Revisiting the performance of the scaled momentum strategies

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Abstract

Purpose – The main purpose of this study is to enunciate the underlying factors that enhance the performance of scaled momentum strategies.

Design/methodology/approach – In previous studies, the negative relationship between the lagged volatility and future return of momentum strategy is exploited to manage the risk. But this negative relationship only holds when volatility is higher, further the volatility is shown to be persistent. The implication of these two characteristics is important and this paper highlights that.

Findings – The higher performance of the scaled momentum strategies for the US market is linked with the length of the investment horizon. The traditional asset pricing models fail to explain this relationship. However, the authors find that the excess variance loaded on the long side of these strategies is one important explanation of this horizon bound performance of these strategies.

Practical implications – This study highlights that the volatility scaled momentum strategy has higher gains as the investment horizon increases. Therefore, it is an advisable investment strategy for the pension fund industry.

Originality/value – Momentum strategy is unique as it fulfils two criteria of performance enhancement through volatility scaling, such as, the persistent in volatility and its negative relationship with the returns. However, the impact on the performance of the negative relationship between volatility and return that only exist in highest volatility related states is not discussed. The authors have shown that this aspect of volatility and return relationship of the momentum strategy has an important bearing on the performance of the volatility scaled momentum strategies.

Highlights of the Paper

(1) This study finds that the Sharpe ratios and the alphas of the volatility scaled strategies increase as the investment horizon increases.

(2) This is because the volatility series are highly persistent and the negative predictive relationship between the volatility and future momentum returns only exist when the volatility is higher. The impact of these two characteristics of the volatility series on the performance of the scaled momentum strategies is not discussed in the literature.

(3) We find that the scaled strategies invest more/less when the volatility of the momentum strategy is lower/higher. By investing less when volatility is higher, the scaled strategies avoid momentum crashes and lessens the contribution of the variance from the short side in the overall variance of these strategies.

JEL Classification — G10, G12, G15

We compare the performance of traditional momentum strategy with volatility scaled momentum strategies over the different investment horizons. We find that the better performance of the volatility scaled strategies is monotonically linked with the length of investment horizon. This connectivity between performance and investment horizon is due to two aspects of the volatility series. First, the persistence in volatility (i.e. the higher volatility related states are followed by higher volatility and vice versa) and second, the negative predictive relationship between volatility and the future momentum returns only exist when volatility of momentum strategy is higher. We also find that the higher performance of scaled momentum strategies is linked with the excess variance loaded on the winner portfolio of these strategies.

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(4) It is further shown that the higher performance of the volatility scaled strategies, at each investment related horizon can be explained by the higher variance loaded on the long side of such strategies in comparison to the traditional momentum strategy.

Keywords Performance, Scaled momentum strategies, Volatility, Investment horizon, Persistence
Paper type Research paper

1. Introduction

The positive returns from momentum strategy have shown resilience over time for different asset classes and across distinct samples [1]. These positive returns can be attained by going long and short simultaneously in winner and loser stocks based on their performance in previous months (Jegadeesh and Titman, 1993). Furthermore, numerous studies have reported that the momentum strategy has negative exposure toward market-, size- and value-related factors and therefore has higher unexplained returns (alphas). This enigmatic risk and reward relationship have placed momentum strategy in unique place in asset pricing framework. This relationship is further compounded as the recently proposed volatility/variance scaled momentum strategies (volatility scaled strategies) have shown to have almost twice higher Sharpe Ratios (SR onwards) and alphas in comparison to momentum strategy (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016).

Does the volatility scaling improve the performance of any strategy? The recent studies such as Bongaerts *et al.* (2020) and Cederburg *et al.* (2020) indicate that such is not the case. The success of volatility scaling for any strategy is linked with the two aspects of the relationship between volatility and return. First that the volatility is persistent and second the negative relationship [2] exist between volatility and returns. As both of aforesaid characteristics exist for the momentum strategy; therefore, Cederburg *et al.* (2020) [3] conclude that the scaling by volatility boost the performance of the momentum strategy. However, it is not discussed in the literature that the persistence in volatility imposes one implicit condition to achieve the consistent performance across different investment horizons. The condition is that the negative relationship between momentum returns, and its previous volatility must exist across different states of volatility.

We find that the significant negative relationship between volatility and return only exist in the fifth quintile of the volatility of the momentum strategy. Accordingly, in the lower quintiles, the SR of both scaled and momentum strategy are roughly the same. Interestingly, by averaging the return and volatility across the quintiles, the superior performance of scaled strategies against momentum strategy become obvious. This observation predisposes that the higher performance of scaling strategies requires an equal mixing of different volatility states in any investment horizon. For full sample this occurs naturally, but the same may not hold for the randomly selected shorter investment horizons. Nevertheless, as the investment horizon increases the mixing of the extreme volatility states along with other states also increase. Therefore, the SR increases too, and this creates a link between the length of the investment horizon and the performance of scaled strategies.

These results that hold for SR of the scaled strategies also hold for alphas. We find that as the investment horizon increases, the alphas associated with scaled strategies also increase and the biggest alpha is for longest investment horizon. Interestingly, we find that the volatility of the winner (long side of the scaled strategies) of the scaled strategies is quite higher than the volatility of the winner of momentum strategy. The same does not hold for loser portfolio. This is despite of the fact that an overall volatility of the scaled strategies and momentum strategy is kept same in our analysis for different investment horizons. Further, the volatility of winner portfolio monotonically increases as investment horizon increases. Lastly, we find that the excess returns on the scaled strategies are positively linked with the increase in the variance of the winners' portfolio of scaled strategies over the momentum strategy.

These results indicate that when the long and short position in the momentum strategy is changed from one dollar to the inverse of the volatility. Then the contribution from the winner side in the overall volatility of the scaled momentum strategy increases. How is this increased volatility of the winner side linked with the performance? The answer is self-explanatory, we notice that when the volatility of the momentum strategy is higher, the momentum collapses, as the returns on the loser side predominate winner. In such times the scaled strategies reduce the amount of investment and minimizes the contribution from the loser side. This at one hand avoids huge loses and at other decrease the volatility related contribution from the loser side towards total volatility of the scaled strategies in high volatile states. In low volatile states, the volatility scaling does the opposite and increases the investment in scaled strategies. This dump and pump of the investment brings about the key role of the winner side for the better performance of the scaled strategies.

Our study contributes to the existing literature on the volatility scaling in two ways. First, it points out that the performance of the scaled strategies for the US market is linked with the length of investment horizon. This horizon bound link is underpinned by the persistence in volatility and its negative relationship with returns that exist when volatility is higher. Second, the higher performance of the scaled strategies can be explained by the higher variance loaded on the long side of these strategies.

In the second section of this paper, we discuss in detail the nature of relationship between volatility and momentum returns. The third section is reserved for discussing the performance of scaled strategies in connection with the variance of long-leg (past winners). In the fourth section we link the difference between the variance of long-leg of the scaled strategies and momentum strategy with the difference in their returns at various investment horizons. The section five concludes the paper.

2. Volatility scaled momentum returns

The data for the construction of scaled strategies and the momentum strategy is downloaded from Kenneth French's data library. We use both daily and monthly data form November 1926 to September 2016, the daily momentum return series is used to construct the realized volatility of momentum strategy. In total four different volatility scaled strategies $MOM_{S,t} = [MOMCV, MOMVS, MOMOS, MOMIS]$ reported in Daniel and Moskowitz (2016) are used. Whereas $MOMCV$, $MOMVS$ use the estimate of realized volatility and variance of preceding 126 trading days of the momentum strategy till the last day of previous month $(\sigma_{mom,t-1})$ [4]. These volatility-based scaling factors are $1/\sigma_{mom,t-1}$, and $1/\sigma^2_{mom,t-1}$.

For other two scaled strategies such as $MOMOS$, $MOMIS$, the estimates of the volatility as spelled out in Daniel and Moskowitz (2016) are used. Here the scaling factors are the optimized SR [5] such as $w_{mom,t-1} = \left(\frac{1}{2\gamma}\right)\frac{\mu_{mom,t-1}}{\sigma^2_{mom,t-1}}$, whereas $\mu_{mom,t-1}$ and $\sigma^2_{mom,t-1}$ are the conditional expectation of momentum returns and variance. These weights are estimated in two different ways. First based on expanding window. Such that these weights are available for making an investment for the coming month. Second, the weights are selected based on whole sample. Accordingly, we have two scaled strategies one is out of sample, which is based on expanding window *MOMOS*, and second is in sample strategy, which is based on weights estimated by using full sample *MOMIS*.

2.1 Relationship between volatility and returns of momentum strategy in quintiles

The volatility scaling improves the performance of any strategy, provided the negative relationship between the realized volatility and returns exist (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Bongaerts *et al.*, 2020) and volatility series is persistent

(Cederburg *et al.*, 2020). Momentum strategy fulfils both attributes. Accordingly, the volatility scaling has shown to improve the performance of the momentum strategy. Nevertheless, in the previous studies the consistency of the negative relationship between volatility and return across different volatility states is not discussed. Given the persistence in the volatility series, the inconsistent relationship between volatility and returns have some implication for the performance of the scaled strategies such that the performance of scaled strategies will not be consistent over different investment horizons. To check the relationship between volatility and returns across different volatility states, we construct quintiles using volatility of the momentum strategy for last 126 days for the sample of 1926–2016. We then test the following model:

$$r_{i,t} = \beta_0 + \beta_{Qi}\left(\sigma_{i,t-1}.Q_{i,t-1}\right) + \varepsilon_{i,t} \quad (1)$$

r_{it} is the monthly series of excess returns on winners, loser and momentum strategy and $\sigma_{i,t-1}$ denotes the volatility [6] of momentum strategy and Q_{it-1} is a dummy indicating a volatility based quintile. It takes the value of 1 for each quintile to represent a volatility state and 0 otherwise. The coefficient β_{Qi} captures an impact of lagged volatility on the returns in some volatility state. Table 1, Panel A, summarizes the finding of equation (1) when Borroso and Santa-Clara (2015) proposed volatility is used. The relationship between returns on loser, winner and momentum and volatility is not consistent across the volatility-based quintiles. Specifically, the negatively significant relationship between momentum returns and volatility only exist for fifth quintile, when the volatility is maximum. The similar relationship exists when Daniel and Moskowitz (2016) proposed that volatility is used as per Panel B of Table 1. The important message from these quintile-based regression is that the volatility scaling is expected to increase the performance of the scaled strategies when the volatility is maximum.

2.2 SR and volatility related quintiles

In this section, we present some descriptive analysis on the SR of the scaled strategies in comparison to momentum strategy within volatility-based quintiles [7]. We analyzed in each quintile the average returns, standard deviations and SR for different strategies. In addition to that we have reported the number of down-market states (DMS) [8] that occurred in any volatility-based quintile of the momentum strategy. We have further reported the average weights [9] in quintiles with which the momentum strategy is scaled.

In Table 2, Panel A, the results for momentum strategy are shown. For the lower quintiles the returns on the momentum strategy and SR are the highest. Especially, in the first quintile the annual returns are 24.81% and SR is 2.02 for the momentum strategy, whereas for the fifth quintile these returns are −0.04% and SR is almost zero. Overall, there is a negative association between volatility-based quintiles and momentum returns and SR. It is because the loser/winner portfolio has lower/higher returns in lowest quintile and then these returns for both portfolios increase till fourth quintile. Nevertheless, for loser portfolio these returns increase more in comparison to winner portfolio therefore the returns and SR on momentum strategy decrease as volatility increases. But, in the fifth quintile the returns on the winner portfolio suddenly drop and become slightly lower than loser portfolio. Resultantly momentum collapses when volatility of momentum returns is the highest.

It is interesting to note that the occurrence of DMS is directly linked with the volatility of momentum strategy. Subsequently, most of the momentum crashes that are shown in Daniel and Moskowitz (2016) occur in DMS and are concentrated in fifth quintile of the volatility (V5) of the momentum strategy. The probability of the occurrence of DMS in V5 is 55% [10], and it seems that higher realized volatility of momentum strategy is an important explanation of momentum crashes. Other explanations are fostered by Grundy and Martin (2001) and

Table 1. Lagged volatility and momentum strategy using quintiles

	Panel A: VOL			Panel B: DVOL		
Coefficients	W	L	MOM	W	L	MOM
β_1	−0.605 (−2.43)	0.645 (1.70)	−1.250 (−4.15)	−0.771 (−2.63)	1.124 (2.51)	−1.895 (−5.37)
Q1	0.264 (0.27)	−2.081 (−1.40)	2.345 (1.98)	0.678 (0.72)	−0.955 (−0.67)	1.633 (1.43)
Q2	0.216 (0.30)	−0.774 (−0.71)	0.990 (1.14)	0.0819 (0.11)	−1.236 (−1.10)	1.318 (1.47)
Q3	0.445 (0.78)	0.627 (0.72)	−0.182 (−0.26)	0.690 (1.15)	0.713 (0.78)	−0.0233 (−0.03)
Q4	0.570 (1.34)	0.823 (1.26)	−0.253 (−0.49)	−0.0652 (−0.14)	0.365 (0.51)	−0.430 (−0.76)
Q5	−0.537 (−2.84)	0.275 (0.95)	−0.812 (−3.54)	−0.536 (−2.48)	0.592 (1.80)	−1.128 (−4.32)

Note(s): This table shows the relationship between the 126 days lagged volatility of momentum strategy on the returns of winners (W), loser (L) of the traditional momentum strategy using the following regression model

$r_{i,t} = \beta_0 + \beta_{Qi}\ (\sigma_{mom,t-1}.Q_{i,t-1}) + \varepsilon_{i,t}$

Where r_{it} is the monthly excess returns on winners, loser and momentum portfolios denoted by W, L, and MOM respectively. $\sigma_{mom,t-1}$ denotes the previous 126 days' momentum volatility and Q_{it-1} are different regimes represented by volatility related quintiles. It takes values 1 in each regime. In Panel A, 126 days lagged volatility as of Barroso and Santa-Clara (2015) is used. In Panel B, the volatility is measured following Daniel and Moskowitz (2016) using GJR-GARCH model and is denoted by *DVOL* in the table. β_{Qi} is the coefficient of lagged volatility and its *t-stat* is shown below in parentheses. The results estimation period is from 1929:01 to 2016:08 and all coefficients are reported on a monthly basis

Table 2. Descriptive statistics of different momentum strategies using quintiles of 126 days momentum volatility

Characteristics	W Q1	W Q2	W Q3	W Q4	W Q5	L Q1	L Q2	L Q3	L Q4	L Q5	MOM Q1	MOM Q2	MOM Q3	MOM Q4	MOM Q5
Panel A: Traditional momentum strategy (MOM)															
AvG	14.87	15.00	18.15	19.13	1.81	−9.94	−5.76	5.46	9.13	1.85	24.81	20.76	12.69	10.00	−0.04
SD	17.57	20.18	21.44	23.47	28.08	17.39	22.61	20.20	29.79	61.27	12.26	17.46	16.30	24.82	48.69
SR	0.85	0.74	0.85	0.82	0.06	−0.57	−0.25	0.27	0.31	0.03	2.02	1.19	0.78	0.40	0.00
DMS	03	11	21	47	101	03	11	21	47	101	03	11	21	47	101
Panel B: Constant volatility Momentum strategy (MOMCV)															
AvG	35.91	25.90	26.29	19.24	1.57	−23.52	−11.27	7.68	9.29	−2.14	59.43	37.17	18.61	9.95	3.71
SD	42.07	35.90	30.16	24.78	16.01	41.90	39.64	28.31	31.03	30.39	29.52	30.56	22.98	25.41	24.36
SR	0.85	0.72	0.87	0.78	0.10	−0.56	−0.28	0.27	0.30	−0.07	2.01	1.22	0.81	0.39	0.15
Weights	199.92	143.54	114.50	87.24	46.55	199.92	143.54	114.50	87.24	46.55	199.92	143.54	114.50	87.24	46.55
Panel C: Variance scaled Momentum strategy (MOMVS)															
AvG	50.47	25.64	21.78	11.15	0.53	−31.92	−12.50	6.20	5.40	−1.80	82.39	38.14	15.58	5.75	2.33
SD	59.39	37.00	24.36	15.32	5.95	59.35	40.13	22.78	19.01	10.01	42.13	30.89	18.57	15.31	8.20
SR	0.85	0.69	0.89	0.73	0.09	−0.54	−0.31	0.27	0.28	−0.18	1.96	1.23	0.84	0.38	0.28
Weights	40,666	20,730	13,154	7,710	2,352	40,666	20,730	13,154	7,710	2,352	40,666	20,730	13,154	7,710	2,352
Panel D: Out of sample Momentum strategy (MOMOS)															
AvG	51.82	27.55	23.69	6.68	1.13	−13.75	−14.96	5.31	−5.17	−0.67	65.56	42.51	18.37	11.85	1.80
SD	52.62	33.63	26.86	23.06	14.46	54.13	36.31	28.50	26.47	28.96	37.25	27.35	22.27	20.48	21.64
SR	0.98	0.82	0.88	0.29	0.08	−0.25	−0.41	0.19	−0.20	−0.02	1.76	1.55	0.83	0.58	0.08
Weights	533.21	319.66	209.14	137.86	46.17	533.21	319.66	209.14	137.86	46.17	533.21	319.66	209.14	137.86	46.17
Panel E: In sample Momentum strategy (MOMIS)															
AvG	56.67	29.75	24.35	9.52	1.87	−15.36	−14.02	4.04	1.14	−1.27	72.03	43.78	20.31	8.38	3.14
SD	57.92	35.55	27.65	18.52	10.80	58.86	38.57	29.48	19.58	18.47	40.10	29.13	23.16	17.18	13.50
SR	0.98	0.84	0.88	0.51	0.17	−0.26	−0.36	0.14	0.06	−0.07	1.80	1.50	0.88	0.49	0.23
Weights	578.21	335.10	212.97	118.57	17.24	578.21	335.10	212.97	118.57	17.24	578.21	335.10	212.97	118.57	17.24

Note(s): This table provides the descriptive statistics (Average returns (AvG), Standard Deviation (SD), SR (SR) and weights (WG)) of traditional and scaled losers (L), winners (W) and momentum strategies (MOM, losers minus winners) across five quintiles using 126 days of momentum volatility. DMS shows the number of bear market states across volatility-based quantile. Panel A shows the summary statistics of momentum strategies (MOM), Panel B, shows the summary statistics of constant volatility momentum strategies (MOMCV). Panel C shows the distributional characteristics of variance scaled momentum strategies (MOMVS). Panel D and E shows the summary statistics of out of sample (MOMOS) and in sample momentum strategies (MOMIS) respectively. All averages, standard deviations and SR are reported annually. The sample period is from 1929:01 to 2016:08

Daniel and Moskowitz (2016). However, as explained in Barroso and Santa-Clara (2015) that the momentum related volatility has one advantage over other explanations of momentum crashes. That it can be used by the investors as an *ex ante* measure to ameliorate the momentum crashes [11].

In Panels B, C, D and E of Table 2 the descriptive statistics for scaled strategies are shown within volatility-based quintiles. As the scaling factor is the inverse of the volatility of the momentum strategy. Therefore, the average investment shown as weights are higher in lower volatility-based quintiles. The scaling increases the returns in lower quintiles for all scaled strategies. However, the volatility of these returns is also higher. Therefore, the SR for these scaled strategies do not increase in lower quintiles in comparison to momentum strategy. The visible increase is noted for the 5th quintile for the most of the scaled momentum strategies, whereas for one of scaled strategy (MOMOS) the significant increase is seen for 4th quintile. This indicates that the higher SR for the scaled strategies is confined to higher volatility states. As the volatility is persistence [12] therefore the higher volatile states are not equally represented in any investment horizon of shorter length than full length. The persistence implies that the higher changes in prices are followed by the higher changes and vice versa [13].

Based on these findings we conjecture that the twice higher SR for the scaled strategies in comparison to momentum strategy is not available for all randomly drawn investment horizons of shorter length. As the extent of representation of the higher volatility states in any randomly chosen investment horizon is a necessary condition for the improved performance of the scaled strategies.

3. Performance of scaled strategies and variance of winner

In this section, we analyze the performance of the scaled strategies in comparison to the momentum strategy. In Table 3, the descriptive statistics and alphas associated with momentum and scaled strategies are shown. The alphas for these scaled strategies are accessed through six different important asset pricing models such that CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966), FF-3 of Fama and French (1993), PS-4 of Pastor and Stambaugh (2003), FF-5 of Fama and French (2015), Q-4 model of Hou *et al.* (2015) and lastly SY-4 model of Lu *et al.* (2017).

As shown in Panel A, the average annualized return is 13.642% for the momentum strategy (MOM). Importantly, the models such as, CAPM, FF-3, PS-4 and FF-5 are unable to explain the excess returns on the momentum strategy. As the monthly alphas from these models are higher than the sample average of the momentum strategy. However, the newly proposed models of Hou *et al.* (2015) and Lu *et al.* (2017) are vital in explaining the momentum returns. Such that, alphas are economically small and statistically insignificant.

A significant observation in Panel A is the difference between the variance of winner and of loser portfolio. Despite having higher returns from winner its contribution in terms of variance for overall momentum strategy is half of the variance of the loser. It is interesting to see how these variances are evolved once weighting scheme for momentum returns is replaced from one dollar to the inverse of the volatility related weights.

In Panel B, C, D and E of Table 3 the results for scaled momentum strategies are shown. The variance for the momentum strategy and of all scaled strategies is kept equal that is 7.453. In this sense, the performance of these strategies is comparable in terms of their SR and alphas. The scaling improves the momentum strategy in many respects. To start with the alphas of CAPM, FF-3, PS-4 and FF-5 are higher than the counterpart sample averages of these scaled strategies. That is, there is no risk-based explanation for these scaled strategies. The models Q-4 and SY-4 models do not explain well the returns on the scaled strategies. As the alphas of these models are economically large and statistically reliable. Further, the

Table 3.
Descriptive statistics and performance comparison of different momentum strategies

Portfolios	AvG p.a %	S.D p.a %	VAR p.a %	S.R p.a	Skew	CAPM (alpha)	FF-3 (alpha)	PS-4 (alpha)	FF-5 (alpha)	Q-4 (alpha)	SY-4 (alpha)
Panel A: Normal Momentum strategy											
W	13.780	22.447	5.039	0.614	−0.537	0.005 (5.03)	0.006 (6.10)	0.005 (4.26)	0.006 (5.00)	0.007 (5.49)	0.001 (1.41)
L	0.138	34.245	11.728	0.004	1.784	−0.009 (−5.88)	−0.011 (−7.74)	−0.011 (−5.40)	−0.008 (−4.03)	0.003 (1.73)	0.000 (0.28)
MOM	13.642	27.300	7.453	0.500	−2.347	0.015 (6.47)	0.017 (8.08)	0.017 (5.63)	0.014 (4.97)	0.004 (1.36)	0.001 (0.50)
Panel B: Constant volatility Momentum strategy											
W	21.776	31.212	9.742	0.698	−0.606	0.011 (5.59)	0.013 (6.72)	0.010 (4.30)	0.008 (3.55)	0.008 (3.55)	0.001 (0.61)
L	−4.007	34.786	12.101	−0.115	−0.102	−0.012 (−6.15)	−0.012 (−6.50)	−0.018 (−6.97)	−0.018 (−7.47)	−0.009 (−3.30)	−0.012 (−4.80)
MOM	25.783	27.300	7.453	0.944	−0.349	0.023 (9.58)	0.025 (10.55)	0.028 (8.11)	0.027 (7.96)	0.017 (5.04)	0.013 (4.57)
Panel C: Variance scaled Momentum strategy											
W	21.922	34.222	11.71	0.641	−0.509	0.012 (4.76)	0.014 (5.55)	0.010 (3.28)	0.007 (2.21)	0.006 (2.00)	0.000 (0.07)
L	−6.942	35.140	12.348	−0.198	−0.514	−0.013 (−4.90)	−0.012 (−4.73)	−0.021 (−6.22)	−0.023 (−7.26)	−0.017 (−4.83)	−0.019 (−5.70)
MOM	28.864	27.300	7.453	1.057	0.679	0.026 (10.03)	0.026 (10.48)	0.031 (8.59)	0.030 (8.53)	0.023 (6.34)	0.020 (5.72)
Panel D: Out of sample Momentum strategy											
W	22.182	33.086	10.947	0.670	−0.003	0.012 (5.10)	0.014 (5.92)	0.013 (4.32)	0.010 (3.35)	0.009 (3.04)	0.004 (1.36)
L	−5.847	36.327	13.197	−0.161	−0.120	−0.012 (−4.75)	−0.012 (−4.68)	−0.016 (−4.87)	−0.019 (−6.02)	−0.013 (−3.95)	−0.016 (−4.69)
MOM	28.030	27.300	7.453	1.027	0.171	0.024 (9.97)	0.026 (10.63)	0.029 (8.71)	0.029 (8.86)	0.022 (6.69)	0.019 (6.17)
Panel E: In sample Momentum strategy											
W	24.442	34.558	11.943	0.707	0.310	0.015 (5.52)	0.017 (6.40)	0.014 (4.17)	0.011 (3.26)	0.010 (2.97)	0.004 (1.26)
L	−5.100	36.185	13.093	−0.141	−0.063	−0.009 (−3.09)	−0.008 (−2.67)	−0.017 (−4.67)	−0.020 (−5.86)	−0.015 (−4.08)	−0.017 (−4.67)
MOM	29.541	27.300	7.453	1.082	0.436	0.024 (9.81)	0.024 (9.96)	0.031 (8.67)	0.031 (8.94)	0.025 (6.95)	0.021 (6.24)

Note(s): This table provides the descriptive statistics (Average returns (AvG), Standard Deviation (S.D), Skewness (Skew) and SR (S.R)) and compares the performance (using alphas from CAPM, FF3, PS-4, FF5, Q-4 and SY-4) of momentum and scaled strategies (using the returns on losers (L), winners (W) and momentum (MOM), portfolios). Panel A depicts the summary statistics and performance of momentum strategies, Panel B, shows the summary statistics and performance of constant volatility momentum strategy (MOMCV). Panel C shows the distributional characteristics and performance of variance scaled momentum strategies (MOMVS). Panel D and E shows the summary statistics and performance of out of sample (MOMOS) and in sample momentum strategies (MOMIS) respectively. All alphas and skewness are reported monthly while averages, standard deviations and SR are reported annually. The sample period is from 1929:01 to 2016:08. The *t-stats* are shown below in parentheses annual SR are 0.944, 1.057, 1.027 and 1.082 for the scaled strategies and these are twice higher than the SR of the momentum strategy. Further the skewness is now positive for most of the scaled strategies, except for smaller negative skewness coefficient for MOMCV.

It is evident from Table 3 that the scaled momentum strategies are performing better than momentum strategy after controlling for strategy specific risks and market-based risks. However, one noticeable omission in the previous studies on the scaled momentum strategies is the higher contribution from the variance of winner portfolio towards total variance of the scaled strategies in comparison to the momentum strategy. At this stage it is a testable proposition that if this difference of variances for the long side of these strategies is the main contributing factor for the better performance of the scaled strategies. For that we conduct in sample analysis for the evaluation of the winner side variance for different investment horizons. Such as, if investor randomly chooses 5 years of the investment horizon out of total sample, then does the variance of the winner of the scaled strategy in comparison to the momentum strategy increase. Further, how this variance evolves when the investment horizons are increased by 5 years each. Lastly it is interesting to see that how this differential in variance is linked with the performance of the scaled strategies over the investment horizons. We gauge the average performance of the scaled strategies over momentum strategy at each investment horizon based on rolling windows [14] and this procedure is like the sampling without replacement.

To see that we decompose the variance of the strategies into the variances of winner and loser portfolios and covariance [15] between them. The variance of the momentum strategy using some weighting scheme that yield zero-cost strategy is $w^2\sigma_W^2 + w^2\sigma_L^2 - w^2\sigma_W\sigma_L\rho_{W,L}$. As for momentum strategy $w = 1$, the variance is $\sigma_W^2 + \sigma_L^2 - \sigma_W\sigma_L\rho_{W,L}$.

In Panel A of Table 4, the difference between the variance of winner of scaled strategies and momentum strategy $(w^2\sigma_W^2 - \sigma_W^2)$ is shown as WCV, WVS, WOS and WIS. These differences are calculated based on rolling windows of 5, 10, 15, 20 years, half sample (HS) and full sample (FS). In Panel B, C and D, the difference between the variance of loser $(w^2\sigma_L^2 - \sigma_L^2)$, correlation $(w^2\rho_{W,L} - \rho_{W,L})$ and covariance $(w^2\sigma_W\sigma_L\rho_{W,L} - \sigma_W\sigma_L\rho_{W,L})$ of winner and loser portfolios is shown. For each rolling window the overall variance of the scaled and momentum strategies is kept the same. Finally, in Panel E and F, the annualized difference between returns and the SR of scaled and momentum strategies are shown.

The difference between the variance of the winner of the scaled momentum strategies and traditional momentum is always positive and it significantly increases when the length of the investment horizon surpasses the half sample [16] and become the maximum for the full sample. Similarly, in Panel B of Table 4, the variance of the loser portfolio for the scaled strategies is higher than the variance of the loser portfolio on momentum strategy, but the extent of this increase is not comparable with the increase in the variance of winner portfolio. Further there is no monotonic pattern in the increase in variance of the loser portfolio. Panel C and D of Table 4 indicate that the differences in the correlations and covariance between scaled and momentum strategies are also positive and linked with the investment horizon. Next in Panel E, the difference in average returns for scaled and momentums strategies are not same across different investment horizons, and they start increasing once the investment horizon approach 20 years and beyond.

In Panel F a more direct link between the difference in SR of these strategies and the investment horizons can be seen. Such as the length of investment horizon increases by 5 years, the difference in SR consistently increases and become the highest in the full sample. This increase in SR is linked with the increasing variance of the winner portfolio of the scaled strategy in comparison to momentum strategy. This emphasis the main finding of this study that the performance of scaled strategies is a function of the investment horizon.

Panel A: Difference in winners variances					Panel B: Difference in losers variances			
	WCV	WVS	WOS	WIS	LCV	LVS	LOS	LIS
5 Y	1.912	3.717	3.242	3.681	0.540	1.268	0.814	1.509
10 Y	1.967	3.691	3.201	3.504	0.430	0.960	0.880	1.256
15 Y	1.981	3.243	2.992	3.207	0.460	0.788	1.035	1.118
20 Y	2.021	3.250	3.004	3.277	0.623	1.060	1.236	1.361
HS	3.882	5.443	5.741	6.215	0.586	0.821	1.274	1.345
FS	4.703	6.673	5.908	6.904	0.373	0.621	1.469	1.366
Panel C: Difference in winners and losers correlation					Panel D: Difference in Co-Variances			
	WCV LCV	WVS LVS	WOS LOS	WIS LIS	WCV LCV	WVS LVS	WOS LOS	WIS LIS
5 Y	0.0309	0.0558	0.0593	0.0621	2.452	4.985	4.056	5.190
10 Y	0.0410	0.0684	0.0753	0.0778	2.397	4.651	4.081	4.760
15 Y	0.0471	0.0744	0.0834	0.0854	2.441	4.031	4.027	4.325
20 Y	0.0539	0.0815	0.0901	0.0933	2.644	4.310	4.240	4.639
HS	0.0561	0.0772	0.0914	0.0965	2.477	3.570	4.152	4.504
FS	0.0569	0.0847	0.0885	0.0973	5.076	7.294	7.377	8.270
Panel E: Difference in average returns					Panel F: Difference in SR			
	MOMCV	MOMVS	MOMOS	MOMIS	MOMCV	MOMVS	MOMOS	MOMIS
5 Y	4.817	7.653	7.099	8.006	17.70	25.80	27.10	29.70
10 Y	4.722	6.952	7.044	7.763	19.50	27.00	29.40	31.50
15 Y	5.043	6.863	7.323	7.923	21.50	28.80	31.90	33.80
20 Y	5.646	7.524	7.939	8.500	24.50	32.50	35.40	37.30
HS	6.675	8.560	9.106	9.626	30.10	38.70	41.70	43.90
FS	12.141	15.222	14.387	15.899	44.50	55.80	52.70	58.20

Note(s): In this table, Panel A and B shows the difference of winners'/losers' variances for scaled strategies in comparison to momentum strategy. As there are four scaled strategies therefore there are four series of average differences of variance over rolling windows of different years. These differences are shown as WCV, WVS, WOS and WIS for winners and LCV, LVS, LOS and LIS for losers, respectively. The Panel C and D reports the difference of winners'/losers', correlations/co-variances for the scaled and traditional momentum strategy. Panel E describes the difference between average returns of scaled momentum strategies relative to momentum strategies. Panel F reports the difference of SR of scaled and momentum strategies. These statistics are reported for different rolling windows i.e. 5, 10, 15, 20years, and half sample (HS). The same statistics are also calculated for full sample (FS). The percentage differences over various rolling windows/investment horizons are annualized

Table 4.
Difference in average returns, SR, variances and Co-Variances of momentum strategies

4. Performance of scaled strategies and investment horizons

To test the proposition that the performance of scaled strategies in comparison to momentum strategy depends on the average representation of different states of volatility in any investment horizon. We created two groups having same investment horizons, but with different average representation of volatility. The first group is based on actual investment horizons of 5, 10 and 15 etc. years. The basic purpose of constructing this group is to gauge the average performance of the scaled strategies for a given investment horizon that is selected randomly from the total sample of momentum returns of 90 years. These investment horizons are selected based on rolling window. We call them random samples as their selection is like random draws of some investment horizon without replacement from the total sample. These random samples are selected for both scaled strategies and for momentum strategy. Further the volatilities at each rolling window corresponding to some investment horizon is equalized for the calculation of average SR. Resultantly, we have the estimates of

SR that are available to an investor on average with the investment horizons of 5, 10, and 15 etc. years in scaled strategies and momentum strategy.

The second group represents the pseudo investment horizon of same length as of random sample. The difference is that they are created to give the volatility states an average representation. This can be achieved by ignoring the persistence in the volatility states of momentum strategies, we call these investment horizons the mixed sample. Obviously, these mixed samples do not represent the actual investment horizons. Such that for the 5 years mixed sample, we take five observations across five quintiles of volatility and repeat this process till the time we have 60 observations. These observations do not follow any chronological pattern. Once all 60 observations are collected, then this procedure is repeated by leaving the first observation. The construction of the mixed samples for longer horizons also follows the same procedure. For mixed sample as well, we keep the volatility same at each horizon for calculating SR for scaled strategies and momentum strategy. This novelty in approach assists us to analyze the role of persistence in volatility for the performance of the scaled strategies.

4.1 Random sample and mixed sample

In Table 5, Panel A, the annual SRs are shown for the momentum strategy (MOM) and scaled strategies (MOMCV, MOMVS, MOMOS, MOMIS) for different investment horizons selected based on random sampling. It is interesting to note that as the investment horizon increases the SR of the traditional momentum strategy decreases monotonically. This is because the representation on average of higher volatile state increases as the length of investment horizon increases. Therefore, the performance of the momentum strategy dampens, as the investment horizon increases. On the other hand, the scaled strategies do better volatility timing and invests less when the volatility is higher. Therefore, the SR remain quite consistent for the scaled strategies as investment horizon increases.

In Panel A(a) of Table 5, the percentage increase in SR of scaled strategies over momentum strategy is shown for different investment horizons. The results show that the proposed twice higher SR in previous studies for scaled strategies in comparison to momentum strategy is not available at each investment horizon. Instead, there is an intrinsic link between the performance of scaled strategies and investment horizons. Higher performance is reserved for those investors who hold the scaled momentum strategies for longer horizon. As for more reasonable investment horizons (5 years–20 years) the increase in SR is within the range of 25–40% for various scaling strategies in comparison to momentum strategy.

On the other hand, in the Panel B of Table 5, the SR of the momentum strategy and scaled strategies for the mixed sample at smaller investment horizons is mimicking the performance of the full sample. For instance, the SR of momentum strategy (MOM) at shorter holding periods [17] and longer holding periods are roughly equal. These results are in contrast with SR of random sample of momentum strategy that monotonically dampens at longer investment horizons. Even for scaled strategies (MOMCV, MOMVS, MOMOS and MOMIS) the SR are broadly same irrespective of the length of investment horizons. Similarly, in Panel B (b) of Table 5, the percentage increase in SR for the scaled strategies in comparison to momentum strategy is now delinked with the investment horizons.

These analyses delineate that the higher performance of scaled strategies as suggested in previous studies depend upon the rare equal mix of time varying volatility states. This equal mix of different volatility states is more probable in longer samples given the higher persistence of volatility series. This is not to overemphasize that the better performance of scaled momentum strategies is possible under strong persistence only if, the negative predictive relationship between volatility and momentum returns is uniform across all different states of volatility [18].

Random sample SR									
Panel A: SR comparison on different investment horizons						Panel A(a): Relative increase			
HP	MOM	MOMCV	MOMVS	MOMOS	MOMIS	MOMCV	MOMVS	MOMOS	MOMIS
5 Y	0.90	1.10	1.17	1.20	1.23	22.22	30.00	33.33	36.67
10 Y	0.89	1.09	1.16	1.19	1.21	22.47	30.34	33.71	35.96
15 Y	0.86	1.07	1.15	1.19	1.20	24.42	33.72	38.37	39.53
20 Y	0.83	1.07	1.14	1.16	1.19	28.92	37.35	39.76	43.37
25 Y	0.83	1.10	1.19	1.21	1.23	32.53	43.37	45.78	48.19
30 Y	0.83	1.11	1.20	1.23	1.25	33.73	44.58	48.19	50.60
HS	0.83	1.13	1.22	1.25	1.27	36.14	46.99	50.60	53.01
50 Y	0.82	1.13	1.22	1.24	1.26	37.80	48.78	51.22	53.66
60 Y	0.78	1.12	1.21	1.23	1.25	43.59	55.13	57.69	60.26
70 Y	0.69	1.06	1.15	1.16	1.19	53.62	66.67	68.12	72.46
80 Y	0.56	0.98	1.08	1.08	1.12	75.00	92.86	92.86	100.00
FS	0.50	0.94	1.06	1.03	1.08	88.00	112.00	106.00	116.00
Mixed sample SR									
Panel B: SR comparison on different investment horizons						Panel B(b): Relative increase			
HP	MOM	MOMCV	MOMVS	MOMOS	MOMIS	MOMCV	MOMVS	MOMOS	MOMIS
5 Y	0.62	0.99	1.11	1.07	1.11	59.85	79.29	72.44	79.57
10 Y	0.54	0.96	1.09	1.08	1.13	77.52	101.91	100.70	109.54
15 Y	0.53	0.95	1.08	1.10	1.15	80.40	105.35	109.38	119.10
20 Y	0.54	0.95	1.07	1.11	1.15	75.45	98.11	104.47	113.23
25 Y	0.55	0.95	1.06	1.09	1.14	71.33	91.96	97.62	105.23
30 Y	0.56	0.95	1.06	1.08	1.12	70.21	89.89	94.60	101.81
HS	0.56	0.94	1.05	1.09	1.13	69.44	89.11	95.59	102.48
50 Y	0.56	0.95	1.06	1.09	1.12	70.64	89.89	94.83	101.49
60 Y	0.54	0.95	1.06	1.09	1.13	75.76	96.04	101.71	108.94
70 Y	0.50	0.94	1.07	1.10	1.15	88.47	113.93	119.22	129.87
80 Y	0.48	0.94	1.08	1.04	1.12	96.55	124.38	117.01	132.43
FS	0.50	0.94	1.06	1.03	1.08	88.00	112.00	106.00	116.00

Note(s): This table shows the comparison of traditional and scaled momentum strategies based on average SR calculated at different investment horizons of 5 years, 10 years, 15 years, 20 years, half sample (HS) and full sample (FS). These investment horizons are selected based on rolling windows for random sample and for mixed sample whereas, in mixed sample each estimated window have equal representation of different volatility states. In Panel A and B, the annualized SR are shown for momentum strategy (MOM), constant volatility momentum strategies (MOMCV), variance scaled momentum strategies (MOMVS) out of sample (MOMOS) and in sample momentum strategies (MOMIS) strategies respectively. In Panel A(a) and B(b) the relative increase in percentages is shown for four scaled strategies over traditional momentum strategy for random and mixed sample. The sample period is from 1929:01 to 2016:08

Table 5. Performance comparison of momentum strategies at different investment horizons

4.2 Time series alphas

As we have noticed that the SR of the scaled strategies constantly improve as the investment horizon increases. In this section we analyze the risk adjusted returns/alphas of the scaled strategies (MOMCV, MOMVS, MOMOS, MOMOS) for using six asset pricing models such as CAPM, FF-3, PS-4, FF-5, Q-4, and SY-4. In Table 6, the average alphas for the rolling windows of 5, 10, 15, 20 years and of half sample are reported for both the random and mixed sample. To keep analysis consistent with the previous sections, the volatility at each horizon for all strategies is kept same.

First, we report the alphas of the 5 years of investment horizon based on random sample of all scaled strategies in the Panel A of Table 6. These alphas across all models, CAPM, FF-3, PS-4, FF-5, Q-4, and SY-4 are smaller in comparison to full sample alphas of these strategies

Table 6. Performance comparison using different asset pricing models

Random sample							Mixed sample					
Portfolios	CAPM	FF-3	PS-4	FF-5	Q-4	SY-4	CAPM	FF-3	PS-4	FF-5	Q-4	SY-4
Panel A: 5Y												
MOMCV	0.016 (27.60)	0.015 (20.88)	0.017 (15.47)	0.013 (11.86)	0.007 (5.89)	0.005 (5.63)	0.022 (35.29)	0.023 (39.32)	0.027 (18.91)	0.022 (19.36)	0.013 (13.78)	0.010 (9.65)
MOMVS	0.018 (25.64)	0.017 (20.11)	0.019 (16.60)	0.017 (14.26)	0.011 (8.40)	0.009 (8.88)	0.025 (31.13)	0.025 (30.04)	0.030 (17.19)	0.027 (18.36)	0.018 (17.07)	0.016 (10.91)
MOMOS	0.017 (25.02)	0.016 (19.29)	0.020 (16.86)	0.019 (15.91)	0.013 (8.95)	0.011 (9.73)	0.022 (28.57)	0.022 (28.10)	0.027 (16.35)	0.027 (16.49)	0.018 (13.07)	0.017 (14.36)
MOMIS	0.017 (22.71)	0.016 (18.88)	0.021 (18.09)	0.019 (17.44)	0.014 (9.73)	0.012 (10.38)	0.023 (27.66)	0.023 (27.15)	0.028 (16.98)	0.028 (16.36)	0.019 (13.75)	0.017 (14.88)
Panel B: 10Y												
MOMCV	0.016 (31.59)	0.017 (27.83)	0.019 (21.32)	0.016 (17.73)	0.009 (9.80)	0.006 (8.29)	0.022 (36.04)	0.023 (38.75)	0.027 (16.81)	0.023 (21.44)	0.013 (17.12)	0.011 (10.75)
MOMVS	0.018 (29.78)	0.018 (27.97)	0.021 (30.52)	0.019 (26.49)	0.013 (15.74)	0.010 (18.01)	0.025 (29.99)	0.025 (28.92)	0.030 (15.58)	0.026 (19.97)	0.019 (23.81)	0.017 (11.60)
MOMOS	0.018 (28.95)	0.018 (25.33)	0.023 (26.57)	0.020 (24.70)	0.015 (13.44)	0.012 (19.22)	0.024 (28.23)	0.024 (27.93)	0.030 (17.28)	0.028 (17.37)	0.020 (14.68)	0.018 (18.67)
MOMIS	0.018 (27.13)	0.018 (24.90)	0.023 (30.08)	0.021 (26.14)	0.016 (14.05)	0.012 (21.50)	0.025 (26.98)	0.025 (26.07)	0.030 (17.75)	0.029 (16.80)	0.021 (15.12)	0.019 (18.56)
Panel C: 15Y												
MOMCV	0.017 (29.98)	0.019 (27.05)	0.022 (27.92)	0.018 (22.01)	0.011 (11.34)	0.008 (9.77)	0.022 (43.98)	0.024 (43.56)	0.027 (16.89)	0.023 (20.05)	0.013 (18.22)	0.012 (10.78)
MOMVS	0.019 (26.24)	0.019 (25.27)	0.023 (33.11)	0.020 (26.31)	0.015 (15.75)	0.011 (14.89)	0.025 (33.79)	0.025 (31.29)	0.031 (15.27)	0.028 (17.43)	0.019 (28.86)	0.017 (10.78)
MOMOS	0.019 (25.88)	0.020 (23.53)	0.024 (30.00)	0.022 (25.38)	0.017 (14.22)	0.013 (16.66)	0.025 (34.05)	0.025 (35.30)	0.031 (17.76)	0.031 (13.45)	0.022 (15.55)	0.019 (19.82)
MOMIS	0.019 (23.74)	0.020 (22.22)	0.025 (31.87)	0.022 (25.69)	0.018 (14.62)	0.013 (17.34)	0.025 (31.56)	0.026 (31.07)	0.031 (18.05)	0.031 (12.67)	0.023 (15.92)	0.020 (18.19)
Panel D: 20Y												
MOMCV	0.018 (32.03)	0.020 (32.58)	0.023 (49.45)	0.020 (32.71)	0.012 (15.75)	0.009 (16.05)	0.022 (50.05)	0.024 (49.85)	0.028 (14.00)	0.024 (20.49)	0.013 (17.18)	0.012 (10.86)
MOMVS	0.020 (26.33)	0.021 (28.93)	0.024 (47.71)	0.021 (30.13)	0.016 (19.35)	0.012 (17.09)	0.024 (38.69)	0.025 (36.13)	0.031 (12.06)	0.028 (17.27)	0.019 (29.04)	0.017 (10.17)
MOMOS	0.020 (27.46)	0.021 (28.83)	0.025 (50.09)	0.022 (29.82)	0.018 (18.41)	0.014 (20.84)	0.025 (41.73)	0.025 (42.97)	0.031 (18.83)	0.032 (10.65)	0.022 (15.96)	0.020 (16.60)
MOMIS	0.020 (25.66)	0.021 (27.49)	0.025 (52.03)	0.022 (29.36)	0.019 (18.89)	0.014 (20.81)	0.025 (36.76)	0.025 (36.48)	0.031 (18.88)	0.033 (9.44)	0.023 (16.41)	0.021 (14.57)
Panel E: HS												
MOMCV	0.020 (29.76)	0.022 (29.25)	0.026 (23.89)	0.024 (17.82)	0.015 (8.91)	0.012 (14.58)	0.022 (66.48)	0.023 (76.47)	0.027 (36.16)	0.026 (23.73)	0.014 (23.15)	0.013 (30.72)
MOMVS	0.021 (25.42)	0.023 (26.30)	0.028 (17.33)	0.026 (15.44)	0.020 (9.45)	0.015 (14.67)	0.023 (48.09)	0.024 (51.06)	0.030 (24.70)	0.029 (20.93)	0.021 (30.46)	0.018 (42.61)
MOMOS	0.022 (28.03)	0.023 (28.38)	0.029 (18.42)	0.026 (17.99)	0.021 (9.83)	0.017 (16.12)	0.024 (50.03)	0.025 (55.38)	0.033 (21.66)	0.031 (21.13)	0.025 (15.28)	0.020 (44.23)
MOMIS	0.022 (27.69)	0.023 (28.06)	0.029 (14.74)	0.027 (14.97)	0.023 (8.92)	0.017 (13.76)	0.024 (46.19)	0.025 (49.13)	0.033 (16.60)	0.031 (16.78)	0.027 (12.04)	0.021 (27.88)

Note(s): This table compares the performance of random and mixed sample (for all investment horizons i.e. 5 years, 10 years, 15 years, 20 years and half sample) based on risk adjusted returns (alphas). The random sample is selected based on rolling windows whereas, the mixed sample contains equal number of observations from five different volatilities related quintile for each investment horizons of 5, 10, 15, 20 years and half sample (HS). To get the risk adjusted returns, six asset pricing models are used. These are CAPM, Fama and French (1993) 3-Factor model, Pastor and Stambaugh (2003) PS-4 model, Fama and French 5 Factor model (2015), Hou *et al.* (2015) Q-4 model and lastly Lu *et al.* (2017) SY-4 model. MOM is momentum strategy, MOMCV denotes momentum strategy scaled by 126 days' momentum volatility, MOMVS is momentum strategy scald by 126 days' momentum variance, MOMOS and MOMIS are scaled strategies constructed by following Daniel and Moskowitz (2016) procedure. All alphas are reported on monthly basis while *t-stat* is shown below in parentheses shown in Panel B, C, D and E of Table 3. However, once we compare the alphas of full sample with the 5 years mixed sample then the difference is quite minuscule. The same holds true for other investment horizons for the mixed sample, however for random sample the alphas increase over investment horizons.

The results for the alphas are in line with the prior results for the SR for the random and mixed sample. Such that, as the investment horizons increase so as the volatility mix, therefore the alphas for the scaled strategies are also linked with investment horizons for random sample. On the other hand, for mixed sample the volatility is equally mixed for shorter investment horizons. Therefore, the alphas for shorter investment horizons are like the alphas of the full sample of the scaled strategies. The main message from these analyses is that the overall SR and alphas are although higher for scaled strategies than momentum strategy. But to achieve higher performance longer investment horizons are required.

5. Decomposing the increased variance of scaled momentum strategies

Results from previous sections confirm that scaled strategies compared to momentum strategy performed better in terms of SR and risk adjusted returns (alphas). Especially in full sample, nevertheless it also holds true, to an extent for smaller investment horizons such as 5, 10, and 15 etc. years. In this section, we provide an explanation for this increased performance of scaled strategies. Insights from Tables 3 and 4 reveal that the increased performance of scaled strategies across different investment horizons is mainly due to the increase in the variance of winners' portfolio. Further, the results of Table 4 depict no significant change in the variance of losers' portfolios. Therefore, we investigate the role of increased variance for the higher returns on the scaled momentum strategies across different investment horizons. We kept the overall variance at each investment horizon the same for both the scaled and momentum strategies. This also indicate that once the variance is the same at each investment horizon, the increase in returns over horizons essentially indicate the increase in the SR [19].

For analysis, we decompose the difference in the variance of scaled and momentum strategies into three components. These components are the increase in the variance of losers' portfolio ($\Delta VAR_{L,h} = VAR_{SL,h} - VAR_{TL,h}$), whereas $VAR_{SL,h}$ is the variance of scaled loser and $VAR_{TL,h}$ is the variance of loser side of momentum strategy. Here, h indicates the length of the investment horizon. Similarly the increase in the variance of winners' portfolio is calculated as ($\Delta VAR_{W,h} = VAR_{SW,h} - VAR_{TW,h}$), now $VAR_{SW,h}$ is the variance of scaled winner and $VAR_{TW,h}$ is the variance of winner of momentum strategy. Lastly the increase in the correlation of winners and losers' portfolios is gauged as ($\Delta COR_{WL,h} = COR_{SWL,h} - COR_{TWL,h}$). We run the following regression for the difference in returns of the scaled and momentum strategies across different investment horizons h:

$$\Delta r_h = \beta_0 + \beta_{L,h}\,\Delta VAR_{L,h} + \beta_{W,h}\,\Delta VAR_{W,h} + \beta_{Cor,h}\,\Delta COR_{WL,h} + \varepsilon_h \tag{2}$$

Whereas Δr_h is the returns on scaled strategies in excess of the returns on momentum strategy for each investment horizon h.

We report the results of equation (2) in Table 7. Consistent with our previous analysis, we find that it is the variance of winners' portfolio which is mainly responsible for the better performance of scaled momentum strategies at each investment horizon. The coefficient of winners' portfolio is positive and statically significant, and it increases as the investment horizon increases. As discussed before that the performance of scaled strategies over momentum strategy gradually increases over investment horizons. We find that the increase in variance of winners' portfolio of the scaled strategies over investment horizons can explain the horizon bound performance of scaled momentum strategies. On the other hand, there is no

Table 7. Variance contribution in scaled strategies

Portfolio	$\Delta VAR_{L,h}$	$\Delta VAR_{W,h}$	$\Delta COR_{WL,h}$	Adj. R^2	% Explained Total	% Explained by Losers	% Explained by Winners	% Explained by Corr W, L
Panel A: 5Y								
MOMCV	−0.343 (−13.89)	1.941 (31.64)	0.00139 (0.41)	60.8	73.4	−3.7	76.7	0.4
MOMVS	−0.259 (−9.73)	1.696 (33.09)	−0.0117 (−3.67)	70.0	66.5	−3.4	74.7	−4.8
MOMOS	−0.386 (−13.02)	2.118 (34.99)	0.00081 (0.32)	70.4	81.9	−5.1	86.6	0.4
MOMIS	−0.303 (−11.11)	1.807 (32.81)	−0.000987 (−0.32)	68.6	72.9	−4.9	78.3	−0.4
Panel B: 10Y								
MOMCV	−0.372 (−12.15)	2.180 (32.30)	−0.0110 (−3.77)	78.80	81.0	−8.8	94.0	−4.2
MOMVS	−0.442 (−14.58)	2.095 (38.06)	−0.0172 (−6.68)	85.00	80.5	−11.6	100.4	−8.3
MOMOS	−0.478 (−16.48)	2.320 (41.71)	−0.00585 (−2.65)	85.80	86.7	−11.5	101.6	−3.4
MOMIS	−0.425 (−15.70)	2.022 (40.78)	−0.0164 (−6.47)	85.70	73.9	−11.7	94.2	−8.6
Panel C: 15Y								
MOMCV	−0.376 (−13.87)	2.306 (43.22)	0.00472 (2.70)	90.10	94.3	−11.9	104.2	2.0
MOMVS	−0.559 (−19.34)	2.348 (49.69)	0.00131 (0.80)	93.20	100.2	−19.5	119.0	0.7
MOMOS	−0.543 (−20.85)	2.491 (55.63)	0.00713 (5.27)	94.10	101.8	−17.2	114.6	4.5
MOMIS	−0.479 (−18.05)	2.164 (49.25)	0.00368 (2.24)	93.50	91.4	−17.0	106.4	2.0
Panel D: 20Y								
MOMCV	−0.307 (−14.05)	2.260 (54.95)	0.0108 (10.58)	94.80	88.5	−11.2	94.7	4.9
MOMVS	−0.489 (−17.05)	2.312 (51.22)	0.0126 (9.02)	94.50	107.2	−19.5	120.1	6.5
MOMOS	−0.479 (−19.98)	2.469 (63.34)	0.0137 (12.96)	96.10	107.8	−17.4	116.5	8.7
MOMIS	−0.489 (−19.36)	2.247 (55.91)	0.0158 (11.65)	95.50	103.0	−19.6	113.7	9.0
Panel E: HS								
MOMCV	−0.806 (−19.46)	3.023 (36.87)	0.00653 (8.61)	91.6	109.6	−33.8	140.7	2.8
MOMVS	−0.615 (−12.65)	2.419 (30.33)	0.0199 (17.26)	91.8	112.2	−27.9	131.7	8.4
MOMOS	−0.839 (−25.63)	2.921 (52.46)	0.00934 (11.27)	95.2	110.1	−34.5	139.2	5.3
MOMIS	−0.846 (−21.36)	2.739 (41.34)	0.0161 (15.71)	93.4	111.9	−38.2	141.7	8.4

Note(s): This table presents the contribution of loser's variance (Var L), winners' variance (Var W) and losers, winners' correlation (Cor W, L) in explaining the returns of scaled strategies over momentum strategy for different investment horizons. We run the following regression

$$\Delta r_h = \beta_0 + \beta_{L,h}\ \Delta VAR_{L,h} + \beta_{W,h}\ \Delta VAR_{W,h} + \beta_{Cor,h}\ \Delta COR_{WL,h} + \varepsilon_h$$

Δr_h is the returns on scaled strategies in excess of the returns of momentum strategy for each investment horizon h. These investments horizons are of 5,10,15,20 years and of half sample (HS) length. Whereas $\Delta VAR_{L,h}$ is the difference in variance of scaled loser in comparison to the traditional loser at each investment horizon and is calculated as $VAR_{SL,h} - VAR_{TL,h}$. Whereas $\Delta VAR_{W,h}$ is the difference in variance of scaled winner in comparison to the traditional winner at each investment horizon and is calculated as $VAR_{SW,h} - VAR_{TW,h}$. Lastly the difference in the correlation of winners and losers' portfolios $\Delta COR_{WL,h}$ is gauged as ($\Delta COR_{WL,h} = COR_{SWL,h} - COR_{TWL,h}$). Whereas the scaled strategies used in this study are constant volatility momentum strategies (MOMCV), variance scaled momentum strategies (MOMV) out of sample (MOMOS) and in sample momentum strategies (MOMIS) strategies respectively. The last four columns report the percentage of excess returns explained by each component in the above regression model. The results estimation period is from 1929:01 to 2016:08 and all coefficients are reported on monthly basis. t-statistics are reported in parentheses significant contributions from the increase in variance of losers' portfolio and the correlation between winners' and losers' portfolio. In fact, the increase in the variance of losers' portfolio is negatively related with the performance of scaled strategies. For brevity, we also present the explanatory power of each component as a percentage of total excess return explained in Table 7 for various investment horizons. We find that almost all the explanatory power of equation (2) shown as *adj* R^2 comes from the side of winners' variance. These results are not confined to just single investment horizon but consistent across all investment horizons.

On the other hand, the constituent risk factors and mispricing factors of CAPM, FF-3, PS-4, FF-5, Q-4 and SY-4 are specifically unable to explain the excess returns on the scaled strategies over the momentum strategy. For instance, when we regress the returns Δr_h of various investment horizons on the explanatory factors of the models such as CAPM, FF-3, PS-4, FF-5, Q-4, and SY-4. Then the alphas are economically large and statistically reliable. Further the is negligible for all model tested for the scaled strategies. These results are reported in Appendix as Table A1.

6. Conclusion

The performance of the volatility scaled strategies has shown to be twice higher than momentum strategy in full sample for the US market in the previous studies. However, we analyzed that in shorter investment horizons the performance of the scaled strategies is not twice higher than the momentum strategy. The main reason is that the scaling factor(volatility) is persistent and the negative relationship between volatility and returns only exists when volatility is higher. The negative relationship is an essential condition for the better performance of the scaled strategies. As we analyzed that the performance of the scaled strategies depends on the extent of average representation of volatile states in any randomly selected investment horizon.

In full sample the volatile states have equal representation, therefore the performance is maximum for the scaled strategies in comparison to momentum strategy. However, in shorter sample periods on average the volatile states are not represented equally due to stronger persistence in the volatility series. This representation increases on average as the length of investment horizon increases. Therefore, we find that the SR for scaled momentum strategies in comparison to momentum strategy monotonically increases as length of investment horizon increases. The same hold true for the alphas of the scaled strategies when the various asset pricing models are used. Hence, there is momentum in the performance of the scaled momentum strategies which is linked with the length of investment horizons. Lastly, we find that the higher performance of these scaled strategies is linked with the excess variance loaded on the winner portfolio of these strategies.

Notes

1. For example: Jegadeesh and Titman (1993), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), Okunev and White (2003), Erb and Harvey (2006), Moskowitz *et al.* (2012), Asness *et al.* (2013), and Israel and Moskowitz (2013).
2. We have also tested this proposition for 14 different long and short strategies and find the same results, these results can be reported upon request.
3. The study affirms the findings of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016).
4. This is as per procedure suggested in Barroso and Santa-Clara (2015).
5. For the derivation of this SR, the interested readers may consider Appendix C of Daniel and Moskowitz (2016).
6. Both version of the volatility as proposed by Borroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) are used.

7. These quintiles are marked based on previous 126 days volatility of momentum strategy.
8. A down market state is when the cumulative returns for the last 24 months is negative.
9. These weights are the inverse of unconditional/conditional volatility of last 126 days till last month.
10. If the occurrence of DMS is equally likely than in any volatility state this probability should be 20%. Further in 4th and 5th volatility-based quintiles the probability of occurrence of DMS is 87%.
11. Barroso and Santa-Clara (2015) showed that the risk of momentum strategy can only be explained to an extent of 23% by the market factor and the important predictable risk of the momentum is the strategy specific.
12. We find that autocorrelation coefficients are between 0.97 and 0.85 for four different types of volatility series used in this study. Figure A1 of Appendix, shows the graphs of these volatility related series.
13. Engle (1982), Bollerslev (1987), Baillie (1996), Gray (1996), Andersen and Bollerslev (1997), Chou (1988), Schwert (1989), Nelson (1991), Engle and Patton (2001), and Poon and Granger (2003).
14. Investment horizon is defined as the length of an investment in some specific strategy by an investor. It indicates the end of period wealth that an investor may have. For instance, if we take the average of monthly continuously compounded returns r_{cc} of an investment over the 5 years. Then the size of investment of $1 by the end of 5 years would be equal to $1 \times exp^{(60 \times r_{cc})}$. In this study choosing the investment horizons based on rolling windows give us an idea that how much an investor on average may earn if she invests in scaled strategies instead of momentum strategy.
15. In addition of the covariance which is predominated by the standard deviations of winner and loser, we have also considered the correlation between the winner and loser portfolio.
16. To converse space, we have not shown the increase in variance of winner portfolio of scaled strategy over momentum strategy for investment horizons beyond half-sample. In all such horizons the variance is increasing, these results are available upon request.
17. There are small differences in SR of the full sample and shorter sample which can be due to sampling issues. For five years' horizon there are just 60 observations to proxy the average volatility for the full sample, that is we are just taking one observation to represent a state. Therefore, here we see for traditional strategy the SR is not that reduced to match the SR of full sample. There is probably lesser representation of the average volatility in 5 years' sample especially in comparison to half sample. However, these differences do not disrupt the spirit of overall analysis.
18. Alternatively, it means that the momentum crashes are equally distributed across all volatility related states of the momentum strategy and as per Table 2 such is not the case.
19. It may be added that the returns on the scaled strategies as shown in Panel E of Table 4, take longer horizons than SR to increase. It is because as the investment horizon increases the volatility decreases more in comparison to the increase in returns.

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Further reading

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Appendix

Table A1.
Excess returns on the scaled strategies and asset pricing models

Horizon	CAPM alpha	FF-3 alpha	PS-4 alpha	FF-5 alpha	Q-4 alpha	SY-4 alpha	CAPM Adj. R^2	FF-3 Adj. R^2	PS-4 Adj. R^2	FF-5 Adj. R^2	Q-4 Adj. R^2	SY-4 Adj. R^2
Constant volatility Momentum strategy (MOMCV)												
5Y	0.011 (13.09)	0.011 (13.08)	0.013 (11.18)	0.013 (11.84)	0.013 (11.24)	0.013 (11.52)	−0.10%	−0.20%	0.10%	−0.20%	−0.10%	−0.40%
10Y	0.011 (15.29)	0.011 (15.21)	0.013 (13.95)	0.013 (15.11)	0.013 (13.85)	0.013 (14.51)	−0.10%	−0.20%	−0.20%	0.00%	0.40%	0.40%
15Y	0.011 (17.48)	0.011 (17.17)	0.013 (16.68)	0.013 (18.19)	0.013 (16.57)	0.013 (17.74)	−0.10%	−0.20%	−0.30%	−0.40%	1.00%	0.50%
20Y	0.012 (21.14)	0.012 (20.84)	0.014 (22.35)	0.013 (23.49)	0.014 (22.24)	0.013 (23.13)	0.00%	−0.10%	−0.30%	−0.30%	0.60%	0.10%
HS	0.013 (37.16)	0.013 (37.85)	0.013 (37.59)	0.013 (37.00)	0.013 (38.40)	0.013 (37.72)	0.30%	0.60%	0.40%	0.90%	0.70%	0.40%
Variance scaled Momentum strategy (MOMV)												
5Y	0.014 (9.72)	0.014 (9.70)	0.017 (8.66)	0.017 (9.17)	0.017 (8.85)	0.017 (9.01)	−0.10%	−0.30%	−0.10%	−0.40%	−0.30%	−0.50%
10Y	0.014 (11.69)	0.014 (11.64)	0.017 (10.85)	0.017 (11.65)	0.017 (10.78)	0.017 (11.23)	−0.10%	−0.20%	−0.10%	0.00%	0.40%	0.20%
15Y	0.015 (13.54)	0.015 (13.28)	0.018 (12.85)	0.018 (14.09)	0.017 (12.79)	0.017 (13.67)	−0.10%	−0.30%	−0.40%	−0.50%	0.80%	0.30%
20Y	0.016 (16.50)	0.016 (16.22)	0.019 (17.08)	0.018 (17.99)	0.019 (17.02)	0.018 (17.64)	0.00%	−0.20%	−0.40%	−0.30%	0.50%	0.00%
HS	0.018 (29.71)	0.018 (30.31)	0.018 (30.06)	0.018 (29.58)	0.018 (30.76)	0.018 (30.03)	0.40%	0.70%	0.60%	1.00%	0.80%	0.50%
In sample Momentum strategy (MOMOS)												
5Y	0.014 (11.63)	0.014 (11.61)	0.017 (10.06)	0.017 (10.81)	0.017 (10.20)	0.017 (10.66)	−0.10%	−0.10%	−0.10%	0.10%	−0.40%	−0.30%
10Y	0.015 (14.10)	0.015 (14.02)	0.017 (12.74)	0.017 (13.92)	0.017 (12.71)	0.017 (13.42)	−0.10%	−0.20%	−0.10%	0.10%	0.20%	0.10%
15Y	0.015 (16.45)	0.015 (16.19)	0.018 (15.39)	0.018 (16.97)	0.018 (15.34)	0.018 (16.57)	−0.10%	−0.20%	−0.30%	−0.40%	0.80%	0.30%
20Y	0.016 (20.04)	0.016 (19.68)	0.019 (20.14)	0.019 (21.70)	0.019 (20.10)	0.018 (21.33)	0.00%	−0.10%	−0.30%	−0.40%	0.40%	−0.10%
HS	0.018 (36.08)	0.019 (36.50)	0.019 (36.22)	0.018 (35.62)	0.018 (36.95)	0.018 (36.12)	0.60%	0.80%	0.60%	1.00%	0.90%	0.60%
Out of sample Momentum strategy (MOMIS)												
5Y	0.012 (11.10)	0.012 (11.10)	0.015 (9.52)	0.015 (10.08)	0.015 (9.64)	0.015 (9.92)	−0.10%	−0.10%	−0.10%	0.00%	−0.40%	−0.30%
10Y	0.013 (13.47)	0.013 (13.37)	0.015 (11.96)	0.015 (12.94)	0.015 (11.90)	0.015 (12.50)	−0.10%	−0.20%	−0.10%	0.10%	0.30%	0.30%
15Y	0.013 (15.59)	0.013 (15.30)	0.016 (14.42)	0.016 (15.78)	0.015 (14.34)	0.015 (15.48)	−0.10%	−0.30%	−0.30%	−0.40%	0.70%	0.40%
20Y	0.014 (18.96)	0.014 (18.63)	0.016 (19.20)	0.016 (20.33)	0.016 (19.12)	0.016 (20.06)	−0.10%	−0.20%	−0.30%	−0.30%	0.40%	0.00%
HS	0.016 (33.04)	0.016 (33.62)	0.016 (33.39)	0.016 (32.88)	0.016 (34.24)	0.016 (33.42)	0.50%	0.80%	0.70%	1.00%	0.90%	0.60%

Note(s): This table presents the alphas and adjusted R^2 of six different asset pricing models for the excess returns of the scaled strategies over the traditional momentum strategy at different investment related horizons. These investments related horizons are of 5,10,15,20 years and of half sample (HS) length. Whereas the scaled strategies used in this study are constant volatility momentum strategies (MOMCV), variance scaled momentum strategies (MOMV) out of sample (MOMOS) and in sample momentum strategies (MOMIS) strategies respectively. The six asset pricing models that are used are CAPM, Fama and French (1993) FF-3 model, Pastor and Stambaugh (2003) PS-4 model, Fama and French (2015) FF-5, Hou, Xue and Zhang (2015) Q-4 model and lastly Lu, Stambaugh and Yuan (2017) SY-4 model. The estimation period is from 1929:01 to 2016:08 and all coefficients are reported on monthly basis and t-statistics are reported in parenthesis

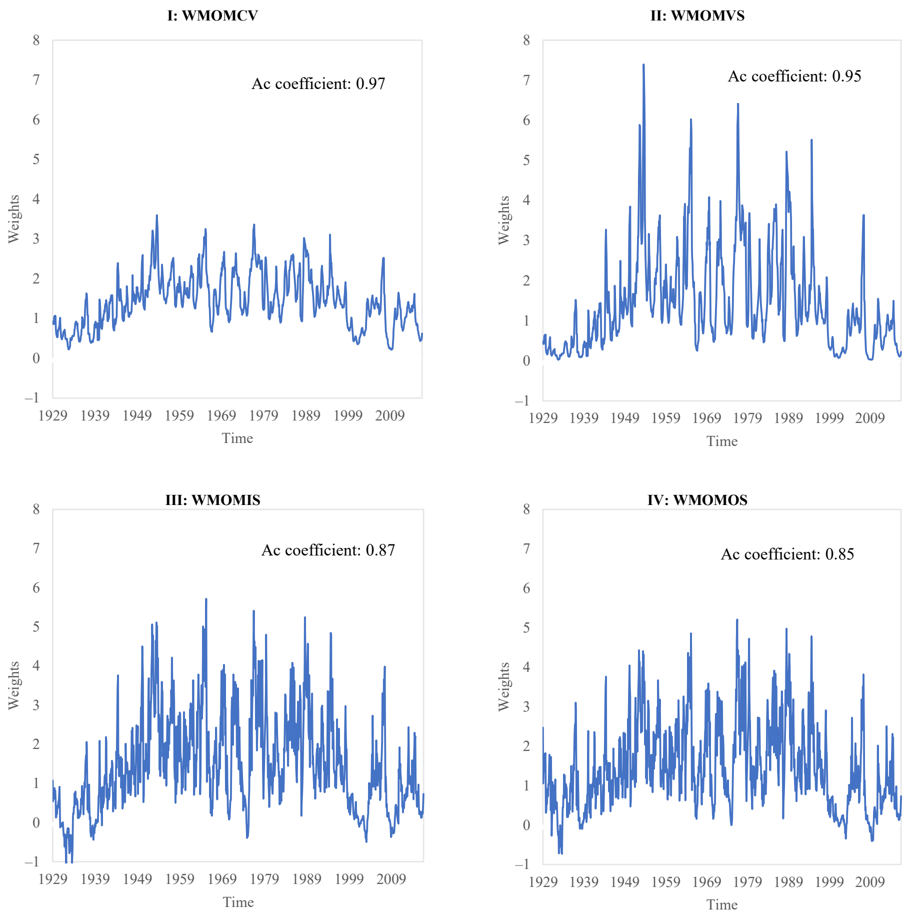

Figure A1.
Volatility/variance weights of momentum strategies

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