Journal of Behavioral and Experimental Finance 39 (2023) 100833

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Stop-loss rules and momentum payoffs in cryptocurrencies

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ARTICLE INFO

Article history:
Received 5 January 2023
Received in revised form 18 May 2023
Accepted 31 July 2023
Available online 4 August 2023

JEL classification:
G11
G12
G14

Keywords:
Cryptocurrencies
Momentum
Stop-loss strategy
Loss aversion
Disposition bias

ABSTRACT

Keeping in view the extreme volatility of cryptocurrencies, this study analyzes the efficacy of stop-loss rules for the momentum strategy across 147 cryptocurrencies for the period of January 2015 to June 2022. We find that the stop-loss momentum strategy provides exceedingly higher returns, the Sharpe ratio, and alphas in comparison to other benchmark momentum strategies. In the context of prospect theory, the stop-loss rules work as self-control for investors to realize losses, thereby controlling the disposition effect and as a result, investors can earn significantly higher payoffs. Furthermore, our results provide evidence that the stop-loss momentum strategy outperforms other momentum strategies in all market states. Finally, the robustness analyses reaffirm the importance of implementing the stop-loss rules in managing the downside risk of cryptocurrencies.

1. Introduction

The cryptocurrency market has grown rapidly in recent years, and it emerges as a new asset class (Zaremba et al., 2021). Not surprisingly, cryptocurrencies are now becoming part of investors' portfolios (Białkowski, 2020). However, compared to other asset classes, cryptocurrencies are more volatile (Chaim and Laurini, 2018), further the correlation of cryptocurrencies as an asset class with traditional asset classes is low (Białkowski, 2020) and investors typically hold cryptocurrencies as a speculative asset (Baur et al., 2018). Despite having potential diversification benefits of the portfolio comprising cryptocurrencies and traditional assets, the higher volatility of cryptocurrencies does not completely compensate for the negative payoffs (Białkowski, 2020). The situation gets more complicated when investors expose to behavioral biases such as the disposition effect which refers to a situation in which investors have a high propensity to hold losers too long and a low propensity to sell winners too early (Talpsepp et al., 2014). As a result, there are high chances of realizing low payoffs despite taking high risks (Biru, 2015).

Finding optimal trading strategies (low risk – high expected returns) has remained the focus for both academicians and practitioners. Among these strategies, the most persistent trading strategy is the momentum strategy of (Jegadeesh and Titman, 1993). The momentum strategy has been studied extensively for other asset classes with ubiquitous presence despite being of mysterious nature.[2] In essence, a momentum strategy is a zero-investment strategy that goes long in past winners and short-sell past losers, and earns anomalous returns (Jegadeesh and Titman, 1993).

Moreover, the momentum strategy is known for both the negative relationship with volatility.[3] and crashes[4] The characteristics such as higher volatility and propensity of crashes are higher for the cryptocurrencies, therefore the analysis of the momentum effect in cryptocurrencies is of some interest. In cryptocurrencies, (Jegadeesh and Titman, 1993) traditional cross-sectional momentum strategy earns significant payoffs at daily (Tzouvanas et al., 2020) and weekly frequencies (Liu and Tsyvinski, 2021; Liu et al., 2022). However, at a monthly frequency, (Grobys and Sapkota, 2019) find insignificant cross-sectional momentum payoffs and report similar results for the Moskowitz et al. (2012) related time series momentum strategy.

The absence of momentum returns at the monthly frequency for cryptocurrencies is surprising because the momentum is

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2 Momentum remains one of the most puzzling anomalies in finance. For details: (Rouwenhorst, 1998; Asness et al., 2013; Cakici et al., 2013; Butt et al., 2021).

3 The negative relationship between market volatility and the momentum returns for the equity market of the US is studies by Wang and Xu (2015).

4 The momentum returns in equities are prone to crashes as suggested by (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Butt et al., 2021).

https://doi.org/10.1016/j.jbef.2023.100833
2214-6350/

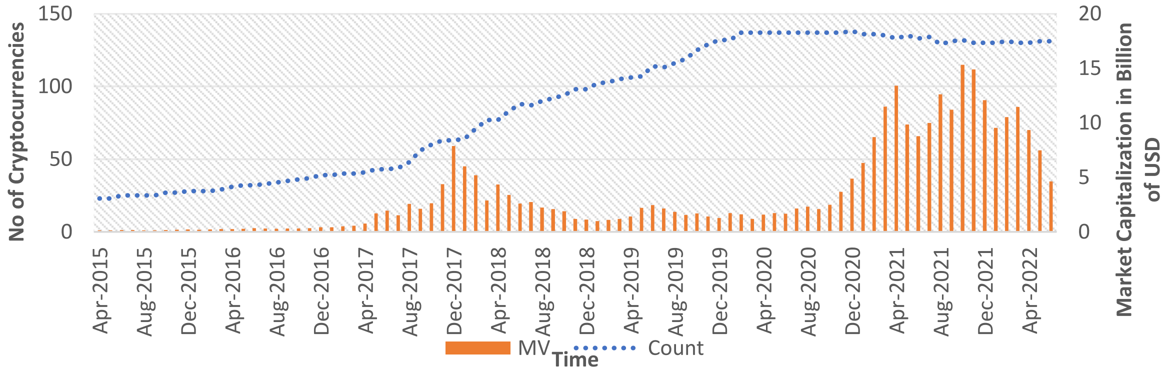

Fig. 1. No of cryptocurrencies and their market capitalization (Billion USD).

present for most of the asset classes, over different markets for different periods (Asness et al., 2013). We conjecture that the higher volatility of the cryptocurrencies can be one reason as momentum is weak under higher volatility-related periods in equity returns (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016; Butt et al., 2021 and others). This higher volatility coupled with negative skewness results in negative returns for the momentum strategy in cryptocurrencies. For instance, the average monthly returns for the cross-sectional momentum strategy are −8.02% with a volatility of 34.28% and skewness of −4.135, for 147 cryptocurrencies for the period of January 2015 to June 2022. Despite negative returns, the volatility is very high, further, the negative skewness indicates the presence of huge momentum crashes in cryptocurrencies.

One way of reducing the volatility is using the predetermined trading rules for inhibiting losses, namely the stop-loss orders. Given the absence of circuit breakers and trading halts in cryptocurrencies, the need for stop-loss rules is further enhanced. Kaya and Mostowfi (2022) highlighted the nature of volatility and the role of extreme losses in cryptocurrencies. They propose the use of simple stop-loss rules to minimize losses and improve the payoffs of cryptocurrencies. Stop-loss rules help to reduce portfolio exposure when the cumulative losses exceed a predetermined threshold level. This is a standard practice used by investors in managing the downside risk of any security. Kaminski and Lo (2014) theoretically explain the effectiveness of stop-loss rules in equities.[5]

We implement the simple stop-loss rule of 30% within any month for any cryptocurrency falling under loser or winner portfolio. Once this limit is reached then crypto is either bought or sold. For the loser portfolio (short side) when monthly cumulative returns or the price of any crypto is increased by 30%, then the stop-loss becomes effective, and vice versa for the winner portfolio. Using these simple trading rules, the average of monthly returns on the momentum strategy is significantly increased to 9.13% with reduced volatility of 21.36%, and the skewness is also turned positive. Further, the stop-loss embedded momentum strategy gives economically significant and large alpha when the three-factor model of Liu et al. (2022) is used for the cryptocurrencies. Moreover, the stop loss momentum strategy outperformed other benchmark momentum strategies such as the times series momentum strategy of Moskowitz et al. (2012), rank based momentum strategy of Chen et al. (2021) and the volatility scaled momentum strategy of Barroso and Santa-Clara (2015). Further, we find qualitatively similar results for the stop loss momentum strategy across all robustness analyses.

Our study contributes empirically and extends the momentum literature on cryptocurrencies by providing evidence of the success of the momentum strategy using the stop-losses. Our results are also linked with the prospect theory of Kahneman (1979) which introduces the loss realization bias in investors under uncertainty. The disposition effect of not realizing the loss associated with any cryptocurrency for a longer time than rationally expected can be costly. The stop-loss rules naturally inhibit this disposition effect on an ex-ante basis and economic gains are quite substantial in the context of the momentum strategy. We also find that the stop-loss rule of realizing the losses at 10%, 20% and 30% is better than the higher limits of 40% or 50%. These results indirectly support that it is better to realize the loss sooner than later.

The rest of the paper is structured as follows. Section 2 describes the data, Section 3 discusses the construction mechanism of momentum strategies, Section 4 discusses the formation of cryptocurrency risk factors, Section 5 explains the construction of volatility states. The results and robustness tests are reported and discussed in Sections 6 and 7. The last section concludes the study.

2. Data

The data is retrieved from https://coinmarketcap.com/ for the period from January 2014 to June 2022. However, the analysis period starts from January 2015,[6] Following the screening criteria as proposed in the literature.[7] we include a cryptocurrency in our sample if (i) the market capitalization is more than 1,000,000 USD, (ii) trading volume data is non-missing, (iii) listed on at least one exchange (iv) publicly available for trading (v) has an operational website (vi) price is nonnegative, and (vii) has an Application Programming Interface (API). In addition, to address survivorship bias, we include dead cryptocurrencies (Zhang et al., 2021). Lastly, to eliminate the influence of the extreme observations, monthly returns are winsorized at the 1% and 99% levels (Dong et al., 2022). Our final sample includes 147 cryptocurrencies and is comparable to the sample used by Grobys and Sapkota (2019). Fig. 1 presents the number of currencies over the sample period. Given the short history of cryptocurrencies, at the start of the sample period, the currencies are fewer in number (minimum of 23 cryptocurrencies in a month), and their market capitalization is low (minimum of 0.135 billion USD in a month). However, as time grows, the number of cryptocurrencies

[5] James and Yang (2010) and Klement (2013) and Han et al. (2016) also report the usefulness of stop-loss rules.

[6] 11 months are used in the construction of momentum strategy and 1 month is skipped as a standard practice in momentum literature to overcome the contrarian effect.

[7] Studies such as Grobys and Sapkota (2019), Liu and Tsyvinski (2021) and Liu et al. (2022).

Table 1
Summary statistics and correlation matrix.

Market	Panel A: Summary Statistics						Panel B: Correlation Matrix			
	Mean	SD	T-Stat	SR	SK	KUR	%>0	*CMKT*	*S&P*	*MSCI*
CMKT	8.247	27.379	2.810	0.3012	1.165	2.413	56.322%	1		
S&P	0.793	4.382	1.688	0.1810	−0.430	1.015	67.816%	28.10%	1	
MSCI (W)	0.483	4.276	1.053	0.113	−0.421	1.317	63.22%	30.52%	97.54%	1
MSCI (EM)	0.151	4.919	0.286	0.031	−0.102	0.480	54.02%	25.07%	72.46%	83.04%

This table displays the summary statistics (panel A) and correlation matrix (Panel B) of cryptocurrencies market returns (CMKT), US equity market returns (S&P), world market returns (MSCI (W)) and emerging market returns (MSCI (EM)). For all markets, average returns (Mean), volatility (SD), the significance of returns (T-Stat), Sharpe ratio (SR), skewness (SK), kurtosis (KUR), and percentage of positive returns (%>0) are reported. The period of the analysis is January 2015 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

Table 2
Summary of extreme events in Cryptocurrencies.

Panel A: Extreme negative events			Panel B: Extreme positive events		
Disasters	Count	%	Miracles	Count	%
<−5%	31	35.63	>5%	45	51.72
<−10%	25	28.74	>10%	36	41.38
<−20%	9	10.34	>20%	25	28.74
<−30%	3	3.45	>30%	15	17.24

This table displays the summary of extreme events in cryptocurrency markets. In panel A, the extreme negative events along with their probability of occurrence are reported. In Panel B, the same numbers are reported for extremely positive events. The period of the analysis is January 2015 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

grows (maximum of 138 cryptocurrencies in a month), and we observe an improvement in the market capitalization (maximum of 15.319 billion USD).[8]

In Table 1, descriptive statistics for the cryptocurrencies index (CMKT), S&P-500 index, world equity markets index (MCSI (W)) and emerging market index (MSCI (EM)) are shown. Cryptocurrencies have (approximately 8 times) higher returns and astoundingly (approximately 7 times) higher volatilities in comparison to equity indexes. Further, the skewness of the cryptocurrency market is positive suggesting that the magnitude of generating large positive returns is higher relative to other counterparts. However, not surprisingly, the probability of positive returns is lower in cryptocurrencies relative to other markets suggesting that in the cryptocurrency market, negative returns occur more frequently than in the other two markets. Moreover, the cryptocurrency market has correlation ranging from 28% to 30% with the other two markets. The cryptocurrency returns are weakly correlated (25.07%) with the emerging markets suggesting the prevalence of potential diversification benefits for the emerging markets. However, the correlation between cryptocurrencies with equity markets has recently increased manyfold negating the safe heaven property of cryptocurrencies (Adrian et al., 2022; Dai et al., 2022).[9] This phenomenon further enhanced the importance of risk management (through stop loss rules) while investing in cryptocurrencies. All these factors indicate that the volatilities and presence of extreme returns are real perils of investing in cryptocurrencies.

In Table 2, we provide some additional characteristics of cryptocurrency returns in terms of extreme positive and negative returns. Consistent with the results of Liu and Tsyvinski (2021), we observe that in the cryptocurrency market, positive returns occur more frequently than negative returns in all states (5%, 10%, 20%, and 30%). Furthermore, there is an 87.36% [(31+45)/87][10] probability that cryptocurrency returns are greater/less than | 5%| and a 21% [(3+15)/87] probability that cryptocurrency returns are greater than or less than | 21%| . This reconciles with our results in the previous table and suggests that cryptocurrencies have a wider returns distribution and therefore confirms that returns are highly volatile.

3. Construction of momentum strategies

Our main objective is to compare and examine the performance of the stop-loss momentum strategy with other momentum strategies in cryptocurrencies. To empirically test this conjecture, we construct cross-sectional, time series, volatility scaled, nonparametric and stop-loss momentum strategies. The construction criteria are described below.[11]

3.1. Cross-sectional momentum strategy

To construct the traditional cross-sectional momentum strategy, we follow Daniel and Moskowitz (2016). Cryptocurrencies are grouped in quintiles in an ascending order based on the past 11 months' average returns (i.e., t-2 to t-12). The first group includes 20% of the worst performers (Losers) and the fifth group includes 20% of the best performers (Winners). We then skip month 't-1' to account for the contrarian effect and predict the month 't' returns for losers' and winners' cryptocurrencies in their respective quintiles. Eq. (1) is used to calculate the past 11 months' average returns.

$$MOM^{CS}_{i,t-2,t-12} = \left(\prod_{t=-2}^{t=-12} r_{i,t}\right) - 1 \quad (1)$$

MOM^{CS} denotes the past 11 months' average returns of the cross-sectional momentum. Losers' and winners' cryptocurrency returns are averaged cross-sectionally to get the return series of losers (L^{CS}_t) and winners (W^{CS}_t) portfolio as shown in Eqs. (2) and (3).

$$W^{CS}_t = \frac{1}{N} * \sum_{i=1}^{N} \left[r^{w}_{i,t}\right] \quad (2)$$

8 Cryptocurrencies used in this study are reported in Appendix A.

9 For instance, the correlation between cryptocurrency and MSCI (W) is about 9.7% during 2015–2019. However, it has increased to 64.5% after 2019. Detailed results are available upon request.

10 87 refers to the total number of monthly observations.

11 The sample programming codes used to construct momentum strategies are provided in online appendix.

$$L_t^{CS} = \frac{1}{N} * \sum_{i=1}^{N} \left[r_{i,t}^{L} \right] \tag{3}$$

The self-financed traditional cross-sectional momentum takes a long position in the winners' portfolio (W_t^{CS}) and a short position in the losers' portfolio (L_t^{CS}). In Eq. (4), WML_t^{CS} displays the returns of the self-financed cross-sectional momentum strategy. Where, W_t^{CS} and L_t^{CS} denotes the short and long legs of the cross-sectional momentum strategy.

$$WML_t^{CS} = W_t^{CS} - L_t^{CS} \tag{4}$$

3.2. Time series momentum strategy

The second benchmark momentum strategy is the time series momentum strategy. Following, Moskowitz et al. (2012) cryptocurrencies are recognized as winners or losers based on the sign of the past 11 months' average returns as shown in Eq. (5).

$$WML_{i,t}^{TS} = \frac{1}{N} \sum_{i=1}^{N} [sign \left[r_{i,t-12,t-2}^{TS} \right] * r_{i,t}^{TS}] \tag{5}$$

Where, $WML_{i,t}^{TS}$ denoted the returns of time series momentum strategy. The *sign* is either + or – depending on the past 11 months average returns $\left[r_{i,t-12,t-2}^{TS} \right]$. Crypto is a loser (winner) if the past 11 months' average is negative (Positive). The time-series momentum takes a long position in winners' cryptocurrencies and a short position in losers' cryptocurrencies.

3.3. Volatility scaled momentum strategy

Barroso and Santa-Clara (2015) proposed volatility scaled momentum strategy based on the optionality effect in momentum returns and document a negative relationship between historical market volatility and momentum payoffs. They scaled the momentum returns by the inverse of 126-days past market volatility to manage the downside losses of momentum strategy. We follow the identical procedure to construct the volatility scaled momentum strategy.

$$WML_t^{vs} = \frac{1}{\sigma_{t-1}} * WML_t^{cs} * \sigma_{target} \tag{6}$$

Where, WML_t^{vs} is the volatility scaled momentum strategy, $\frac{1}{\sigma_{t-1}}$ is the inverse of past 126 days cryptocurrency market volatility, WML_t^{cs} is the traditional cross-sectional momentum strategy described above and σ_{target} is the constant such that it forces the volatility of the scaled strategy equal to the traditional strategy.

3.4. Nonparametric rank momentum strategy

Contrary to other momentum strategies such as traditional, time series and volatility scaled momentum strategies that are based on the return's distribution (skewness, kurtosis), Chen et al. (2021) recently proposed nonparametric rank-based momentum strategy based on the average rank instead of average returns. To construct the rank-based momentum strategy, we follow the identical procedure proposed by Chen et al. (2021). Assume there are 'N' cryptocurrencies $[1, 2, 3, \ldots., N]$. On day 'd', cryptocurrencies are sorted based on daily returns 'r' in ascending order and assigned a rank 'R' to respective cryptocurrency $[R(i, d)]$. Next, at day 'D', standardized rank is calculated as follows:

$$standardized\ rank_{i,d} = \frac{(R\,(i_d)) - \frac{N_d+1}{2}}{\sqrt{\frac{(N_d-1)(N_d+1)}{12}}} \tag{7}$$

To estimate the average rank of a cryptocurrency, the standardized ranks are averaged every month and then averaged over 11-month formation period as follows:

$$standardized\ rank_{i,d}(11) = \frac{1}{11} \sum_{j=t-2}^{t-12} \left(\frac{1}{d} \sum_{d=1}^{d_m} standardized\ rank_{i,d} \right) \tag{8}$$

The losers' and winners' strategies are constructed in a similar fashion as described in section (a) above.

3.5. Stop-loss momentum strategy

The last momentum strategy is based on the stop-loss rules. Stop-loss rules are set on an ex-ante basis such that the buy/sell order executes automatically if a certain threshold level is triggered. We set price limits of $\pm 30\%$ on both sides of the momentum strategy. To construct the stop-loss strategy, we allocated stocks to one of the quintile groups based on past 11-month cumulative returns like the traditional momentum strategy. The top 20% performers are assigned to the winners' portfolio and bottom 20% performers are assigned to the losers' portfolio. However, before calculating the portfolio average returns across stocks, we implement the stop loss rules. Eq. (9) is used to calculate the winner's portfolio returns.

$$W_{i,t}^{SL} = \left\{ \begin{array}{c} Sell\ if\ \prod_{d=1}^{n} r_{i,d} \le SL \\ Hold\ if\ \prod_{d=1}^{n} r_{i,d} > SL \end{array} \right\} \tag{9}$$

Where, $W_{i,t}^{SL}$ refers to the returns of winners' cryptocurrencies. *SL* is the threshold level set equal to 30%. As per the stop-loss rule, on the long side, we sell a cryptocurrency if its price decreases by 30% or the cumulative return in a month approaches the threshold level. Similarly, we hold the cryptocurrency if the loss does not exceed the threshold level.

$$L_{i,t}^{SL} = \left\{ \begin{array}{c} Hold\ if\ \prod_{d=1}^{n} r_{i,d} \le SL \\ Sell\ if\ \prod_{d=1}^{n} r_{i,d} > SL \end{array} \right\} \tag{10}$$

Where, $L_{i,t}^{SL}$ refers to the returns of losers' cryptocurrencies. On the short side, we buy back a cryptocurrency if its price increases by 30% and hold the position until the threshold level is not breached as shown in Eq. (10). Potentially, the returns are given an upper limit of -30% on the long side and 30% of losses on the short side. The stop-loss momentum strategy is computed by taking a long position in winners and a short position in losers' portfolios as shown in Eq. (11).

$$WML_t^{SL} = W_t^{SL} - L_t^{SL} \tag{11}$$

$$W_t^{SL} = \frac{1}{N} * \sum_{i=1}^{N} \left[W_{i,t}^{SL} \right] \tag{12}$$

$$L_t^{SL} = \frac{1}{N} * \sum_{i=1}^{N} \left[L_{i,t}^{SL} \right] \tag{13}$$

The W_t^{SL} and L_t^{CS} are the stop-loss winners and losers' portfolios. For robustness, we also used 10%, 20%, 40% and 50% threshold levels to assess the performance of the stop-loss momentum strategy.

4. Cryptocurrency factor model

To assess the risk-adjusted performance and check the systematic risk exposures of momentum strategies, we compute the cryptocurrency risk factors. Following Liu et al. (2022) we employ a three-factor model that includes a market risk factor, size factor, and momentum factor. The three-factor econometric model is shown in Eq. (14).

$$r_t^p = \alpha_0^p + \beta_{MKT}^p MKT_t + \beta_{SMB}^p SMB_t + \beta_{MOM}^p PRET_t + \mu_t^p \tag{14}$$

In the above equation, r_t^p refers to the returns of three versions of momentum strategies defined in section (III). α_0^p denotes the risk-adjusted returns and should be equal to zero and insignificant if the risk factors explain the returns of momentum strategies. $\beta_{MKT}^P, \beta_{SMB}^P, and \beta_{MOM}^P$ are the loadings on risk factors and $MKT_t, SMB_t, and PRET_t$ are the risk factors defined below.

MKT_t is the value-weighted average of all cryptocurrencies and computed using Eq. (15).

$$MKT_t = \sum_{i=1}^{N} \frac{MV_{i,t-1}}{\sum_{i=1}^{N} MV_{i,t-1}} * r_{i,t} \tag{15}$$

Here, $MV_{i,t-1}$ is the market capitalization of stock "i" in month "$t-1$". To calculate the SMB_t factor, in month t, cryptocurrencies are divided into three groups based on market capitalization such that the bottom 30% represents the small (S), capitalized cryptocurrencies, the middle 40% are medium-sized (M) cryptocurrencies and the top 30% are a big size (B) cryptocurrency. We then calculate the value-weighted returns of each group. The size factor is equal to the difference in small size and big size portfolio average returns as shown in Eq. (16).

$$SMB_t = (\sum_{i=1}^{N} w_{s,i,t-1} * r_{s,i,t}) - (\sum_{i=1}^{N} w_{b,i,t-1} * r_{b,i,t}) \tag{16}$$

To construct the momentum factor, we calculate 6 portfolios based on the intersection of $2X3$ size and momentum information. Precisely, the momentum factor $PRET_t$ as shown in Eq. (14), is computed by subtracting the average of the winner's portfolio returns $(SW + BW)$ from the average loser's portfolio returns $(SL + BL)$, after controlling for the size effect.

$$PRET_t = \frac{1}{2}(SW + BW)_t - \frac{1}{2}(SL + BL)_t \tag{17}$$

5. Market states

Numerous studies document the performance of momentum strategies in different market states. For instance, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) examine that momentum crashes adversely affect momentum profitability and yield huge losses. Kim and Suh (2018) report that the momentum strategy yields higher returns during growing market states. Furthermore, Griffin et al. (2003) provide evidence that momentum strategy yields in good as well as bad market states. Cooper et al. (2004) also highlighted the importance of market states for the performance of momentum strategy. Based on the findings of the above-mentioned studies and coupled with the volatile nature of cryptocurrencies, we test and compare the performance of momentum strategies in different market states. Following Barroso and Santa-Clara (2015), market states are calculated based on the realized volatility of the past 126 days' cryptocurrency market returns as shown in Eq. (18).

$$\sigma_t = \sqrt{\frac{1}{126}\sum_{d=1}^{126}(r_d - \bar{r})^2}_t \tag{18}$$

Based on this volatility measure, we identify the quintile volatility states and assess whether the stop-loss momentum strategy yields higher returns relative to the crash-prone momentum strategies.

Table 3
Performance of momentum strategies.

Strategy	μ	T-stat	SK	SR
Panel A: Traditional Momentum Strategy				
L	14.209***	2.665	2.884	0.282
W	6.185*	1.713	1.158	0.182
W-L	−8.024**	−2.221	−4.135	−0.235
Panel B: Volatility Scaled Momentum Strategy				
L	13.543***	2.604	2.994	0.276
W	5.61*	1.787	1.031	0.189
W-L	−7.932**	−2.195	−3.564	−0.233
Panel C: Time Series Momentum Strategy				
L	7.049**	2.094	2.253	0.222
W	10.388**	2.313	2.208	0.245
W-L	3.340	0.802	2.713	0.085
Panel D: Rank Based Momentum Strategy				
L	28.041*	1.793	8.034	0.190
W	18.923**	2.347	5.223	0.249
W-L	−9.118	−0.941	−7.118	−0.100
Panel E: Stop Loss Momentum Strategy				
L	−1.429	−0.731	−0.024	−0.077
W	7.698***	2.232	1.355	0.237
W-L	9.127***	4.054	1.683	0.430

This table shows the average returns (μ), statistical significance (T-stat), Skewness (SK), and Sharpe ratios (SR) of different momentum strategies. L represents losers, W represents winners and W-L represents winners minus losers' portfolios. The period is from January 2015 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

6. Empirical results

We begin our analysis by assessing the return characteristics of different momentum strategies reported in Table 3. The traditional cross-sectional momentum strategy generates an average payoff of −8.024% (t-stat = −2.221) per month. Further negative skewness (−4.135) indicates the presence of extreme losses. Moreover, the worst performance of the traditional momentum strategy is also evident from the negative Sharpe ratio (−0.235). The volatility scaled momentum strategy produces monthly average returns of 7.932% suggesting no significant improvement in the payoffs despite scaling by the inverse of cryptocurrency market volatility. Though we observe very slight improvement in Sharpe ratio and skewness, nevertheless scaled strategy has no significant advantage over traditional strategy. The corresponding average raw payoffs are 3.340% per month for the time series momentum strategy. The time series momentum strategy has higher raw returns, positive skewness, and improved Sharpe ratio. However, the returns are not statistically significant. The rank-based strategy has performed even worse compared to all other strategies. It generated the worst returns and Sharpe ratio. The proposed stop-loss momentum strategy has 9.127% average monthly returns which are significant at the 1% level. Moreover, the downside losses are reduced as indicated by positive skewness (1.683) and the reward-to-risk ratio has improved (0.430) compared to other strategies. For cross-sectional and time series momentum strategy, our results reconciled with Grobys and Sapkota (2019) who reported absence of momentum payoffs.

Figs. 2 and 3, present the year-wise average payoffs and Sharpe ratios of momentum strategies. Consistent with the results of Table 3, the stop-loss momentum strategy has performed better compared to other momentum strategies. Only in the year 2015, the time series momentum has superior returns compared to the stop-loss momentum strategy. Similarly, in terms of the Sharpe ratio, the stop-loss momentum strategy performs better than other strategies except for the year 2022. In all the years, we observe positive returns and Sharpe ratio for the stop-loss

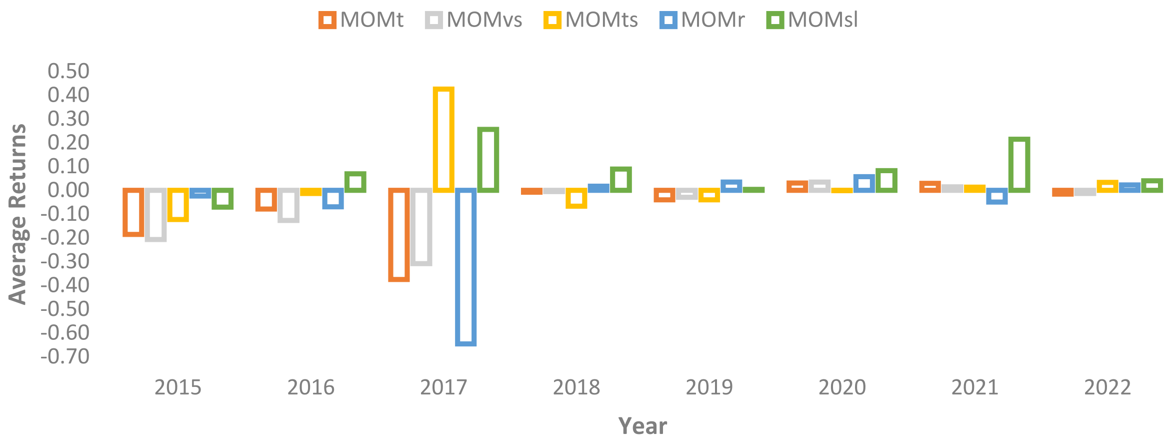

Fig. 2. Year wise average returns of momentum strategies.

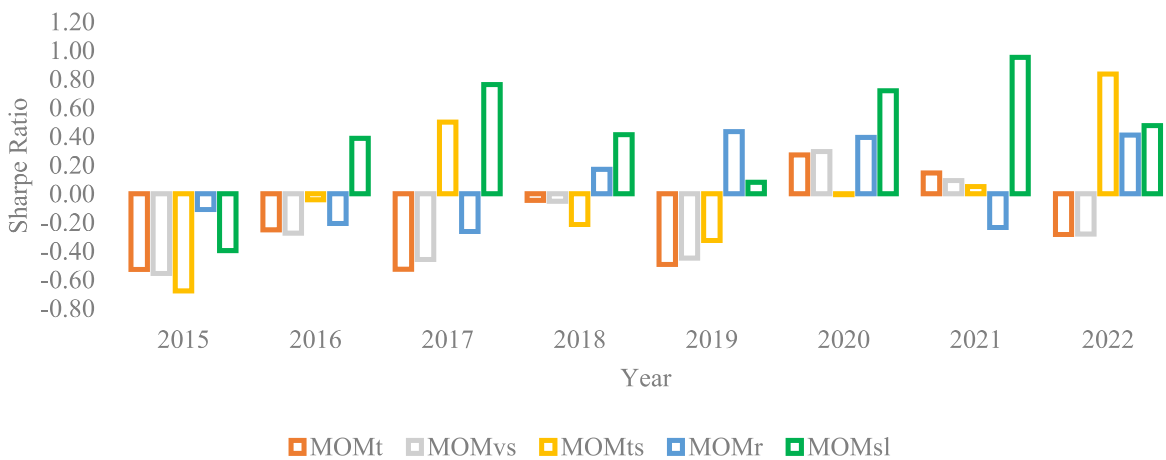

Fig. 3. Year wise sharpe ratios of momentum strategies.

strategy except 2015. This is intuitive as in early years there were fewer cryptocurrencies (See: Fig. 1) in the market with relatively smaller market capitalization and as a result the diversification opportunities were limited. Nonetheless, the stop-loss momentum strategy is useful in managing downside risk.

Given the better performance of the stop-loss momentum strategy in terms of higher returns and improved Sharpe ratios, we next investigate whether this improved performance is due to the increased exposure to systematic risk factors.

In Table 4, we report the risk-adjusted returns for the momentum strategies. Consistent with the results of Table 3, the risk-adjusted returns are insignificant for all conventional momentum strategies. Although, the improved performance of the stop-loss momentum strategy is partially due to the significant exposures of the market (coefficient = 0.244) and size factors (coefficient = 0.186), but the stop-loss momentum strategy generates risk-adjusted returns (coefficient 0.057) that are higher and statistically significant at 1% level relative to other momentum strategies. Resultantly, the known risk factors do not completely capture the returns evolution of the stop-loss momentum strategy. Our results are in line with Han et al. (2016) who reported that stop-loss rules lead to optimal portfolios.

In Table 5, we show the extreme losses for each strategy. In Panel A, extreme losses are reported for the cross-sectional momentum strategy. To examine how stop-loss rules behave in the same months, we report the stop-loss momentum returns as well. Our results show that the stop-loss momentum reduces the extreme losses, and in most periods, it produces positive payoffs. For instance, the average of 10 worst losses from the traditional momentum strategy is −75.131%, and when a stop-loss of ±30% is used, the average of these 10 returns turns out to be 11.527%. One similarity between the traditional momentum returns for cryptocurrencies and stocks is that the overall market returns are positive, when such crashes occur (Daniel and Moskowitz, 2016).

In Panel B, we depict the extreme losses for the volatility scaled momentum strategy. Surprisingly, the average of the 10 worst losses is 77.931% suggesting that the past volatility is unable to control the downside risk and endure enormous losses. While the stop-loss strategy is useful in controlling the losses. In Panel C we show the extreme losses for the time series momentum and report the returns in the same months for the stop-loss momentum strategy. Our results confirm that the time series momentum has a relatively smaller magnitude of extreme payoffs compared to cross-sectional momentum, however, the stop-loss momentum strategy not only reduces the extreme crashes but also produces positive payoffs. On average, the time series momentum strategy has an average monthly return of −44.097%, and the stop-loss reduced the extent of these losses to an average of 6.574%. In Panel E, we report results for the rank-based strategy. The performance of rank-based strategy is the worst among all momentum strategies. Consistent with the results of Tables 3 and 4, the stop-loss momentum strategy has significantly reduced the extreme losses and the improvement in the performance of the momentum strategy shows the usefulness of stop-loss rules.

In Table 6, we discuss the number of stop-loss that are automatically triggered on both the losers' and winners' sides. In the overall sample, the stop loss on the loser's side, is triggered 184 times which is equal to 17.13% of the total return

Table 4
Risk-adjusted returns of momentum strategies.

Variables	L	W	W-L
Panel A: Cross-sectional Momentum Strategy			
MKT	1.326***	0.856***	−0.470
	(4.146)	(8.427)	(−1.278)
SMB	0.457***	0.313***	−0.144
	(4.566)	(3.182)	(−1.493)
PRET	−0.619***	−0.186*	0.433***
	(−6.248)	(−1.781)	(4.614)
Constant	−0.004	−0.034*	−0.031
	(−0.191)	(−1.911)	(−1.513)
Panel B: Volatility Scaled Momentum Strategy			
MKT	1.1734***	0.6724***	−0.5009
	(3.770)	(8.022)	(−1.532)
SMB	0.4775***	0.3130***	−0.1644
	(5.141)	(3.354)	(−1.647)
PRET	−0.7736***	−0.2696***	0.5039***
	(−5.679)	(−2.799)	(4.144)
Constant	0.0007	−0.0251	−0.0258
	(0.035)	(−1.311)	(−1.326)
Panel C: Time Series Momentum Strategy			
MKT	0.535***	1.166***	0.632***
	(3.958)	(8.711)	(3.122)
SMB	0.333***	0.370***	0.037
	(3.604)	(5.051)	(0.711)
PRET	−0.674***	−0.104	0.570***
	(−4.827)	(−1.118)	(6.351)
Constant	0.000	−0.023*	−0.023
	(0.009)	(−1.693)	(−1.095)
Panel D: Rank Based Momentum Strategy			
MKT	1.4022***	1.5377***	0.1356
	(5.557)	(4.576)	(0.286)
SMB	2.1473***	0.7361***	−1.4111***
	(7.944)	(7.910)	(−5.730)
PRET	0.7210***	0.2995***	−0.4214**
	(3.396)	(2.962)	(−2.208)
Constant	−0.0297	−0.0035	0.0262
	(−0.927)	(−0.172)	(0.962)
Panel C: Stop-loss Momentum Strategy			
MKT	0.544***	0.789***	0.244***
	(12.609)	(8.729)	(3.286)
SMB	0.127***	0.313***	0.186**
	(3.873)	(3.295)	(2.312)
PRET	−0.222***	−0.174*	0.0478
	(−8.175)	(−1.681)	(0.441)
Constant	−0.070***	−0.013	0.057***
	(−7.983)	(−0.707)	(2.994)
# Months	87	87	87

This table shows the risk-adjusted returns of momentum strategies. Three-factor models that include market, size, and momentum risk factors are used to calculate risk-adjusted returns. The data runs from January 2015 to June 2022. Newey and West adjusted *t*-statistics are reported at lag 6. ***, **, and * denote the significance at 1%, 5%, and 10% respectively.

observations in the loser's portfolio. On the winners' side, 157 times the stop loss is triggered which is equal to 14.69% of the total returns' observations in the winner's portfolio. The stop-loss orders are more helpful on the loser side in numbers but more than numbers it is the impact of these stop-loss orders on the loser side that is important. For instance, as per Table 3, the average returns decreased from 14.209% for the short log of traditional momentum strategy to −1.429 for the short log of stop-loss momentum strategy. This helped in boosting the overall returns for the momentum strategy.

Our results for the potential benefits of using the stop-loss for cryptocurrencies are economically meaningful and statistically reliable. But the use of stop-loss is also linked with the prospect theory of Kahneman (1979) as it embeds the self-control mechanism (Shefrin and Statman, 1985) for the momentum-driven investors to exit when losses have reached a pre-determined threshold. Keeping in view the volatile nature of cryptocurrencies, the disposition effect may have serious implications for an investor. To avoid that, the predetermined orders such as exiting from the trade within a month when losses are 30% or higher can inhibit the disposition effect for the investors. To an extent,

Table 5
Maximum drawdowns.

S. No	Month	Cross-Sectional MOM	Stop-Loss MOM	MKT
Panel A: Worst Losses in Cross-sectional Momentum				
1	5/31/2017	−246.492	27.809	106.789
2	6/30/2015	−94.062	−10.747	17.955
3	3/31/2017	−75.300	53.648	12.223
4	6/30/2016	−65.820	7.842	22.527
5	11/30/2017	−60.021	−0.430	66.854
6	3/31/2016	−55.795	5.406	−1.592
7	4/30/2017	−49.540	54.912	31.854
8	9/30/2015	−42.290	−23.837	0.926
9	1/31/2021	−33.604	29.056	31.528
10	5/31/2015	−28.384	−28.384	−1.137
Average		−75.131	11.527	28.793
S. No	Month	Volatility Scaled MOM	Stop-Loss MOM	MKT
Panel B: Worst Losses in Volatility Scaled Momentum				
1	5/31/2017	−223.157	27.809	106.789
2	6/30/2016	−129.124	7.842	22.527
3	6/30/2015	−101.880	−10.747	17.955
4	3/31/2017	−80.656	53.648	12.223
5	9/30/2015	−49.349	−23.837	0.926
6	3/31/2016	−47.390	5.406	−1.592
7	4/30/2017	−44.807	54.912	31.854
8	11/30/2017	−35.230	−0.430	66.854
9	7/31/2015	−34.695	−25.664	5.458
10	1/31/2021	−33.023	29.056	31.528
Average		−77.931	11.799	29.452
S. NO	Month	Time Series MOM	Stop-Loss MOM	MKT
Panel C: Worst Losses in Time Series Momentum				
1	6/30/2016	−79.907	7.842	22.527
2	3/31/2017	−69.546	53.648	12.223
3	6/30/2021	−53.021	−4.399	−11.618
4	3/31/2018	−46.699	15.565	−42.132
5	6/30/2015	−41.543	−10.747	17.955
6	6/30/2018	−31.770	−8.268	−22.297
7	10/31/2015	−31.066	−9.912	28.756
8	3/31/2019	−29.354	2.234	8.652
9	7/31/2017	−29.128	−9.280	−7.190
10	1/31/2021	−28.931	29.056	31.528
Average		−44.097	6.574	3.840
S. No	Month	Rank Based MOM	Stop-Loss MOM	MKT
Panel D: Worst Losses in Rank Based Momentum				
1	12/31/2017	−790.422	98.671	102.619
2	6/30/2017	−219.210	55.649	16.068
3	3/31/2021	−57.160	62.701	32.103
4	6/30/2016	−56.147	7.842	22.527
5	3/31/2016	−55.268	5.406	−1.592
6	7/31/2015	−52.398	−25.664	5.458
7	1/31/2016	−50.055	−0.886	−11.538
8	10/31/2017	−48.423	−9.508	22.470
9	1/31/2021	−31.343	29.056	31.528
10	8/31/2016	−28.818	12.412	−6.906
Average		−138.924	23.568	21.273

This table shows the 10 extreme losses of momentum strategies in a month during the period from January 2015 to June 2022. In panel A, the worst losses are reported for the cross-sectional momentum strategy and the corresponding returns for the stop-loss momentum strategy and cryptocurrency market returns. In panel B the worst losses are reported for the time series momentum strategy and the corresponding returns for the stop-loss strategy and cryptocurrency market returns. The average of the 10 worst returns is shown in the last column of Panel A and B for all strategies.

Table 6
Year wise stop-loss triggered in losers and winners.

Year	#LSL	% LSL	#WSL	%WSL
2015	03	13.64%	01	5.88%
2016	07	17.07%	02	5.41%
2017	31	53.45%	09	16.07%
2018	12	11.11%	35	32.41%
2019	22	11.11%	14	7.18%
2020	39	15.79%	20	8.06%
2021	63	23.68%	42	15.44%
2022	07	5.22%	34	25.00%
–	184	17.13%	157	14.69%

This table shows the year-wise details of stop-loss hits in losers and winners. #LSL and %LSL denote the total number and percentage of stop-loss hits in losers' portfolios during a year. #WSL and %WSL denote the total number and percentage of stop-loss hits in the winner's portfolio during the year. The last row shows the total number and percentage of stop-loss triggered. The reporting period is from January 2015 to June 2022.

Table 7
Volatility states and the performance of momentum strategies.

Strategy	Q1	Q2	Q3	Q4	Q5
Panel A: Cross-Sectional Momentum Strategy					
μ	−1.989	−12.961	−19.040	−2.506	−3.928
SD	26.473	28.879	60.574	14.898	21.821
SR	−0.075	−0.449	−0.314	−0.168	−0.180
SK	−0.392	−2.186	−3.446	0.390	−0.148
Panel B: Volatility Scaled Momentum Strategy					
μ	−4.704	−13.634	−17.133	−1.861	−2.488
SD	41.728	31.011	54.550	10.736	12.260
SR	−0.113	−0.440	−0.314	−0.173	−0.203
SK	−1.345	−2.251	−3.512	0.368	−0.431
Panel C: Time Series Momentum Strategy					
μ	−2.392	−4.452	10.167	8.428	5.116
SD	27.947	29.334	47.565	51.866	38.889
SR	−0.086	−0.152	0.214	0.162	0.132
SK	−0.695	0.518	3.474	3.626	0.678
Panel D: Rank Based Momentum Strategy					
μ	4.383	−16.408	11.858	−47.963	−0.773
SD	29.309	54.973	52.526	191.984	15.559
SR	0.150	−0.298	0.226	−0.250	−0.050
SK	−0.780	−3.510	3.570	−4.077	−1.802
Panel C: Stop-Loss Momentum Strategy					
μ	3.899	11.184	11.102	11.451	8.533
SD	19.384	19.052	18.996	30.240	19.342
SR	0.201	0.587	0.584	0.379	0.441
SK	0.891	1.472	1.431	1.838	2.158
Count	18	17	18	17	18

This table shows the performance of momentum strategies in market volatility states. Market volatility is measured by taking the standard deviation of the past 126 days of daily value-weighted market returns. Q1 (Q5) represents the state when 126 days of market volatility lowest (highest). We report the average (μ), standard deviation (SD), Sharpe ratio (SR), and skewness (SK) of all momentum strategies during each state of volatility quintile. The last column (Count) shows the total number of months within each quintile. The analysis period is from January 2015 until June 2022.

these stop-loses inhibit the disposition effect, this study shows that potential economic gains are significantly higher.

Lo and Remorov (2017) document that stop-loss rules are useful in certain situations and the risk reduction is often negligible. To test this proposition, we assess the performance of momentum strategies in different market states. Following Butt et al. (2022) and Barroso and Santa-Clara (2015), we use the past 126 days of daily cryptocurrency value-weighted market returns to estimate the volatility measure. Based on this volatility measure, we identify the quintile volatility states. We report the performance of each momentum strategy in quintile volatility states. Our results show that the momentum returns, and the Sharpe ratios are negative for the cross-sectional momentum strategy in all states suggesting the poor performance of the cross-sectional momentum strategy. The performance is slightly improved in the case of time series momentum. However, the stop-loss momentum strategy produces positive and higher returns in all states compared to other momentum strategies. Moreover, the skewness is positive, and the Sharpe ratio is also better relative to its counterparts. In terms of risk (SD), the stop-loss strategy has outperformed all other strategies including the volatility scaled and rank based strategy. We conclude that in cryptocurrencies, the stop-loss reduces the downside risk and is equally effective in all market states (see Table 7).

Table 8
Performance of stop loss momentum strategy across size.

Strategy	μ	T-stat	SK	SR
Panel A: Stop Loss Momentum in Small Cryptocurrencies				
L	−2.367	−1.169	0.037	−0.125
W	11.731***	2.475	2.030	0.265
W-L	14.097***	3.698	2.291	0.396
Panel B: Stop Loss Momentum in Big Cryptocurrencies				
L	−0.394	−0.188	−0.065	−0.020
W	7.377**	2.014	1.734	0.214
W-L	7.77***	3.016	1.870	0.320

This table shows the average returns (μ), statistical significance (T-stat), Skewness (SK), and Sharpe ratios (SR) of Stop Loss momentum strategy across small and big size cryptocurrencies. L represents losers, W represents winners and W-L represents winners minus losers' portfolios. The period is from January 2014 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

7. Additional tests

We conducted additional tests to further understand the dynamics of stop loss momentum strategy. First, we assessed the performance of the proposed strategy after controlling for size effect. To investigate this, in every month, we divided the universe of cryptocurrencies in median using market capitalization and within small and big sized cryptocurrencies.[12] Subsequently, we constructed the stop loss strategy by following the same procedure explained in the preceding sections. The results are reported in Table 8 Al though, in small sized group, the stop loss strategy has almost two times higher returns than big size cryptocurrencies. However, in both groups the payoffs are statistically significant at the 1% level. Crucially, this suggests that a stop loss strategy helps to control the downside losses regardless of the size of cryptocurrency.

Second, we repeat the analysis with different threshold levels in Table 9. There are investors with different levels of risk tolerance and risk aversion. We repeat the analysis from a risk-averse investors' perspective by using tight threshold levels of 10% and 20%. We also use the threshold levels of 40% and 50% to assess the payoffs for a less risk-averse investor. Our results indicate that strict stop loss thresholds of 10% and 20% produce higher payoffs and vice versa.

Third, in Table 10, we analyzed the performance of momentum strategies when the holding period is one week. There are several studies in which weekly data has been used (see for instance: Burggraf and Rudolf, 2021; Liu and Tsyvinski, 2021; Liu et al., 2022, among others). Following the standard procedure described in Section 3, we repeat the analyses with weekly holding period. Yet again the proposed stop loss strategy has outperformed all other strategies in terms of average returns and

[12] Cryptocurrencies that have market capitalization below median breakpoint are in the small size group whereas the big group contains the cryptocurrencies that have market capitalization above median.

Table 9
Performance of stoploss momentum at different threshold levels.

Strategy	μ	T-stat	SK	SR
Panel A: 10% Threshold Level				
L	−6.704	−4.689	−0.605	−0.497
W	13.402	4.464	1.814	0.473
W-L	20.106	8.508	1.977	0.902
Panel B: 20% Threshold Level				
L	−3.736	−2.196	−0.295	−0.233
W	9.831	3.012	1.546	0.319
W-L	13.566	5.820	1.825	0.617
Panel C: 40% Threshold Level				
L	0.450	0.205	0.210	0.022
W	6.652	1.872	1.235	0.198
W-L	6.202	2.887	1.548	0.306
Panel D: 50% Threshold Level				
L	2.077	0.860	0.413	0.091
W	6.277	1.745	1.179	0.185
W-L	4.200	2.028	1.362	0.215

This table shows the average returns (μ), statistical significance (T-stat), Skewness (SK), and Sharpe ratios (SR) of stop-loss momentum strategies at 10%, 20%, 40% and 50% threshold levels. L represents losers, W represents winners and W-L represents winners minus losers' portfolios. The period is from January 2014 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

Table 10
Performance of Momentum Strategies Using Weekly Sorting.

Strategy	μ	T-stat	SK	SR
Panel A: Traditional Momentum Strategy				
L	9.101***	3.195	1.080	0.154
W	9.506***	3.277	1.348	0.157
W-L	0.405	0.172	0.101	0.008
Panel B: Volatility Scaled Momentum Strategy				
L	8.325***	3.159	0.941	0.152
W	8.600***	3.135	1.568	0.151
W-L	0.275	0.117	0.031	0.006
Panel C: Time Series Momentum Strategy				
L	9.101***	3.195	1.080	0.154
W	9.506***	3.277	1.348	0.157
W-L	0.405	0.172	0.101	0.008
Panel D: Rank Based Momentum Strategy				
L	8.107***	2.821	1.451	0.136
W	10.848***	3.919	1.415	0.188
W-L	2.742	1.497	0.053	0.072
Panel E: Stop Loss Momentum Strategy				
L	1.919	0.876	−0.179	0.042
W	10.228***	3.612	1.578	0.174
W-L	8.309***	3.892	1.401	0.187

This table shows the average returns (μ), statistical significance (T-stat), Skewness (SK), and Sharpe ratios (SR) of different momentum strategies. L represents losers, W represents winners and W-L represents winners minus losers' portfolios. The period is from January 2015 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively. Returns are reported in monthly percentage for consistency.

Sharpe ratio. This suggests that regardless of the holding period, the stop loss strategy is useful in curbing the extreme losses as evident from the improved Sharpe ratio.[13]

Lastly, past evidence suggests that the cryptocurrency data is noisy, and results may be misleading (Alexander and Dakos, 2020). For robustness, we downloaded data from https://coincodex.com/ for all cryptocurrencies.[14] This database provides data on both active as well as dead cryptocurrencies, which addresses the problem of survivorship bias. The results are reported in Table 11. Al though, the returns are inflated for all strategies, but similar patterns are observed. That is, the stop loss strategy outperformed all other strategies.

Table 11
Performance of momentum strategies using alternate data source.

Strategy	μ	T-stat	SK	SR
Panel A: Traditional Momentum Strategy				
L	18.535***	2.703	4.845	0.288
W	14.537*	1.784	6.361	0.190
W-L	−3.997	−0.501	2.188	−0.053
Panel B: Volatility Scaled Momentum Strategy				
L	20.833***	2.762	4.734	0.294
W	14.869*	1.947	5.475	0.208
W-L	−5.964	−0.747	0.286	−0.080
Panel C: Time Series Momentum Strategy				
L	7.017*	1.798	2.065	0.192
W	14.423***	2.470	3.631	0.263
W-L	7.407	1.279	3.633	0.136
Panel D: Rank Based Momentum Strategy				
L	30.143*	1.674	8.416	0.178
W	14.866***	2.351	4.761	0.251
W-L	−15.277	−1.166	−8.592	−0.124
Panel E: Stop Loss Momentum Strategy				
L	−0.480	−0.243	−0.082	−0.026
W	16.264**	2.017	6.518	0.215
W-L	16.744**	2.287	7.454	0.244

This table shows the average returns (μ), statistical significance (T-stat), Skewness (SK), and Sharpe ratios (SR) of different momentum strategies. L represents losers, W represents winners and W-L represents winners minus losers' portfolios. The period is from January 2015 to June 2022. ***, **, * denotes significance at 1%, 5% and 10% respectively.

Overall, our results correspond to the results of the studies of Grobys and Sapkota (2019) who did not find conventional momentum strategies profitable. But we have shown that significant profits can be earned in momentum strategies by using the stop-loss orders. Our findings confirm the results of Kaya and Mostowfi (2022) who reported that stop-loss rules are useful in managing downside risk.

8. Conclusions

Momentum anomaly prevails universally across different asset classes. Further the momentum payoffs collapse in certain market states and incur huge losses. Cryptocurrencies are exceptional as momentum is not ubiquitously available. Keeping in view the recent exponential growth of cryptocurrencies and investor related interest, we analyzed the momentum related anomaly for the cryptocurrencies in detail. Given the high volatility of the cryptocurrencies (Chaim and Laurini, 2018) and the importance of the volatility for the momentum strategy in general (Daniel and Moskowitz, 2016) remains our key motivation. And for that we propose an alternate momentum strategy called the "Stop-loss momentum strategy" by implementing the stop-loss rules in cryptocurrencies. On the one hand the stop-loss controls for excess volatility and on other inhibits the investors disposition effect which may entice them to hold the losers too long and sell the winners too early. Stop-loss rules help to overcome this disposition bias.

[13] We have also conducted analysis for different formation periods i.e., 1, 3, 6 and 9 months. The results are qualitatively unchanged. To conserve space, the results are not reported but can be acquired upon request.

[14] In several studies, the data is extracted from CoinCodex. See for instance: (Chen et al., 2022; Wasiuzzaman et al., 2023).

We provided evidence that the stop-loss rules turn momentum returns positive. For instance, the cross-sectional and time series momentum strategies provide monthly returns of −8.024% (t-stat = −2.221) and 3.340% (t-stat = 0.802) respectively but stop-loss momentum strategy provides 9.127% returns (t-stats = 4.054). The stop-loss avoids huge crashes to which other traditional strategies are exposed to. Such that the average of 10 largest crashes amount to −75.131% and −44.097% respectively for traditional momentum strategies but they reduced to 11.527% and 6.574% by the stop-loss momentum strategy. This is also the first study that used Liu et al. (2022) for the momentum returns for cryptocurrencies that provided the evidence of efficacy of using stop-loss for the momentum strategy. As, the alpha for stop-loss momentum strategy is 5.70% which is superior to any other momentum strategy. We provide evidence that the stop-loss momentum strategy has better yields in different market states. Our results are qualitatively unchanged at different threshold levels of stop-loss, controlling for the size effect in cryptocurrencies, across different formation/holding periods. Furthermore, our results are reconciled when using cryptocurrencies data from alternate sources. Overall, the findings of this study are helpful for investors to mitigate the downside risk and earn better risk-adjusted returns. Moreover, examining the usefulness of stop-loss rules for other trading strategies can be the potential gap for future research(see Table 11).

Acknowledgments

Authors are thankful to the School of Business Studies (IBA, Karachi) for providing the financial support.

Appendix A. List of cryptocurrencies used in this study:

See Table A.1.

Table A.1
List of Cryptocurrencies used in this study.

ABBC	BTC2	EMC2	IOST	NEO	QTUM	VITE
ACT	BTG	EOS	IRIS	NEW	RDD	VLX
ADA	BTM	EOSC	JUL	NKN	RVN	VSYS
ADK	BTS	ETC	KMD	NMC	SAFE	VTC
AE	CCA	ETH	LBTC	NRG	SC	WAN
AION	CLOAK	ETN	LCC	NULS	SFT	WAVES
ALGO	CMT	ETP	LSK	NXS	SKY	WAXP
APL	CNX	FCT	LTC	NXT	STEEM	WGR
ARDR	CSC	FO	LUNA	NYE	STRAX	WICC
ARK	CUT	GBYTE	MAN	ONT	STREAM	XEM
ATOM	CVCC	GO	MB8	OTO	SYS	XLM
BCD	DASH	GRIN	MBC	PAI	TFUEL	XMC
BCH	DCR	GRN	MED	PART	THETA	XMR
BCN	DDK	GRS	META	PCX	TOMO	XNO
BDX	DGB	GXC	MHC	PGN	TRX	XRP
BEAM	DIVI	HBAR	MIOTA	PIVX	TT	XSN
BHD	DOGE	HC	MOAC	PLC	TTC	XTZ
BHP	ECA	HYC	MONA	POLIS	UNO	XVG
BNB	EDC	ICX	NAS	PPC	VET	ZEC
BSV	ELA	ILC	NAV	PZM	VIA	ZEN
BTC	EMC	INT	NEBL	QRL	VITAE	ZIL

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbef.2023.100833.

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