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Should Mutual Fund Investors Time Volatility?

Feifei Wang, CFA, Xuemin (Sterling) Yan, and Lingling Zheng

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Increasing (decreasing) investment in an actively managed mutual fund when fund volatility has recently been low (high) leads to a significant improvement in investment performance. Specifically, volatility-scaled fund returns exhibit significantly higher alphas and Sharpe ratios than the original (unscaled) fund returns. Scaling by past downside volatility leads to even greater performance improvement than scaling by total volatility. The superior performance of volatility-managed mutual fund trading strategies is attributable to both volatility timing and return timing. Fund flows are negatively related to past fund volatility, suggesting that fund investors are aware of the benefit of volatility management.

In our study, we examined a trading strategy in which investors increase (decrease) their investment in a mutual fund when fund volatility was recently low (high). Specifically, we scaled a fund's return by its past realized volatility. We show in this article that volatility scaling leads to a significant improvement in risk-adjusted performance. Without volatility scaling, the median fund exhibits a CAPM (capital asset pricing model) alpha of -0.79% per year after fees. The numbers we found are in line with those documented in prior studies (e.g., Fama and French 2010) and suggest that actively managed mutual funds, on average, underperform their benchmarks. With volatility scaling, the median fund exhibited an alpha of 1.75% , representing an improvement of more than 2 percentage points per year over unscaled returns. Without volatility scaling, only 37% of the funds exhibited positive CAPM alphas after fees; with volatility scaling, this percentage increased to 69%. The improvement in Sharpe ratios is also significant. The median fund delivered a Sharpe ratio of 0.40 before volatility scaling and 0.49 after volatility scaling.

We found that both volatility timing and return timing contribute to the superior performance of volatility-scaled strategies in mutual funds. Past volatility significantly and positively predicted future volatility for all funds in our sample. Past volatility also negatively predicted future returns for 76% of our sample funds and did so significantly for more than 20% of the funds. Therefore, volatility scaling works because decreasing investment in a fund when its past volatility has been high not only avoids high future volatility but also avoids low future returns.

Our work was inspired by several recent studies examining volatility-managed equity strategies. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) found that volatility-managed momentum strategies virtually eliminate crashes and almost double the Sharpe ratio of the original momentum strategy. Moreira and Muir (2017) expanded the analysis to several equity factors and showed that volatility-managed portfolios produce significant alphas relative to

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their unmanaged counterparts. More recently, however, some controversy has arisen about the systematic benefit of volatility management. Cederburg, O'Doherty, Wang, and Yan (2020), for example, examined a comprehensive sample of equity factors and anomalies and found no systematic evidence that volatility-managed portfolios outperform unmanaged portfolios in direct comparisons.

We extended these studies, which focused on equity factors, to mutual funds. Volatility-managed strategies are ideally suited for mutual funds for at least two reasons. First, mutual funds are tradable investment vehicles that are easily accessible to average investors. In contrast, most equity factor portfolios (e.g., portfolios based on the momentum factor) are not tradable or marketed to individual investors. Second, mutual funds can be bought and sold on a daily basis at the net asset value without incurring bid-ask spreads or market impact costs. Therefore, trading mutual funds, unlike trading stocks or stock portfolios, is essentially “free,” which significantly increases the appeal of volatility-managed trading strategies in mutual funds.¹

We also considered a strategy that scales fund returns by prior downside volatility instead of total volatility. The motivation for this analysis was twofold. First, a long-standing literature contends that downside volatility is a more appropriate measure of risk than standard deviation because investors typically associate risk with downside losses rather than upside gains (Markowitz 1959; Ang, Chen, and Xing 2006). Second, considerable evidence supports the idea that downside volatility and upside volatility contain different information about future volatility and future returns (Patton and Sheppard 2015; Bollerslev, Li, and Zhao 2019; Atilgan, Bali, Demirtas, and Gunaydin 2020). Our empirical results indicate that the performance improvement from volatility scaling is even greater when fund returns are scaled by past downside volatility. For example, the median fund exhibits a CAPM alpha of 2.32% per year when scaled by past downside volatility, compared with 1.75% when scaled by total volatility. In particular, we found that our strategy worked well during the financial crisis of 2008–2009, when downside volatility was extremely high.

We show that volatility-scaled trading strategies in mutual funds yield significantly higher risk-adjusted returns and Sharpe ratios than simple buy-and-hold strategies. To gauge the extent to which fund

investors actually follow volatility-scaled strategies, we examined the relationship between fund flows and past fund volatility. After controlling for standard determinants of fund flows, we found evidence of a negative relationship between fund flows and past fund volatility. This finding suggests that fund investors are aware of the benefit of volatility management.

Our article contributes to two strands of literature. The performance of actively managed mutual funds has been the subject of extensive research. Beginning with Jensen (1968), most prior studies (e.g., Malkiel 1995; Gruber 1996; Wermers 2000) have shown that actively managed mutual funds underperform passive benchmarks after fees. This finding has been interpreted by many as suggesting that investors should not hold active funds. Yet, the vast majority of the total net assets in the mutual fund industry are managed by active funds.² We add to this literature by showing that volatility-scaled trading strategies lead to positive alphas, thus providing at least a partial justification for investing in actively managed mutual funds.

Our article also contributes to the volatility management literature by extending the existing analyses of equity portfolios to mutual funds. We argue that the ease and low cost of trading mutual funds make volatility-managed trading strategies particularly attractive for mutual fund investors. We demonstrate that the impressive performance of volatility-managed equity portfolios documented in the literature (e.g., Barroso and Santa-Clara 2015; Moreira and Muir 2017) extends to equity mutual funds. Moreover, we show that scaling by downside volatility further improves the performance relative to scaling by total volatility.

Our work is closely related to the study of Jordan and Riley (2015), who showed that funds with high past volatility underperform funds with low past volatility. Jordan and Riley focused on the cross-sectional relationship between fund volatility and future fund returns, whereas our article focuses on the time-series relationship. Fully exploiting the predictability documented in Jordan and Riley would require shorting mutual funds, which is not feasible. Our article is also related to Clarke, de Silva, and Thorley (2020), who found that managing intertemporal volatility significantly improves the performance of optimally constructed multifactor equity portfolios. The innovation of our work is

that we examined equity mutual funds instead of equity portfolios.

Data, Sample, and Methods

We obtained daily and monthly fund returns, total net assets (TNA), expense ratios, turnover rates, and other fund characteristics from the CRSP Survivor-Bias-Free US Mutual Fund Database.³ We used daily fund returns to estimate fund volatility. Our sample period extends from September 1998 (when the data for daily fund returns became available) through December 2019. We obtained Fama and French (1996, 2015) factors—small minus big (SMB), high book-to-market value minus low book-to-market value (HML), robust operating profitability minus weak operating profitability (RMW), and companies with conservative investment minus companies with aggressive investment (CMA)—and the momentum factor from Kenneth French's website.⁴

Many funds have multiple share classes, which typically differ only in fee structure (expense ratio, 12b-1 fee, and load charge). We combined these different share classes into a single fund. In particular, we calculated the TNA of each fund as the sum of the TNA of each share class and defined fund age as the age of its oldest share class. For all other fund characteristics (e.g., the expense ratio), we used the TNA-weighted average across all share classes.

We excluded all load funds from our sample because if a fund charges a load fee, the fee will likely offset any gains from volatility scaling. Today, the vast majority of equity mutual funds are no-load funds. According to the latest *Investment Company Fact Book*, load funds manage only 12% of the total assets of long-term mutual funds (Investment Company Institute 2020). We also removed any fund that charged a redemption fee.

We limited our analysis to US domestic actively managed equity mutual funds. We followed the procedures of Doshi, Elkamhi, and Simutin (2015) and relied on the CRSP investment objective code to identify funds. We excluded international, balanced, sector, bond, money market, and index funds from our sample. We also excluded funds that had less than 80% of their holdings in common stocks.

To mitigate the effect of incubation bias, we included a fund only after its TNA had surpassed \$15 million (Elton, Gruber, and Blake 2001). Once a fund entered our sample, we did not exclude it

even if its TNA dropped below \$15 million. We also excluded observations prior to the first offer date of the fund (i.e., the date of organization) to reduce incubation bias (Evans 2010). We required a minimum of 36 monthly returns for a fund to be included in our sample. This requirement increases the power to identify the effect of volatility scaling but introduces a small survivorship bias. We show that the average performance of our sample funds is very similar to that documented by prior studies, which suggests that any additional survivorship bias is small. More importantly, survivorship bias should not affect our inferences based on the *difference* between scaled performance and unscaled performance.

Our final sample included 1,817 distinct funds.

Summary Statistics. Table 1 presents the summary statistics for our sample funds during our sample period. Note that the average TNA is \$837.74 million, whereas the median (the 50th percentile) is only \$233.59 million, suggesting that fund size is skewed to the right. The average fund is almost 16 years old and has an expense ratio of 1.20% and a turnover rate of 86.17% per year. The average fund flow was 0.22% per month during our sample period. The average fund return was 0.63% per month.

Volatility-Scaled Returns. Following prior literature (e.g., Patton and Sheppard 2015; Bollerslev et al. 2019), we calculated a fund's realized variance each month as the sum of squared daily returns within the month:

$$\sigma_t^2 = \frac{22}{J_t} \sum_{j=1}^{J_t} (r_j)^2, \quad (1)$$

where J_t is the number of trading days in the month.

We then constructed volatility-scaled fund returns as follows:

$$r_{\sigma,t} = \frac{c}{\sigma_{t-1}} r_t, \quad (2)$$

where r_t is the monthly fund excess return, $r_{\sigma,t}$ is the monthly volatility-scaled fund excess return, σ_{t-1} is the past-month realized fund volatility estimated from Equation 1, and c is a constant to control the average volatility of $r_{\sigma,t}$. We followed Moreira and

Table 1. Summary Statistics, September 1998–December 2019

Characteristic	Mean	Std. Dev.	10th Percentile	Median	90th Percentile
Total net assets (\$ millions)	837.74	2,012.83	30.15	233.59	1,986.30
Age (years)	15.84	10.29	5.42	14.00	27.17
Expense ratio (%)	1.20	0.47	0.71	1.14	1.80
Turnover rate (% per year)	86.17	82.84	26.55	71.50	152.93
Fund flow (% per month)	0.22	1.28	-1.13	0.08	1.81
Fund return (% per month)	0.63	0.59	0.06	0.70	1.07

Note: Fund flow is calculated as the percentage change in TNA minus the fund return.

Muir (2017) and set c so that the scaled and unscaled returns would have the same full-sample volatility. This parameter is not known to investors in real time, but most of the performance measures, including Sharpe ratios and alpha t -statistics, were invariant to the choice of c .⁵

In volatility-scaled trading strategies, the investment weight is proportional to the inverse of past volatility. Therefore, low volatility implies high leverage. A concern might be that high leverage would not be feasible for average investors. To mitigate this concern, we imposed a maximum leverage ratio of 2 to 1.⁶ Specifically, if the investment weight implied in Equation 2 was greater than 2, we replaced it with 2.

Downside Volatility. We also examined a trading strategy that scaled fund returns by past downside volatility. We estimated downside volatility similarly to the way we estimated total volatility but considered only *negative* daily returns. We then constructed downside volatility-scaled fund returns by replacing total volatility in Equation 2 with downside volatility. Specifically,

$$\sigma_{Down,t}^2 = \frac{22}{J_t} \sum_{j=1}^{J_t} (r_j)^2 I[r_j < 0] \quad (3)$$

and

$$r_{Down,t} = \frac{c}{\sigma_{Down,t-1}} r_t \quad (4)$$

We examined downside volatility for two reasons. First, a long-standing literature contends that downside volatility is a more appropriate measure

of risk than standard deviation because investors typically associate risk with downside losses rather than upside gains. Markowitz (1959), for example, advocated the use of semivariance as a measure of risk and suggested that semivariance produces efficient portfolios that are preferable to those achieved using variance. Second, considerable evidence also suggests that downside volatility and upside volatility contain different information about future volatility and future returns. For example, Patton and Sheppard (2015) showed that downside volatility has stronger predictive power for future volatility than upside volatility. Atilgan et al. (2020) showed that downside risk is a negative predictor for the cross-section of stock returns. If the results of these papers carried over to mutual funds—that is, if downside volatility better predicts future volatility for mutual funds and is more negatively related to future returns—then we would expect downside volatility-scaled strategies to exhibit even better performance than total volatility-scaled strategies.

Empirical Results

In the following subsections, we present and discuss our baseline results, results when we allowed a choice of target volatility, and results related to Sharpe ratios, volatility timing, return timing, and fund flows. Finally, we present the results of our robustness tests.

Baseline Results. We began our empirical analysis by comparing the risk-adjusted performance of original fund returns, total volatility-scaled fund returns, and downside volatility-scaled fund returns. We estimated CAPM one-factor alpha (Equation 5a), Fama–French three-factor alpha (Equation 5b), and

Carhart four-factor alpha (Equation 5c) by running the following respective time-series regressions:

$$r_{i,t} = \alpha_i + \beta_i \text{MKT}_t + e_{i,t}, \quad (5a)$$

$$r_{i,t} = \alpha_i + \beta_i \text{MKT}_t + s_i \text{SMB}_t + h_i \text{HML}_t + e_{i,t}, \quad (5b)$$

and

$$r_{i,t} = \alpha_i + \beta_i \text{MKT}_t + s_i \text{SMB}_t + h_i \text{HML}_t + u_i \text{UMD}_t + e_{i,t}, \quad (5c)$$

where $r_{i,t}$ is the fund excess return (unscaled or volatility-scaled), MKT , SMB , HML , and UMD

(for up minus down) are, respectively, market, size, value, and momentum factors (Fama and French 1996; Carhart 1997).

We estimated regression Equations 5a, 5b, and 5c fund by fund and present the results in **Table 2**. For each model, we report the average alpha, the percentage of funds with a positive alpha, and various cross-sectional percentiles of alpha estimates. In our discussion, we focus on the mean and the median because the mean captures the average performance across funds and the median represents the performance of the average fund. In addition to the alphas of (1) unscaled fund returns, (2) total volatility-scaled returns, and (3) downside volatility-scaled returns,

Table 2. Volatility-Scaled Fund Returns vs. Unscaled Fund Returns, September 1998–December 2019

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
<i>CAPM</i> α_1					
Unscaled	-0.74	37%	-4.61	-0.79	2.56
Total volatility	1.19	69	-4.72	1.75	5.22
Downside volatility	1.59	70	-5.07	2.32	6.12
Total volatility - Unscaled	1.93**	81	-1.33	2.18**	4.60
Downside volatility - Unscaled	2.33**	80	-1.55	2.69**	5.58
<i>Fama-French</i> α_3					
Unscaled	-1.02	28%	-3.99	-0.97	1.36
Total volatility	0.40	61	-4.94	1.03	4.31
Downside volatility	0.83	65	-5.07	1.61	5.04
Total volatility - Unscaled	1.41**	75	-2.16	1.95**	4.14
Downside volatility - Unscaled	1.85**	75	-2.38	2.43**	5.15
<i>Carhart</i> α_4					
Unscaled	-1.09	27%	-3.97	-1.04	1.26
Total volatility	0.09	59	-5.19	0.76	3.85
Downside volatility	0.57	63	-5.33	1.35	4.76
Total volatility - Unscaled	1.18**	73	-2.49	1.69**	4.00
Downside volatility - Unscaled	1.66**	74	-2.81	2.26**	5.06

Notes: Alphas are expressed in percent per year. Volatility-scaled fund excess returns are unscaled excess returns multiplied by c/σ_{t-1} , where σ_{t-1} is past-month fund volatility or downside volatility, and c was chosen so that the scaled and unscaled fund returns would have the same average volatility. Downside volatility was estimated by using negative daily returns only. We imposed a maximum leverage of 2 to 1. We estimated one-, three-, and four-factor alphas based on, respectively, the CAPM, the Fama and French (1996) three-factor model, and the Carhart (1997) four-factor model.

**Statistically significant at the 1% level based on bootstrap p -values.

we also computed the differences in alphas between volatility-scaled returns and unscaled returns—that is, row 2 – row 1 and row 3 – row 1—to show the performance improvement achieved by volatility-scaled strategies.

Table 2 reports that the average one-factor alpha in our sample funds is -0.74% per year and the median is -0.79% per year, suggesting that funds, on average, underperformed their benchmarks after fees. These numbers are in line with those documented in prior studies (e.g., Fama and French 2010). In contrast to the negative risk-adjusted performance of unscaled returns, volatility-scaled returns exhibit positive one-factor alphas. Specifically, the mean (median) alpha of total volatility-scaled returns is 1.19% (1.75%) per year. We found an even greater performance improvement for downside-volatility scaling. Specifically, the mean (median) alpha of downside volatility-scaled returns is 1.59% (2.32%) per year.

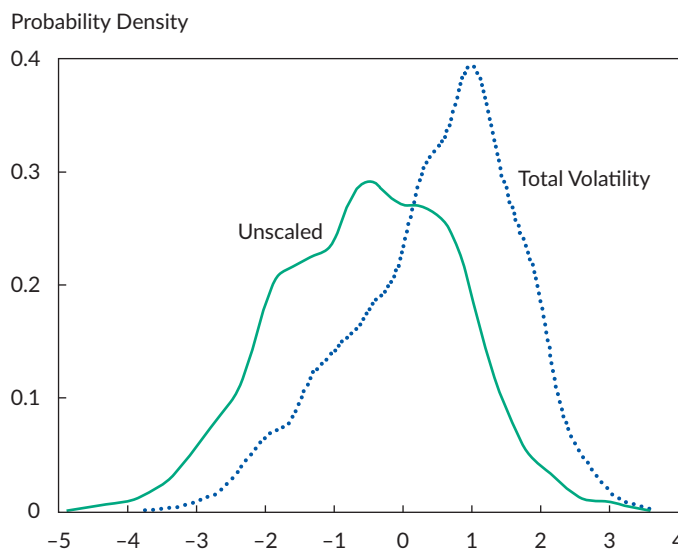
In addition to the alphas of scaled and unscaled fund returns, we also calculated the difference between scaled and unscaled alphas for each fund, and we report various statistics for this difference. We found for the one-factor model that the mean difference in alphas between total volatility-scaled and unscaled returns is 1.93% per year and the median difference, 2.18% per year.⁷ The corresponding numbers for the difference between downside volatility-scaled and unscaled returns in Table 2 are even larger—at 2.33% and 2.69%, respectively. Standard statistical tests indicate that these mean and median differences

in alphas are highly significant. These tests do not account for the effect of correlated fund returns, however, and correlated alphas. To perform a more rigorous test, we evaluated whether these mean and median differences in alphas are statistically significant by using a bootstrap procedure.⁸ Our results indicate that the mean and median differences in alphas between scaled returns and unscaled returns are all significant at the 1% level.

The results in Table 2 for three- and four-factor alphas are quantitatively lower than but qualitatively similar to those for one-factor alphas. For example, the mean (median) three-factor alpha for unscaled returns is -1.02% (-0.97%) per year, indicating that funds, on average, underperform their benchmarks after fees. In contrast, the mean (median) three-factor alpha for total volatility-scaled returns is 0.40% (1.03%) per year, representing a 1.42 percentage point (2.00 percentage point) improvement over unscaled returns. The mean (median) three-factor alpha for downside volatility-scaled returns is 0.83% (1.61%) per year, resulting in a greater performance improvement than total volatility-scaled returns. The four-factor results are qualitatively similar. All the performance improvements between scaled returns and unscaled returns are statistically significant at the 1% level based on bootstrap *p*-values.

In addition to alphas, we also calculated *t*-statistics of alpha estimates. **Figure 1** shows the distribution of one-factor alpha *t*-statistics for the sample of 1,817 funds. In particular, we plotted the distribution of $t(\alpha)$ for unscaled returns and for total volatility-scaled

Figure 1. Distribution of $t(\alpha)$ of Total Volatility-Scaled Returns vs. Unscaled Returns, September 1998–December 2019



Note: We estimated one-factor alphas for each fund based on the CAPM.

returns. We found, as shown, that the distribution of alpha t -statistics for total volatility-scaled returns represents a rightward shift relative to the distribution of alpha t -statistics for unscaled returns. This shift is most significant in the middle of the distribution but also evident in the tails. Overall, Table 2 and Figure 1 indicate that volatility scaling leads to a significant improvement in investment performance.

Target Volatility. In the volatility-scaled trading strategy defined in Equation 2, the constant parameter c controls the average volatility of scaled fund returns. Following Moreira and Muir (2017), we set c so that the scaled and unscaled returns would have the same full-sample volatility. We acknowledge that, although most of the performance measures (including the Sharpe ratio and alpha t -statistics) are invariant to the choice of c , this parameter is not known to investors in real time.

An alternative and equivalent strategy is to choose a target volatility level *ex ante* (Barroso and Santa-Clara 2015). To demonstrate this approach, we examined a volatility-scaled strategy that has a target volatility level of 20% per year. This strategy, unlike the strategy specified in Equation 2, can be implemented in real time. We present the results for this volatility-scaled strategy in Table 3. The format of the table is identical to that of Table 2, and the results are qualitatively unchanged. We continued to find that volatility-scaled returns exhibit significantly higher one-, three-, and four-factor alphas than unscaled returns. For example, we show that without volatility scaling, the median fund exhibits one-, three-, and four-factor alphas of, respectively, -0.79%, -0.97%, and -1.04% per year. After volatility scaling, these numbers increased, and scaling by downside volatility improved the performance even further. All these differences in performance

Table 3. Volatility-Scaled Fund Returns vs. Unscaled Fund Returns: Target Volatility Approach, September 1998–December 2019

Measure	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
<i>CAPM α_1</i>					
Unscaled	-0.74	37%	-4.61	-0.79	2.56
Total volatility	0.97	68	-5.44	1.92	5.83
Downside volatility	1.33	70	-6.07	2.48	6.78
Total volatility - Unscaled	1.71**	78	-2.33	2.40**	5.16
Downside volatility - Unscaled	2.07**	78	-2.82	2.90**	6.17
<i>Fama-French α_3</i>					
Unscaled	-1.02	28%	-3.99	-0.97	1.36
Total volatility	0.26	62	-5.58	1.17	4.84
Downside volatility	0.65	65	-6.09	1.71	5.66
Total volatility - Unscaled	1.27**	73	-2.93	2.15**	4.59
Downside volatility - Unscaled	1.67**	74	-3.51	2.67**	5.57
<i>Carhart α_4</i>					
Unscaled	-1.09	27%	-3.97	-1.04	1.26
Total volatility	-0.08	59	-5.90	0.81	4.42
Downside volatility	0.37	63	-6.33	1.43	5.33
Total volatility - Unscaled	1.01**	72	-3.38	1.89**	4.44
Downside volatility - Unscaled	1.46**	73	-3.84	2.49**	5.58

Note: Alphas are expressed in percent per year.

**Statistically significant at the 1% level based on bootstrap p -values.

between scaled and unscaled alphas are statistically significant at the 1% level.

We note that the choice of a 20% target volatility is somewhat arbitrary. We chose 20% because the average volatility for our sample funds during the 1998–2019 period was 19%. In practice, target volatility is likely to be investor specific and fund specific. In untabulated robustness tests, we found that setting a target volatility level of 15% or 25% generated qualitatively the same results as described here.

Sharpe Ratios. So far, we have shown that volatility scaling leads to a significant improvement in risk-adjusted returns. For a mean–variance utility–maximizing investor with a long-term horizon, the Sharpe ratio might be a more relevant performance measure. Sharpe ratios have the additional benefit of being model free. We present our findings for the Sharpe ratio in **Table 4**.

We found a significant increase relative to the Sharpe ratios of unscaled returns. Downside volatility–scaled returns display slightly higher Sharpe ratios (average of 0.44; median of 0.50) than total volatility–scaled returns. Overall, volatility scaling increased the Sharpe ratio of the average fund by about 20% during our sample period.

Volatility Timing and Return Timing.

Volatility-scaled mutual fund portfolios discussed in this article are managed portfolios in which the investment weight is proportional to the inverse of past fund volatility. Prior studies (e.g., Lewellen and Nagel 2006; Boguth, Carlson, Fisher, and Simutin 2011) have shown that the unconditional performance of a managed strategy is driven by return timing and/or volatility timing. Return timing contributes to the performance if the investment weight is positively correlated with future returns. Volatility timing adds to the performance if the investment weight is negatively correlated with future volatility.⁹

By construction, volatility timing plays an important role in volatility-scaled strategies because the investment weight in volatility-scaled strategies is the inverse of past volatility and volatility is persistent. Return timing may also enhance the performance of volatility-scaled strategies if past volatility is negatively related to future fund returns. For example, Barroso and Santa-Clara (2015) showed that a negative relationship exists between momentum volatility and future momentum profits, suggesting that return timing can contribute to the value of volatility-scaled momentum strategies. In contrast, Moreira and Muir (2017) showed that the relationship between volatility and future market returns is flat, and therefore, the value of volatility-managed market portfolios comes entirely from volatility timing rather than return timing.

To gauge the importance of the volatility-timing and return-timing effects, we examined the relationships between past fund volatility and future fund volatility and between past fund volatility and future fund returns. Specifically, **Table 5** provides estimates of a regression of one-month-ahead fund volatility on past-month fund volatility. The statistical significance was assessed by using Newey–West (1987) standard errors with 12 lags. We estimated a similar regression of one-month-ahead fund returns on past fund volatility. For the predictor variable, we used both past total volatility and past downside volatility. We estimated the regressions fund by fund and report in **Table 5** the distribution of Newey–West *t*-statistics of the regression coefficients.

When predicting future volatility with past total volatility, we found that the regression coefficient is positive and statistically significant for all sample funds. The results for downside volatility are similar, with all regression coefficients being positive and statistically significant. The above results are not surprising because volatility persistence is one of the most important stylized facts in the volatility literature. What may be a little surprising is that the

Table 4. Sharpe Ratios, September 1998–December 2019

Scaling	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
Unscaled	0.36	85%	–0.11	0.40	0.80
Total volatility	0.43	86	–0.08	0.49	0.86
Downside volatility	0.44	87	–0.08	0.50	0.87

Table 5. Predicting Future Volatility and Future Fund Returns from Past Volatility: *t*-Statistics on the Regression Coefficients, September 1998–December 2019

	Mean	Percentage Positive	10th Percentile	Median	90th Percentile
<i>Predicting volatility by</i>					
Total volatility	9.39	100%	3.04	10.05	13.82
Downside volatility	7.84	100%	2.92	8.29	11.44
<i>Predicting return by</i>					
Total volatility	-0.76	24%	-1.97	-0.99	0.91
Downside volatility	-0.75	25%	-2.04	-1.07	1.07

Notes: Total volatility is the square root of the sum of squared daily returns within a month. Downside volatility is the square root of the sum of squared daily returns within a month with only negative daily returns used.

relationship is statistically significant for each of the 1,817 sample funds.

When predicting future returns from past volatility, we found that 76% of the coefficients were negative and more than 20% of them were statistically significant at the 10% level. Because investment weight is the inverse of past volatility, investment weight is positively related to future fund returns for most funds.¹⁰ This finding confirms that return timing plays a significant role in explaining the outperformance of volatility-scaled strategies. Overall, we show in Table 5 that both volatility timing and return timing contribute to the improved performance of volatility-scaled returns.

Moreira and Muir (2019) showed that an important feature in the US data that renders volatility-managed strategies beneficial to investors is that shocks to expected returns are more persistent than shocks to volatility. They argued that, as a result, “investors can avoid the short-term increase in volatility by first reducing their exposure to equities when volatility initially increases and capture the increase in expected returns by coming back to the market as volatility comes down” (Moreira and Muir 2019, p. 509). Our findings that return timing plays an important role in the value of volatility-scaled strategies and that downside-volatility scaling is particularly beneficial are consistent with Moreira and Muir’s (2019) argument. Moreover, this argument suggests that volatility-scaled strategies should work well during market downturns, such as the financial crisis of 2008–2009, and our results confirm the superior performance of volatility-scaled fund returns during 2008–2009. We show in **Figure 2** the

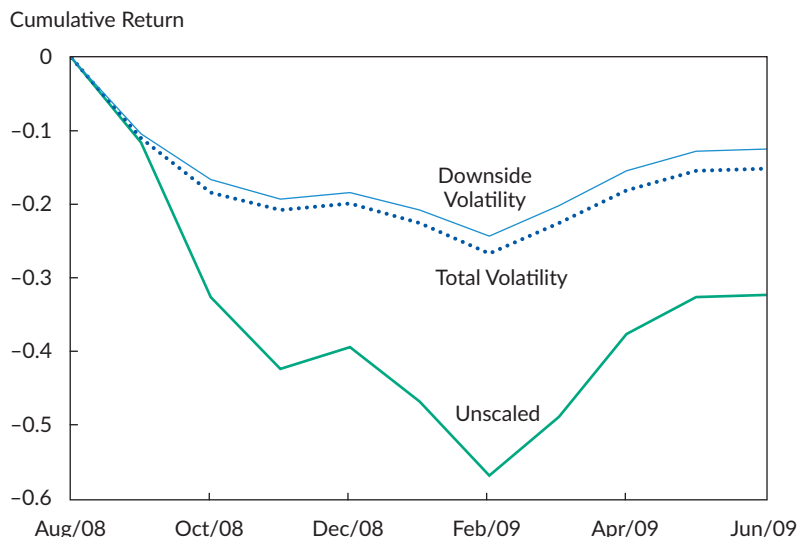
cumulative returns of three strategies: no scaling, total-volatility scaling, and downside-volatility scaling. All three strategies experienced negative returns in 2008–2009, but returns to the volatility-scaled strategies are far less negative than returns to the original, unscaled strategy.

Fund Flows. We have shown that volatility-scaled trading strategies yield significantly higher risk-adjusted returns and Sharpe ratios than an unscaled trading strategy for investors. This finding provides a justification for investing in actively managed mutual funds based on past volatility. To investigate the extent to which fund investors have implemented such a strategy in practice, we next examine the relationship between fund flows and past fund volatility. We followed prior studies (e.g., Sirri and Tufano 1998) by estimating monthly fund flows as follows:

$$\text{Flow}_{i,t} = \frac{\text{Asset}_{i,t} - \text{Asset}_{i,t-1} \times (1 + \text{Return}_{i,t})}{\text{Asset}_{i,t-1}} \quad (6)$$

We regressed fund flows on past fund volatility and other fund characteristics, such as past performance and fund size, for our sample. We estimated the regression each month and present in **Table 6** the average regression coefficients and Fama–MacBeth (1973) *t*-statistics (Newey–West adjusted with three lags). We found evidence of a negative relationship between fund flows and past fund volatility. The coefficients on lagged fund volatility are statistically significant at the 1% level whether we were examining lagged total volatility (in Regression 1) or lagged downside volatility (in Regression 2). Our finding

Figure 2. Cumulative Returns to Volatility-Scaled and Unscaled Strategies during the 2008–09 Financial Crisis



Note: Funds are equal weighted.

Table 6. Impact of Fund Volatility on Fund Flows, September 1998–December 2019

	Total-Volatility Model	Downside-Volatility Model
Intercept	1.671**	1.552**
Lagged total volatility	-0.146**	
Lagged downside volatility		-0.105**
Log (fund age)	-0.450**	-0.452**
Log (total net assets)	0.012	0.011
Expense ratio	-0.127**	-0.137**
Lagged fund flow	0.296**	0.297**
R_{t-1}	11.829**	11.668**
R_{t-1}^2	12.971**	12.681**
R_{t-2}	5.255**	5.191**
R_{t-2}^2	-1.155	-0.741
Average # of observations	850	850
Average R^2	18.83%	18.77%

Notes: The dependent variable, fund flow, was calculated as the percentage change in TNA minus the fund return and was winsorized at the 1st percentile and 99th percentile each month. R_{t-1} is the annual market-adjusted fund return over the previous 12 months; R_{t-2} is the annual market-adjusted fund return over the 12 months for the year $t - 2$; R_{t-1}^2 and R_{t-2}^2 are the annual adjusted fund returns squared for, respectively, year $t - 1$ and year $t - 2$.

**Statistically significant at the 1% level based on bootstrap p -values.

suggests that investors have some knowledge of the value of volatility timing.

Robustness Tests. In this section, we describe a number of robustness tests we performed. To conserve space, the results for these tests are not tabulated, but they are available from the authors upon request.

Quarterly rebalancing. Since the 2003 trading scandal in the mutual fund industry, many funds, particularly index funds, have charged a short-term-trading fee or imposed limits on trading frequency. Some funds prohibit round-trip trading within 30 days; others impose the more stringent restriction of no round-trip trading within 90 days. Our baseline strategy would entail trading at a monthly frequency. Thus, it is implementable for funds that impose a minimum of 30 days between round-trip trades. In this section, we report a robustness test in which we rebalanced our portfolios quarterly instead of monthly. Quarterly rebalancing would make our trading strategy implementable for the vast majority (if not all) of our sample funds.

We found that quarterly rebalancing leads to slightly lower volatility-scaled alphas than monthly rebalancing. Nevertheless, we continued to find that volatility scaling produces significant performance improvement relative to unscaled fund returns. The slightly lower alphas for quarterly rebalancing suggest that it is beneficial to trade in a timely fashion and act quickly on the latest volatility information whenever possible.

Alternative measures of volatility. In Equation 1, we followed prior literature by estimating volatility as the sum of squared returns over the past month, but we also considered three alternative measures of volatility. The first alternative is based on the standard deviation of returns. The second (third) alternative is similar to Equation 1 but estimated over the past two (three) months instead of the past one month.

We repeated our methodology (i.e., Table 2) for these three measures. We found the results based on the standard deviation measure to be nearly identical to those in Table 2. We found the results based on past two- or three-month volatility measures to be slightly weaker than the Table 2 results but qualitatively similar to the results based on past one-month volatility. This finding suggests, as did our finding for quarterly rebalancing, that trading on timely volatility information is beneficial.

Alternative leverage constraint. In our main analysis, we capped the leverage at 2 to 1. Regulation T, however, limits the leverage to 1.5 to 1 for retail investors. Therefore, we repeated our analysis but imposed the maximum leverage of 1.5 to 1. We found quantitatively lower but qualitatively similar results when we imposed this tighter leverage constraint.¹¹

Fama and French five- and six-factor models. In this robustness test, we used the Fama and French (2015) five-factor model or six-factor model (the five-factor model augmented by the momentum factor) to evaluate fund performance. The importance of this robustness test is that Jordan and Riley's (2015) results completely disappeared when they used the five-factor model to evaluate fund performance. The reason for the disappearance, Jordan and Riley argued, is that the Fama–French five-factor model does a good job of explaining the volatility anomaly found by Ang et al. (2006).

Overall, we found that the performance improvement resulting from volatility scaling is somewhat reduced when the five- or six-factor model is used. However, it is still economically significant. Thus, we consider our results to be robust to the Fama–French five- and six-factor models.

Removing closet index funds. After the mutual fund scandal of 2003, a number of funds, typically index funds and funds that closely follow the market

index, began to charge a short-term-trading fee. We had already excluded all self-proclaimed index funds from our sample. In this robustness test, we also excluded closet index funds. Following Cremers and Petajisto (2009) and Cremers, Ferreira, Matos, and Starks (2016), we classified a fund as a closet index fund if its active share was less than 0.6.¹² Our main results were qualitatively unchanged by excluding closet index funds.

Conclusion

Considerable attention has been paid to the performance of actively managed mutual funds. Given that active funds underperform their passive benchmarks, on average, an ongoing debate concerns whether investors should buy any active funds. We have contributed to this debate by examining a simple trading strategy in which investors increase (decrease) their investment in an actively managed mutual fund when its past volatility has been low (high). We showed that such volatility-scaled strategies lead to a significant improvement in investment performance. During our sample period, volatility-scaled fund returns exhibited one-, three-, and four-factor alphas that were, on average, 2 percentage points per year higher than the original fund returns.

We found that the enhanced performance of volatility-scaled returns is attributable to both volatility timing and return timing. We also documented evidence that investors are aware of the value of volatility scaling.

Our article also contributes to the literature on volatility-managed strategies by extending the existing analyses to mutual funds and by showing that the significant benefits of volatility management can be captured by trading equity mutual funds. Furthermore, we demonstrated that managing downside volatility improves performance relative to strategies based on managing total volatility.

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Notes

1. We excluded from our sample load funds and funds that charge redemption fees. In addition, we removed index funds from our analysis because these funds tend to impose strict trading restrictions.
2. The Investment Company Institute (2020) has reported that actively managed mutual funds accounted for 70% of the total net assets of all equity funds at the end of 2019.
3. We used net returns in all of our analyses in order to focus on the performance experienced by actual investors. The results based on gross returns are slightly stronger than those based on net returns.
4. Kenneth French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
5. The fact that c is not known in real time is not an issue. The volatility-scaled strategy specified in Equation 2 is equivalent to a strategy in which investors choose a target level of volatility *ex ante*. We show in the section "Target Volatility" that setting a target level of volatility produced qualitatively the same results.
6. Although Federal Reserve Board Regulation T limits leverage to 1.5 for retail investors, we argue that these investors might have access to alternative funding or financing beyond their brokers—for example, home equity loans. More importantly, institutional investors can take on much higher leverage, and according to the Investment Company Institute (2020), they own a large percentage of US equity mutual funds. Institutional share classes accounted for nearly 40% of the total assets of long-term US mutual funds at the end of 2019. That said, our results were qualitatively similar if we imposed a maximum leverage ratio of 1.5 instead of 2.
7. We note that the mean difference in alphas is identical to the difference in mean alphas, but the median difference in alphas is not the same as the difference in median alphas.
8. Specifically, in each simulation run, we kept the fund returns intact and redrew fund volatility. We then reconstructed volatility-managed returns with the simulated data. We used the same asset pricing models as used previously to evaluate the funds' performance. By redrawing fund volatility in the simulated data, we altered the dynamics of volatility and the volatility–return relationship. Therefore, by construction, the value of volatility timing should be zero in the simulated data. We compared the actual alphas (estimated from actual data) to the distribution of alphas obtained from simulated data. This procedure allowed us to obtain the bootstrapped p -value for the hypothesis that the actual mean and median alphas are zero.
9. The intuition for volatility timing is that if investment weight (i.e., beta) is positively correlated with volatility, beta will tend to be high at extreme return levels. This tendency would result in an overestimate of the unconditional beta of the strategy and push down the estimate of the unconditional alpha (Lewellen and Nagel 2006).
10. Two potential explanations exist for why past fund volatilities negatively predict future fund returns. First, if fund volatility and contemporaneous fund returns are negatively correlated (i.e., volatility is higher in down markets) and fund returns are persistent, then high past fund volatility will be negatively related to low future fund returns. Second, high fund volatility may induce fund outflows. If funds incur a significant cost when meeting investor redemptions (e.g., the need to sell stocks at inopportune times), then fund outflows will drag down fund performance. This result would imply a negative relationship between past fund volatility and future returns. In untabulated tests, we found evidence consistent with both of these explanations.
11. Another, related issue is margin interest rate. In our baseline analysis, as in most prior academic studies in this literature (e.g., Moreira and Muir 2017), we implicitly assumed that investors could borrow and lend at the risk-free rate. In practice, the borrowing rate could be significantly higher than the risk-free rate. To examine the impact of margin interest rate on the profitability of our strategies, we calculated the level of margin rate that would drive the alpha of the volatility-scaled strategy to zero. Our analysis shows that this margin rate would be, on average, 11%–12% per year.
12. We obtained active share data from Martijn Cremers's website: <https://mcremers.nd.edu/>.

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