J Asset Manag
https://doi.org/10.1057/s41260-018-0080-0

ORIGINAL ARTICLE

A critique of momentum strategies

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Revised: 22 May 2018

Abstract Given the key role of momentum-based trading strategies in active investing, assessing the merits of various trading strategies based on momentum should be of value to investors and managers alike. We summarise five momentum-based trading strategies which are well analysed in the academic literature, and introduce our new strategy named partial moment momentum (PMM) which distinguishes between upside and downside risks in the calculation of positions. Some empirical analyses suggest PMM outperforms the existing strategies.

Keywords Momentum · Trend · Portfolio management

JEL Classification G11 · G12 · G17

Introduction

Momentum investing in many ways represents the quintessential financial strategy. It is appealing to proponents of behavioural finance as there are clear behavioural explanations for its presence. Moreover, active quantitative managers of the rational school can motivate momentum through the existence of signals in that they can look for measures of trend and autocorrelation that deliver momentum returns.

Our key contribution is the introduction of a new strategy. Following an overview of momentum trading strategies, we compare their performances with our new procedure. Using a US sample from 1927 through 2017, we first show that our partial moment momentum-based strategy (henceforth, the PMM strategy) outperforms other momentum-based strategies such as cross-sectional momentum, time-series momentum, volatility momentum, relative strength, and the 52-week high strategy. This result is also consistent with Panel A of Fig. 1 where the PMM line is above that of volatility momentum. Second, we discuss how the PMM strategy provides practitioners with a robust way to resolve issues such as the management of downside risk variation during times of deteriorating business conditions/market states; these times are often when liquidity in markets contract.

The rest of the paper is organised as follows. Second section provides a brief history of momentum. Third section describes five main momentum-based trading strategies with their applications. Fourth section introduces partial moment momentum, a new volatility-based momentum trading strategy. Fifth section presents the performances of momentum strategies. Last section concludes.

A brief history of momentum

We provide a definition of a momentum strategy that covers most known cases that we are aware of. In the broadest terms, a momentum strategy in returns is to use past information over what is termed the formation period on stock returns to select a list of stocks (called the momentum portfolio) to hold long and/or short in a subsequent period, referred to as the holding period. Portfolios

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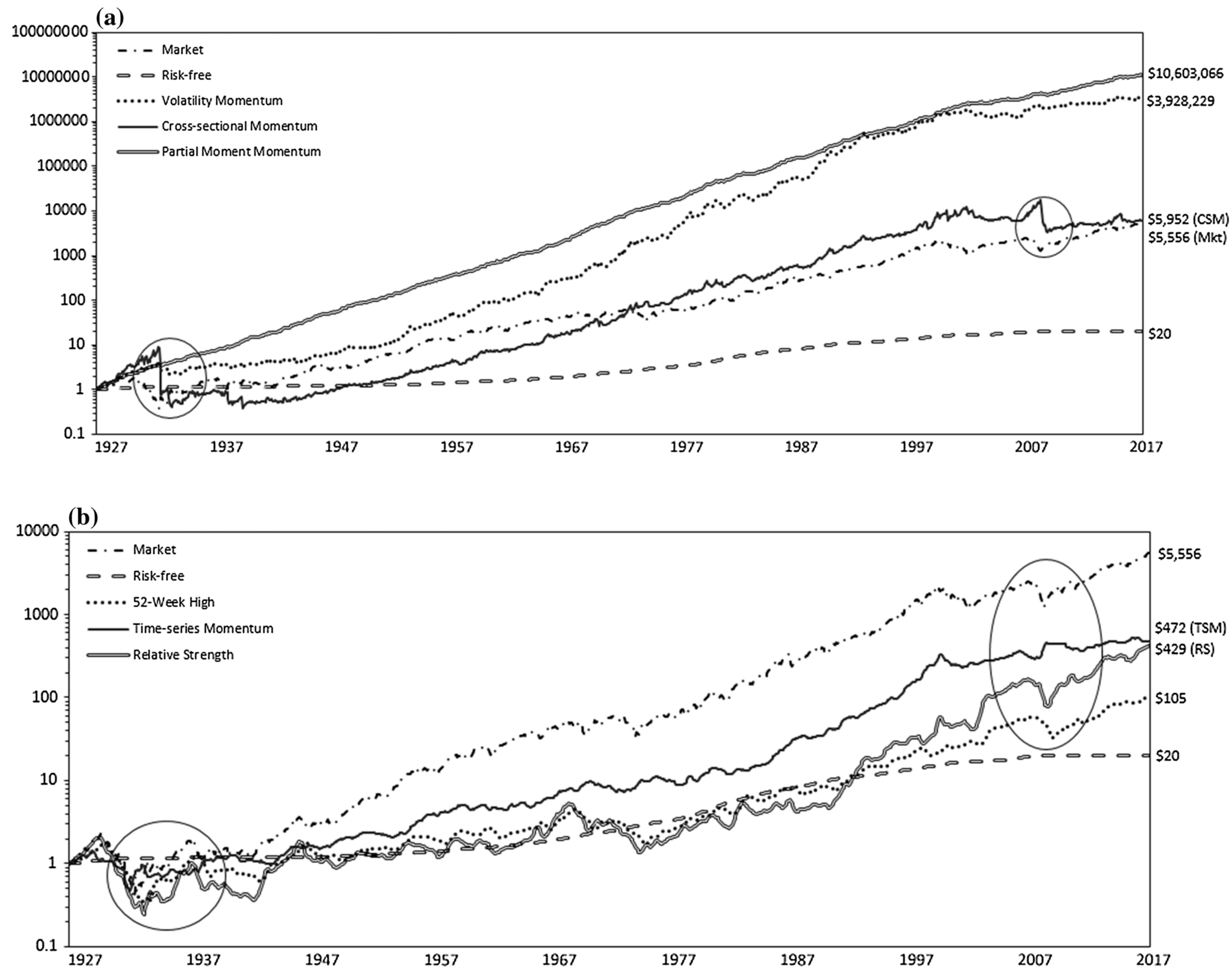

Fig. 1 Momentum-type strategies, 1927–2017. This figure plots the dollar value of investment for seven assets including five momentum-type strategies, the market portfolio, and the risk-free asset given a $1 initial investment in January 1927 over an investment period of 1927–2017. **a** and **b** show the investment performances of three best-performing and three-worst performing momentum-type strategies based on Table 1, respectively. Two main market/momentum crashes are marked and highlighted in the figure, the Great Depression in the 1930s and the Global Financial Crisis over 2007–2009. To keep consistency, all strategies are monthly rebalanced, and consequently, strategies based on weekly performances (RS and 52 WH) may not benefit from this mechanism

might consist of a single stock; portfolio weights could be equal, capitalisation weighted, price weighted, or indeed arbitrarily weighted.

One of the pioneering trend-following/momentum-type trading strategy in the literature was that proposed by Levy (1967). He argued that by buying stocks with current prices which are substantially higher than their average prices over the past 27 weeks, which he coined the relative strength trading strategy, significant abnormal returns could be obtained.

In the late 1980s and early 1990s, studies on the predictability of cross-sectional stock returns encouraged proponents of momentum-based trading strategies. Inspired by the standpoint that investors overreact to information, De Bondt and Thaler (1985, 1987) demonstrated that a contrarian strategy, which is to buy the past losers and selling the past winners, realises abnormal returns over a long horizon of three to 5 years. Jegadeesh (1990), Lehmann (1990), and Jegadeesh and Titman (1995) find this contrarian strategy also successful over a short horizon of one to four weeks. However, contrarian strategies are limited to certain time periods (for instance, 1926–1946). Jegadeesh and Titman (1993) propose a more robust trend-following trading strategy by buying the past winners and short selling the past losers over an intermediate horizon of 3 to 12 months. This strategy is named the (cross-sectional) momentum trading strategy and has been one of the most well-known and widely accepted momentum-type trading strategies.

Table 1 Performance of momentum-type strategies

	Cross-sectional momentum	Time-series momentum	Volatility momentum	Relative strength	52-week high strategy	Partial moment momentum	Market	Risk-free
Panel A: Portfolio construction								
Lookback period	11 months + 1-month gap	11 months + 1-month gap	11 months + 1-month gap	27 weeks	52 weeks	11 months + 1-month gap		
Holding period	1 month	3 months	1 month	26 weeks	26 weeks	1 month		
Winners	Top decile	Positive return	Top decile	Top decile	Top 30%	Top decile		
Losers	Bottom decile	Negative return	Bottom decile	–	–	Bottom decile		
Rebalancing	Monthly	Monthly	Monthly	Weekly	Weekly	Monthly		
Weight	VW	VW	VW	EW	EW	VW	VW	
Panel B: Performance from January 1927 to December 2017								
Return (%)	1.17	0.59	1.54	1.24	0.92	1.63	0.94	0.28
t-statistics	4.98***	2.54**	9.32***	3.58***	2.50**	14.65***	5.78***	35.71***
Sharpe ratio	0.15	0.11	0.28	0.24	0.20	0.57	0.12	–
Skewness	− 2.34***	− 0.75***	− 0.22***	− 0.11	− 0.36***	0.48***	0.16**	1.08***
Kurtosis	17.55	3.02	1.56	1.42	2.10	2.01	7.87	1.27

This table reports the performance of five momentum-type strategies, the market portfolio, and the risk-free asset from January 1927 to December 2017, respectively. For cross-sectional momentum, we follow Jegadeesh and Titman's (1993) $J \times K$ trading model; for time-series momentum, we follow Moskowitz et al.'s (2012) (k, h) trading strategy; for volatility momentum, we follow risk-managed momentum proposed by Barroso and Santa-Clara (2015); for relative strength and 52-week high strategies, we follow rules employed by Levy (1967) and George and Hwang (2004), respectively; for partial moment momentum, we follow our partial moment-decomposed momentum with a 200% leverage constraint (PMD_C); for market portfolio and risk-free asset, we use the value-weighted index of all firms in CRSP and the 1-month treasury bill rate as the proxy, respectively. The Sharpe ratio for momentum-type strategies is the practitioner's version as the long–short portfolio return divided by its standard deviation. All continuous series are converted to monthly equivalents

, and * represent significance levels of 5, and 1%, respectively

Following studies in the 2000s and 2010s, we observe the exploration of new or adapted momentum-type trading strategies. For instance, the 52-week high strategy proposed by George and Hwang (2004); time-series momentum by Moskowitz et al. (2012); volatility momentum by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016); and partial moment momentum by Gao et al. (2017).

Overall, the academic literature holds a firm point of view that momentum-type strategies generate significant abnormal returns. This strong profitability has been shown to be robust across global equity markets and other asset classes over multiple time periods. Questions remain, however, as to how real these profits are for institutional investors who need to invest many billions as much of the analysis has been based on stock universes with limited filters on liquidity.

Momentum-based trading strategies

Cross-sectional momentum

Cross-sectional momentum strategies (henceforth, CSM) are employed by buying previous winners and selling previous losers.[1] The literature shows convincing evidence in favour of the CSM in global markets and asset classes across different sample periods.[2] Explanations for such profitability include firm-specific factors such as systematic

[1] Jegadeesh and Titman (1993) find that momentum strategies are profitable in the US equities markets over the short to medium horizons (3–12 months) from 1965 to 1989. Jegadeesh and Titman (2001) continue to show similar results for the period 1990–1998. Israel and Moskowitz (2013) extend momentum evidence to two periods: from 1927 to 1965 and from 1990 to 2012.

[2] See, for instance, Richards (1997) for evidence of momentum in stock market indexes; Asness et al. (1997) for that in country indexes; and Rouwenhorst (1998) for that in European developed stock markets; Chan et al. (2000), Griffin et al. (2003), and Fong et al. (2005) for that in international equity markets. See, for instance, Okunev and White (2003) for momentum in exchange rates; Erb and Harvey (2006) for that in commodities; Grinblatt et al. (1995) for that in mutual funds; and Asness et al. (2013) for that in markets across regions (European Union, Japan, UK, and USA) and asset classes (fixed income, commodities, foreign exchange, and equity).

risk, size, industry, and earnings announcement; and behavioural side explanations include investor sentiment.[3] The literature also finds that CSM is attributable to seasonality. For example, Jegadeesh and Titman (1993) show that the January effect is significant in CSM profits.

Jegadeesh and Titman's (1993) $J \times K$ trading model is the widely used model to construct CSM portfolios. Assuming a CSM strategy based on monthly returns is to be constructed; then, the construction process is as follows.

Sorting/Formation Period First, at construction time t, all valid sample stocks are ranked in a descending order based on their past *J-month* formation period cumulative returns (CR) and then sorted into one of the groups with an equal number of stocks. The cumulative returns (CR) of stock i over the *J-month* formation period, $CR_{i,J}$, are calculated as follows:

$$CR_{i,J} = \left[\prod_{t=-1}^{-J} \left(1 + R_{i,t}\right) \right] - 1 \tag{1}$$

where $R_{i,t}$ is the return of stock i in month t. The literature has shown the following nuances to sorting the sample of stocks:

1. There are three main methods to sort on the number of groups. For example, Asness et al. (2013) use the *tercile* sort, which is mainly found in CSM in other asset classes or international equity markets. Griffin et al. (2003) utilise the *quintile* sort, which is mainly employed in CSM in international equity markets, particularly in emerging and smaller sized developed markets. Jegadeesh and Titman (1993) use the *decile* sort, which is mainly used in CSM in the USA and large international equity markets.
2. There are two main methods on the selection of breakpoints in the US equity market. The all-firm breakpoints (each group contains an equal number of all valid sample firms) and the NYSE breakpoints (each group contains an equal number of valid NYSE firms). The NYSE breakpoints are shown to be more practical because it reduces the effect of small and illiquid stocks.

The best and the worst performing groups from the above sorting mechanisms are referred to as the winner and the loser portfolios, respectively.

Gaps To avoid the side effects of bid–ask bounce and short-term reversal (Jegadeesh 1990; Lehmann 1990), normally 1 day, 1 week, or 1 month is filtered out after the sorting on the winner and loser portfolios (Jegadeesh and Titman 1993; Fong et al. 2005; Asness et al. 2013).

Holding Period Then, the winner and loser portfolios are being bought and short sold for the *K-month* holding period. In the meantime, an offsetting position of cash asset is also being held to keep the overall portfolio fully invested. The equally weighted or value-weighted holding period returns are computed as follows.

$$\begin{aligned} CSM\_Return_t = {} & Winner\_Return_t - Loser\_Return_t \\ & + Cash\_Return_t \end{aligned} \tag{2}$$

where CSM_Return_t is the CSM return in month t. $Winner\_Return_t$, $Loser\_Return_t$, and $Cash\_Return_t$ are the holding period returns of the winner, loser, and cash asset in month t, respectively.

Rebalancing The winner and loser portfolios can be rebalanced on a monthly basis. Thus, in any month t, one certain strategy holds not only the winner and loser portfolios constructed in month t, but also those portfolios in the previous $K - 2$ months assuming a 1-month gap between the formation period J and holding period K.

The issue that momentum strategies face is the vulnerability to crashes. Both winner portfolio and winner-minus-loser portfolio suffer from negative skewness. So our typical pattern is frequent gains with the occasional large losses. This will be further explored in our empirical analysis.

Time-series momentum

Moskowitz et al. (2012) propose the time-series momentum trading strategy (henceforth, TSM) which varies from the CSM in the stock selection process. They argue that "Rather than focus on the relative returns of securities in the cross section, time-series momentum focuses purely on a security's own past return". Thus, whether an asset is classified as a "winner" or "loser" in the TSM portfolio construction methodology depends on its own past performance, rather than the CSM procedure which compares an asset's performance with the performance of all the other assets in the whole sample. To construct a TSM portfolio, the following process could be followed according to the (k, h) trading model by Moskowitz et al. (2012). Our description follows theirs closely (see Moskowitz et al. 2012, section 3.2). We note that there is an infinity of different ways we could construct such strategies and the example given is actually a volatility-scaled version of TSM.

One could determine the sign of the excess return (relative to an appropriate cash instrument) over the past k months for each asset s and month t. If the sign is positive (negative), then take a long (short) position. Hold the position for h months. In each month, set the size of the

[3] See, for example, Chan et al. (1996), Hong and Stein (1999), Moskowitz and Grinblatt (1999), Hong et al. (2000), and Jegadeesh and Titman (2001) for firm-specific explanations of CSM; see, for example, Conrad and Kaul (1998) and Daniel et al. (1998) for behavioural explanations of CSM.

long-short position to be inversely proportional to the asset's ex-ante volatility, $1/\sigma^s_{t-1}$.

For each trading strategy (k, h), and asset s, obtain a *single* time series of monthly returns per trading strategy (k, h) even if the holding period h is more than 1 month. This avoids overlapping observations. Then, one could employ Jegadeesh and Titman (1993) to determine a single time series of returns. Average returns are computed across all active portfolios at time t for a holding period of h months. However, one could employ alternative sets of weights over the live positions.

One could compute the time t return based on the sign of the past returns from time $t-k-n$ to $t-n$ for each asset, where n is [1, h]. For each (k, h), one could get a single time series of monthly returns by computing the average returns of all of these h currently "active" portfolios. One could average the returns across all assets (or all assets within an asset class), to obtain our time-series portfolio momentum strategy returns, $r_t^{\mathrm{TSMOM}(k,h)}$. Here, one could use equal weights, but we could use other weighting schemes. We could optimise the portfolio, for example.

It is noteworthy that the (k, h) in Moskowitz et al. (2012) is chosen from 1, 3, 6, 9, 12, 24, 36, and 48 months. Furthermore, the authors use futures (commodity, equity index, bond) and currency forwards rather than stocks in their empirical study.

Bird et al. (2017, section 4) propose an alternative TSM approach which uses equity data in 24 major stock markets over horizons of three to 12 months for both the formation and holding periods. In their version of TSM, the cut-off (i.e. the number of positions in winner and loser portfolios) for identifying winners and losers is an absolute number(s) (for instance, an annualised return of 3%). Recall that Moskowitz et al. (2012) use the sign of the historical excess return of the instrument as the cut-off to determine the long/short positions of instruments. Another benchmark which may be employed to differentiate winners and losers is the market return over the formation period. In both these examples, all assets are either winners or losers; there are, however, many examples where this is not the case.

Whilst it is possible to give behavioural interpretations of TSM, the simplest explanations are drift and autocorrelation. We are choosing assets to go long which have positive mean returns and are likely to be associated with positive autocorrelation so there is some time-series predictability at the univariate level. Similar remarks apply to losers with negative drift (negative mean returns) and positive autocorrelation. What this process misses out on is lagged cross-correlation. So, for example, in industry returns we find patterns of high returns in supplier industries leading to future low returns in those industries who use the former industries' products or conversely. For example, a slump in steel production will lower subsequent returns on mining shares. This suggests that there may be more general TSM structures that can use information more efficiently (Hong and Stein 1999).

Volatility momentum

Existing literature has shown that momentum gains, in particular, CSM profits benefit from an expansionary, persistent, and liquid market state (Chordia and Shivakumar 2002; Cooper et al. 2004; Avramov et al. 2016). However, momentum crashes seem to be ubiquitous.

Daniel and Moskowitz (2016) examine CSM in the US equity markets over 1927–2013. The authors find that extreme losses of momentum occur when market rises contemporaneously during market downturn, are clustered, and have relatively long duration. The loser portfolio, rather than the winner portfolio, drives this result (Daniel and Moskowitz 2016, section 2.3).

To mitigate the extreme losses of momentum, volatility-scaled momentum strategies (henceforth, VM) have been suggested, in both a cross-sectional momentum setting (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016) and in a time-series momentum setting (Moskowitz et al. 2012). This involves an ancillary equation which one uses to model volatility, either of the market or of momentum itself. Both cases involve the notion of the use of target volatility to scale momentum returns to produce risk-managed momentum returns.

We now turn to a detailed discussion of Barroso and Santa-Clara (2015). To avoid momentum crashes, they utilise the high level of predictability of the risk of momentum returns. They scale the long–short WML momentum portfolio[4] by the last 6 months' realised volatility based on daily returns. This risk-managed momentum strategy results in much reduced negative returns during the crashes, large increases in the Sharpe ratio, and a reduction in both excess kurtosis and left skewness.

$$\hat{\sigma}^2_{\mathrm{WML},t} = 21\sum_{j=0}^{125} r^2_{\mathrm{WML},d_{t-1-j}} \Big/ 126 \tag{3}$$

$$r_{\mathrm{WML}^*,t} = \frac{\sigma_{\mathrm{target}}}{\hat{\sigma}_{\mathrm{WML},t}} r_{\mathrm{WML},t} \tag{4}$$

where $r_{\mathrm{WML},t}$ and $r_{\mathrm{WML}^*,t}$ are the return of plain (unscaled) and risk-managed CSM return in month t; $\hat{\sigma}^2_{\mathrm{WML},t}$ is the monthly variance of plain CSM from its daily returns in the

[4] WML, winners-minus-losers, stands for an 11 × 1 plain (unscaled) CSM strategy with a 1-month gap between the formation and holding periods.

precious 6 months (assuming 21 trading days each month, then there are 126 trading days in 6 months); σ_{target} is the target level of volatility and the authors pick a level of 12% for target annualised volatility.

A similar approach due to Daniel and Moskowitz (2016) results in an exposure to the risky asset given below;

$$W_{t-1}^{*} = \left(\frac{1}{2\lambda}\right)\frac{\mu_{t-1}}{\sigma_{t-1}^{2}} \tag{5}$$

where W_{t-1}^{*} is the optimal weight on CSM return (R_{WML}) at time $t-1$. The optimisation involved is a conditional mean variance problem, where $\mu_{t-1} \equiv E_{t-1}\left[R_{\text{WML},t}\right]$ is the conditional expected return on the (zero-investment) WML portfolio; $\sigma_{t-1}^{2} \equiv E_{t-1}\left[\left(R_{\text{WML},t}^{2} - \mu_{t-1}\right)^{2}\right]$ is the conditional variance of the WML portfolio; and λ is scalar.

Moskowitz et al. (2012) In addition to the scaling of $1/\sigma_{t-1}^{s}$ on individual instrument in each month, the authors also scale the exposure of both long and short positions. A 40% annual volatility is chosen to fit the risk of an individual instrument s.

$$r_{t,t+1}^{\text{TSMOM},s} = \text{sign}\left(r_{t-12,t}^{s}\right)\frac{40\%}{\sigma_{t}^{s}} r_{t,t+1}^{s} \tag{6}$$

where $\text{sign}(r_{t-12,t}^{s})$ is the sign of the previous excess return of asset s with a value of either $+1$ and -1; $r_{t,t+1}^{s}$ is the return of s over month t to $t+1$; σ_{t}^{s} is the annualised volatility of assets s in month t.

The authors point out that after sizing the positions of long and short, "*every* single futures contract exhibits positive predictability from past one-year returns. All 58 futures contracts exhibit positive time-series momentum returns and 52 are statistically different from zero at the 5% significance level". Formula 3 in section 2.2 shows how Moskowitz et al. (2012) size their TSM positions.

The problems with these exercises are twofold. Firstly, the weights are uncontrolled in the sense that we could be gearing by thousands of per cent and secondly, we treat up and down volatility as equal.

Relative strength

The relative strength strategy was first documented in Levy (1967). He showed that buying stocks with current prices that are substantially higher than their average prices over the past 27 weeks yields significant abnormal returns over a 26-week investment horizon. Despite the criticism by Jensen and Benington (1970), relative strength has developed to be an important indicator for choosing outperforming assets.

There are many alternative ways of constructing relative strength portfolio.[5] However, the trading rules are all similar as follows.

Ratio The first step is to calculate the relative strength ratio $\text{RS}_{j,t}$ of stock j at week t. Let $\text{RS}_{j,t} = P_{j,t}/\overline{P_{j,t}}$ be the relative strength ratio of the current stock price $P_{j,t}$ to the averaging stock price in the previous periods $\overline{P_{j,t}}$ from t to $t-27$.

Ranking Then sort all stocks by ratio RS_t in a descending order and invest the stocks with the highest X% (X could be 1, 5, 10,….) values of ratio.

Holding and Rebalancing In the following weeks starting from $t+1$, sort all stocks by ratio $\text{RS}_{t+i}(i = 1, 2, \ldots)$, sell the stocks currently held with ranking lower than X%, and reinvest these amount into those stocks within the highest X% value of ratio in that week.

An alternative version of relative strength follows the analysis of Lo and MacKinlay (1990), Jegadeesh and Titman (1993), and Lewellen (2002).

Let r_{mt} be the return to some long-only benchmark portfolio at time with weight ω_{mit} be the weight to asset in this portfolio; then, a relative strength weight ω_{rit-1} at time $t-1$ can be defined as

$$\omega_{\text{rit}-1} = \omega_{\text{mit}-1}(r_{\text{it}-1} - r_{\text{mt}-1}) \tag{7}$$

It is straightforward to see that the relative strength portfolio has weights that add to zero and that stocks that have outperformed the portfolio will be held long assuming the benchmark is long-only. In the case that the benchmark is equal-weighted with N assets,

$$\omega_{\text{rit}-1} = \frac{(r_{\text{it}-1} - r_{\text{mt}-1})}{N} \tag{8}$$

Suppose that the vector of assets,

$$r_t = \mu + Ar_{t-1} + \epsilon_t \tag{9}$$

where ϵ_t is a vector of *iid* returns N (0, Ω), then relative strength portfolios can be described by $\omega_{\text{rt}-1}' r_t$ which combined with above equations can be used to describe the return distribution, its mean and time-series structure; we omit details.

It is interesting that versions of relative strength portfolios have been popular with fund managers; cynically, one might say that one can charge active fees with relatively low research costs. The fact is that their success will depend upon trend and autocorrelation as the above structures indicate.

[5] Due to a limited number of stocks in the sample, early researchers further restrict a "cast out rank" K for stocks to be invested. See, for example, Levy (1967), Jensen and Benington (1970) and Brush (1986) for more detailed trading rules in their respective studies.

52-week high strategy

Following on from CSM and relative strength portfolios, George and Hwang (2004) propose a trading strategy which focuses on how close the stock's current price is to its highest price over the previous 1 year. The raw return of this strategy, the 52-week high strategy (henceforth, 52 WH), is almost identical to a traditional CSM strategy; however, the performance of the 52-week high strategy is doubled after controlling for size and bid–ask bounce.

The trading rules of the 52-week high strategy are similar to those of the relative strength strategy. The main difference lies in the denominators of their respective "strength ratio". In the relative strength strategy, its ratio $\mathrm{RS}_{i,t}$ of stock i in week t is computed as the current price $P_{i,t}$ divided by the average stock price in the previous periods $\overline{P_{i,t}}$; in the 52-week high strategy, it is the ratio $52\,\mathrm{WH}_{i,t}$ of stock i in week t is computed as the current price $P_{i,t}$ divided by its highest stock price in the past 52-week periods $P\_highest_{i,t} = \max\{P_{i,t}, P_{i,t-1}, \ldots, P_{i,t-52}\}$. As such, the winner (loser) portfolio for the 52-week high strategy is the portfolio with the highest (lowest) ratio of $52\,\mathrm{WH}_{i,t}$.

Partial moment momentum: a broad picture

Partial moment momentum

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) agree that the volatility momentum strategy, by scaling the weights of momentum portfolios, increases the Sharpe ratio of the traditional CSM strategy. Following Black (1976), volatility is larger when markets fall than when they rise. Furthermore, the economic consequences of volatility in falling or rising markets are not equal. Rather than scaling plain momentum portfolios, which does not distinguish between upside and downside risk, partial moment momentum strategy (PMM strategy) uses the partial moment decompositions of squared market returns in a manner which we describe below (Gao et al. 2017).

The method involves constructing a sample realised volatility using equi-spaced data for $[t-1, t]$. This is defined for $n+1$ prices or their logarithms to define n returns, r_i, $i = 1, \ldots, n$. We call this *RV*, the realised variance for $[t-1, t]$. We define RV as

$$\mathrm{RV}_t = \sum_{i=1}^{n} r_{i,t}^2 \tag{10}$$

The properties of RV and its related measures can be found in Andersen et al. (2001), Barndorff-Nielsen and Shephard (2002), Barndorff-Nielsen et al. (2010), and Baruník et al. (2016). Following the literature, we define two statistics, lower partial moment RPM^- and upper partial moment RPM^+, as

$$\mathrm{RPM}_t^- = \sum_{i=1}^{n} r_{i,t}^2 I\left(r_{i,t} < 0\right) \tag{11}$$

and

$$\mathrm{RPM}_t^+ = \sum_{i=1}^{n} r_{i,t}^2 I\left(r_{i,t} \geq 0\right) \tag{12}$$

where $I()$ is the indicator function, these being sample lower and upper partial moments of order 2 with truncation at zero in both cases, $r_{i,t}$ is the return of stock i in day t, and n is the number of valid sample stocks in day t. There is an identity,

$$\mathrm{RV}_t = \mathrm{RPM}_t^- + \mathrm{RPM}_t^+ \tag{13}$$

Volatility momentum shows that momentum strategies can be improved by weighting the momentum positions using volatility in various forms. These methods do not differentiate between upside or downside risk and typically maintain net zero funds. Practitioner methods based on optimisation, however, scale momentum mean forecasts by their standard deviations. We extend this class of strategies by tilting our strategy long or short towards favourable/unfavourable volatility signals and holding an offsetting position in cash.

We define a portfolio with a $\left(\varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right), \varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)\right)$ strategy as a net zero portfolio long $\varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)$ in winners and short $\varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)$ in losers with an offsetting position of $\varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right) - \varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)$ in cash. We denote its return at time $t+1$ as

$$\begin{aligned} r_{p,t+1} = {} & \varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right) r_{w,t+1} - \varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right) r_{l,t+1} \\ & + \left(\varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)\right) - \varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right) r_{f,t+1} \end{aligned} \tag{14}$$

where $r_{w,t+1}$, $r_{l,t+1}$, and $r_{f,t+1}$ are the returns at time $t+1$ to the winners, losers, and "cash" portfolios, respectively.

In practice, leverage is an issue in long–short portfolios and defined as the sum of absolute value of long and short weights (ignoring cash positions). Further, many institutional hedge funds such as 130/30 funds employ constrained leverage in practice. Academic volatility portfolios often exhibit alarming levels of leverage. As such, we place strict restrictions on leverage, with 200% leverage being a typical upper bound.

Zero-net position

Equation (14) shows that we hold cash long or short to maintain a zero-net position in our PMM strategies, where $\left(\varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)\right) - \varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)$ is the weight in the cash position used to offset the weights in the winner $\left(\varphi_1\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)\right)$ and loser $\left(\varphi_2\left(\mathrm{RPM}_t^+, \mathrm{RPM}_t^-\right)\right)$ portfolios. The reasons to keep a zero-net position are twofold. First, we minimise the overall risk exposure of the portfolio. Second, this way of portfolio construction enables an unequal weighting scheme between winner and loser portfolios, thereby enabling unconstrained leverage to take place.

Performance of momentum-type strategies

We present the performance, using US equity data, of the aforementioned five momentum-type strategies discussed in "Momentum-Based Trading Strategies" section. Daily data of all common stocks listed in NYSE, Amex, and Nasdaq are downloaded from the Centre for Research in Security Prices (CRSP) over 1927–2017. The value-weighted index of all firms in the sample and the 1-month Treasury bill rate are proxied for the market and risk-free indices, respectively. In Panel A of Table 1, we report the detailed construction conditions for each strategy. To keep consistency, for CSM, VM, TSM, and PMM, we rebalance on a monthly basis; look back over the past 11-month performance with a 1-month gap between the formation period and the holding period; and value weight the returns of each group (winners/losers); for RS and 52 WH, we rebalance on a weekly basis, hold the constructed portfolio for 26 weeks, and use equally weight returns for the winners. This is in keeping with most of the literature.

In Panel B of Table 1, results show that all five momentum-type strategies yield positive returns during the 91-year whole sample period. VM, PMM, RS, and CSM all report outperformance compared to the market portfolio. In particular, the PMM strategy outperforms all other strategies by reporting a monthly profit of 1.63% with a monthly Sharpe ratio of 0.57, a reduction in kurtosis to 2.01, and a positive skewness of 0.48. The other five momentum-type strategies are all negatively skewed, and significantly so with the exception of RS. It is noteworthy that our strategy exhibits positive skewness, uniquely among the momentum-type strategies considered.

We also plot the cumulative monthly returns of all five momentum-type strategies with the market portfolio and the risk-free asset over 1927–2017. Panel A of Fig. 1 shows that volatility-adjusted cross-sectional momentum strategies (VM, and PMM) outperform the market. The PMM, in particular, reports strong profitability with low volatility by showing a smooth uptrend despite the crashes of the market and other momentum-based strategies. Panel B shows the changes of the dollar value of investments of three strategies that underperform the market. We note that in Fig. 1, all five strategies follow a monthly rebalancing mechanism to maintain consistency with each other.[6] Momentum-type strategies based on weekly performances, RS and 52 WH, may not benefit from this mechanism (compared to results in Table 1) and consequently, underperform the market compared to other strategies.

In Fig. 1, we also highlight two main market/momentum crash periods, the Great Depression in the 1930s and the Global Financial Crisis over 2007–2009. We observe that in general, compared to market crashes, momentum-type strategies crash slower but harder after the market starts to fall. However, our downside risk-managed momentum strategy, the PMM strategy, is less volatile and shows robust outperformance over the whole sample period.

Discussions

Our paper looks at a range of well-known momentum strategies and suggests a new alternative, which we call partial moment momentum. Some empirical calculations on US data suggest that our strategy outperforms existing ones in that it has higher returns, in both absolute and risk-adjusted terms. Our strategy also seems to perform in various market conditions, allaying the conventional concerns of momentum crashes. We do not claim that our returns are achievable; they suffer from the usual academic ailments of trading very small stocks, zero-transaction costs, no turnover constraints, etc. However, we do not build our models dynamically, so we suggest that a more careful analysis would not automatically contradict our findings.

Acknowledgements A version of this paper was presented at the 11th Financial Risks International Forum. We would like to thank the organisers and participants for their kindness and comments.

References

Andersen, T.G., T. Bollerslev, F.X. Diebold, and H. Ebens. 2001. The distribution of realized stock return volatility. *Journal of Financial Economics* 61: 43–76.

Asness, C., J. Liew, and R. Stevens. 1997. Parallels between the cross-sectional predictability of stock and country returns. *Journal of Portfolio Management* 6: 79–86.

[6] In Table 1, the results involve RS and 52 WH are at a weekly frequency, the others are monthly (see Panel A).

Asness, C.S., T.J. Moskowitz, and L.H. Pedersen. 2013. Value and momentum everywhere. *The Journal of Finance* 68(3): 929–985.

Avramov, D., S. Cheng, and A. Hameed. 2016. Time-varying liquidity and momentum profits. *Journal of Financial and Quantitative Analysis* 51: 1897–1923.

Barndorff-Nielsen, O.E., and N. Shephard. 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society: Series B Statistical Methodology* 64: 253–280.

Barndorff-Nielsen, O.E., S. Kinnebrouk, and N. Shephard. 2010. Measuring downside risk: Realised semivariance. In *Volatility and time series econometrics: Essays in honor of Robert F. Engle*, ed. T. Bollerslev, J. Russell, and M. Watson, 117–136. Oxford: Oxford University Press.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116(1): 111–120.

Baruník, J., E. Kočenda, and L. Vácha. 2016. Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. *Journal of Financial Markets* 27: 55–78.

Bird, R., X. Gao, and D. Yeung. 2017. Time-series and cross-sectional momentum strategies under alternative implementation strategies. *Australian Journal of Management* 42(2): 230–251.

Black, F. 1976. Studies of stock price volatility changes. In *Proceedings of the 1976 Meetings of the American Statistical Association Business and Economic Statistics Section*, 177–181.

Brush, J.S. 1986. Eight relative strength models compared. *The Journal of Portfolio Management* 13(1): 21–28.

Chan, K., A. Hameed, and W. Tong. 2000. Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis* 35(2): 153–172.

Chan, L.K.C., N. Jegadeesh, and J. Lakonishok. 1996. Momentum strategies. *The Journal of Finance* 51(5): 1681–1713.

Chordia, T., and L. Shivakumar. 2002. Momentum, business cycle, and time-varying expected returns. *The Journal of Finance* 57: 985–1019.

Conrad, J., and G. Kaul. 1998. An anatomy of trading strategies. *The Review of Financial Studies* 11(3): 489–519.

Cooper, M.J., R.C. Gutierrez, and A. Hameed. 2004. Market states and momentum. *The Journal of Finance* 59: 1345–1365.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and overreactions. *The Journal of Finance* 53(6): 1839–1885.

Daniel, K., and T.J. Moskowitz. 2016. Momentum crashes. *Journal of Financial Economics* 122(2): 221–247.

De Bondt, W.F.M., and R.H. Thaler. 1985. Does the stock market overreact? *The Journal of Finance* 40(3): 793–805.

De Bondt, W.F.M., and R.H. Thaler. 1987. Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance* 42(3): 557–581.

Erb, C.B., and C.R. Harvey. 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal* 62(2): 69–97.

Fong, W.M., W.K. Wong, and H.H. Lean. 2005. International momentum strategies: A stochastic dominance approach. *Journal of Financial Markets* 8(1): 89–109.

Gao, Y., H. Leung, and S. Satchell. 2017. *Partial moment momentum.* The University of Sydney, finance discussion paper series, DP-2017-002.

George, T.J., and C.Y. Hwang. 2004. The 52-week high and momentum investing. *The Journal of Finance* 59(5): 2145–2176.

Griffin, J.M., X. Ji, and J.S. Martin. 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance* 58(6): 2515–2547.

Grinblatt, M., S. Titman, and R. Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *The American Economic Review* 85(5): 1088–1105.

Hong, H., and J.C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance* 54(6): 2143–2184.

Hong, H., T. Lim, and J.C. Stein. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance* 55(1): 265–295.

Israel, R., and T.J. Moskowitz. 2013. The role of shorting, firm size, and time on market anomalies. *Journal of Financial Economics* 108(2): 275–301.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *The Journal of Finance* 45(3): 881–898.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance* 48(1): 65–91.

Jegadeesh, N., and S. Titman. 1995. Overreaction, delayed reaction, and contrarian profits. *The Review of Financial Studies* 8(4): 973–993.

Jegadeesh, N., and S. Titman. 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance* 56(2): 699–720.

Jensen, M.C., and G.A. Benington. 1970. Random walks and technical theories: Some additional evidence. *The Journal of Finance* 25(2): 469–482.

Lehmann, B.N. 1990. Fads, martingales, and market efficiency. *The Quarterly Journal of Economics* 105(1): 1–28.

Levy, R.A. 1967. Relative strength as a criterion for investment selection. *The Journal of Finance* 22(4): 595–610.

Lewellen, J. 2002. Momentum and autocorrelation in stock returns. *The Review of Financial Studies* 15(2): 533–564.

Lo, A.W., and A.C. MacKinlay. 1990. When are contrarian profits due to stock market overreaction? *The Review of Financial Studies* 3(2): 175–205.

Moskowitz, T.J., and M. Grinblatt. 1999. Do industries explain momentum? *The Journal of Finance* 54: 1249–1290.

Moskowitz, T.J., Y.H. Ooi, and L.H. Pedersen. 2012. Time series momentum. *Journal of Financial Economics* 104(2): 228–250.

Okunev, J., and D. White. 2003. Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis* 38(2): 425–447.

Richards, A.J. 1997. Winner-Loser reversals in national stock market indices: Can they be explained? *The Journal of Finance* 52(5): 2129–2144.

Rouwenhorst, K.G. 1998. International momentum strategies. *The Journal of Finance* 53(1): 267–284.

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