatility index (VIX) observed from the daily data over the past month. Using a large set of test assets involving ten equity factors, six classes of mean-variance efficient portfolios and 176 anomaly portfolios, we show that the proposed VIX-managed strategies generally outperform the one based on realized volatility in terms of spanning regression alphas, with limited improvements in the Sharpe ratios. This situation changes dramatically in the presence of trading frictions. Spanning regression alphas of VIX-managed portfolios survive under the majority of realistic transaction costs. In contrast, the alphas for management strategies relying on realized volatility generally diminish under the same assumptions.

The observed effect can be closely associated with the substantial difference in the stability of scaling weights. VIX-managed portfolios require the least rebalancing among the tested strategies and are, therefore, least burdened with frequent trading costs. We show that this property can be understood by the well-established ability of VIX to time both variance and kurtosis, creating a potential to buffer the losses originating from near-term volatility and tail risk. In addition, for the market portfolio in particular, VIX also has a moderate return timing ability, which can be particularly interesting to a typical investor in real-time.

The proposed VIX-based portfolio management strategy is easy to implement and offers a robust real-time after-cost performance. It exploits the forward-looking information embedded in options traded by the most sophisticated market participants. This information carries the overall market sentiment and is closely tied to the macroeconomy. The implied volatility smiles bring an additional layer in timing the extreme returns on top of the volatility. This property is not observed in strategies relying on realized variance. A more formal theoretical explanation of how it affects the utility gains of risk-averse investors in equilibrium would be an obvious candidate for an immediate extension of this paper that would help better comprehend the empirical findings presented here.

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