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On survivor cryptocurrency momentum

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ABSTRACT

Motivated by the significant illiquidity observed in the cryptocurrency market—exemplified by phenomena such as "defaulted coins"—this study is the first to investigate a cryptocurrency-specific analog of currency momentum, as implemented among G10 currencies. We analyze nine free-floating cryptocurrencies that remained within the top 100 altcoins by market capitalization during the sample period, spanning January 2017 to August 2024. Using weekly data, we evaluate two cryptocurrency momentum strategies: one focused solely on survivor coins and another utilizing the largest 30 coins for a given year (referred to as "plain cryptocurrency momentum"). Our main findings are as follows: (a) Cryptocurrency momentum is not evident when applied to survivor coins; (b) plain cryptocurrency momentum is profitable only after the dataset is trimmed; (c) the profitability of trimmed plain cryptocurrency momentum does not result from leveraging survivor coin-based cryptocurrency momentum; (d) even after trimming, the profitability of plain cryptocurrency momentum is highly sample-dependent.

1. Introduction

The study of cryptocurrency momentum was first introduced by Grobys and Sapkota (2019), who investigated the profitability of various momentum strategies using monthly returns on 143 cryptocurrencies from 2014 to 2018. Their findings revealed no statistically significant momentum payoffs. Conversely, Liu et al. (2020) observed substantial average weekly payoffs of 36 % when employing a cryptocurrency momentum strategy over a 2015–2018 sample of 78 coins. Liu et al. (2022) extended this analysis to 1827 coins spanning 2014–2020 and found statistically significant average payoffs of 3 % per week. Interestingly, Zaremba et al. (2021) emphasized that inconclusive results in the literature could stem from methodological differences and sample construction, particularly the inclusion of illiquid small coins, which pose significant implementation challenges.

Grobys et al. (2025) addressed these issues by focusing on a rolling investment opportunity set of 30 cryptocurrencies with the highest market capitalizations from 2016 to 2023. Their cryptocurrency momentum strategy was only profitable after trimming extreme values. Moreover, the authors documented that the turnover of coins in their investment opportunity set was 37 % annually, on average, highlighting a considerable stability issue in the digital currency market.

Is coin stability, in terms of liquidity and market relevance, a key determinant of momentum profitability? If momentum is a pervasive phenomenon, as suggested by Asness et al. (2013), it implies that asset prices must have sufficiently smooth and persistent trends for momentum strategies to exploit, rather than patterns of high return volatility and discontinuity. Based on this argument, we

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hypothesize that the profitability of other momentum strategies may result from leveraged exposure to survivor-coin momentum. In other words, the returns of the Grobys et al. (2025) momentum portfolio, after excluding extreme values, might mainly be driven by the momentum effect of survivor coins. Conversely, if this hypothesis does not find empirical support, the momentum anomaly may manifest through other cryptocurrencies that gain popularity and suddenly transition from a passive management state to an active one, then reverting to their previous price levels or even defaulting, once their popularity vanishes. Intuitively, in such instances, a momentum strategy would be profitable as it would take long positions on these coins until they lose popularity and revert, at which point they would be shorted. However, this process may not be monotonic, potentially causing drawdowns in the strategy.

This study examines the profitability of cryptocurrency momentum implemented in a time-invariant liquidity space defined by survivor coins, a purpose-built research design to isolate the effect of stability. Survivor coins are free-floating cryptocurrencies that remained among the top 100 altcoins by market capitalization throughout the sample period (January 2017 to August 2024), thereby demonstrating stability and liquidity over time. We analyze the strategy's profitability on raw and trimmed data (removing outliers within the 2.5th and 97.5th percentiles). Additionally, we evaluate the profitability of a "plain cryptocurrency momentum portfolio," formed using the top 30 coins by market capitalization at the end of each calendar year. Finally, we investigate whether the profitability of this strategy is attributable to leveraged exposure against the survivor cryptocurrency momentum portfolio by regressing its payoffs on survivor coin momentum.

This study makes several key contributions to the growing literature on cryptocurrency momentum. First, by focusing on survivor coins, this study isolates the effects of liquidity and stability, which are fundamental for understanding momentum effects in cryptocurrency markets. For example, Grobys (2024) emphasizes that cryptocurrencies undergoing sharp declines in liquidity fail to exhibit stable data-generating processes, undermining the reliability of statistical inference.[1] Second, this research is the first to explore cryptocurrency momentum within a framework analogous to G10 currency momentum, providing a novel basis for cross-market comparisons. Specifically, this study relates to the recent work of Aloosh and Bekaert (2022) on foreign exchange rates by distinguishing between "active and passive cryptocurrency management spaces." In a manner analogous to the foreign exchange market, significant payoffs in momentum strategies associated with coins that are only temporarily available for trading reflect a passive management space. Third, this study addresses inconsistencies in prior findings on the profitability of cryptocurrency momentum (e.g., Zaremba et al., 2021). Specifically, we extend the work by Grobys et al. (2025) by analyzing whether momentum profitability is mainly generated by coins with stable liquidity.

Survivor coins are rare: coinmarketcap.com shows that of the top 100 by market capitalization in December 2016, only nine remain in the top 100 in 2024. Using these nine cryptocurrencies, we construct tercile and equally weighted Survivor Cryptocurrency Momentum Portfolios (SCMP) and, consistent with G10 currency-momentum evidence, find statistically insignificant SCMP payoffs even after trimming (Harris et al., 2022). By contrast, among top-30 coins, a Plain Cryptocurrency Momentum Portfolio (PCMP) delivers a statistically significant trimmed average payoff of 0.93 % per week (Grobys et al., 2025). Regressing the trimmed plain momentum portfolio on SCMP yields positive, statistically significant (a) SCMP loading and (b) intercept, with beta < 1, implying trimmed plain momentum profitability is not due to leveraged SCMP. We therefore conclude that large cryptocurrency-momentum payoffs reflect coins only temporarily tradable, creating a "passive" cryptocurrency management space, and are theoretically consistent with market frictions and limits to arbitrage that may render them impractical to exploit (Lesmond et al. 2004; Shleifer and Vishny, 1997).

The remainder of this study is structured as follows: Section 2 describes the data. Section 3 outlines the methodology and results. Section 4 concludes with a discussion of the implications and avenues for future research.

2. Data

Cryptocurrency data were collected from coinmarketcap.com, a widely recognized source in the relevant literature (Liu et al., 2022). Specifically, the dataset includes prices for nine survivor coins: Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Dogecoin (DOGE), Litecoin (LTC), Stellar (XLM), Ethereum Classic (ETC), Monero (XMR), and Neo (NEO). Survivor coins are defined as 'free-floating cryptocurrencies' that consistently ranked among the top 100 in terms of market capitalization throughout the sample period, spanning January 2017 to August 2024.[2]

Descriptive statistics for these nine cryptocurrencies are presented in Table A1, while Table A2 provides a comparison of their market capitalizations as of December 2016 and December 2023. Notably, these nine coins accounted for approximately 96 % of the total market capitalization at the end of 2016. Although this share decreased by 2023, it remained significant at approximately 67 %, with Bitcoin and Ethereum continuing to dominate the market share.

To construct tercile survivor cryptocurrency momentum portfolios, we utilized weekly price data spanning from the first week of

[1] Unsurprisingly, currency-momentum research often focuses on G10 currencies because of their (a) market capitalization, (b) high liquidity, and (c) lack of extreme discontinuities (Colacito et al., 2018; Greenwood-Nimmo et al., 2016). Lee and Wang (2020) find currency jump frequency exceeds that of the U.S. stock market, with non-G10 currencies showing even more frequent discontinuities; such jumps can collapse strategies like carry trades. Statistically, G10 data-generating processes should closely match those of survivor coins: to remain in the top 100 cryptocurrencies by market capitalization, a coin's growth must track overall cryptocurrency market-cap growth. Recent work examines momentum portfolios among G10 currencies (Harris et al., 2022; Aloosh and Bekaert, 2022), with Aloosh and Bekaert (2022) labeling the G10 implementation the "Deutsche Bank momentum factor," highlighting the potential relevance of applying similar frameworks to highly liquid, stable cryptocurrencies for deeper comparison.

[2] Lacking the 'free-floating characteristic', Tether USD (USDT) is excluded from the analysis.

January 2017 to the fourth week of August 2024, resulting in a dataset comprising 398 weekly observations. Additionally, to create quintile plain cryptocurrency momentum portfolios, we adopted the methodology of Grobys et al. (2025), retrieving data for the top 30 cryptocurrencies by market capitalization over the same period.

3. Empirical analysis

3.1. Implementing cryptocurrency momentum strategies

We sort the survivor coins into three groups based on their past 30-day returns. Following Grobys et al. (2025), we skip the most recent daily price quotation to compute the previous month's formation period (FP) return on survivor coin *i*:

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

where $p_{t,j-1}$ denotes the closing price of survivor coin *i* on the previous trading day for a given week *t*, $p_{t,j-30}$ denotes the closing price of survivor coin *i* in the past 30 trading days for a given week *t*, and $r_{i,t}^{FP}$ is the corresponding formation period return on survivor coin *i* in week *t*. The survivor coin momentum portfolio is long (short) on the three survivor coins with the highest (lowest) formation period returns. We hold the equal-weighted zero-cost survivor coin portfolio one week ahead and rebalance our portfolio at the beginning of each week. Statistical significance of strategies is tested using Newey-West (1987) standard errors with 5 lags.[3]

We observe from Panel A of Table 1 that whereas the average formation period returns monotonically increase as we move from the loser group to the winner group from −8.25 % to 44.30 % per week, the average returns do not. Similar to that observed for G10 momentum (e.g., Harris et al., 2022), the zero-cost SCMP strategy produced an average return of 0.36 % per week with a *t*-statistic of 0.75, suggesting that the average payoff is economically sizable (about 17 % per year) but not statistically different from zero.

Next, following Grobys et al. (2025), we also consider a cryptocurrency momentum portfolio consisting of 30 large-cap cryptocurrencies exhibiting the highest market capitalization at the end of each December. Since this strategy comprises more assets than the survivor coin portfolio, we employ quintile sorts. We refer to this strategy as the plain cryptocurrency momentum strategy .[4] From Panel B of Table 1, we observe that the zero-cost PCMP produced an economically meaningful average return of 0.56 % per week, but statistically not different from zero (Grobys et al., 2025).

What could be the explanation for insignificant average returns of these strategies? In Table 2 we notice that the maximum drawdown is −211.74 % for PCMP and "only" −56.28 % for SCMP. Also, the kurtosis values for both strategies are 80.67 and 27.46, indicating the presence of extremely heavy tails. This is also confirmed in Fig. 1, where it can be observed that both strategies are subject to severe crashes, which are, however, considerably more pronounced for PCMP as opposed to SCMP.

3.2. Trimming the return data on cryptocurrency momentum strategies

Following Grobys et al. (2025), we explore whether the unprofitability of our cryptocurrency momentum strategies is driven by "outliers." To do so, we trim the full-sample return distribution at the 1 %, 5 %, and 10 % levels. Consistent with Grobys et al. (2025), the descriptive statistics documented in Table 3 show that the trimmed data (5 % level) on PCMP exhibits an average payoff corresponding to 0.93 % per week, which is statistically significant on a common 1 % level (*t*-statistic 2.62). On the other hand, trimming does not change the profitability of SCMP, which is −0.10 % per week and statistically not different from zero (*t*-statistic −0.33). Interestingly, this result suggests that the unprofitability of the SCMP is not an artefact of extreme events. Since the trimming procedure is applied ex post, the resulting payoffs may not be feasible from an investment perspective and are intended as only a diagnostic of momentum expected returns.

3.3. Can the exposure to survivor cryptocurrency momentum portfolio explain the returns on the plain cryptocurrency momentum strategy?

A natural question that arises is as to whether the returns on PCMP are an artefact of leveraging the SCMP. Although SCMP has *average* returns statistically not different from zero, it is possible that the PCMP strategy occasionally leverages survivor coins during periods in which their returns are positive, resulting in better risk-adjusted performance. To explore whether some exposure to SCMP could explain the returns on PCMP, we regress the returns of PCMP on an intercept term and SCMP as follows:

$$r_t^{MOM\ 30} = a_j + \beta_1\, r_t^{MOM9} + \varepsilon_t \tag{2}$$

where $r_t^{MOM\ 30}$ denotes the return on PCMP at time *t*, r_t^{MOM9} denotes the return on SCMP at time *t*, a_j and β_1 measure the regression intercept and PCMP's exposure to SCMP for model specification *j*, and ε_t denotes an error term that is assumed to be a white noise process. As a robustness check, we also control for the market factor.

We observe from Panel A of Table 4 that $\widehat{\beta}_1 = 0.25$ regardless of whether or not the cryptocurrency market factor is accounted for.

[3] The number of lags is determined by following the Newey and West's (1994) plug-in procedure [(4 * (T/100)2/9 ≈ 5].

[4] Note that the implementation of this strategy and the corresponding coins used are detailed in Grobys et al. (2025).

Table 1
Portfolio sorts for the momentum strategy.
This table reports the portfolio sorts for the cryptocurrency momentum strategy. Using tercile (quintile) sorts for the top 9 (30) cryptocurrencies in terms of their market capitalization, the momentum portfolio 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. In tercile sorting, Portfolio 1 (P1) corresponds to the loser portfolio, and portfolio 3 (P3) corresponds to the winner portfolio, while in quintile sorting 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 2017 to the fourth week of August 2024 comprised of 398 observations. The t-statistics for the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

Panel A. Sorted momentum portfolios for top 9 coins						
Portfolio	P1		P2		P3	(P3-P1)
$\bar{r}_i$	1.83		2.45		2.20	0.36
$\bar{r}_i^{FP}$	−8.25		6.73		44.30	(0.75)
Panel B. Sorted momentum portfolios for top 30 coins						
Portfolio	P1	P2	P3	P4	P5	(P5-P1)
$\bar{r}_i$	1.60	1.19	1.49	1.88	2.17	0.56
$\bar{r}_i^{FP}$	−17.69	−5.09	3.95	16.22	62.68	(0.65)

Table 2
Descriptive statistics for the cryptocurrency market and momentum strategies.
This table reports the descriptive statistics of the cryptocurrency market and momentum portfolios. The market factor is an equal-weighted portfolio of cryptocurrencies consisting of the top 30 cryptocurrencies based on their market capitalization. Using tercile (quintile) sorts and these top 9 (30) cryptocurrencies, the momentum portfolio 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 2017 to the fourth week of August 2024 period comprised of 398 observations. Newey-West (1987) standard errors with 5 lags are employed.

	Momentum (30 coins)	Momentum (9 coins)	Market
Mean	0.56	0.36	1.67**
(t-statistic)	(0.65)	(0.75)	(2.33)
Median	0.89	−0.41	0.83
Max	64.85	107.13	65.11
Min	−211.74	−56.28	−34.41
Std. Dev.	16.12	12.47	12.24
Skewness	−5.76	2.77	1.09
Kurtosis	80.67	27.46	7.70
Jarque-Bera test (JB)	102,235.90	10,431.92	445.31
p-value (JB)	0.00	0.00	0.00
Observations	398	398	398

*** Statistically significant on a 1 % level.

This provides strong evidence that (a) PCMP is not leveraged on SCMP as $\widehat{\beta}_1 < 1$ in all model specifications and (b) the average risk-adjusted payoff of PCMP does not reach statistical significance after controlling for SCMP or SCMP and the cryptocurrency market factor. To check the robustness of our findings, we use the trimmed data on the returns on PCMP and re-run the regression models.[5] From Panel B of Table 4, we observe that the average returns using the trimmed data on PCMP remain statistically significant and that again $\widehat{\beta}_1 < 1$ in both specifications.

Since the vast majority of coins that comprised PCMP exits the group of selected coins on an annual basis, its trimmed profitability must arise from coins that eventually end up in “default” (Grobys and Sapkota, 2020). This casts doubt on the practical feasibility of this investment strategy and points to the impact of financial frictions. We explore this issue by considering a range of transaction costs (25, 50, and 75 bps) for the PCMP and report its net average returns in Table 5. We observe that financial frictions are indeed responsible for the economic and statistical significance of the momentum portfolio, further corroborating this view.[6]

[5] We only report results using data trimmed at 5% level. Using different trimmed samples, the results do not change.

[6] A standard transaction-cost level of 50 bps, as considered in the literature (Fieberg et al., 2025), fully offsets the statistical significance of the trimmed PCMPs. Moreover, break-even costs are around 100 bps, which are economically plausible in light of short-selling frictions and the additional costs associated with volatility-management approaches, such as those in Grobys et al. (2025), required to obtain the trimmed momentum payoffs.

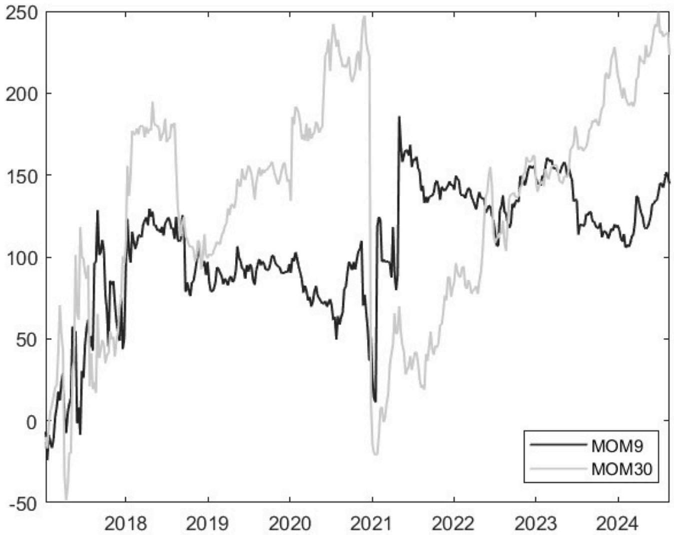

Fig.. 1. Cumulative returns on the cryptocurrency momentum strategies.
Using tercile (quintile) sorts and the top 9 (30) cryptocurrencies, the momentum portfolio is a strategy that is long in cryptocurrencies with the highest return in the 1-month formation period and short in those with the lowest return 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 on both momentum portfolios from the first week of January 2017 to the fourth week of August 2024.

Table 3
Descriptive statistics for the trimmed momentum strategy.
This table reports the descriptive statistics of the cryptocurrency momentum portfolio after trimming the data. Using tercile (quintile) sorts and the top 9 (30) cryptocurrencies in terms of their market capitalization, the momentum portfolio is a strategy that is long in cryptocurrencies with the highest return in the 1-month formation period and short in 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 2017 to the fourth week of August 2024 comprised of 398 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the trimmed zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

	Trimming 1 %		Trimming 5 %		Trimming 10 %	
	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)
Mean	0.99*	0.10	0.93***	−0.10	0.89***	−0.11
(*t*-statistic)	(1.90)	(0.24)	(2.62)	(−0.33)	(2.84)	(−0.40)
Median	0.89	−0.41	0.89	−0.41	0.89	−0.41
Max	51.40	53.55	21.81	27.49	18.11	14.60
Min	−74.14	−39.55	−19.24	−21.42	−14.00	−13.70
Std. Dev.	10.69	9.56	7.56	6.56	6.45	5.18
Skewness	−0.10	0.91	0.13	0.10	0.08	0.04
Kurtosis	12.77	10.11	3.34	4.78	2.94	3.01
Jarque-Bera test (JB)	1567.24	884.44	2.86	50.52	0.46	0.11
p-value (JB)	0.00	0.00	0.24	0.00	0.80	0.95
Observations	394	394	378	378	358	358

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

3.4. Additional tests

To further explore the profitability of cryptocurrency momentum, we implement sample split tests using the trimmed data on PCMP, which produced statistically significant average returns for the whole sample. Surprisingly, from Table 6, it is evident that trimmed PCMP produces only significant risk-adjusted average returns in subsample 2, implying that the apparent profitability of the cryptocurrency momentum strategy is subject to sample-specificity.

To enhance comparability with the SCMP, we also construct the PCMP using tercile sorting. As shown in Table A3, the results do not differ from those of the main analysis. In addition, Table A4 reports results based on an inverse-volatility weighting scheme for both the SCMP and PCMP, which assigns lower weights to more volatile coins. The findings again indicate that the strategies are unprofitable. Moreover, the trimmed payoffs are lower, which may reflect reduced exposure to non-survivor coins under this weighting scheme.

Table 4
Risk-adjusting the cryptocurrency momentum portfolio.
This table reports the results for the following regression: $r_t^{(T)MOM\ 30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$ where $r_t^{(T)MOM\ 30}$ is the (trimmed) momentum portfolio computed utilizing the top 30 cryptocurrencies in terms of market capitalization, r_t^{MOM9} is the momentum portfolio computed utilizing the top 9 cryptocurrencies in terms of market capitalization, r_t^{MKT} is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top −30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. Newey-West (1987) standard errors with 5 lags are employed.

Strategy	$r_t^{(T)MOM\ 30}$	$r_t^{(T)MOM\ 30}$
Panel A. Momentum portfolio		
$\hat{a}_j$	0.47	0.75
	(0.56)	(1.47)
$\hat{\beta}_1$	0.25**	0.25**
	(2.35)	(2.20)
$\hat{\beta}_2$		−0.16
		(−0.62)
R^2	0.04	0.05
Panel B. Trimmed momentum portfolio		
$\hat{a}_j$	0.85**	0.88**
	(2.36)	(2.44)
$\hat{\beta}_1$	0.14***	0.14***
	(2.98)	(2.95)
$\hat{\beta}_2$		−0.05
		(−0.91)
R^2	0.04	0.05

***,** Statistically significant on a 1 % and 5 % level, respectively.

Table 5
Transaction costs.
This table reports the average returns for the PCMP after accounting for transaction costs. Similar to Fieberg et al. (2025), a range of 25, 50, and 75 bps is applied, and the break-even costs zeroing average returns are calculated. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

	Momentum Portfolio	Trimming 1 %	Trimming 5 %	Trimming 10 %
Gross return	0.56	0.99*	0.93***	0.89***
	(0.65)	(1.90)	(2.62)	(2.84)
Net return (25 bps)	0.35	0.78	0.72**	0.68**
	(0.41)	(1.49)	(2.02)	(2.16)
Net return (50 bps)	0.14	0.57	0.51	0.47
	(0.16)	(1.09)	(1.42)	(1.49)
Net return (75 bps)	−0.07	0.36	0.30	0.26
	(−0.08)	(0.68)	(0.83)	(0.82)
Break-even TC (bps)	66.68	117.69	111.01	106.42

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

Finally, to assess the sensitivity of our design choices, (i) we change the starting date used to identify the survivor coins by a window of ±1 year, and (ii) we exclude Dogecoin from the sample, as it exhibits extreme observations. For the former test, we identify 7 survivor coins when starting the identification process at the end of December 2015 and 18 survivor coins when starting at the end of December 2017.[7] Tables A5 and A6 show that these changes do not affect our main results.

4. Conclusion

The cryptocurrency momentum effect appears to be driven by digital coins that temporarily gain popularity and become actively

[7] Consistently, the smaller the difference between the start and end date, the higher the probability that a cryptocurrency remained in the Top 100 ranking.

Table 6
Risk-adjusting the trimmed cryptocurrency momentum portfolio – Subsample split.
This table reports the results for the following regression.
$r_t^{TMOM\ 30} = a_j + \beta_1 r_t^{MOM9} + \beta_2 r_t^{MKT} + \varepsilon_t$.
where $r_t^{TMOM\ 30}$ is the trimmed momentum portfolio computed utilizing the top 30 cryptocurrencies in terms of market capitalization, r_t^{MOM9} is the momentum portfolio computed utilizing the top 9 cryptocurrencies in terms of market capitalization, r_t^{MKT} is the market factor computed as an equal-weighted portfolio of cryptocurrencies consisting of the top −30 cryptocurrencies. ε_t denotes a white noise error. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. Subsample 1 covers the subperiod from the first week of January 2017 to the third week of October 2020. Subsample 2 covers the subperiod from the fourth week of October 2020 to the fourth week of August 2024. Newey-West (1987) standard errors with 5 lags are employed.

Strategy Panel A. Subsample 1	$r_t^{TMOM\ 30}$	$r_t^{TMOM\ 30}$
$\hat{a}_j$	0.25	0.32
	(0.60)	(0.76)
$\hat{\beta}_1$	0.21***	0.20***
	(2.69)	(2.57)
$\hat{\beta}_2$		−0.11**
		(−2.30)
R^2	0.07	0.10
Panel B. Subsample 2		
$\hat{a}_j$	1.37**	1.36**
	(2.46)	(2.41)
$\hat{\beta}_1$	0.10**	0.10**
	(2.06)	(2.10)
$\hat{\beta}_2$		0.04
		(0.38)
R^2	0.03	0.03

***,** Statistically significant on a 1 % and 5 % level, respectively.

traded, before eventually falling into a passive management space (Aloosh and Bekaert, 2022). In contrast, a cryptocurrency momentum strategy built on coins exhibiting stability and liquidity does not earn a significant payoff, similarly to the results documented in currency momentum literature (Harris et al., 2022).

The implications of this study are relevant for investors and asset management firms looking to implement momentum strategies in the cryptocurrency market. Our findings suggest that such strategies may be infeasible in practice, as the apparent profitability might be driven by financial frictions (Lesmond et al., 2004). Furthermore, with the prominent entrance of banks and financial intermediaries into this emerging market, as sanctioned by the upcoming crypto-asset framework developed by the Basel Committee (Bank for International Settlements, 2022), this research suggests that traditional financial products of the forex market, such as the Deutsche Bank index (Aloosh and Bekaert, 2022), may offer limited appeal in terms of expected returns.

A potential limitation is survivorship bias: our methodology uses ex post survival information unavailable when trading. While valid, we argue that rational investors would avoid strategies that do not generate significant payoffs anyway. Our goal is not to propose a tradable strategy but to assess theoretical drivers of the momentum premium. Future work should examine the microstructure and sample-specific nature of cryptocurrency momentum returns and the determinants of non-survivor coin returns.

CRediT authorship contribution statement

Klaus Grobys: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Investigation, Conceptualization. **Davide Sandretto:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Janne Äijö:** Supervision.

Declaration of competing interest

The authors declare they have no competing interests.

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Appendix

Table A5, Table A6.

Table A1
Descriptive statistics for the 9 survivor cryptocurrencies.
This table reports the descriptive statistics for the 9 survivor coins, with daily returns spanning from January 2017 to August 2024.

Coins	Bitcoin (BTC)	Dogecoin (DOGE)	Ethereum (ETH)	Ethereum Classic (ETC)	Litecoin (LTC)	Monero (XMR)	Neo (NEO)	Stellar (XLM)	XRP (XRP)
Mean	0.22	0.52	0.33	0.28	0.24	0.23	0.40	0.36	0.39
Median	0.13	−0.04	0.08	0.00	0.03	0.21	0.05	−0.05	−0.08
Maximum	25.25	355.57	33.66	58.04	66.77	53.80	122.69	106.08	179.37
Minimum	−37.17	−40.26	−42.35	−39.73	−36.18	−41.39	−37.23	−33.63	−46.01
Std. Dev.	3.79	9.77	5.03	6.16	5.55	5.33	7.40	7.24	7.43
Skewness	−0.05	18.30	0.36	1.14	1.39	0.53	3.42	4.34	6.98
Kurtosis	10.15	632.89	9.94	13.46	18.66	14.75	48.41	53.35	139.84
Jarque-Bera	5967.99	46,428,341.00	5682.19	13,369.40	29,502.52	16,235.77	245,971.50	304,471.10	2206,640.00
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	2799	2799	2799	2799	2799	2799	2799	2799	2799

Table A2
Survivor coins and market capitalization.
This table provides the market capitalization for the 9 surviving cryptocurrency as of December 2016 and December 2023, along with a comparison to the total market capitalization for both years.

Cryptocurrency	Mkt Capitalization as of December 2016	% of total mkt capitalization	Mkt Capitalization as of December 2023	% of total mkt capitalization
Bitcoin (BTC)	14,396,198,729.33	87.86 %	827,811,209,384.41	47.74 %
Ethereum (ETH)	626,189,615.98	3.82 %	274,194,287,336.35	15.81 %
XRP (XRP)	232,006,578.41	1.42 %	33,283,785,350.85	1.92 %
Litecoin (LTC)	213,168,549.82	1.30 %	5390,137,464.63	0.31 %
Monero (XMR)	132,525,971.58	0.81 %	3032,945,820.76	0.17 %
Ethereum Classic (ETC)	93,536,872.97	0.57 %	3172,554,930.65	0.18 %
Dogecoin (DOGE)	24,708,711.86	0.15 %	12,746,626,943.45	0.74 %
Stellar (XLM)	17,845,296.56	0.11 %	3643,117,124.30	0.21 %
Neo (NEO)	7339,395.58	0.04 %	982,991,919.33	0.06 %
Total	15,743,519,722.09	96.08 %	1164,257,656,274.73	67.15 %

Table A3
Tercile sorted plain cryptocurrency momentum portfolio.
This table reports in Panel A the descriptive statistics for the tercile sorted PCMP before and after trimming the data. Moreover, Panel B reports the outcomes when risk-adjusting the new tercile sorted cryptocurrency momentum portfolio. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

Panel A. Descriptive statistics				
	Momentum Portfolio	Trimming 1 %	Trimming 5 %	Trimming 10 %
Mean	0.57	0.66*	0.66***	0.63**
(*t*-statistic)	(0.88)	(1.88)	(2.50)	(2.46)
Median	0.54	0.54	0.54	0.54
Max	84.39	35.09	16.14	12.57
Min	−139.93	−36.41	−13.71	−10.09
Std. Dev.	11.82	7.30	5.48	4.74
Skewness	−3.01	−0.04	0.11	0.04
Kurtosis	62.21	8.42	3.10	2.70
Jarque-Bera test (JB)	58,732.91	482.19	0.91	1.41
p-value (JB)	0.00	0.00	0.63	0.49
Observations	398	394	378	358
Panel B. Risk-adjusted analysis				
Strategy	$r_t^{(T)MOM\ 30}$	$r_t^{(T)MOM\ 30}$		
Panel B1. Momentum portfolio				
$\widehat{a}_j$	0.48	0.55		
	(0.78)	(1.50)		
$\widehat{\beta}_1$	0.23***	0.23**		

(continued on next page)

Table A3 (*continued*)

	(2.52)	(2.40)
$\widehat{\beta}_2$		−0.04
		(−0.21)
R^2	0.06	0.06
Panel B2. Trimmed momentum portfolio		
$\widehat{a}_j$	0.62**	0.63**
	(2.32)	(2.38)
$\widehat{\beta}_1$	0.11***	0.11***
	(2.93)	(2.90)
$\widehat{\beta}_2$		−0.04
		(−0.91)
R^2	0.04	0.04

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

Table A4

Different portfolio weighting scheme.

This table reports in Panel A the descriptive statistics for the inverse-volatility weighted SCMP and PCMP before and after trimming the data. Moreover, Panel B reports the outcomes when risk-adjusting the new inverse-volatility weighted SCMP and PCMP. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

Panel A. Descriptive statistics	Portfolios		Trimming 1 %		Trimming 5 %		Trimming 10 %	
	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)
Mean	0.68	0.31	0.85*	0.02	0.72*	−0.08	0.70**	0.00
(*t*-statistic)	(1.02)	(0.64)	(1.66)	(0.04)	(1.87)	(−0.24)	(2.19)	(0.02)
Median	0.71	−0.08	0.71	−0.08	0.71	−0.08	0.71	−0.08
Max	65.85	128.92	56.86	45.93	25.28	21.80	17.30	13.46
Min	−116.42	−45.52	−55.84	−42.15	−21.37	−24.48	−15.60	−13.50
Std. Dev.	13.21	12.31	10.49	9.27	7.95	6.37	6.75	5.04
Skewness	−1.46	3.33	0.28	0.30	0.03	−0.31	−0.04	−0.11
Kurtosis	23.18	37.76	8.36	9.51	3.40	4.70	2.84	3.12
Jarque-Bera test (JB)	6897.19	20,774.00	476.45	702.12	2.63	51.37	0.44	0.96
p-value (JB)	0.00	0.00	0.00	0.00	0.27	0.00	0.80	0.62
Observations	398	398	394	394	378	378	358	358

Panel B. Risk-adjusted analysis Strategy	$r_t^{(T)MOM\ 30}$	$r_t^{(T)MOM\ 30}$
Panel B1. Momentum portfolio		
$\widehat{a}_j$	0.59	0.70
	(0.90)	(1.46)
$\widehat{\beta}_1$	0.29***	0.29***
	(2.92)	(2.85)
$\widehat{\beta}_2$		−0.06
		(−0.34)
R^2	0.07	0.08
Panel B2. Trimmed momentum portfolio		
$\widehat{a}_j$	0.60	0.62*
	(1.58)	(1.67)
$\widehat{\beta}_1$	0.20***	0.20***
	(4.10)	(4.26)
$\widehat{\beta}_2$		−0.18
		(−0.24)
R^2	0.08	0.08

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

Table A5

Different starting dates for survivor coins assessment.

This table reports in Panel A the main analyses presented in Sections 3.1 to 3.3 for the SCMP based on coins assessed as of the end of December 2015. Panel B reports the corresponding results when the SCMP is based on coins assessed as of the end of December 2017. The weekly data sample for Panel A is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. The weekly data sample for Panel B is from the first week of January 2018 to the fourth week of August 2024 comprised of 346 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

Panel A Descriptive statistics	Momentum Portfolio	Trimming 1 %	Trimming 5 %	Trimming 10 %
Mean	0.38	0.25	0.23	0.25
(*t*-statistic)	(0.75)	(0.56)	(0.77)	(1.01)
Median	0.26	0.26	0.26	0.26
Max	107.13	49.31	17.76	12.48
Min	−60.36	−44.44	−16.55	−12.66
Std. Dev.	11.18	8.51	5.98	5.04
Skewness	1.88	0.15	−0.10	−0.13
Kurtosis	29.62	10.34	3.60	3.13
Jarque-Bera test (JB)	11,986.52	886.96	6.27	1.23
p-value (JB)	0.00	0.00	0.04	0.54
Observations	398	394	378	358
Risk-adjusted analysis				
Strategy	$r_t^{(T)MOM\ 30}$	$r_t^{(T)MOM\ 30}$		
Momentum portfolio				
$\hat{a}_j$	0.50	0.78		
	(0.60)	(1.55)		
$\hat{\beta}_1$	0.16	0.15		
	(1.36)	(1.21)		
$\hat{\beta}_2$		−0.17		
		(−0.62)		
R^2	0.01	0.03		
Trimmed momentum portfolio				
$\hat{a}_j$	0.89**	0.91***		
	(2.46)	(2.55)		
$\hat{\beta}_1$	0.11**	0.10**		
	(2.26)	(2.23)		
$\hat{\beta}_2$		−0.51		
		(−0.91)		
R^2	0.02	0.02		

Panel B Descriptive statistics	Momentum Portfolio	Trimming 1 %	Trimming 5 %	Trimming 10 %
Mean	0.77	0.35	0.31	0.30
(*t*-statistic)	(1.63)	(1.30)	(1.18)	(1.26)
Median	0.13	0.13	0.13	0.13
Max	138.38	32.08	13.51	9.77
Min	−23.68	−19.95	−12.86	−9.09
Std. Dev.	10.05	5.98	4.76	4.15
Skewness	7.78	0.33	0.01	−0.05
Kurtosis	104.94	6.21	2.95	2.38
Jarque-Bera test (JB)	153,299.10	153.30	0.03	5.03
p-value (JB)	0.00	0.00	0.98	0.08
Observations	346	342	328	312
Risk-adjusted analysis				
Strategy	$r_t^{(T)MOM\ 30}$	$r_t^{(T)MOM\ 30}$		
Momentum portfolio				
$\hat{a}_j$	0.08	0.23		
	(0.10)	(0.37)		
$\hat{\beta}_1$	0.34***	0.37***		
	(4.47)	(5.13)		
$\hat{\beta}_2$		−0.34		
		(−1.04)		
R^2	0.06	0.12		
Trimmed momentum portfolio				

(*continued on next page*)

Table A5 (*continued*)

Panel A Descriptive statistics	Momentum Portfolio	Trimming 1 %	Trimming 5 %	Trimming 10 %
$\widehat{a}_j$	0.70**	0.70**		
	(2.12)	(2.12)		
$\widehat{\beta}_1$	0.45***	0.45***		
	(4.43)	(4.53)		
$\widehat{\beta}_2$		−0.03		
		(−0.54)		
R^2	0.17	0.17		

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

Table A6

Portfolios without Dogecoin.This table reports the descriptive statistics for the SCMP and PCMP before and after trimming the data excluding Dogecoin from the sample. The weekly data sample is from the first week of January 2017 to the fourth week of August 2024 comprised of 398 observations. We apply a trimming procedure that shrinks the 1 %, 5 % and 10 % of the return distribution. The *t*-statistics for the payoffs of the zero-cost portfolios are given in parenthesis. Newey-West (1987) standard errors with 5 lags are employed.

	Portfolios		Trimming 1 %		Trimming 5 %		Trimming 10 %	
	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)	Momentum (30 coins)	Momentum (9 coins)
Mean	0.56	0.67	0.99*	0.31	0.91**	0.12	0.87***	0.03
(*t*-statistic)	(0.65)	(1.17)	(1.87)	(0.77)	(2.51)	(0.42)	(2.73)	(0.16)
Median	0.78	−0.09	0.78	−0.09	0.78	−0.09	0.78	−0.09
Max	64.85	138.36	51.40	51.63	21.81	21.17	18.11	12.08
Min	−211.74	−39.55	−74.14	−34.65	−19.24	−17.51	−14.00	−10.78
Std. Dev.	16.16	12.05	10.75	8.61	7.70	5.67	6.59	4.51
Skewness	−5.71	4.70	−0.07	1.06	0.13	0.36	0.09	0.09
Kurtosis	79.86	51.62	12.45	11.38	3.29	4.54	2.87	2.72
Jarque-Bera test (JB)	100,124.50	40,671.79	1465.97	1227.64	2.42	45.40	0.70	1.61
p-value (JB)	0.00	0.00	0.00	0.00	0.30	0.00	0.71	0.45
Observations	398	398	394	394	378	378	358	358

*,**, *** Statistically significant on a 10 %, 5 % and 1 % level.

Data availability

Data will be made available on request.

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