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Cryptocurrency momentum has (not) its moments

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Abstract
This paper explores the tail behavior of cryptocurrency momentum strategies and the profitability of volatility-managed momentum portfolios. Our main results derived from using a sample of large-cap cryptocurrencies and equal-weighted momentum portfolios indicate that cryptocurrency momentum is subject to severe crashes. Even a single cryptocurrency can cause insignificant momentum portfolio returns. In line with the literature on volatility-managing equity portfolios, our findings suggest that volatility management is a useful tool for mitigating cryptocurrency momentum crashes. Further corroborative evidence suggests that cryptocurrency momentum appears to be a phenomenon associated with large-cap cryptocurrencies.

Keywords Cryptocurrencies · Efficient markets · Momentum · Volatility scaling · Tail risk

JEL Classification G10 · G11 · G14 · G15

1 Introduction

Stock price momentum, first documented by Jegadeesh and Titman (1993), has received enormous attention among scholars. This simple trading strategy—a zero-investment portfolio that is long past winner stocks and short past loser stocks—not only holds in expanded samples (Jegadeesh and Titman 2001) but is pervasive across unrelated asset classes (Asness et al. 2013) and holds up to scientific

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replications (Hou et al. 2020). Unfortunately, momentum strategies suffer from reoccurring crashes or drawdowns that are so severe that it can take more than a decade to recover (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). To remedy the problem of momentum crashes, several studies have proposed to scale past returns using volatility or variance (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016; Moreira and Muir 2017). Despite this intuitively appealing approach, volatility scaling has shortcomings. Liu et al. (2019) have argued that volatility scaling suffers from look-ahead bias. Also, Cederburg et al. (2020) conducted a comprehensive empirical investigation using a broad sample of 103 equity portfolios and concluded that volatility management often diminished real-time performance. Contrarily, Liu et al. (2019) found that the approach proposed by Barroso and Santa-Clara (2015) was not subject to look-ahead bias and yielded reliable results. In sum, some controversy surrounds the performance of volatility-managing momentum strategies.

In recent years, momentum strategies have been applied to cryptocurrencies. Using monthly return data on cryptocurrencies, Grobys and Sapkota (2019) investigated the profitability of crypotcurrency momentum strategies. Unlike Asness et al. (2013), who documented momentum across different asset classes, the authors did not find support for cryptocurrency momentum using monthly returns from 2014 to 2018. By contrast, Liu et al. (2022) implemented cryptocurrency momentum strategies using weekly data from 2014 to 2020 and documented large positive payoffs of 3% per week. Also, in an earlier study, Liu et al. (2020) implemented a cryptocurrency momentum strategy from 2015 to 2018 sample and reported outsized average payoffs of 36% per week. However, confirming the findings in Grobys and Sapkota (2019), Shen et al. (2020) found that, regardless of the momentum strategy using weekly data from 2013 to 2019, insignificant negative returns on cryptocurrency portfolios occurred. Thus, no consensus exists on cryptocurrency momentum profits.

Motivated by this literature, the present study re-examines cryptocurrency momentum strategies using weekly observations in the period 2016 to 2023. To control for liquidity, we focus on the top 30 cryptocurrencies with the highest market capitalization. From a practical standpoint, if an investor seeks to implement cryptocurrency momentum strategies in a market dominated by only a few coins, they must be tradable in the real world. Of particular interest, we examine the magnitudes of momentum crashes for cryptocurrency strategies by comparing the payoffs of the plain strategy with various trimming approaches. Potential increases in the statistical significance of cryptocurrency momentum payoffs after trimming would suggest that their performance depends on the tails of the distribution. Additionally, we explore the profitability of various volatility-managed approaches to scale cryptocurrency momentum payoffs. These analyses yield further insights into how volatility management affects the tail risk of cryptocurrency momentum profits.

Our study contributes to relevant literature in several ways. First, as discussed earlier, since studies on cryptocurrency momentum are inconclusive, it is possible that sample specificity explains disparate findings on cryptocurrency momentum. In this regard, the market for cryptocurrencies is notorious for recurring bubble formations (e.g., Grobys 2024a; Kyriazis et al. 2020; Wheatley et al. 2019) that can generate (seemingly) significant cryptocurrency momentum payoffs. Furthermore, it is a well-known stylized fact that the profitability of momentum strategies is more pronounced among microstocks (Fama and French 2008, 2018). Is the profitability of cryptocurrency momentum driven by micro-cryptocurrencies, which would be difficult to implement in practice due to liquidity problems? Our study addresses these important questions by using a considerably longer sample period than earlier studies and focusing on 30 large cryptocurrencies with the highest market capitalization.

Second, potential profitability of cryptocurrency momentum could be driven by extreme events arriving with low probability. That is, inconclusiveness about the profitability of cryptocurrency momentum could be an artifact of tail events that occurred in some samples. As already mentioned, momentum equity strategies are plagued by recurring crashes (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). We extend this research by exploring this issue for cryptocurrency momentum strategies. More specifically, we investigate the profitability of Barroso and Santa-Clara's (2015) risk-managed cryptocurrency momentum strategies. According to Liu et al. (2019), these strategies are not subject to look-ahead bias.

Third, and last, we document evidence that sheds light on the implied risk associated with cryptocurrency momentum and risk-managed strategies. As noted in Taleb (2020), power laws provide a simple yet useful methodological framework to derive the implied risk of payoff series. Specifically, the power law exponent gives us via extrapolation information on the implied risk—that is, the lower the economic magnitude of the power law exponent, the higher is the implied risk of the strategy. Even if large standard deviations (viz. crashes) were not observed, power law functions allow us to form probabilistic assessments about the potential arrival of crashes.[1] Hence, contributing to the literature on cryptocurrency momentum (i.e., Liu et al. 2020, 2022; Zaremba et al. 2021), we explore the implied risk of cryptocurrency momentum strategies by modeling the tail returns of cryptocurrency momentum as power laws.

Using large-capitalization cryptocurrencies and implementing cryptocurrency momentum for various sample periods, we find profits of 1.74% per week from January 2016 to July 2020.[2] These raw payoffs are only nominally significant at the 10% level, which suggests that results in Liu et al. (2022) are possibly attributable to small-cap cryptocurrencies lacking liquidity. In the ex post July 2020 sample period, the average return on cryptocurrency momentum is negative and statistically insignificant consistent with Grobys and Sapkota (2019) and Shen et al. (2020). For the overall sample, cryptocurrency momentum produced an insignificant average raw payoff of 0.90% per week.

[1] Previously documented by Mandelbrot (1963) for cotton price changes, Lux and Alfarano (2016) argued that the power law behavior of financial assets is a stylized fact. In this respect, Mandelbrot's proposed Lévy-stable hypothesis has been subject to extensive investigations across asset classes for over five decades. Interestingly, a recent study of Grobys (2024b) explores the momentum variance risk for stock price momentum and documents that the realized variance risk is infinite.

[2] Note that this sample mainly overlaps with the sample used in Liu et al. (2022), and the end of the chosen sample coincides with the end of the sample used in Liu et al. (2022).

What explains these ambiguous findings? Using various trimming techniques, we find that cryptocurrency momentum is subject to severe crashes. For example, in December 2020 corresponding to the ex post sample period used in Liu et al. (2022), cryptocurrency momentum crashed by -255.23%. Even though the presence of severe crashes is in line with the literature on stock price momentum (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016), we find that this crash is *not* related to market reversals but instead to an extreme price jump in a single cryptocurrency in the short leg of the portfolio. Excluding this single event by means of data trimming increases the weekly average return on cryptocurrency momentum to 1.51% per week for the overall sample with a t-statistic of 2.63 (i.e., significant at the 1% level). Likewise, risk-managed techniques increase the average payoffs by a substantial margin. Indeed, most of our risk-managed strategies increase the weekly average raw return by more than 200% compared to plain strategy payoffs. Upon risk adjustment of payoffs using asset pricing factors, including a cryptocurrency market factor and plain cryptocurrency momentum factor, risk-managed payoffs as measured by the intercepts of the regression models are statistically significant at the 5% level. These findings are consistent with earlier studies on risk-managed stock price momentum (e.g., Barroso and Santa-Clara 2015; Moreira and Muir 2017).

Finally, our empirical evidence reveals that one single outlier corresponds to 37% of the overall compounded return of the cryptocurrency momentum strategy. Using power laws to model the returns on cryptocurrency momentum shows that the variance of this strategy is statistically undefined as implied by a power law exponent of $\alpha < 3$. This finding suggests that the returns on cryptocurrency momentum are as risky as the returns on cotton price changes (Mandelbrot 1963) or venture capital (Lux and Alfarano 2016). Remarkably, risk-managing cryptocurrency momentum does not significantly change the tail risk of cryptocurrency momentum (i.e., the power law exponents are statistically the same for both the plain strategy and various risk-managed counterparts). Based on this evidence, we conclude that cryptocurrency momentum is riskier than previously believed.

2 Literature review

2.1 Cryptocurrency momentum

Since the seminal paper by Jegadeesh and Titman (1993), momentum has continued to be one of the most persistent anomalies in the asset pricing literature. This investment strategy involves taking a long position in assets that have performed well in the recent past and a short position in assets that have performed poorly. Several theoretical models that highlight investors' behavioral biases, including Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and others, have sought to explain momentum.

A growing number of studies have investigated the momentum strategy in the cryptocurrency market. One of the pioneering studies in this area was by Grobys and Sapkota (2019). They analyzed a dataset consisting of 143 cryptocurrencies from 2014 to 2018. Employing portfolio analysis across different time windows ranging from 2 to 12 months, as well as evaluating time series momentum effects (Moskowitz et al. 2012), their findings indicated an insignificant payoff for the momentum strategy in the cryptocurrency market.

Liu et al. (2020) used a dataset of 78 cryptocurrencies to identify the common risk factors that explain their returns. Among the factors studied, including market and size, they found that a momentum factor well explains average returns in both time series and cross-sectional analyses. In contrast with Grobys and Sapkota (2019), they identified a positive payoff for a one-year momentum strategy that tends to diminish as the market capitalization of coins increases.

Liu and Tsyvinski (2021) identified a strong influence of time series momentum within one-to-four week horizons. Unlike equity market momentum, they argued that cryptocurrencies do not show an interaction between momentum and investor attention that could arise from a common latent mechanism. In their subsequent study, Liu et al. (2022) expanded their analysis by demonstrating that a three-factor model with market, size, and momentum factors explains the cross section of cryptocurrency returns. They utilized a dataset of 1827 coins with market capitalization over 1 million USD from the beginning of 2014 to July 2020 and sorted portfolios using a one-to-four week formation period. In their analysis, they documented that a long/short momentum strategy produced significant average payoffs of roughly 3% excess weekly returns. Using similar weekly formation periods and the 2000 largest cryptocurrencies, Dobrynskaya (2023) arrived at similar conclusions.

However, Shen et al. (2020) reported contrasting results. They collected data for 1786 coins from 2013 to 2019 using equally weighted portfolios and a weekly updated momentum strategy. Their results documented a negative momentum payoff increasing from larger to smaller cryptocurrencies. Moreover, consistent with the presence of a reversal effect, Borgards and Czudaj (2020) showed that persistent price overreactions occurred for twelve cryptocurrencies.

On the whole, empirical evidence on cryptocurrency momentum is inconclusive. Zaremba et al. (2021) have pointed out that mixed results may stem from differences in methodological approaches and sample construction. Moreover, they documented a liquidity dependency of cryptocurrency returns, especially for the smaller ones. Notably, small coins often exhibit extremely illiquid characteristics, which could pose significant challenges, especially when attempting to implement strategies that short cryptocurrencies. Hence, liquidity constraints can contribute to mixed evidence also.

2.2 Risk-managed strategy

Although the stock price momentum anomaly continues to persist, it can suffer from periods of poor performance. In the equity market, research has demonstrated that, during economic and financial downturns, the high returns of momentum strategies tend to diminish. This downtrend appears to occur in the wake of large market declines followed by rebounds. As argued by Daniel and Moskowitz (2016), the returns on the stock price momentum strategy can be viewed as a written call option on the market. The intuition is that, during a market decline, high-beta stocks tend to suffer more significant losses compared to low-beta stocks, which tend to fare relatively better. For this reason, the portfolio strategy tends to be long low-beta past winners and short high-beta past losers. However, when the market rebounds, high-beta stocks experience rapid increases in returns. These returns can lead to losses for the momentum strategy due to the portfolio's conditional large negative beta with respect to the market (Grundy and Martin 2001).

Seminal work by Barroso and Santa-Clara (2015) demonstrated that crashes can be mitigated by managing the risk of the strategy. To do so, they scaled long/short momentum portfolio returns by the inverse of their six-month realized variance and a target constant. Using this simple approach, they documented an improvement in the strategy that not only diminished the impact of the worst crashes but also improved the overall performance in normal periods, nearly doubling the Sharpe ratio. The performance of the risk-managed strategy was robust to different subsamples and different international markets. Moreover, they found that the turnover of this strategy was comparable to that of a plain momentum strategy, thereby avoiding high transaction costs that makes the strategy feasible for real world implementation.

Moreira and Muir (2017) investigated the performance of different volatility-managed strategies using a similar approach. They constructed stock portfolios for market, momentum, value, profitability, return-on-equity (ROE), investment, and betting-against-beta (BAB) factors using the previous one-month realized variance and a scaling factor. They showed that these portfolios achieve higher risk-adjusted returns compared to their naive counterparts and generate substantial alphas when regressed on a broad range of asset pricing factors. They also emphasized the effectiveness of these strategies, demonstrating strong evidence of a relationship between past volatility and current volatility, which tends to increase as the time horizon shortens.

However, this volatility scaling approach is not without criticism. Liu et al. (2019) identified a look-ahead bias in the scaling factor of Moreira and Muir (2017) related to the constant chosen in order to obtain the same full-sample variance. Upon correcting this issue, they found that risk-managed portfolios did not outperform the market in the sample period from 1936 to 2017. Furthermore, they observed that these portfolios exhibited an unattractive high maximum drawdown, which could make them less appealing to investors. Subsequently, they replicated their analysis by considering the volatility-targeting strategy of Barroso and Santa-Clara (2015). Although this approach does not suffer from look-ahead bias, as the constant is specified ex ante, the authors once again found evidence that volatility-managed portfolios did not outperform the market.

Another study by Cederburg et al. (2020) studied the performance of volatility-managed portfolios using a comprehensive set of 103 equity strategies with mixed results. They found that these portfolios do not consistently provide significantly higher payoffs than their plain momentum counterparts (e.g., 50 of them failed to outperform). While they obtained a positive alpha from spanning regressions in sample, the instability of the parameters in out-of-sample tests indicated a less impressive Sharpe ratio for the strategy. It should be noted that they used the look-ahead bias approach of Moreira and Muir (2017) to construct their portfolios.

More recently, Angelidis and Tessaromatis (2023) suggested that the disappearing profitability of volatility-managed portfolios may be linked to a reduction in arbitrage costs. After the implementation of trading and information rule changes in the USA during the early 2000s, which enhanced market liquidity, volatility management strategies became redundant.

3 Data

We download cryptocurrency data from coinmarketcap.com, a leading source commonly used in the literature. To determine the investment opportunity set for each year, we retrieve the price time series of the 30 cryptocurrencies with the highest market capitalization at the end of December[3] of the previous year from December 2015 to December 2022. We make this choice to obtain a sample of liquid cryptocurrencies that are tradable in the real world and, therefore, avoid issues associated with smaller coins that likely alter momentum strategy payoffs (Fama and French 2008, 2018; Zaremba et al. 2021).[4] The final sample contains daily prices and market capitalization data denominated in US dollars for 89 unique cryptocurrencies. Table 10 in Appendix provides the list of all sample coins by year. Using these data, we construct equal-weighted long/short portfolios from the first week of January 2016 to the fourth week of December 2023, viz. 416 weekly observations.

A potential data issue is that the composition of the investment opportunity set may not systematically include 30 coins each year. Some of the top cryptocurrencies in the earlier years defaulted over time and were thereafter no longer tracked by coinmarketcap.com. To mitigate this potential survivor bias, we retrieve missing observations from other sources, such as finance.yahoo.com and coincodex.com, in order to complete data series as much as possible. Any remaining missing data, for which we could not obtain information, are excluded from the sample. Additionally, we exclude stablecoins from the investment set. These coins are tethered to another asset class to maintain a stable value. For this reason, they do not provide a return and are not a relevant investment opportunity.

It is worth mentioning that, on average, the turnover of coins in the investment opportunity set is 37% annually. This high turnover underlines the considerable difference in the stability between the equity market and the cryptocurrency market. Only 8 cryptocurrencies—namely, Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Dogecoin (DOGE), Litecoin (LTC), Monero (XMR) and Stellar (XLM)—maintained their positions in the top 30 from 2015 to 2022.

[3] To do so, we utilize Cryptocurrency Historical Data Snapshots provided by coinmarketcap.com. The website offers a historical overview of the market for each week. Since these data are not provided daily, we select for each year the top 30 coins based on the data from the last Sunday of December.

[4] Note that this is also in line with the literature on foreign exchange rates that often focuses on the G10 currencies due to liquidity issues (Assness et al., 2013). Using the G10 currencies to form momentum portfolios leaves us with three equal-weighted currencies in both the long and short leg.

4 Empirical analysis

4.1 Portfolio sorts

Using 30 large cryptocurrencies in December of the previous year, we sort all available cryptocurrencies into quintiles based on their past 30-day returns. We skip the most recent daily price quotation to compute the previous month's formation period (FP) return on cryptocurrency i:

$$r_{i,t}^{FP} = \frac{100\left(p_{i,j-1,t} - p_{i,j-30,t}\right)}{p_{i,j-30,t}}, \tag{1}$$

where $p_{i,j-1,t}$ denotes the closing price of cryptocurrency i on the previous trading day j-1 for a given week t, $p_{i,j-30,t}$ denotes the closing price of cryptocurrency i in the past 30 trading days for a given week t, and $r_{i,t}^{FP}$ is the corresponding formation period return on cryptocurrency i in week t. The momentum portfolio is long (short) cryptocurrencies with the highest (lowest) formation period returns. Using quintile sorts, our momentum portfolio is long on portfolio group 5 ("winners") and short on portfolio group 1 ("losers"). We hold the equal-weighted zero-cost portfolio one week ahead and rebalance our portfolio at the beginning of each week. This plain momentum approach ensures that the investment opportunity set consists of

Table 1 Descriptive statistics for the cryptocurrency market and momentum factor

Sample	Sample 1		Sample 2		Sample 3	
Return vector	Momentum	Market	Momentum	Market	Momentum	Market
Mean	0.90	1.70	1.74	2.72	−0.19	0.40
Median	1.38	0.83	1.33	1.69	1.44	0.18
Maximum	61.34	65.11	61.34	62.72	22.08	65.11
Minimum	−255.28	−34.41	−73.86	−34.41	−255.28	−30.34
Std. deviation	17.20	11.78	14.42	13.28	20.21	9.40
Skewness	−8.02	1.18	−0.27	0.88	−11.14	1.72
Kurtosis	121.81	8.50	10.18	6.31	141.19	15.20
Jarque–Bera (JB)	249,133.90	621.56	505.30	137.08	148,582.10	1217.95
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	416	416	234	234	182	182

This table reports the descriptive statistics of the cryptocurrency market and momentum factors. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using quintile sorts and these top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 period comprised of 416 observations. Sample 1 corresponds to the overall period (i.e., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the last week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the last week of December 2023

Table 2 Portfolio sorts for the momentum factor

Portfolio	P1	P2	P3	P4	P5	(P5-P1)
Panel A. Portfolio sorts for sample 1						
$\bar{r}_i$	1.46	1.30	1.37	1.88	2.36	0.90
$\bar{r}_i^{FP}$	– 19.60	– 6.30	2.68	14.28	64.14	(1.06)
Panel B. Portfolio sorts for sample 2						
$\bar{r}_i$	1.91	2.39	2.49	2.95	3.66	1.74*
$\bar{r}_i^{FP}$	– 20.96	– 5.43	5.46	20.29	88.39	(1.85)
Panel C. Portfolio sorts for sample 3						
$\bar{r}_i$	0.87	– 0.10	– 0.07	0.50	0.68	– 0.19
$\bar{r}_i^{FP}$	– 17.84	– 7.40	– 0.90	6.56	32.96	(– 0.13)

This table reports the portfolio sorts for the cryptocurrency momentum factor. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. Portfolio 1 (P1) corresponds to the loser portfolio, and portfolio 5 (P5) corresponds to the winner portfolio. The average return for portfolio $i = \{1,2,3,4,5\}$ is denoted as $\bar{r}_i$, whereas the average portfolio return for the formation period (FP) is denoted as $\bar{r}_i^{FP}$. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 comprised of 416 observations. Sample 1 corresponds to the overall period (e.g., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the fourth week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the fourth week of December 2023. The t-statistics for the zero-cost portfolios are given in parenthesis

*Statistically significant on a 10% level

the same assets for a given year. At the end of December of each year, we re-assess which cryptocurrencies are in the top 30 in terms of market capitalization.

Descriptive statistics for both the cryptocurrency momentum portfolio and the market factor are reported in Table 1. The results from our portfolio sorts are shown in Table 2. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 period comprising 416 weekly observations. Sample 1 corresponds to the overall sample period (i.e., January 2016 to December 2023), sample 2 covers the subperiod from the first week of January 2016 to the fourth week of July 2020, and sample 3 spans the subperiod from the first week of August 2020 to the fourth week of December 2023. In Table 1, we see that the market factor outperformed the momentum strategy in these three sample periods. Notice that the momentum strategy performed remarkably well at 1.74% per week in sample 2, which ends in the fourth week of July 2020 as in Liu et al. (2022). Table 2 indicates that this payoff is significant at the 10% level. As expected, Table 2 documents that the average formation period returns are linearly increasing from portfolio group 1 (loser) to group 5 (winner) for all samples. Holding period returns also linearly increase for samples 1 and 2, but this pattern does not hold for sample 3. Concerning the latter subperiod, if we exclude one discontinuity that occurred at the end of December 2020, Figs. 1 and 2 show that the cumulative returns on the cryptocurrency momentum portfolio are linearly increasing. Of particular note, the aforementioned one-week discontinuity manifests a large momentum crash equal to −255.28%.

4.2 Trimming

To further investigate whether the poor performance of cryptocurrency momentum is attributable to an outlier, we apply various trimming approaches to the data. Specifically, trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation in terms of absolute value (i.e., −255.28%). We report the corresponding descriptive statistics for sample 1 (overall sample period) in Table 3. Regardless of the trimming procedure, now the average raw return of the cryptocurrency momentum portfolio is highly significant at a 1% level. These results confirm that the poor overall performance of the

Fig. 1 Cumulative returns on the cryptocurrency momentum strategy. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. This figure plots the evolution of the cumulative returns for the zero-cost momentum portfolio from the first week of January 2016 to the last week of December 2023

Fig. 2 Cumulative returns on the cryptocurrency market factor and the momentum portfolio. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using quintile sorts and the top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. This figure plots the evolution of the cumulative returns for the market factor and momentum portfolio from the first week of January 2016 to the last week of December 2023

cryptocurrency momentum strategy in the sample period in Liu et al. (2022) is due to an extreme heavy tail produced from a single outlier arriving in the end of the year 2020. Interestingly, given that the Jarque–Bera test in Table 3 does not reject the null hypothesis of normally distributed cryptocurrency momentum portfolio returns (p-value 0.18), we infer that returns between the 5th and 95th percentiles are normally distributed. The critical question that remains is: How can cryptocurrency momentum crash risk be managed?

4.3 Risk-managed cryptocurrency momentum

Appendix Figure 6 plots the evolution of a rolling time window of the standard deviation of four momentum portfolio returns over our weekly sample from January 2016 to the fourth week of December 2023. In line with earlier studies on momentum crashes, the realized volatility process of cryptocurrency momentum exhibits persistent periods of high and low volatility. Following Barroso and Santa-Clara (2015), we implement a risk-managed cryptocurrency momentum portfolio as follows:

$$r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM}, \tag{2}$$

Table 3 Descriptive statistics after trimming

Method	Trimming 1	Trimming 2	Trimming 3
Mean	1.33***	1.47***	1.51***
(*t*-statistic)	(3.94)	(3.23)	(2.63)
Median	1.38	1.38	1.39
Maximum	18.93	43.22	61.34
Minimum	− 13.70	− 31.14	− 73.86
Std. deviation	6.54	9.22	11.73
Skewness	0.23	0.40	− 0.28
Kurtosis	3.14	5.54	13.34
Jarque–Bera (JB)	3.48	120.20	1855.04
(*p*-value JB)	(0.18)	(0.00)	(0.00)
Observations	374	408	415

This table reports the descriptive statistics of the cryptocurrency momentum factor after trimming the data. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This strategy employs equal-weighted asset allocations and is rebalanced weekly. The weekly data sample is from the first week of January 2016 to the fourth week of December 2023 comprised of 416 observations. Trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation measured in terms of the absolute economic magnitude. The *t*-statistics for the payoffs of the trimmed zero-cost portfolios are given in parenthesis

*** Statistically significant on a 1% level

where c denotes a scaling factor corresponding to the target level of volatility, r_t^{MOM} denotes the return on the plain momentum strategy in week t as described in Sect. 4.1, $r_{j,t}^{RM,MOM}$ denotes the return on the risk-managed momentum portfolio of strategy j in week t, and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$ defined as:

$$\hat{\sigma}_{t,j} = \sqrt{\sum_{k=1}^{j} \frac{\left(r_{t-k}^{MOM}\right)^2}{j}}. \tag{3}$$

In Fig. 3, we plot the time series evolution of the scaling factor, or $\frac{c}{\hat{\sigma}_{t,j}}$, used for volatility-managing cryptocurrency momentum payoffs (i.e., $j = 8$ in association with $c = 10$ from the second week of April 2016 to the fourth week of December 2023). Similar to the results documented by Barroso and Santa-Clara, as shown in Fig. 3, the scaling factor leverages (deleverages) the cryptocurrency momentum payoffs when past volatility was low (high). Subsequently, we risk adjust the

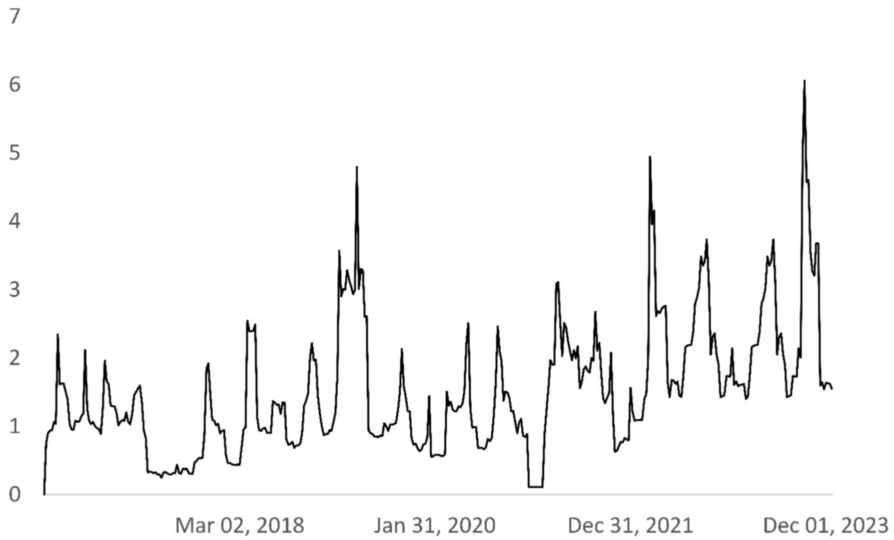

Fig. 3 Evolution of a scaling factor used for volatility-managing cryptocurrency momentum payoffs. Using quintile sorts and the top 30 cryptocurrencies in terms of their market capitalization, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility, and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This figure plots the evolution of the scaling factor derived from $j = 8$ in association with $c = 10$. The weekly data sample is from the second week of April 2016 to the last week of December 2023 period comprised of 404 observations

risk-managed cryptocurrency momentum payoffs using the following factor regression model:

$$r_{j,t}^{RM,MOM} = \alpha_j + \beta_{j,1} r_t^{Mkt} + \beta_{j,2} r_t^{MOM} + \varepsilon_{j,t}, \tag{4}$$

where r_t^{Mkt} denotes the cryptocurrency market factor in week t, which is simply an equal-weighted portfolio of our cryptocurrencies used for implementing the momentum strategy, r_t^{MOM} denotes the return on the plain cryptocurrency momentum strategy in week t, $\varepsilon_{j,t}$ denotes a white noise error at time t, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is a vector of estimated parameters.

Descriptive statistics in Table 4 are shown for risk-managed cryptocurrency momentum portfolios using $c = 10$ to implement the scaling factor. In the sample period April 2016 to December 2023, we observe that the mean weekly payoffs for most risk-managed cryptocurrency momentum strategies are greater than cryptocurrency market returns at 1.59% per week and higher than the plain strategy at 0.71% per week. Specifically, using an 8-week rolling time window strategy to estimate the past realized volatility of the cryptocurrency momentum

Table 4 Descriptive statistics for volatility-managed cryptocurrency momentum portfolios

Factor/strategy	Market factor	r_t^{MOM}	$r_{1,t}^{RM,MOM}$	$r_{2,t}^{RM,MOM}$	$r_{3,t}^{RM,MOM}$
Mean	1.59***	0.71	2.40*	1.86**	1.33
(t-statistic)	(2.69)	(0.83)	(1.81)	(2.09)	(1.45)
Median	0.78	1.28	1.81	1.44	1.28
Maximum	65.11	61.34	124.95	70.11	78.22
Minimum	−34.41	−255.28	−335.26	−226.30	−262.64
Std. Dev	11.87	17.25	26.69	17.93	18.47
Skewness	1.20	−8.16	−4.55	−4.67	−6.93
Kurtosis	8.52	123.48	68.75	68.22	106.45
Jarque–Bera (JB)	609.62	248,847.00	74,162.62	73,082.99	183,380.10
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	404	404	404	404	404

Using quintile sorts using the top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the descriptive statistics for the volatility-managed momentum portfolios. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations

*** Statistically significant on a 1% level, ** statistically significant on a 5% level, * statistically significant on a 10% level

portfolio, we obtain risk-managed raw payoffs that are statistically significant at a 5% level with an impressive 1.86% per week. Moreover, a strategy using a 4-week rolling time window shows even higher payoffs at 2.40% per week, but significance drops to the 10% level. Whereas Table 1 shows that the kurtosis of the plain cryptocurrency momentum strategy equals 121.81, risk-managed counterparts in Table 4 exhibit lower kurtosis values ranging from 68.22 (strategy using $j = 8$) to 106.45 (strategy using $j = 12$). This evidence suggests that risk managing the cryptocurrency momentum strategy diminishes the occurrence of crashes, which has been reported for risk-managed momentum strategies in the equity market (e.g., Barroso and Santa-Clara 2015).

The regression results reported in Table 5 show that risk management of cryptocurrency momentum generates risk-adjusted returns ranging between 0.76% and 1.69% per week with t-statistics from 2.00 to 3.21 that are significant at the 5% level or lower. The R-square values range from 71 to 83 percent, i.e., most of risk-managed cryptocurrency return variation is explained by the market factor and plain momentum factors. Consistent with earlier risk-managed equity momentum studies, the loadings with respect to the cryptocurrency market factor are economically low but statistically significant.

Table 5 Risk adjusting the volatility-managed cryptocurrency momentum portfolio

Strategy	$\widehat{\alpha}_j$	$\widehat{\beta}_{j,1}$	$\widehat{\beta}_{j,2}$	R^2
$r_{1,t}^{RM,MOM}$	1.69*** (2.32)	−0.12** (−1.96)	1.29*** (30.74)	0.71
$r_{2,t}^{RM,MOM}$	1.32*** (3.21)	−0.07** (−2.05)	0.91*** (37.94)	0.79
$r_{3,t}^{RM,MOM}$	0.76** (2.00)	−0.07** (−2.30)	0.97*** (43.58)	0.83

The market factor (r_t^{Mkt}) is an equal-weighted portfolio of cryptocurrencies consisting of the top −30 cryptocurrencies based on their market capitalization. Using quintile sorts using these top 30 cryptocurrencies, the momentum factor is a strategy that is long cryptocurrencies with the highest return in the 1-month formation period and short those with the lowest return in the 1-month formation period. We skip 1 trading day between the holding period and formation period. This plain momentum strategy employs equal-weighted asset allocations and is rebalanced weekly. Risk-managed (RM) cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM}$) scale plain momentum returns as follows: $r_{j,t}^{RM,MOM} = \frac{c}{\widehat{\sigma}_{t,j}} r_t^{MOM}$, where c is scaling factor corresponding to the target level of volatility and $\widehat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the results for the following regression: $r_{j,t}^{RM,MOM} = \alpha_j + \beta_{j,1} r_t^{Mkt} + \beta_{j,2} r_t^{MOM} + \varepsilon_{j,t}$, where $\varepsilon_{j,t}$ denotes a white noise error, $c = 10$, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is the vector of parameters to be estimated. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations. This table reports the point estimates for the regression models, and t-statistics are given in parentheses

*** Statistically significant on a 1% level, ** statistically significant on a 5% level

4.4 Further analysis: power laws governing cryptocurrency momentum returns

In Sect. 4.2, we found that 90% of the cryptocurrency momentum return distribution is normally distributed. A natural question is: What is the distribution of the remaining 10%? In Appendix Fig. 7 in Appendix, we illustrate the impact of momentum crashes by computing the compounded returns of two cryptocurrency momentum return series. Graphially displaying our findings, the blue (red) line in Appendix Fig. 7 shows the evolution of compounded cryptocurrency momentum returns using all observed data (excluding the most extreme return corresponding to −255.28%). Strikingly, one outlier—a single observation corresponding to 0.24% of sample observations—contributes 37% of the overall compounded return. Hence, it is clear that the distribution of the most extreme 5% of cryptocurrency momentum returns is far from normal.

In line with these data, we posit that the distribution of cryptocurrency momentum returns is governed by a power law capable of generating high impact events with low probability. Following Taleb (2020), who advocated to model financial market data using power laws, we model the absolute amount of cryptocurrency momentum returns as:

$$p(x) = Cx^{-\alpha}, \tag{5}$$

where $C = (\alpha - 1)x_{MIN}^{\alpha-1}$ with $\alpha \in \{\mathbb{R}_+ | \alpha > 1\}$, x denotes the absolute amount of return for a cryptocurrency momentum strategy (e.g., plain or risk managed) provided that $x \in \{\mathbb{R}_+ | x_{MIN} \leq x < \infty\}$, x_{MIN} is the minimum observation governed by the power law and α is the magnitude of the corresponding power law exponent. Given the functional form of Eq. (5), it can be shown that conditional moments of order k, or $E[x | x > x_{MIN}]$, are defined as:

$$E[X^k | x > x_{MIN}] = \frac{(\alpha - 1)}{(\alpha - 1 - k)} x_{MIN}^k. \tag{6}$$

From this relation, we see that the theoretical mean (variance) only exists for $\alpha > 2$ ($\alpha > 3$).

Following White et al. (2008) and Clauset et al. (2009), who argued that maximum likelihood estimation (MLE) is the optimal method for calculating power law exponents, the tail exponents $\widehat{\alpha}$ can be estimated as follows:

$$\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}, \tag{7}$$

where $\widehat{\alpha}$ denotes the MLE estimator, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. Like Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data, or Kolmogorov–Smirnov distance (D). This distance is defined as the maximum distance between the cumulative density functions (CDFs) of the data and the fitted model:

$$D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|, \tag{8}$$

where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN}, $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \geq x_{MIN}$, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. In this regard, Clauset et al. (2009) have shown that the standard deviation for estimated power law exponents is:

$$\sigma = \frac{\hat{\alpha} - 1}{\sqrt{N}} + O\left(\frac{1}{N}\right). \tag{8}$$

Summary statistics for the estimated power law exponents are presented in Table 6. A number of new insights into risk-managed momentum strategies are revealed. First, regardless of whether or not risk management is implemented, the estimated power law exponents are close to $\widehat{\alpha} \approx 3$. Upon testing the following hypotheses:

$$H_0 : \alpha \leq 3 \,\text{versus}\, H_0 : \alpha > 3,$$

the evidence in Table 6 fails to reject the null hypothesis. Based on Eq. (6), we infer that the variance of cryptocurrency momentum returns is statistically undefined. Second, applying the goodness-of-fit (GoF) test in Clauset et al. (2009), we cannot reject the power law null model regardless of the strategy analyzed.[5] Overall, this evidence suggests that even though the vast majority of observations are governed by a thin-tailed distribution (e.g.., the normal distribution), the tails of the distribution are governed by a power law process with $\alpha \approx 3$ implying the absence of variance or higher moments.

4.5 Robustness checks

A recent study of Hou et al. (2020) finds that the vast majority of asset pricing studies fails scientific replication and therefore calls for re-examining documented results using a "similar but not identical statistical model." The results documented in the present study are derived from 30 large-cap cryptocurrencies used to construct both an equal-weighted cryptocurrency market factor and an equal-weighted cryptocurrency momentum factor. Consequently, a reader could argue first that our chosen methodology deviates from the established practice to use value-weighted portfolios of assets. Second, because our methodology results in portfolios with only six constituents, a reader could argue that our cryptocurrency momentum portfolio could be subject to a significant exposure to idiosyncratic risk. Fisher and Lorie (1970) and Surz and Price (2000) document that the minimum number of assets required to reach reasonable diversification levels corresponds to 30 constituents. Therefore, one could argue that the large tail risk for our cryptocurrency momentum strategy could be a manifestation of lacking diversification.

Hence, to address these concerns, we follow Zaremba et al (2021) and obtain additional data on cryptocurrencies from coinmarketcap.com, a commonly used data provider for research on the pricing of cryptocurrencies. The data provided from coinmarketcap.com are volume weighted averages of prices across 200 crypto-exchanges. We match the data sample with the sample used in our main analysis and retrieve daily data from January 1, 2016, until December 31, 2023, a total of 2919 daily observations of 2500 cryptocurrencies. Following Liu et al. (2021), we exclude cryptocurrencies with less than 1 million market capitalization and we cater for outliers by filtering the returns of less than -99% or greater than $+200\%$. The market index of cryptocurrencies is the value weighted cross-section average of returns. For the computation of the momentum factor, we divide the coins into deciles based on the past seven days returns while skipping the last one day to avoid short reversal effects (see Zaremba et al. 2021) and form value-weighted portfolios for each momentum group. The momentum factor is the return difference between the top and the bottom momentum portfolios. Data retrieval and portfolio constructions are detailed in Zaremba et al. (2021). Note that using (a) an expanded data set, (b)

[5] The GoF test assuming the power law hypothesis as the null model is described in Clauset et al. (2009).

value-weighted portfolios, and (c) a similar but not identical methodology to form the cryptocurrency momentum portfolio ensures that our robustness checks are in line with the requirements for a scientific replication (see Hou et al. 2020).

Next, because the vast majority of asset pricing studies in cryptocurrency research employs weekly data (e.g., Liu et al. 2020, 2022; Shen et al. 2020)—and to make the results derived from using value-weighted portfolios comparable to results derived from our main analysis—we transform daily data into weekly data by summing up seven consecutive returns leaving us with 416 weekly observations covering the sample from the first week of January 2016 until the last week of December 2023. In Fig. 4, we plot the cumulative returns on our equal-weighted cryptocurrency market factor used in our main analysis and the value-weighted cryptocurrency market factor over the sample from January 2016 to December 2023. From Fig. 4, we observe that until the end of 2019 both indices exhibit virtually the same cumulative return paths, whereas afterward the value-weighted index appears to exhibit a drift. Unsurprisingly, principal component analysis (unreported) suggests that the returns on both cryptocurrency indices exhibit one dominant eigenvalue corresponding to $\lambda = 1.41 > 1$, explaining 70.65% of the overall variation. This strongly suggests that both indices share a common stochastic component despite of being derived from (a) different weighting schemes and (b) different number of constitutes.

Next, in Fig. 5 we plot the evolution of the cumulative returns on both the equal-weighted cryptocurrency momentum factor derived from 30 coins, the value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins, and the value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. Again, the sample is from January 2016 to December 2023. From visual inspection of Fig. 5, a few interesting issues arise: First, regardless the weighting scheme or number of constitutes used to form cryptocurrency momentum portfolios, cryptocurrency momentum strategies appear to be subject to severe crashes. Second, crashes across cryptocurrency momentum strategies do not coincide—and neither do they seem to be related to market reversals. Third, the value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins underperforms both the value-weighted market index and the equal-weighted counterpart by a substantial margin.

We continue our analysis by evaluating the descriptive statistics for our value-weighted cryptocurrency portfolios. In Table 7, we report the descriptive statistics of the value-weighted cryptocurrency market factor, the value-weighted cryptocurrency momentum factor, and the value-weighted cryptocurrency momentum factor after trimming the data. We use the same trimming procedures as outlined in Sect. 4.2. Table 7 provides some interesting insights. First, it becomes evident that the value-weighted cryptocurrency momentum portfolio produces statistically significantly negative returns corresponding to − 3.40% per week. Second, although trimming somewhat increases average returns, average returns remain statistically significantly negative regardless the trimming approach adopted, with average payoffs ranging between − 1.18% and − 2.69% per week. Third, using trimming 1, the payoff distribution comprising 90% of the value-weighted cryptocurrency momentum returns is statistically distributed as normal, as indicated by the Jarque–Bera test exhibiting a p-value > 5%. Interestingly, this result is in line with our result documented earlier for the equal-weighted cryptocurrency momentum strategy. Fourth, the value-weighted cryptocurrency momentum portfolio is subject to crashes manifested in extreme negative returns: Specifically, 1% of the observed return distribution exhibits payoffs ranging between −154.75% and −297.30%. Risk managing only partially remedies this issue.

Then we implement various risk-managing strategies as outlined in Sect. 4.3. The results are reported in Table 8. From Table 8, we observe that even though risk managing successfully removes the crashes as indicated by payoff minimum ranging between −1.12% and −1.82% per week for risk-managed value-weighted cryptocurrency momentum portfolios, average payoffs remain statistically significantly negative, with average payoffs ranging between −0.02% and 0.03% and corresponding t-statistics ranging between −2.71 and −3.50 indicating statistical significance on a 1% level. Unsurprisingly, risk adjusting the volatility-managed value-weighted cryptocurrency momentum portfolio does not result in positive average returns as implied by the results documented in Table 11 in appendix.

Finally, we explore the tail risk associated with various value-weighted cryptocurrency momentum strategies. To do so, we estimate power law models as outlined in Sect. 4.4 for the plain value-weighted cryptocurrency momentum strategy and various risk-managed counterparts. The results are reported in Table 9. Strikingly, the estimated power law exponent for the plain strategy is $\hat{\alpha} = 2.4462$ which is in line with the estimate for the equal-weighted counterpart corresponding to $\hat{\alpha} = 2.8653$ (see Table 6). Moreover, the GoF tests do not reject the power law null hypothesis for any strategy as indicated by p-values ranging between 0.3960 and 0.9200. Again, these results corroborate the results documented for equal-weighted portfolios. Furthermore, only for the strategy using $j = 4$, the hypothesis $\alpha > 3$ can be rejected on a common 5% level, as indicated by $\hat{t} = 1.7279 > 1.65$.

Overall, whereas equal-weighted cryptocurrency momentum using only 30 coins with highest market capitalization and value-weighted cryptocurrency momentum using a data set comprising 2500 coins produce different average payoffs, the results of our robustness checks reveal at least two important commonalities: First, regardless the weighting scheme or number of coins included, cryptocurrency momentum strategies are subject to crash risks that are different from momentum crashes documented in the literature on equities (Daniel and Moskowitz 2016). Second, regardless the weighting scheme or number of coins included, the tail risk of the plain strategies is qualitatively the same.

5 Discussion

5.1 Comparisons to earlier studies

Our main analysis indicates that a momentum strategy implemented within the cryptocurrency market does not yield a significant payoff. This result mainly occurs because the distribution of cryptocurrency momentum returns has severe fat tails and, as such, extreme negative events nullify the efficacy of such a strategy. This fact aligns with prior literature on momentum crashes, which asserts that this anomaly is

Table 6 Estimated power law exponents for various cryptocurrency momentum strategies

	r_t^{MOM}	$r_{1,t}^{RM,MOM}$	$r_{2,t}^{RM,MOM}$	$r_{3,t}^{RM,MOM}$
$\hat{\alpha}$	2.8653	2.9437	3.3036	3.2685
x_{MIN}	9.8708	25.5242	21.4018	16.4004
$\hat{\sigma}$	0.1897	0.2803	0.3700	0.3017
N (in %)	107 (25.72%)	55 (13.35%)	44 (10.78%)	63 (15.59%)
p-value (GoF)	0.9820	0.8210	0.7970	0.5290
$\hat{t}$	−0.7101	−0.2009	0.8205	0.8900

Using maximum likelihood estimation (MLE), the tail exponents $\hat{\alpha}$ are estimated for various cryptocurrency momentum strategies as follows: $\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}$, where x denotes the absolute amount of return on a cryptocurrency momentum strategy (e.g., plain or risk managed), $\hat{\alpha}$ denotes the MLE estimator, and $N \leq T$ is the number of observations greater than x_{MIN}. In line with Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data defined as Kolmogorov–Smirnov distance (D), which is maximum distance between the cumulative density functions (CDFs) of the data and the fitted model: $D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|$, where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN} and $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \geq x_{MIN}$, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. Clauset et al. (2009) showed that the standard deviation for estimated power law exponents is defined as: $\sigma = \frac{\hat{\alpha}-1}{\sqrt{N}} + O(\frac{1}{N})$. This table reports the estimates for power law functions and corresponding descriptive statistics. In our notation, r_t^{MOM} denotes the return on the plain equal-weighted cryptocurrency momentum strategy, whereas $r_{i,t}^{RM,MOM}$ denotes the return on risk-managed equal-weighted cryptocurrency momentum strategy i. The statistic $\hat{t}$ tests the following hypotheses: $H_0 : \alpha \leq 3$ against $H_1 : \alpha > 3$. Given a significance level of 5% and a one-sided test, the null hypothesis is rejected if $\hat{t} > 1.65$.

susceptible to substantial negative movements (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). However, we find that outliers tend to exhibit considerably larger economic magnitudes compared to those observed in the equity market. As documented in Daniel and Moskowitz's study (2016), the lowest monthly returns for stock price momentum occurred in 1932 with a decline of −74.36%. Similarly, Barroso and Santa-Clara (2015) computed a maximum decline of −91.59% in 1932. In our case, the momentum portfolio experienced a crash of −255% at the end of 2020, which is three times larger than the largest equity momentum crash. What can explain this large disparity in crash risk?

Cryptocurrencies represent a novel asset class distinct from traditional financial assets in that they lack an intrinsic economic value based on tangible assets (Corbet et al. 2019). Their value is derived from their underlying algorithms that facilitate transaction tracing and, in turn, is linked to the level of trust in this emerging technology. It is important to note that unlike other asset classes, cryptocurrencies do not offer promises of future payments or dividends that render them inherently riskier investments. Indeed, as pointed out by Chaim and Laurini (2019), cryptocurrencies show very high levels of unconditional volatility, suffer from large outliers that are mostly right-skewed, and have leptokurtic return distributions. Moreover, Baek and Elbeck (2015) showed that Bitcoin is 26 times more volatile than the S&P 500

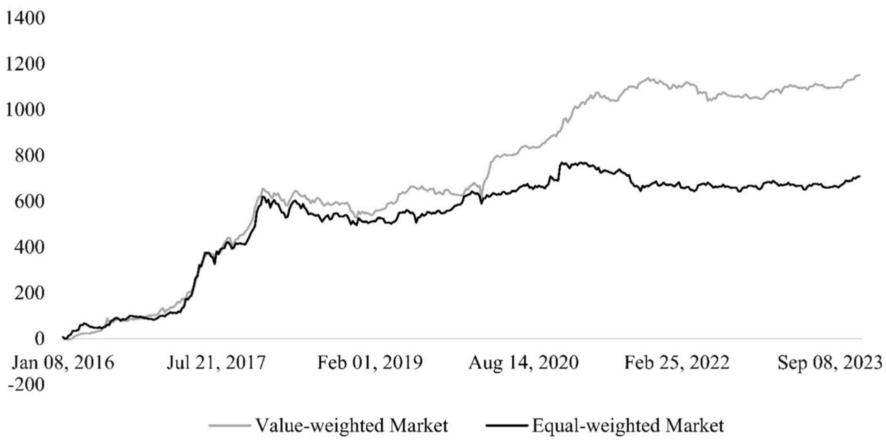

Fig. 4 Cumulative returns on the equal-weighted and value-weighted cryptocurrency market factor. This figure plots the evolution of the cumulative returns for the equal-weighted cryptocurrency market factor derived from 30 coins and the value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. The sample is from the first week of January 2016 to the last week of December 2023

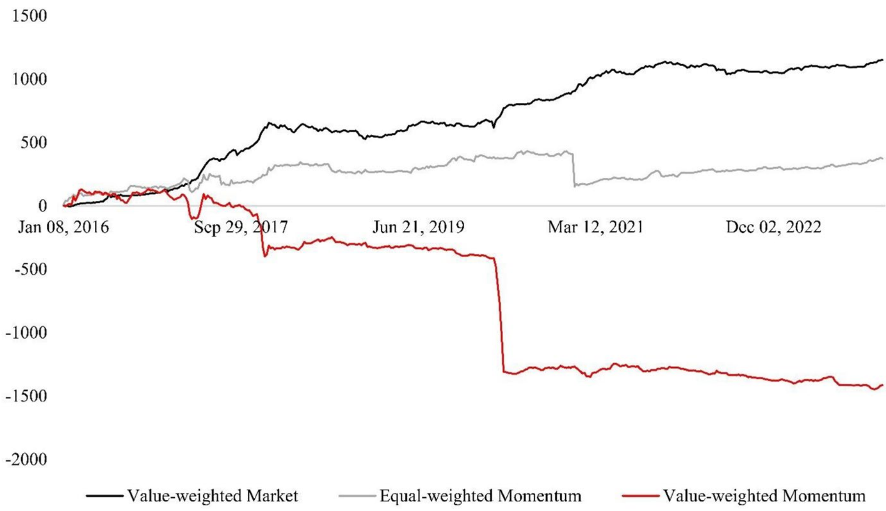

Fig. 5 Cumulative returns on different cryptocurrency momentum factors and the value-weighted cryptocurrency market factor. This figure plots the evolution of the cumulative returns for the equal-weighted cryptocurrency momentum factor derived from 30 coins, value-weighted cryptocurrency momentum factor derived from a data set comprising 2500 coins, and value-weighted cryptocurrency market factor derived from a data set comprising 2500 coins. The sample is from the first week of January 2016 to the last week of December 2023

index, and their returns appear to be internally driven by buyers and sellers rather than influenced by fundamental economic factors. Consistent with the latter, Grobys and Junttila (2021) found evidence of a lottery-like demand in digital currencies markets guided by speculation. Investors' influence can contribute to bubbles

Table 7 Descriptive statistics for value-weighted portfolios

	Market	Cryptocurrency momentum strategies			
	Factor	Plain strategy	Trimming 1	Trimming 2	Trimming 3
Mean	2.77***	−3.40***	−1.18***	−1.99***	−2.69**
(*t*-statistic)	(5.08)	(−2.54)	(−2.91)	(−2.69)	(−2.36)
Median	1.87	−1.02	−1.02	−1.02	−0.95
Maximum	53.09	69.10	15.79	49.63	69.10
Minimum	−50.35	−297.30	−21.81	−143.47	−242.36
Std. deviation	11.12	27.28	7.82	14.99	23.17
Skewness	0.15	−5.96	−0.24	−3.14	−4.91
Kurtosis	6.31	55.81	2.76	27.87	45.41
Jarque–Bera (JB)	191.13	50,798.31	4.39	11,184.78	32,765.55
p-value (JB)	0.00	0.00	0.11	0.00	0.00
Observations	416	416	374	408	415

This table reports the descriptive statistics of the value-weighted cryptocurrency market factor, the value-weighted cryptocurrency momentum factor, and the value-weighted cryptocurrency momentum factor after trimming the data. Using a data set comprising 2500 coins, the value-weighted cryptocurrency market factor at time t corresponds to the value weighted cross-section average of returns. For the value-weighted momentum factor, we divide the coins into deciles based on the past seven days returns, skipping the last day to avoid short reversal (see Zaremba et al (2021), and form value-weighted portfolios for each momentum group. The momentum factor is the return difference between the top and the bottom momentum portfolios. Daily data are transformed into non-overlapping weekly data by summing up seven consecutive holding period returns. The weekly data sample is from the first week of January 2016 to December 2023 comprised of 416 observations. Trimming 1 is a procedure that shrinks the distribution between the 5th and 95th percentiles, trimming 2 shrinks the distribution between the 1st and 99th percentiles, and trimming 3 excludes only the largest observation measured in terms of the absolute economic magnitude. The t-statistics are given in parenthesis

*** Statistically significant on a 1% level, ** Statistically significant on a 5% level

in cryptocurrency prices. Their speculative behavior, combined with the absence of a central authority regulating the supply and potential network effects, makes this phenomenon highly probable (Wei and Dukes 2021). Not surprisingly, the market for cryptocurrencies may experience severe price fluctuations and extreme outliers.

Aside from the magnitude of these events, the mechanisms through which they occur in the context of cryptocurrency are substantially different. Equity momentum crashes typically originate during times of market decline followed by a rebound. This phenomenon arises because the momentum portfolio during prolonged recessions, as discussed earlier, tends to be long on firms with low conditional beta on the market and short on those with high beta. Subsequently, when the market rebounds, the short positions in the portfolio yield extreme negative returns. According to Daniel and Moskowitz (2016), these extreme negative returns occur because momentum effectively embeds a written (short) call option on the market. This optionality effect, as described by Daniel et al. (2018), follows Merton's (1974) framework, wherein a stock can be considered as a call option on the underlying firm's assets in the presence of debt. During a recession, past losers experience significant value

Table 8 Descriptive statistics for volatility-managed value-weighted cryptocurrency momentum portfolios

Factor/strategy	Market factor[a]	$r_t^{MOM(VW)}$	$r_{1,t}^{RM,MOM(VW)}$	$r_{2,t}^{RM,MOM(VW)}$	$r_{3,t}^{RM,MOM(VW)}$
Mean	2.79***	−3.77***	−0.03***	−0.02***	−0.03***
(t-statistic)	(4.99)	(−2.78)	(−2.71)	(−3.18)	(−3.50)
Median	1.84	−1.08	−0.01	−0.01	−0.01
Maximum	53.09	69.10	0.49	0.40	0.42
Minimum	−50.35	−297.30	−1.82	−1.12	−1.34
Std. deviation	11.26	27.22	0.19	0.15	0.15
Skewness	0.15	−6.20	−2.69	−1.85	−2.80
Kurtosis	6.17	57.50	24.47	13.23	21.29
Jarque–Bera (JB)	170.12	52,587.63	8247.01	1989.64	6159.96
(p-value JB)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	404	404	404	404	404

Risk-managed (RM) value-weighted cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM(VW)}$) scale plain value-weighted cryptocurrency momentum returns as follows: $r_{j,t}^{RM,MOM(VW)} = \frac{c}{\hat{\sigma}_{t,j}} r_t^{MOM(VW)}$, where c is scaling factor corresponding to the target level of volatility and $\hat{\sigma}_{t,j}$ is the estimated standard deviation of the momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the descriptive statistics for the volatility-managed value-weighted cryptocurrency momentum portfolios. The weekly data sample is from the second week of April 2016 to December 2023 comprised of 404 observations

***Statistically significant on a 1% level

[a]This table uses the value-weighted cryptocurrency market factor

losses, which causes their stocks to behave like at- or out-of-the-money call options on the firm's assets. The convexity of their payoffs results in slight changes in value for even large downward moves in their underlying assets, whereas the opposite occurs for upward moves, i.e., when the market rises. Even though the aforementioned mechanism may not be directly applicable in their context, Daniel and Moskowitz (2016) note that index futures, commodities, fixed income securities, and currency momentum exhibit option-like behavior.

Contrarily, in the case of cryptocurrency portfolios, crash risk originates from a *single* cryptocurrency that experiences a significant price surge, thereby impacting the short leg of the portfolio. For example, the cryptocurrency Mindol (MIN) experienced a price increase from 0.54 USD to 7.86 USD on December 23, 2020. This movement of 1400% explains how a short-leg portfolio of 6 cryptocurrencies can produce a loss of the cryptocurrency momentum strategy corresponding to −255%. Thus, as demonstrated when applying trimming techniques, this single currency movement accounts for the insignificant payoff of cryptocurrency momentum. Of course, this crash is substantially different from the optionality effect documented in the equity market. Hence, we conclude that cryptocurrency

Table 9 Estimated power law exponents for various value-weighted cryptocurrency momentum strategies

	$r_t^{MOM(VW)}$	$r_{1,t}^{RM,MOM(VW)}$	$r_{2,t}^{RM,MOM(VW)}$	$r_{3,t}^{RM,MOM(VW)}$
$\hat{\alpha}$	2.4462	4.3428	2.8936	3.0419
x_{MIN}	7.6821	0.3697	0.1132	0.1291
$\hat{\sigma}$	0.1194	0.7771	0.2725	0.2225
N (in %)	163 (40.35%)	21 (5.20%)	120 (29.70%)	93 (23.02%)
p-value (GoF)	0.6400	0.4160	0.3960	0.9200
$\hat{t}$	−4.6382***	1.7279**	−0.4969	0.1883

Using maximum likelihood estimation (MLE), the tail exponents $\hat{\alpha}$ are estimated for various value-weighted cryptocurrency momentum strategies as follows: $\hat{\alpha} = 1 + N\left(\sum_{i=1}^{N} \ln\left(\frac{x_i}{x_{MIN}}\right)\right)^{-1}$, where x denotes the absolute amount of return on a value-weighted cryptocurrency momentum strategy (e.g., plain or risk-managed), $\hat{\alpha}$ denotes the MLE estimator and $N \leq T$ is the number of observations greater than x_{MIN}. In line with Clauset et al. (2009), we select x_{MIN} by minimizing the distance between the power law model and the empirical data defined as Kolmogorov–Smirnov distance (D), which is maximum distance between the cumulative density functions (CDFs) of the data and the fitted model: $D = MAX_{x \geq x_{MIN}} |S(x) - P(x)|$, where $S(x)$ represents the cumulative distribution function (CDF) of the data for observations with values greater than or equal x_{MIN} and $P(x)$ is the CDF for the power law model that provides the best fit to the data in the range of $x \geq x_{MIN}$, $N \leq T$ is the number of observations greater than x_{MIN}, and other notation is as before. Clauset et al. (2009) showed that the standard deviation for estimated power law exponents is defined as: $\sigma = \frac{\hat{\alpha}-1}{\sqrt{N}} + O(\frac{1}{N})$. This table reports the estimates for power law functions and corresponding descriptive statistics. In our notation, $r_t^{MOM(VW)}$ denotes the return on the plain value-weighted cryptocurrency momentum strategy, whereas $r_{i,t}^{RM,MOM(VW)}$ denotes the return on risk-managed value-weighted cryptocurrency momentum strategy i. The statistic $\hat{t}$ tests the following hypotheses: $H_0 : \alpha \leq 3$ against $H_1 : \alpha > 3$. Given a significance level of 5% and a one-sided test, the null hypothesis is rejected if $\hat{t} > 1.65$.

*** Statistically significant on 1 % level,** Statistically significant on a 5% level

momentum crashes are not related to market reversals but rather arise from an extreme price jump in a single cryptocurrency.[6]

Could the crash risk be an artifact of using equal-weighted portfolios and 30 coins only? Expanding the data set to 2500 coins and using value-weighted cryptocurrency momentum portfolios, the results from our robustness checks show that the crash risk associated with cryptocurrency momentum is not a manifestation of potential exposure to some idiosyncratic risk. On the other hand, our results are in line with Zaremba et al. (2021) who scrutinized the momentum and reversal effects in cryptocurrencies. The authors found that only the 2% of cryptocurrencies that exhibit the highest market capitalization produce return momentum, whereas 98% of

[6] Note also from Figs. 2 and Appendix Fig. 7 that the cryptocurrency market was in a clear upwards move ex ante the cryptocurrency momentum crash which supports our claim that the market did not experience any reversal when the crash occurred.

the remaining coins—representing only a small fraction of the total market capitalization—exhibit average momentum payoffs that are negative.

5.2 Implications

The unprofitability of the momentum strategy can be mitigated by implementing some type of risk management. By adopting the non-look-ahead biased strategy proposed by Barroso and Santa-Clara (2015), we can effectively avoid crashes and achieve impressive returns that cannot be explained by the market factor or its plain counterpart. These economically significant payoffs are in line with previous literature on equity markets. Also, they are consistent with the recent findings by Angelidis and Tessaromatis (2023), who found that a volatility-managed strategy is effective in a high-cost arbitrage environment. However, while this strategy enhances risk-adjusted returns, it does not change the tail risk behavior of the momentum portfolio.

A reader might argue that the three risk-managed cryptocurrency momentum strategies all have lower kurtosis and larger skewness than the un-managed momentum strategy which seems inconsistent with our results derived from power laws. However, while the kurtosis of the plain cryptocurrency momentum portfolio is 123.48, as documented in Table 4, the risk-managed counterparts still exhibit extremely heavy tails manifested in kurtosis values that exceed 3 by a substantial margin: Specifically, from Table 4 we observe that the lowest kurtosis value is achieved for strategy $r_{2,t}^{RM,MOM}$ exhibiting a kurtosis value of 68.22. For comparison, the excess kurtosis of the Chi-square (exponential) distribution with one degree of freedom—which exhibits considerably heavier tails than the standard normal—is 12 (6). It is evident that standard distributions cannot generate the heavy tails we observe for risk-managed cryptocurrency momentum strategies. A manifestation of the empirical result that kurtosis values decrease after risk-managing cryptocurrency momentum is that power law exponents for the returns on risk-managed cryptocurrency momentum strategies exhibit economic magnitudes that are larger than $\hat{\alpha} = 2.8653$ which is the estimated tail exponent for the plain strategy. It is important to note that a lower (higher) tail exponent suggests more (less) extreme outliers. However, the results documented in Table 6 suggest that, statistically, the hypothesis that $\alpha < 3$ cannot be rejected for any strategy regardless risk management.

Next, employing power laws to model the returns of cryptocurrency momentum and its risk-managed counterpart, we observe that the theoretical variance of both strategies is statistically undefined as implied by a power law exponent of $\alpha < 3$. This result is in line with recent research documenting that the realized variance risk of stock price momentum is infinite (Grobys 2024b). Hence, because the variance is not finite, a major implication is that traditional statistical methodologies may lead to invalid inferences.

Is risk-managed cryptocurrency momentum profitable? If the theoretical variance is undefined, despite impressive cryptocurrency momentum returns using volatility scaling, these payoffs are subject to considerable uncertainty. Whereas Moreira and Muir (2017) concluded that risk management expands the mean–variance frontier, our results suggest that we can only make clear inferences about a *mean-only space*; that is, volatility scaling likely increases average payoffs but no theoretically defined variance exists.

6 Conclusion

The momentum anomaly has been subject of extensive studies in the asset pricing literature. However, published research is inconclusive regarding its applicability to digital currencies. This paper explored the feasibility of a momentum strategy implemented in the cryptocurrency market and investigated whether volatility risk management can enhance its risk-adjusted returns. To do so, we collected cryptocurrency data for the top 30 coins in terms of market capitalization at year end and constructed equally weighted cryptocurrency momentum portfolios based on weekly rebalancing. Our sample spanned from the first week of January 2016 to the fourth week of December 2023, resulting in 416 weekly return observations.

We found that cryptocurrency momentum did not yield a significant payoff due to a severe crash. Unlike the equity market, this crash was idiosyncratic to a single cryptocurrency and, therefore, not subject to an optionality effect as documented by Daniel and Moskowitz (2016) for stocks. In an effort to control crash risk, we implemented risk management strategies based on past return volatility scaling. Using different past volatility windows, impressive risk-managed payoffs from 1.86% to 2.40% per week were generated. After risk adjusting momentum returns using a factor model, consistent with equity market studies, significant payoffs persisted.

Using power laws to model tail returns of cryptocurrency momentum and risk-managed counterparts, further analyses indicated that the theoretical variance is undefined (i.e., power law exponent $\alpha < 3$). For this reason, traditional statistical methodologies can yield invalid inferences. Additionally, because risk management does not change the tail risk of cryptocurrency momentum, we conclude that this strategy is subject to considerable uncertainty that implies greater risk than previous cryptocurrency research has suggested.

Our findings have important implications for investors seeking to implement momentum strategies in the cryptocurrency market. First and foremost, risk management is critical to earning cryptocurrency momentum profits. Second, even after risk adjustment via volatility scaling, investors should be aware that tail risk can still be very high due to undefined return variance. Future research is recommended to investigate the performance of volatility-scaling risk management for other cryptocurrency anomalies. For example, Liu et al. (2022) constructed zero-cost strategies based on 24 cryptocurrency characteristics broadly classified into four groups, including size, volume, volatility, and momentum. Hence, future studies are encouraged to explore the profitability and the tail risk of zero-cost strategies derived from other characteristics apart from past return performance.

Appendix

See Figs. 6 and 7, Tables 10 and 11.

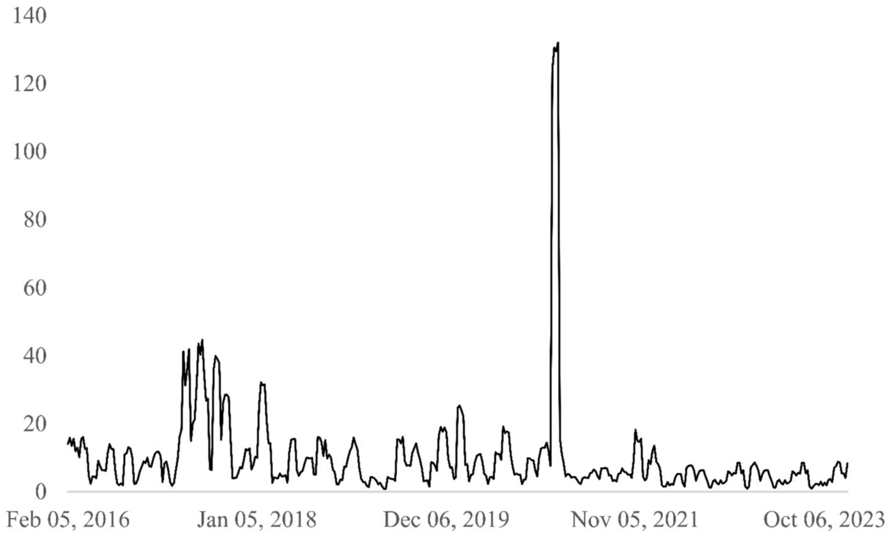

Fig. 6 Realized volatility of the cryptocurrency momentum portfolio using a rolling time window of 4 weeks. This figure shows the evolution of a rolling time window of the standard deviation of four consecutive momentum portfolio returns over the weekly sample January 2016 to December 2023

Fig. 7 Compounded return on the cryptocurrency momentum portfolio. This figure shows the evolution of the compounded return on cryptocurrency momentum portfolio returns over the weekly sample January 2016 to December 2023. The blue line shows the evolution of compounded cryptocurrency momentum returns, whereas the red line shows the evolution of compounded cryptocurrency momentum returns excluding the most extreme return corresponding to − 255.28%

Table 10 Investment opportunity set

Panel A. Top 30 Cryptocurrencies—27 December 2015				Panel B. Top 30 Cryptocurrencies—25 December 2016				Panel C. Top 30 Cryptocurrencies—31 December 2017				Panel D. Top 30 Cryptocurrencies—30 December 2018			
Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap
1	Bitcoin	BTC	$6,348,303,535.49	1	Bitcoin	BTC	$14,396,198,729.33	1	Bitcoin	BTC	$237,466,518,547.07	1	Bitcoin	BTC	$67,475,512,827.39
2	XRP	XRP	$212,734,466.03	2	Ethereum	ETH	$626,189,615.98	2	XRP	XRP	$89,121,967,114.06	2	XRP	XRP	$15,076,740,856.33
3	Litecoin	LTC	$152,353,682.59	3	XRP	XRP	$232,006,578.41	3	Ethereum	ETH	$73,170,132,771.99	3	Ethereum	ETH	$14,560,066,114.19
4	Ethereum	ETH	$64,913,889.24	4	Litecoin	LTC	$213,168,549.82	4	Bitcoin Cash	BCH	$42,774,236,530.93	4	Bitcoin Cash	BCH	$2,869,903,437.91
5	Dash	DASH	$16,121,933.07	5	Monero	XMR	$132,525,971.58	5	Cardano	ADA	$18,659,588,487.38	5	EOS	EOS	$2,430,234,521.47
6	Dogecoin	DOGE	$14,837,666.78	6	Ethereum Classic	ETC	$93,536,872.97	6	Litecoin	LTC	$12,663,197,417.17	6	Stellar	XLM	$2,250,048,215.08
7	Peercoin	PPC	$9,872,343.12	7	Dash	DASH	$69,834,088.36	7	IOTA	IOTA	$9,869,763,787.81	7	Litecoin	LTC	$1,912,263,647.77
8	BitShares	BTS	$8,999,976.20	8	MaidSafeCoin	MAID	$44,717,207.22	8	NEM	XEM	$9,306,424,139.90	8	Tether**	USDT	$1,893,629,500.50
9	Stellar	XLM	$8,319,858.32	9	NEM	XEM	$32,455,741.19	9	Dash	DASH	$8,189,388,164.00	9	Bitcoin SV	BSV	$1,553,228,295.25
10	MaidSafeCoin	MAID	$6,532,958.12	10	Steem	STEEM	$31,444,070.65	10	Stellar	XLM	$6,442,724,493.37	10	TRON	TRX	$1,329,143,863.30
11	Nxt	NXT	$6,435,492.48	11	Augur	REP	$30,404,634.00	11	Monero	XMR	$5,426,210,002.08	11	Cardano	ADA	$1,122,116,467.72
12	Bytecoin	BCN	$5,575,055.92	12	Iconomi*	ICN	$29,921,653.84	12	EOS	EOS	$5,041,642,753.40	12	IOTA	IOTA	$1,002,877,280.23
13	Namecoin	NMC	$5,541,075.54	13	Dogecoin	DOGE	$24,708,711.86	13	Neo	NEO	$4,937,436,141.97	13	Monero	XMR	$806,939,516.43
14	Monero	XMR	$4,746,216.19	14	Factom	FCT	$21,824,198.16	14	Qtum	QTUM	$4,603,333,032.82	14	BNB	BNB	$784,234,811.60
15	Factom	FCT	$3,973,903.24	15	Waves	WAVES	$20,314,945.28	15	Bitcoin Gold	BTG	$4,380,775,196.80	15	Dash	DASH	$698,091,182.88
16	GridCoin	GRC	$3,318,853.66	16	Stellar	XLM	$17,845,296.56	16	Verge	XVG	$3,208,728,455.06	16	NEM	XEM	$619,220,627.98
17	Rubycoin	RBY	$3,242,739.75	17	DigixDAO	DGD	$16,789,319.99	17	TRON	TRX	$2,942,336,038.18	17	Ethereum Classic	ETC	$568,817,905.13
18	Emercoin	EMC	$2,497,094.42	18	Lisk	LSK	$14,298,781.50	18	Nano	XNO	$2,885,869,971.17	18	Neo	NEO	$527,716,102.54
19	Clams	CLAM	$2,130,115.66	19	Zcash	ZEC	$13,741,401.91	19	Ethereum Classic	ETC	$2,765,755,613.58	19	Maker	MKR	$347,476,493.39
20	BlackCoin	BLK	$1,961,088.04	20	Swiscoin*	SCN	$12,459,317.54	20	BitConnect	BCC	$2,593,243,079.16	20	Zcash	ZEC	$332,048,193.21
21	YbCoin*	YBC	$1,889,851.70	21	EDC Blockchain	EDC	$11,893,201.05	21	Lisk	LSK	$2,377,903,943.13	21	Waves	WAVES	$309,381,632.54
22	MonaCoin	MONA	$1,591,595.30	22	GameCredits	GAME	$11,857,561.08	22	OmiseGO	OMG	$2,029,570,238.64	22	Tezos	XTZ	$302,665,930.63
23	Counterparty	XCP	$1,498,862.55	23	Xenixcoin*	XEN	$11,624,658.54	23	ICON	ICX	$2,017,629,553.50	23	Dogecoin	DOGE	$278,470,304.32
24	Startcoin	START	$1,395,709.41	24	BitShares	BTS	$11,047,151.13	24	Ardor	ARDR	$1,718,412,421.71	24	USD Coin**	USDC	$249,383,514.72
25	NeuCoin*	NEU	$1,379,275.02	25	Ardor	ARDR	$10,862,223.99	25	BitShares	BTS	$1,714,041,929.34	25	Bitcoin Gold	BTG	$238,520,472.35
26	NEM	XEM	$1,350,448.76	26	LoMoCoin*	LMC	$9,790,908.08	26	Populous	PPT	$1,536,709,576.52	26	VeChain	VET	$233,909,929.16
27	Global Currency Reserve	KWD	$1,325,873.75	27	Bytecoin	BCN	$8,276,082.86	27	Zcash	ZEC	$1,495,222,601.73	27	TrueUSD**	TUSD	$207,286,489.45
28	BitcoinDark*	BTCD	$1,290,322.82	28	Golem	GLM	$7,800,898.11	28	Tether**	USDT	$1,384,856,529.14	28	Qtum	QTUM	$206,333,378.42
29	AmberCoin	AMBER	$1,254,452.07	29	Emercoin	EMC	$7,663,821.18	29	Stratis	STRAX	$1,384,480,444.68	29	OmiseGO	OMG	$199,283,833.25
30	Novacoin	NVC	$1,139,684.13	30	Gulden	NLG	$7,606,658.43	30	Waves	WAVES	$1,259,664,154.05	30	Zilliqa	ZIL	$194,575,018.05

Table 10 (continued)

Panel E. Top 30 Cryptocurrencies—29 December 2019				Panel F. Top 30 Cryptocurrencies—27 December 2020				Panel G. Top 30 Cryptocurrencies—26 December 2021				Panel H. Top 30 Cryptocurrencies—25 December 2022			
Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap	Rank	Name	Symbol	Market Cap
1	Bitcoin	BTC	$134,570,835,775.06	1	Bitcoin	BTC	$488,213,268,382.01	1	Bitcoin	BTC	$960,899,995,734.94	1	Bitcoin	BTC	$324,093,186,300.92
2	Ethereum	ETH	$14,698,483,422.09	2	Ethereum	ETH	$77,828,069,141.05	2	Ethereum	ETH	$483,620,188,465.02	2	Ethereum	ETH	$149,169,092,950.40
3	XRP	XRP	$8,536,136,120.35	3	Tether**	USDT	$20,729,387,121.49	3	BNB	BNB	$91,239,389,442.48	3	Tether**	USDT	$66,243,849,258.58
4	Tether**	USDT	$4,125,339,508.86	4	XRP	XRP	$12,851,124,973.13	4	Tether**	USDT	$78,020,576,206.34	4	USD Coin**	USDC	$44,348,890,607.38
5	Bitcoin Cash	BCH	$3,874,556,156.19	5	Litecoin	LTC	$8,439,551,136.23	5	Solana	SOL	$61,170,181,005.50	5	BNB	BNB	$38,894,316,962.85
6	Litecoin	LTC	$2,783,708,411.61	6	Bitcoin Cash	BCH	$6,290,438,770.71	6	Cardano	ADA	$48,735,884,302.66	6	XRP	XRP	$17,438,570,226.36
7	EOS	EOS	$2,548,344,835.55	7	BNB	BNB	$4,839,330,613.85	7	XRP	XRP	$43,789,189,735.81	7	Binance USD**	BUSD	$17,393,414,909.52
8	BNB	BNB	$2,200,851,434.24	8	Chainlink	LINK	$4,833,804,693.48	8	USD Coin**	USDC	$42,392,023,711.45	8	Dogecoin	DOGE	$10,076,566,956.65
9	Bitcoin SV	BSV	$1,813,274,573.35	9	Cardano	ADA	$4,804,453,143.56	9	Terra	LUNC	$36,262,543,327.79	9	Cardano	ADA	$8,945,785,641.41
10	Stellar	XLM	$926,843,557.23	10	Polkadot	DOT	$4,592,307,413.22	10	Polkadot	DOT	$30,943,660,939.69	10	Polygon	MATIC	$6,944,943,117.07
11	TRON	TRX	$916,441,896.99	11	USD Coin**	USDC	$3,582,730,027.76	11	Avalanche	AVAX	$28,024,471,317.76	11	Dai	DAI	$5,847,586,517.37
12	Tezos	XTZ	$911,327,053.77	12	Stellar	XLM	$3,170,263,194.62	12	Dogecoin	DOGE	$25,210,069,507.96	12	Polkadot	DOT	$5,168,182,598.74
13	Cardano	ADA	$888,882,223.76	13	Bitcoin SV	BSV	$3,113,350,011.74	13	SHIBA INU	SHIB	$21,036,265,565.30	13	TRON	TRX	$5,042,409,485.27
14	UNUS SED LEO	LEO	$823,580,467.65	14	Wrapped Bitcoin	WBTC	$3,035,975,344.15	14	Polygon	MATIC	$20,411,914,262.07	14	Litecoin	LTC	$4,976,584,253.49
15	Cosmos	ATOM	$813,804,080.92	15	Monero	XMR	$2,798,785,869.76	15	Cronos	CRO	$15,811,859,284.42	15	Shiba Inu	SHIB	$4,551,453,927.84
16	Monero	XMR	$813,746,410.83	16	EOS	EOS	$2,549,025,780.05	16	Binance USD**	BUSD	$14,632,314,648.34	16	Solana	SOL	$4,180,006,175.80
17	Huobi Token	HT	$678,721,856.55	17	NEM	XEM	$2,123,154,048.23	17	Wrapped Bitcoin	WBTC	$13,129,214,895.89	17	Uniswap	UNI	$3,929,874,440.08
18	Chainlink	LINK	$665,841,558.77	18	TRON	TRX	$2,067,107,839.20	18	Uniswap	UNI	$11,745,630,155.55	18	Avalanche	AVAX	$3,637,468,062.45
19	Neo	NEO	$652,749,972.22	19	Tezos	XTZ	$1,510,425,125.03	19	Litecoin	LTC	$10,806,756,315.88	19	UNUS SED LEO	LEO	$3,447,947,960.08
20	MINDOL	MIN	$638,796,576.01	20	UNUS SED LEO	LEO	$1,354,911,353.37	20	Chainlink	LINK	$10,745,755,661.49	20	Wrapped Bitcoin	WBTC	$3,100,946,665.40
21	Ethereum Classic	ETC	$541,875,099.12	21	THETA	THETA	$1,346,225,507.91	21	Algorand	ALGO	$10,216,971,621.55	21	Chainlink	LINK	$3,040,866,462.10
22	999	999	$523,189,674.97	22	Cronos	CRO	$1,273,375,675.08	22	TerraUSD**	USTC	$9,952,448,734.27	22	Toncoin	TON	$2,969,682,082.98
23	USD Coin**	USDC	$520,939,799.33	23	Dai	DAI	$1,106,811,793.68	23	NEAR Protocol	NEAR	$9,724,360,291.45	23	Monero	XMR	$2,646,679,380.68
24	HedgeTrade	HEDG	$516,827,656.56	24	Neo	NEO	$1,064,818,715.88	24	Dai	DAI	$9,371,280,978.02	24	Cosmos	ATOM	$2,583,178,816.23

Table 10 (continued)

Panel E. Top 30 Cryptocurrencies—29 December 2019				Panel F. Top 30 Cryptocurrencies—27 December 2020				Panel G. Top 30 Cryptocurrencies—26 December 2021				Panel H. Top 30 Cryptocurrencies—25 December 2022			
25	IOTA	IOTA	$468,403,923.48	25	Dash	DASH	$1,061,465,798.16	25	Bitcoin Cash	BCH	$8,564,343,857.77	25	Ethereum Classic	ETC	$2,244,205,310.39
26	Maker	MKR	$448,314,261.26	26	VeChain	VET	$1,061,121,307.65	26	TRON	TRX	$8,309,592,456.12	26	Bitcoin Cash	BCH	$1,952,616,106.12
27	Cronos	CRO	$441,270,132.30	27	Celsius	CEL	$1,016,716,288.48	27	Cosmos	ATOM	$7,285,398,828.95	27	Stellar	XLM	$1,928,352,970.45
28	Dash	DASH	$413,310,785.85	28	Cosmos	ATOM	$1,003,531,564.11	28	Stellar	XLM	$7,206,705,407.49	28	Cronos	CRO	$1,510,925,684.13
29	Ontology	ONT	$348,595,243.81	29	Filecoin	FIL	$992,839,784.49	29	Decentraland	MANA	$7,050,454,756.85	29	OKB	OKB	$1,388,940,572.39
30	VeChain	VET	$310,542,537.66	30	Revain	REV	$989,937,349.40	30	Axie Infinity	AXS	$6,551,674,566.11	30	ApeCoin	APE	$1,297,707,700.33

This table reports the investment opportunity set for each year, which consists of the 30 cryptocurrencies with the highest market capitalizations as of the last Sunday of December. The data span from December 2015 to December 2022. An asterisk (*) indicates that a cryptocurrency has been excluded from the sample due to a lack of related data. A double asterisk (**) identifies a stablecoin that has been excluded from the sample

Table 11 Risk adjusting the volatility-managed value-weighted cryptocurrency momentum portfolio

Strategy	$\widehat{\alpha}_j$	$\widehat{\beta}_{j,1}$	$\widehat{\beta}_{j,2}$	R^2
$r_{1,t}^{RM,MOM(VW)}$	−0.0106 (−1.25)	−0.0008 (−1.02)	0.0034*** (11.06)	0.25
$r_{2,t}^{RM,MOM(VW)}$	−0.0083 (−1.42)	−0.0008 (−1.62)	0.0034*** (15.84)	0.41
$r_{3,t}^{RM,MOM(VW)}$	−0.0095 (−1.63)	−0.0012** (−2.33)	0.0036*** (17.16)	0.46

The market factor ($r_t^{Mkt(VW)}$) is a value-weighted portfolio of cryptocurrencies derived from a data set comprising 2,500 coins. Risk-managed (RM) value-weighted cryptocurrency momentum strategies ($r_{j,t}^{RM,MOM(VW)}$) scale plain value-weighted cryptocurrency momentum returns as follows: $r_{j,t}^{RM,MOM(VW)} = \frac{c}{\widehat{\sigma}_{t,j}} r_t^{MOM(VW)}$, where c is scaling factor corresponding to the target level of volatility and $\widehat{\sigma}_{t,j}$ is the estimated standard deviation of the value-weighted cryptocurrency momentum portfolio between week $t-j$ and week $t-1$ with $j \in \{4,8,12\}$. This table reports the results for the following regression: $r_{j,t}^{RM,MOM(VW)} = \alpha_j + \beta_{j,1} r_t^{Mkt(VW)} + \beta_{j,2} r_t^{MOM(VW)} + \varepsilon_{j,t}$, where $\varepsilon_{j,t}$ denotes white noise error, $c = 10$, and $\theta_j = (\alpha_j, \beta_{j,1}, \beta_{j,2})$ is the vector of parameters to be estimated. The weekly data sample is from the second week of April 2016 to the fourth week of December 2023 comprised of 404 observations. This table reports the point estimates for the regression models, and t-statistics are given in parentheses

***Statistically significant on a 1% level

**Statistically significant on a 5% level

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Declarations

Conflict of interest The authors declare that they have no interests to declare.

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