

Decoupling Momentum in Cryptocurrency Markets: Underreaction to Residuals and Overreaction to Information Discreteness

Ao Yang, Qing Ye, Jia Zhai*¹

Xi'an Jiaotong Liverpool University, International Business School of Suzhou

Abstract

We investigate the cross-sectional return predictability and behavioral origins of momentum in the cryptocurrency market by decoupling it into residual momentum (RMOM) and information discreteness momentum (IDMOM). Using a comprehensive sample of over 2,000 digital assets from 2014 to 2023, we find that both strategies generate economically significant premiums with annualized Sharpe ratios exceeding unity. We find that a two-factor model incorporating these components successfully captures the return variations of 12 out of 14 prominent cryptocurrency characteristics. Our analysis identifies a marked difference in the underlying behavioral mechanisms: RMOM exhibits prolonged persistence (over 15 weeks), consistent with investor underreaction to idiosyncratic information; conversely, IDMOM generates transient profits that reverse within two weeks, signaling a speculative overreaction to the structure of information arrival. This "flash-in-the-pan" overreaction in IDMOM represents a significant divergence from the "frog-in-the-pan" underreaction documented in equity markets. Our findings suggest that cryptocurrency momentum arises from concurrent yet distinct behavioral channels, challenging unified asset pricing frameworks and highlighting the unique information-processing dynamics of digital asset investors.

Keywords: residual momentum, information discreteness, cryptocurrency returns, underreaction, overreaction.

JEL Classification: G12, G14, G40, G41, G15

EFM Classification: 320, 350, 620

¹ Ao Yang: ao.yang19@student.xjtlu.edu.cn; Qing Ye: qing.ye@xjtlu.edu.cn; Jia Zhai (Corresponding author): jia.zhai@xjtlu.edu.cn.

1. Introduction

The cryptocurrency market, characterized by high speculative intensity and the dominance of retail investors, provides a unique laboratory to test the boundaries of behavioral asset pricing theories. Owing to its emergent nature, this market exhibits distinct investor behavior patterns (Cai and Zhao, 2024). Recent studies have documented a wide array of behavioral biases shaping cryptocurrency price dynamics, ranging from speculative demand (Babiak and Bianchi, 2025), trend chasing, penny-stock-like trading, and lottery preferences (Hackethal et al., 2022) to overconfidence, gambling preferences, naïve reinforcement learning (Li et al., 2025), and herding behavior (Fieberg et al., 2025). These psychological frictions often manifest in unique return-volatility dynamics that deviate significantly from traditional efficient market hypotheses. Recent evidence by Babiak and Bianchi (2025) further identifies that systematic mispricing, driven by behavioral channels and liquidity frictions, constitutes a substantial portion of cryptocurrency return variation. While the literature has documented significant momentum effects in cryptocurrency market (Liu et al., 2022), the underlying economic drivers—specifically whether they stem from investor underreaction or overreaction—remain a subject of intense debate. This paper reconciles these competing narratives by decomposing cryptocurrency returns into residual components and information discreteness. This decomposition aligns with the dual-component nature of crypto returns proposed by Babiak and Bianchi (2025), who emphasize that both systematic mispricing and risk compensation mechanisms are at play through distinct economic channels. We uncover a dual-channel mechanism where investor underreaction to idiosyncratic fundamentals and overreaction to price-trend structures coexist, offering a more nuanced understanding of price discovery in cryptocurrency markets.

Our paper is motivated by two seminal strands of literature in traditional equity markets. First, Blitz et al. (2011) demonstrate that Residual Momentum (RMOM), which strips away systematic risk exposures, exhibits greater persistence than total

return momentum, suggesting that investors slowly incorporate firm-specific information. Second, Da et al. (2014) introduce the Information Discreteness (IDMOM) strategy, arguing that investors underreact to information that arrives in small, continuous increments—a phenomenon termed "Frog-in-the-Pan" (FIP). While these strategies are well-established in equities, their efficacy and, more importantly, their underlying behavioral mechanisms in the volatile, 24/7 trading environment of cryptocurrencies remain underexplored.

Using a comprehensive sample of over 2,000 cryptocurrencies from 2014 to 2023, we construct and evaluate RMOM and IDMOM strategies. Our empirical results reveal a striking dichotomy in return persistence that challenges the conventional "one-size-fits-all" behavioral explanation. We find that both strategies yield economically significant returns: RMOM generates peak average weekly returns of 3.2%, while IDMOM produces an even higher 6.4%. However, their time-series profiles diverge sharply. RMOM profits are remarkably persistent, lasting for over 15 weeks, which aligns with the gradual information diffusion and underreaction models of Hong and Stein (1999). In contrast, IDMOM profits in the cryptocurrency market are transient, reversing within a mere two weeks.

This rapid reversal of IDMOM is a pivotal finding. In traditional equity markets, IDMOM is a proxy for underreaction (Da et al., 2014); however, our results suggest that in the cryptocurrency ecosystem, the FIP effect transforms into a "flash-in-the-Pan" overreaction. The speculative nature of crypto investors appears to trigger an aggressive overshooting when faced with continuous price movements, leading to quick price corrections.

To further validate the asset pricing implications of these findings, we construct a stylized two-factor momentum model. Following the methodology of Liu et al. (2022), we test our model against 24 prominent cryptocurrency characteristics. The dual-factor model (RMOM + IDMOM) demonstrates superior explanatory power, successfully accounting for the return variations in 12 out of 14 statistically significant anomalies.

Notably, this model explains away several "unexplained" premiums in prior literature, leaving only market capitalization and trading volume as remaining outliers. Our findings complement the work of Babiak and Bianchi (2025), who utilize an instrumented principal component analysis (IPCA) to demonstrate that coin-specific characteristics carry significant information for both mispricing and risk exposure. This suggests that residual returns and information discreteness are fundamental building blocks of the cryptocurrency risk-return cross-section.

We further explore the economic mechanism through the lens of investor attention. Using market capitalization and trading volume as proxies for visibility, we find that RMOM remains robust among high-attention coins. This contradicts the traditional intuition that high visibility mitigates underreaction, suggesting that coin-specific "idiosyncratic" information is inherently harder to process even for prominent digital assets. Conversely, the overreaction observed in IDMOM is intensified during periods of heightened attention, confirming that speculative bubbles in this market are often fueled by the very visibility of the price trend itself.

Our study makes three primary contributions to the literature. First, we expand the systematic framework of cryptocurrency return predictors by introducing residual and information-discreteness dimensions. We show that these components are not merely variations of traditional momentum but represent distinct pricing factors with independent explanatory power. Second, we provide empirical evidence to disentangle the concurrent behavioral channels of underreaction and overreaction. By showing that the persistence of momentum depends on the structure of the information (residual vs. discrete), we offer a resolution to the theoretical tension between delayed price adjustment and reflexive overcorrection. Finally, we highlight a significant cross-asset divergence. While residual momentum behaves similarly across equities and cryptocurrencies, the transformation of the FIP effect from underreaction (in stocks) to overreaction (in crypto) underscores the unique psychological profile of cryptocurrency market participants.

These findings hold important implications for both practitioners managing digital asset portfolios and regulators concerned with market efficiency. Our results suggest that the "momentum" observed in cryptocurrencies is a complex journey of slow information integration and rapid speculative bursts, requiring a more granular approach to risk management and strategy implementation.

The remainder of this study is organized as follows. Section 2 details data and methodology. Section 3 examines momentum strategy performance. Section 4 develops pricing factors and tests explanatory power. Section 5 investigates behavioral mechanisms. Section 6 conducts robustness checks. Section 7 concludes with implications.

2. Data and Methodology

2.1 Data sources

Following prior studies, we collect the cryptocurrency prices from CoinMarketCap.com (Liu et al., 2022, Cai and Zhao, 2024). Our sample period starts from 3rd, January, 2014 to 28th, August 2023. The collected dataset included cryptocurrency symbols, daily prices, market capitalization and trading volume in USD of the included cryptos. The dataset does not contain cryptos with a market capitalization below \$1,000,000.

Coins are traded on centralized or decentralized electric exchanges, 24 hours a day, 7 days a week. In general, the cryptocurrency market has no exchange close time. We include all calendar days with cryptocurrency transactions and calculate the returns using the whole day closing price.

Table 1 presents the summary statistics of cryptocurrency data over the sample period. The number of cryptos meeting the filtering criteria rose from 72 in 2014 to 2,072 in 2023. Similarly, both the mean and median market capitalization exhibited significant growth during this period. The notable disparity between the mean and median values suggests the presence of substantial outliers. Additionally, the trading volume grew at a significantly faster rate than market capitalization, highlighting the

rapid expansion of this market.

Table 1 Summary Statistics of Cryptocurrency Data: This table reports annual summary statistics for the sample of cryptocurrencies from January 2014 to August 2023. For each year, we present the number of included cryptocurrencies, and the cross-sectional mean and median of price (in USD), market capitalization (in millions USD), and trading volume (in tens of thousands USD). The final row provides full-sample summary statistics across all included cryptocurrencies and time periods. The sample is filtered to include only coins with a market capitalization above \$1 million.

Year	Number	Price		Market Cap		Volume	
		Mean	Median	Mean (*10 ⁶)	Median (*10 ⁶)	Mean (*10 ⁴)	Median (*10 ⁴)
2014	72	734.43	0.02	155.08	0.53	72.97	0.39
2016	119	9.88	0.02	105.7	0.76	118.7	0.23
2017	306	88.22	0.28	699.18	12.95	3113.35	18.57
2018	581	96.63	0.15	639.64	15.43	3774.78	36.41
2019	796	71.19	0.03	310.11	4.44	7992.82	14.62
2020	1187	115.48	0.03	353.43	4.49	12920.14	19.44
2021	1786	410.89	0.19	1297.52	13.51	17092.89	71.64
2022	1950	185.55	0.06	693.58	5.41	7278.82	26.16
2023	2072	131.22	0.03	562.41	3.92	3520.08	12.71
Full	207372	192.26	0.06	689.28	6.19	8768.29	23.28

2.2 Momentum Strategies

We outline the methodologies of constructing the conventional momentum and two stylized momentum strategies (residual and information discreteness) in cryptocurrency returns. These strategies are documented to have significant alphas in equity market.

2.2.1 Conventional Momentum

Following Jegadeesh and Titman (1993), we construct the conventional momentum strategy (hereafter *c_mom*) for cryptos across different formation and holding periods. We consider formation periods ranging from 1 to 7 days and 2 to 8 weeks, while holding periods ranging from 1 to 7 days². Overall, we have 98 unique combinations. For each combination, we sort cryptos into quintiles based on their cumulative returns of the formation period. Then we form a value-weighted, zero-investment portfolio by long

² This selection extends the work of Liu et al. (2022), who document significant returns for conventional momentum with a 1 to 4 weeks formation period and a 1-week holding period. We broaden their approach to provide a more comprehensive analysis of strategy performance.

the highest quintile and short the lowest quintile. We calculate the excess portfolio returns for the next period.

We intentionally introduce a 1-day formation gap³ between the formation and holding periods for two key reasons. First, aligning with equity market practices (Jegadeesh and Titman, 1993) and recent studies documenting short-term reversals (Shen et al., 2020; Zaremba et al., 2021; Kozłowski et al., 2021), a gap mitigates the effect of immediate price reversals in cryptocurrency returns. Second, given the cryptocurrency market’s emerging and highly volatile nature, a 1-day gap helps isolate momentum effects from intraday noise. For robustness, we also construct portfolios without this gap (see Online Appendix Table OA1). Notably, the 1-day holding period columns in Table A1 reveal pronounced evidence of a short-term reversal in cryptocurrency returns, empirically validating the necessity of using the gap.

2.2.2 Residual momentum

To address conventional momentum’s sensitivity to Fama-French factors, Blitz *et al.* (2011) proposed RMOM strategy, which sorts assets based on residual returns rather than raw past returns. Adapting this framework to cryptocurrencies, we calculate residual momentum using the following steps. First, for each coin i on day t , the residual is calculated using a cryptocurrency three-factor model (Liu et al., 2022):

$$r_i = \alpha_i + \beta_{1,i}CMKT_t + \beta_{2,i}CSMB_t + \beta_{3,i}CMOM_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ represents the excess return of coin i on day t , $CMKT_t$, $CSMB_t$, $CMOM_t$ are the cryptocurrency market capitalization, size and momentum factors, and $\varepsilon_{i,t}$ is the residual. This regression is estimated over a rolling window of 36 days. Second, we standardized the residuals by their standard deviation over the same period, and the residual returns are calculated across formation periods. We sort the coins into quintiles based on the cumulative residual returns over the formation periods. To validate our findings, we replicate the residual momentum strategy using a 2-factor model (excluding the momentum factor, CMOM). We recalculate residuals using only the

³ We adhere to the identical formation and holding periods across the construction of various momentum strategies.

market (CMKT) and size (CSMB) factors, then reconstruct portfolios under identical formation and holding periods.

$$r_i = \alpha_i + \beta_{1,i}CMKT_t + \beta_{2,i}CSMB_t + \varepsilon_{i,t} \quad (2)$$

2.2.3 Information discreteness momentum

Following Da *et al.* (2014), the IDMOM strategy exploits the empirical observation that momentum effects are amplified for assets exhibiting gradual, persistent return trends rather than abrupt price changes. To capture this, they construct an information discreteness (hereafter *ID*) proxy, which quantifies the smoothness of return patterns over time. This proxy is then combined with a conventional momentum signal (*MOM*), defined as cumulative past returns, through a double sorting procedure. The double-sorting isolates assets with both strong momentum and low information discreteness (i.e., gradual price trends), aligning with the Fama-French portfolio construction framework. The ID proxy is defined as follows:

$$ID_t^i = \text{sgn}(MOM_t^i) * [\%neg_{t-x-1:t-1}^i - \%pos_{t-x-1:t-1}^i] \quad (3)$$

where $\text{sgn}(MOM_t^i)$ indicates the sign of the cumulative return over the formation period, with a value of 1 for positive returns and -1 for negative returns. The terms $\%neg_{t-x-1:t-1}^i$ and $\%pos_{t-x-1:t-1}^i$ represent the percentages of days with negative and positive returns, respectively, during the formation period. Thus, stocks with lower *ID* values are considered to have a higher continuity of information.

In this study, we calculate the *ID* proxy and employ both independent and sequential double-sorting methodologies. For the double-sort, coins are initially ranked into quintiles based on raw momentum (*MOM*). Within the highest (or lowest) *MOM* quintile, a secondary sort is then conducted using the *ID* proxy (*ID*), and the final portfolio combines the highest (or lowest) momentum quintile (*MOM5* or *MOM1*) with the lowest *ID* quintile (*ID1*). For robustness, we also perform independent quintile sorts on *MOM* and *ID* and intersect the highest (or lowest) *MOM* groups with the lowest *ID* groups, ensuring methodological rigor in isolating assets with persistent return trends and smooth information flow.

Furthermore, the IDMOM strategy extends its framework by integrating two specialized proxies for quantifying information discreteness (Da *et al.*, 2014):

ID_{MAG} is calculated by sorting daily returns within the formation period into quintiles based on their absolute magnitudes. The smallest returns are placed in the first quintile, and the largest in the fifth. Each quintile is assigned a weight, w_j , decreasing monotonically from 5/15 for the quintile with the largest returns to 1/15 for the quintile with the smallest returns, corresponding to the respective $|daily\ return_j|$ quintiles.

Specifically:

$$ID_{MAG}_t^i = -\frac{1}{N} sgn(MOM_t^i) * \sum_{j=t-x-1}^{t-1} sgn(daily\ return_j) * w_j \quad (4)$$

ID_Z differs from ID by mitigating the impact of days with zero returns in ID , and as defined as follow:

$$ID_Z_t^i = sgn(MOM_t^i) * \frac{[\%neg_{t-x-1:t-1}^i - \%pos_{t-x-1:t-1}^t]}{[\%neg_{t-x-1:t-1}^i + \%pos_{t-x-1:t-1}^t]} \quad (5)$$

Following above, we calculate the two ID proxies for each cryptocurrency and employ both independent and sequential double-sorting methodologies to construct the portfolios.

2.2.4 Cryptocurrency 3-factor model and test asset

Building upon the previous momentum strategies, we further examine their effectiveness as factors in explaining return anomalies identified in cryptocurrency markets. To achieve this, we construct the cryptocurrency three-factor model, strictly following Liu et al. (2022). We define the market factor (CMKT) as the difference in returns between a value-weighted, weekly-rebalanced cryptocurrency market portfolio and the risk-free rate, with the latter being represented by the one-month Treasury bill rate. For the size factor (CSMB), cryptocurrencies are classified based on market capitalization into three segments: the smallest 30% (S), the middle 40%, and the largest 30% (B). We then construct a value-weighted, weekly-rebalanced portfolio that

captures the small-minus-big (SMB) differential to represent the CSMB factor. The momentum factor (CMOM) is determined through a sequential double-sorting process, initially dividing coins into two groups by size (below and above median) and subsequently sorting each size group into three momentum portfolios based on their past 3-week returns: the lowest 30%, the middle 40%, and the highest 30%.

The CMOM factor is then calculated as:

$$CMOM_t = \frac{1}{2}(Small\ top_t + Big\ top_t) - \frac{1}{2}(Small\ bottom_t - Big\ bottom_t) \quad (6)$$

We present the summary statistics for the three factors in Table 2. Our sample's mean of CMKT stands at 0.011, and the standard deviation of 0.104. In general, these statistics closely aligns with the sample included in Liu *et al.* (2022).

Table 2 Summary Statistics of Cryptocurrency Common Risk Factors: This table presents the weekly summary statistics for the three factors in the cryptocurrency three-factor model constructed following Liu *et al.* (2022), over the full sample period from January 2014 to August 2023. The market factor (CMKT) is the excess return of the value-weighted crypto market portfolio. The size factor (CSMB) is constructed as the return difference between small- and large-cap portfolios. The momentum factor (CMOM) is based on past 3-week returns using a sequential size-momentum double-sorting procedure.

	Mean	Median	SD	Skewness	Kurtosis
Market (CMKT)	0.011	0.008	0.104	0.17	4.765
Size (CSMB)	0.055	0.031	0.139	3.97	28.875
Momentum (CMOM)	0.005	-0.004	0.125	1.28	11.492

Furthermore, we construct the same 24 test assets as in Liu *et al.* (2022), with definitions documented in Online Appendix Table OA2. These assets serve to evaluate the explanatory power of factors derived from conventional and stylized momentum strategies.

3. Performance of momentum strategies in cryptocurrency returns

We begin our analysis by assessing the performance of each stylized momentum strategy in cryptocurrency markets, and subsequently compare them with the conventional momentum benchmark. To evaluate portfolio performance, we calculate three measures for each combination of formation and holding periods: the mean

holding period return (MR), the t-statistic of the return (t-stat), and the annualized Sharpe Ratio (SR).

3.1 Residual momentum

Table 3 reports the performance of residual momentum (RMOM) portfolios. Panel A details results for the two-factor residual model (RMOM2), which derives residuals using the cryptocurrency market (CMKT) and size (CSMB) factors. Panel B presents the three-factor residual model (RMOM3), incorporating additional momentum (CMOM) alongside CMKT and CSMB.

Table 3 Performance of Residual Momentum Portfolios: This table reports the performance of portfolios constructed using the residual momentum strategy with a 1-day formation gap between the formation and holding periods. Residual returns are computed using standardized residuals from rolling 36-day regressions based on two different factor models. Panel A uses a two-factor model including the market (CMKT) and size (CSMB) factors. Panel B uses a three-factor model that additionally includes the momentum factor (CMOM). Portfolios are formed by sorting cryptocurrencies into quintiles based on cumulative standardized residual returns over various formation periods (1 to 7 days and 2 to 8 weeks). We report the mean holding-period return (MR), the corresponding t-statistic, and the annualized Sharpe ratio (SR). Bold figures indicate statistically significant positive returns at the 10%, 5%, or 1% levels, denoted by *, **, and ***, respectively.

Panel A: Residual Momentum (2-factor)								
Formation Period		Holding Periods (Days)						
		1	2	3	4	5	6	7
1 day	Return	0.001	0.002	0.004	0.006*	0.007*	0.007	0.008
	t-stats	(1.27)	(1.12)	(1.46)	(1.91)	(1.69)	(1.41)	(1.29)
	SR	0.41	0.36	0.47	0.62	0.55	0.45	0.42
2 day	Return	0.002**	0.004**	0.002	0.012***	0.009**	0.01*	0.017***
	t-stats	(2.3)	(2.11)	(0.96)	(3.67)	(2.01)	(1.73)	(2.67)
	SR	0.74	0.68	0.31	1.18	0.65	0.55	0.86
3 day	Return	0.002**	0.004**	0.003	0.009***	0.005	0.007	0.019**
	t-stats	(2.55)	(2.33)	(1.17)	(2.96)	(0.95)	(1.38)	(2.25)
	SR	0.83	0.75	0.38	0.96	0.31	0.44	0.73
4 day	Return	0.002***	0.004***	0.007***	0.016***	0.009**	0.012*	0.021***
	t-stats	(2.95)	(2.86)	(2.62)	(3.72)	(2.21)	(1.96)	(3.54)
	SR	0.95	0.92	0.84	1.2	0.72	0.63	1.14
5 day	Return	0.003***	0.005***	0.009***	0.014***	0.01	0.019***	0.023***
	t-stats	(3.65)	(3.31)	(3.08)	(3.28)	(1.43)	(3.13)	(2.6)
	SR	1.18	1.07	0.99	1.06	0.46	1	0.84
6 day	Return	0.003***	0.007***	0.009***	0.011***	0.014*	0.018***	0.025**
	t-stats	(3.75)	(3.76)	(3.22)	(2.61)	(1.93)	(2.85)	(2.37)
	SR	1.21	1.22	1.04	0.84	0.63	0.92	0.77
7 day	Return	0.003***	0.006***	0.006**	0.007**	0.015*	0.014***	0.026**
	t-stats	(3.85)	(3.12)	(2.46)	(2.25)	(1.79)	(2.58)	(2.32)
	SR	1.25	1.01	0.79	0.73	0.58	0.83	0.75
2 week	Return	0.003***	0.007***	0.01***	0.013***	0.019**	0.023***	0.023***

	t-stats	(3.75)	(3.47)	(2.78)	(3.1)	(2.51)	(3.59)	(3.39)
	SR	1.21	1.12	0.9	1	0.81	1.15	1.09
3 week	Return	0.004***	0.007***	0.013***	0.016***	0.016***	0.022***	0.028***
	t-stats	(5.11)	(4.22)	(5.19)	(4.92)	(3.34)	(4.0)	(4.23)
	SR	1.65	1.36	1.67	1.59	1.08	1.28	1.36
4 week	Return	0.005***	0.008***	0.011***	0.014***	0.018***	0.018***	0.023***
	t-stats	(5.82)	(4.84)	(4.32)	(4.58)	(3.85)	(3.52)	(3.9)
	SR	1.88	1.56	1.39	1.48	1.25	1.13	1.26
5 week	Return	0.004***	0.007***	0.013***	0.013***	0.018***	0.021***	0.027***
	t-stats	(4.83)	(4.23)	(5.13)	(4.15)	(4.28)	(4.1)	(4.19)
	SR	1.56	1.37	1.65	1.34	1.38	1.32	1.35
6 week	Return	0.004***	0.008***	0.011***	0.016***	0.022***	0.024***	0.026***
	t-stats	(4.87)	(4.67)	(4.45)	(4.61)	(5.2)	(4.8)	(4.02)
	SR	1.58	1.51	1.43	1.49	1.68	1.54	1.3
7 week	Return	0.005***	0.009***	0.016***	0.016***	0.021***	0.026***	0.03***
	t-stats	(6.03)	(5.6)	(6.08)	(4.81)	(4.49)	(4.69)	(4.81)
	SR	1.95	1.81	1.96	1.55	1.45	1.51	1.55
8 week	Return	0.004***	0.008***	0.012***	0.016***	0.02***	0.021***	0.032***
	t-stats	(4.93)	(5.02)	(5.0)	(4.39)	(4.41)	(3.89)	(5.35)
	SR	1.59	1.62	1.61	1.42	1.43	1.25	1.73

Panel B: Residual Momentum (3-factor)

Formation Period		Holding Periods (Days)						
		1	2	3	4	5	6	7
1 day	Return	0.001	0.001	0.001	0.005	0.006	0.003	0.005
	t-stats	(0.84)	(0.6)	(0.31)	(1.38)	(1.63)	(0.45)	(0.96)
	SR	0.27	0.19	0.1	0.45	0.53	0.15	0.31
2 day	Return	0.001	0.002	0.004	0.01**	0.009**	0.014**	0.011**
	t-stats	(1.4)	(1.42)	(1.43)	(2.45)	(2.24)	(2.28)	(2.04)
	SR	0.45	0.46	0.46	0.79	0.72	0.73	0.66
3 day	Return	0.002***	0.004**	0.005*	0.011***	0.007	0.008	0.016*
	t-stats	(2.62)	(2.35)	(1.69)	(2.7)	(1.43)	(1.46)	(1.89)
	SR	0.85	0.76	0.55	0.87	0.46	0.47	0.61
4 day	Return	0.002**	0.004**	0.006**	0.014***	0.007*	0.013**	0.021***
	t-stats	(2.25)	(2.2)	(2.22)	(3.23)	(1.7)	(2.02)	(2.95)
	SR	0.73	0.71	0.72	1.04	0.55	0.65	0.95
5 day	Return	0.004***	0.007***	0.01***	0.012***	0.014*	0.02***	0.028***
	t-stats	(4.23)	(3.78)	(3.45)	(2.92)	(1.91)	(3.33)	(2.76)
	SR	1.37	1.22	1.11	0.94	0.62	1.07	0.89
6 day	Return	0.003***	0.007***	0.009***	0.011***	0.014**	0.02***	0.028***
	t-stats	(3.89)	(3.56)	(3.42)	(2.7)	(2.04)	(3.35)	(2.63)
	SR	1.26	1.15	1.1	0.87	0.66	1.08	0.85
7 day	Return	0.003***	0.006***	0.007***	0.008**	0.016**	0.011**	0.028***
	t-stats	(3.55)	(2.98)	(2.69)	(2.43)	(2.19)	(2.17)	(2.58)
	SR	1.15	0.96	0.87	0.78	0.71	0.7	0.83
2 week	Return	0.003***	0.006***	0.009***	0.013***	0.009*	0.024***	0.025***
	t-stats	(3.35)	(3.4)	(2.59)	(2.81)	(1.83)	(3.52)	(3.53)
	SR	1.08	1.1	0.83	0.91	0.59	1.13	1.14
3 week	Return	0.004***	0.007***	0.013***	0.015***	0.016***	0.027***	0.029***
	t-stats	(4.93)	(4.53)	(5.04)	(3.8)	(3.58)	(4.63)	(4.84)
	SR	1.59	1.46	1.63	1.23	1.16	1.49	1.56
4 week	Return	0.004***	0.008***	0.009***	0.013***	0.015***	0.018***	0.025***
	t-stats	(4.87)	(4.57)	(3.6)	(4.18)	(3.22)	(3.25)	(4.02)
	SR	1.57	1.48	1.16	1.35	1.04	1.04	1.3
5 week	Return	0.003***	0.006***	0.011***	0.012***	0.015***	0.021***	0.023***
	t-stats	(4.04)	(3.97)	(4.39)	(3.79)	(3.87)	(4.1)	(3.73)
	SR	1.3	1.28	1.41	1.22	1.25	1.32	1.2

6 week	Return	0.004***	0.007***	0.011***	0.014***	0.019***	0.02***	0.027***
	t-stats	(4.45)	(4.65)	(4.41)	(4.54)	(4.52)	(4.07)	(4.25)
	SR	1.44	1.5	1.42	1.46	1.46	1.31	1.37
7 week	Return	0.005***	0.009***	0.015***	0.017***	0.022***	0.026***	0.03***
	t-stats	(6.05)	(5.49)	(6.29)	(5.29)	(5.1)	(5.31)	(5.0)
	SR	1.95	1.77	2.03	1.71	1.65	1.71	1.61
8 week	Return	0.004***	0.008***	0.011***	0.015***	0.018***	0.021***	0.024***
	t-stats	(5.11)	(5.13)	(4.79)	(4.79)	(4.07)	(4.09)	(4.08)
	SR	1.65	1.66	1.54	1.54	1.32	1.31	1.32

The RMOM portfolios generate significant positive mean returns (MR) across nearly all formation and holding periods. Notably, their Sharpe ratios (SR) improve markedly with extended formation periods (over 4 weeks), regardless of holding duration. For instance: RMOM2 (2-factor model) achieves a peak SR of 1.96 for a 7-week formation period. RMOM3 (3-factor model) reaches an even higher SR of 2.03, also under a 7-week formation period. These results confirm the profitability of residual momentum strategies in cryptocurrency markets, whether using two factors (market, size) or three factors (market, size, momentum). The superior risk-adjusted returns for longer formation periods suggest that residual momentum benefits from prolonged trend-filtering in cryptocurrency's high-volatility environment.

3.2 Information discreteness Momentum

Table 4 evaluates the performance of the information discreteness momentum (IDMOM) strategy proposed by Da et al. (2014). The strategy is constructed via sequential double sorts on three proxies of information discreteness: Panel A: ID , Panel B: ID_{MAG} , and Panel C: ID_Z , respectively.⁴

Table 4 Performance of Sequential Double-Sorted Information discreteness Momentum Portfolios: This table reports the performance of portfolios constructed using the sequential double-sorted information discreteness momentum strategy with a 1-day formation gap between the formation and holding periods. Portfolios are formed through a two-step sorting process: cryptocurrencies are first ranked by conventional momentum signals and then sorted by proxies for information discreteness. Panel A uses the ID proxy, Panel B uses the ID_{MAG} proxy, and Panel C uses the ID_Z proxy. Due to insufficient data for short horizons, formation periods of 1 to 3 days are excluded. The remaining formation periods range from 4 days to 8 weeks. We report the mean holding-period return (MR), the corresponding t-statistic, and the annualized Sharpe ratio (SR). Bold figures indicate statistically significant positive

⁴ The formation period of 1 to 3 days is too short to calculate a valid information discreteness proxy, hence it is not presented in the table

returns at the 10%, 5%, or 1% levels, denoted by *, **, and ***, respectively.

Panel A: Sequential Double-Sorting Information discreteness Momentum (ID proxy)								
Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.005***	0.011***	0.013***	0.024***	0.019**	0.021**	0.031**
	t-stats	(3.24)	(3.29)	(2.66)	(3.71)	(2.28)	(2.09)	(2.42)
	SR	1.05	1.06	0.86	1.2	0.74	0.67	0.78
5 day	Return	0.006***	0.014***	0.02***	0.028***	0.019*	0.032**	0.039**
	t-stats	(3.72)	(4.12)	(3.22)	(3.29)	(1.85)	(2.53)	(2.57)
	SR	1.2	1.33	1.04	1.06	0.6	0.81	0.83
6 day	Return	0.006***	0.011***	0.019***	0.026***	0.017*	0.027**	0.048***
	t-stats	(3.7)	(3.13)	(3.22)	(2.85)	(1.96)	(2.2)	(3.09)
	SR	1.2	1.01	1.04	0.92	0.63	0.71	1
7 day	Return	0.004*	0.009**	0.013**	0.025***	0.021**	0.022*	0.052***
	t-stats	(1.85)	(2.45)	(2.16)	(2.82)	(2.31)	(1.86)	(3.63)
	SR	0.6	0.79	0.7	0.91	0.75	0.6	1.17
2 week	Return	0.006***	0.012***	0.018***	0.023***	0.029***	0.029***	0.048***
	t-stats	(3.19)	(3.4)	(3.21)	(3.89)	(3.7)	(3.02)	(3.25)
	SR	1.03	1.1	1.03	1.26	1.2	0.97	1.05
3 week	Return	0.006***	0.011***	0.017***	0.026***	0.032***	0.029***	0.049***
	t-stats	(3.34)	(2.91)	(3.47)	(3.82)	(3.21)	(2.8)	(4.17)
	SR	1.08	0.94	1.12	1.23	1.04	0.9	1.35
4 week	Return	0.005***	0.011***	0.018***	0.024***	0.025***	0.021**	0.019
	t-stats	(2.75)	(3.2)	(3.79)	(3.7)	(2.81)	(2.36)	(1.56)
	SR	0.89	1.03	1.22	1.19	0.91	0.76	0.5
5 week	Return	0.004**	0.01***	0.015***	0.018***	0.018**	0.009	0.017
	t-stats	(2.57)	(3.28)	(3.17)	(3.11)	(2.46)	(0.84)	(1.49)
	SR	0.83	1.06	1.02	1	0.79	0.27	0.48
6 week	Return	0.002	0.006**	0.006	0.008	0.009	0.001	0.005
	t-stats	(1.21)	(1.97)	(1.47)	(1.33)	(1.19)	(0.07)	(0.52)
	SR	0.39	0.63	0.47	0.43	0.39	0.02	0.17
7 week	Return	0.001	0.001	0.003	0.006	0.006	0.001	0.007
	t-stats	(0.85)	(0.48)	(0.65)	(1.04)	(0.84)	(0.07)	(0.77)
	SR	0.27	0.16	0.21	0.34	0.27	0.02	0.25
8 week	Return	0.002	0.004	0.005	0.01*	0.008	0.008	0.012
	t-stats	(1.47)	(1.61)	(1.09)	(1.77)	(1.0)	(0.97)	(1.26)
	SR	0.47	0.52	0.35	0.57	0.32	0.31	0.41

Panel B: Sequential Double-Sorting Information discreteness Momentum (IDMAG proxy)								
Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.004**	0.01**	0.016**	0.028***	0.023**	0.018	0.046***
	t-stats	(2.03)	(2.48)	(2.43)	(2.96)	(2.42)	(1.39)	(2.8)
	SR	0.66	0.8	0.78	0.96	0.78	0.45	0.9
5 day	Return	0.006***	0.016***	0.018**	0.033***	0.021*	0.032**	0.042***

	t-stats	(3.1)	(4.3)	(2.34)	(3.44)	(1.95)	(2.44)	(2.62)
	SR	1	1.39	0.75	1.11	0.63	0.78	0.85
6 day	Return	0.005***	0.01**	0.018***	0.023**	0.017*	0.029***	0.056***
	t-stats	(2.99)	(2.57)	(2.94)	(2.14)	(1.89)	(2.19)	(3.49)
	SR	0.97	0.83	0.95	0.69	0.61	0.7	1.13
7 day	Return	0.004*	0.011***	0.01	0.023**	0.018**	0.007	0.048***
	t-stats	(1.72)	(2.74)	(1.59)	(2.49)	(2.02)	(0.53)	(3.13)
	SR	0.55	0.88	0.51	0.8	0.65	0.17	1.01
2 week	Return	0.006***	0.011***	0.018***	0.02***	0.038***	0.032***	0.059***
	t-stats	(2.9)	(3.05)	(3.43)	(3.18)	(4.94)	(3.33)	(3.09)
	SR	0.94	0.99	1.1	1.03	1.6	1.07	1
3 week	Return	0.006***	0.012***	0.014***	0.021***	0.03***	0.029***	0.047***
	t-stats	(3.69)	(3.12)	(2.83)	(3.0)	(3.13)	(2.87)	(3.06)
	SR	1.19	1.01	0.91	0.97	1.01	0.92	0.99
4 week	Return	0.004**	0.007**	0.01**	0.016**	0.012	0.013	0.011
	t-stats	(2.35)	(1.96)	(1.99)	(2.3)	(1.17)	(1.24)	(0.84)
	SR	0.76	0.63	0.64	0.74	0.38	0.4	0.27
5 week	Return	0.003*	0.007**	0.01**	0.013**	0.01	0.008	0.016
	t-stats	(1.76)	(2.07)	(2.11)	(2.02)	(1.2)	(0.77)	(1.36)
	SR	0.57	0.67	0.68	0.65	0.39	0.25	0.44
6 week	Return	0.001	0.003	0.008*	0.0	-0.006	0.005	0.0
	t-stats	(0.69)	(0.98)	(1.73)	(0.07)	(-0.49)	(0.58)	(0.02)
	SR	0.22	0.32	0.56	0.02	-0.16	0.19	0.01
7 week	Return	0.0	0.002	0.002	0.005	0.01	0.004	0.014
	t-stats	(0.23)	(0.68)	(0.46)	(0.84)	(1.42)	(0.5)	(1.41)
	SR	0.07	0.22	0.15	0.27	0.46	0.16	0.45
8 week	Return	0.002	0.002	0.002	0.004	0.004	0.006	0.007
	t-stats	(0.96)	(0.73)	(0.36)	(0.64)	(0.48)	(0.69)	(0.63)
	SR	0.31	0.24	0.11	0.21	0.15	0.22	0.2

Panel C: Sequential Double-Sorting Information discreteness Momentum (IDZ proxy)

Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.006***	0.01***	0.012**	0.024***	0.022***	0.021**	0.032**
	t-stats	(3.16)	(2.94)	(2.46)	(3.69)	(2.6)	(2.09)	(2.48)
	SR	1.02	0.95	0.79	1.19	0.84	0.67	0.8
5 day	Return	0.006***	0.013***	0.018***	0.028***	0.02**	0.03**	0.037**
	t-stats	(3.45)	(3.69)	(2.95)	(3.26)	(1.97)	(2.41)	(2.47)
	SR	1.11	1.19	0.95	1.05	0.64	0.77	0.8
6 day	Return	0.006***	0.011***	0.017***	0.026***	0.015*	0.026**	0.045***
	t-stats	(3.6)	(3.17)	(2.99)	(2.79)	(1.79)	(2.06)	(2.86)
	SR	1.16	1.02	0.96	0.9	0.58	0.66	0.92
7 day	Return	0.003*	0.008**	0.011*	0.025***	0.024***	0.021*	0.05***
	t-stats	(1.7)	(2.25)	(1.84)	(2.72)	(2.64)	(1.76)	(3.5)
	SR	0.55	0.73	0.59	0.88	0.85	0.57	1.13

2 week	Return	0.005**	0.011***	0.018***	0.021***	0.03***	0.032***	0.044***
	t-stats	(2.37)	(3.06)	(2.89)	(3.0)	(3.57)	(3.31)	(3.01)
	SR	0.77	0.99	0.93	0.97	1.15	1.06	0.97
3 week	Return	0.003*	0.009**	0.014***	0.02***	0.025**	0.027**	0.044***
	t-stats	(1.81)	(2.45)	(2.6)	(2.59)	(2.44)	(2.54)	(3.8)
	SR	0.58	0.79	0.84	0.84	0.79	0.81	1.23
4 week	Return	0.004**	0.005	0.011**	0.01	0.019**	0.011	0.015
	t-stats	(2.2)	(1.52)	(2.06)	(1.57)	(2.05)	(1.24)	(1.26)
	SR	0.71	0.49	0.66	0.51	0.66	0.4	0.41
5 week	Return	0.003	0.006**	0.011**	0.01	0.008	0.004	0.011
	t-stats	(1.48)	(2.04)	(2.03)	(1.38)	(1.09)	(0.4)	(0.94)
	SR	0.48	0.66	0.65	0.45	0.35	0.13	0.3
6 week	Return	0.001	0.004	0.004	0.002	0.006	0.001	0.002
	t-stats	(0.56)	(1.25)	(0.73)	(0.34)	(0.79)	(0.09)	(0.19)
	SR	0.18	0.4	0.23	0.11	0.26	0.03	0.06
7 week	Return	0.001	-0.001	0.002	0.001	0.004	-0.003	0.004
	t-stats	(0.33)	(-0.16)	(0.4)	(0.12)	(0.51)	(-0.4)	(0.39)
	SR	0.11	-0.05	0.13	0.04	0.16	-0.13	0.12
8 week	Return	0.002	0.003	0.004	0.006	0.004	0.008	0.006
	t-stats	(0.95)	(1.05)	(0.71)	(0.82)	(0.52)	(0.92)	(0.56)
	SR	0.31	0.34	0.23	0.27	0.17	0.3	0.18

The results highlight two key patterns: first, the information discreteness momentum strategy generates significant returns for formation periods between 4 days and 3 weeks, regardless of the proxy used (*ID*, *ID_{MAG}*, or *ID_Z*). For simplicity, we stick to *ID* as proxy for measuring the information discreteness in the following analysis.

Also, the returns increase monotonically from short holding periods to longer periods. Similar to conventional momentum strategies, *IDMOM*'s performance declines sharply for formation periods exceeding 4 weeks, as illustrated by the *c_mom* results reported in Section 3.3 (Table 6). For example, returns become less statistically insignificant for all three proxies when formation periods extend beyond 4 weeks. Second, in contrast, *c_mom* sustain significantly positive returns even with formation periods as long as 7 weeks, underscoring their relative robustness to extended period. The results remain hold when using an independent double-sorting methodology for portfolio construction, as demonstrated in Table 5.

Table 5 Performance of Independently Double-Sorted Information discreteness Momentum Portfolios: This table reports the performance of portfolios constructed using the independently double-sorted information discreteness momentum strategy with a 1-day formation gap between the formation and holding periods. Portfolios are formed by independently sorting cryptocurrencies into quintiles based on conventional momentum signals and on information discreteness proxies. Panel A uses the ID proxy, Panel B uses the IDMAG proxy, and Panel C uses the IDZ proxy. Due to insufficient observations, formation periods of 1 to 3 days are excluded. The remaining formation periods range from 4 days to 8 weeks. We report the mean holding-period return (MR), the corresponding t-statistic, and the annualized Sharpe ratio (SR). Bold figures indicate statistically significant positive returns at the 10%, 5%, or 1% levels, denoted by *, **, and ***, respectively.

Panel A: Independent Double-Sorting Information discreteness Momentum (ID proxy)								
Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.006***	0.011***	0.011***	0.021***	0.023***	0.016*	0.033***
	t-stats	(3.83)	(3.32)	(2.65)	(3.34)	(2.77)	(1.7)	(2.76)
	SR	1.24	1.07	0.85	1.08	0.9	0.55	0.89
5 day	Return	0.006***	0.013***	0.018***	0.029***	0.02**	0.031**	0.034**
	t-stats	(3.41)	(3.67)	(3.08)	(3.26)	(2.53)	(2.53)	(2.56)
	SR	1.1	1.19	0.99	1.05	0.82	0.81	0.83
6 day	Return	0.004***	0.01***	0.019***	0.023***	0.02***	0.024**	0.039***
	t-stats	(2.7)	(3.05)	(3.86)	(2.88)	(2.63)	(2.53)	(2.75)
	SR	0.87	0.99	1.24	0.93	0.85	0.81	0.89
7 day	Return	0.005***	0.008**	0.013**	0.024***	0.024***	0.013	0.049***
	t-stats	(2.63)	(2.38)	(2.41)	(3.08)	(2.67)	(1.27)	(3.43)
	SR	0.85	0.77	0.78	0.99	0.86	0.41	1.11
2 week	Return	0.007***	0.015***	0.018***	0.03***	0.028***	0.037***	0.064***
	t-stats	(3.71)	(4.07)	(3.82)	(5.03)	(3.66)	(4.02)	(4.44)
	SR	1.2	1.31	1.23	1.62	1.18	1.29	1.43
3 week	Return	0.007***	0.011***	0.018***	0.024***	0.03***	0.031***	0.035***
	t-stats	(4.07)	(3.11)	(4.06)	(3.56)	(3.56)	(3.12)	(2.77)
	SR	1.32	1	1.31	1.15	1.15	1	0.89
4 week	Return	0.003**	0.004	0.008*	0.008	0.015**	0.009	0.008
	t-stats	(2.18)	(1.52)	(1.92)	(1.37)	(2.1)	(0.89)	(0.69)
	SR	0.7	0.49	0.62	0.44	0.68	0.29	0.22
5 week	Return	0.003*	0.007**	0.011**	0.02***	0.014*	0.014	-0.005
	t-stats	(1.88)	(2.35)	(2.53)	(3.52)	(1.89)	(1.55)	(-0.2)
	SR	0.61	0.76	0.81	1.14	0.61	0.5	-0.07
6 week	Return	0.001	0.002	0.004	0.0	-0.003	-0.012	0.006
	t-stats	(0.99)	(0.74)	(0.94)	(0.03)	(-0.27)	(-0.66)	(0.62)
	SR	0.32	0.24	0.3	0.01	-0.09	-0.21	0.2
7 week	Return	0.001	0.003	0.005	0.002	0.008	0.005	0.008
	t-stats	(0.95)	(1.03)	(1.2)	(0.41)	(1.08)	(0.64)	(0.75)
	SR	0.31	0.33	0.39	0.13	0.35	0.21	0.24
8 week	Return	0.003**	0.007***	0.011***	0.013**	0.014*	0.02**	0.018
	t-stats	(2.37)	(2.72)	(2.65)	(2.39)	(1.75)	(2.5)	(1.63)
	SR	0.76	0.88	0.86	0.77	0.57	0.8	0.53

Panel B: Independent Double-Sorting Information discreteness Momentum (IDMAG proxy)								
Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.005**	0.008**	0.014**	0.022**	0.023**	0.012	0.031*
	t-stats	(2.29)	(2.06)	(2.3)	(2.4)	(2.34)	(1.06)	(1.82)
	SR	0.74	0.67	0.74	0.77	0.76	0.34	0.59
5 day	Return	0.006***	0.014***	0.015**	0.025***	0.013	0.022*	0.035**
	t-stats	(2.97)	(3.62)	(2.35)	(2.67)	(1.37)	(1.78)	(2.29)

6 day	SR	0.96	1.17	0.76	0.86	0.44	0.57	0.74
	Return	0.005**	0.01***	0.019***	0.029***	0.024***	0.027**	0.046***
	t-stats	(2.3)	(2.61)	(2.84)	(2.84)	(2.78)	(2.13)	(2.77)
7 day	SR	0.74	0.84	0.92	0.92	0.9	0.68	0.89
	Return	0.004*	0.007*	0.01	0.017*	0.017**	0.007	0.043***
	t-stats	(1.82)	(1.89)	(1.61)	(1.85)	(1.99)	(0.5)	(2.84)
2 week	SR	0.59	0.61	0.52	0.6	0.64	0.16	0.92
	Return	0.007***	0.015***	0.019***	0.027***	0.034***	0.039***	0.071***
	t-stats	(3.59)	(3.93)	(3.68)	(4.27)	(4.31)	(3.78)	(3.64)
3 week	SR	1.16	1.27	1.19	1.38	1.39	1.21	1.18
	Return	0.005***	0.009**	0.017***	0.02***	0.027***	0.02**	0.037***
	t-stats	(3.09)	(2.39)	(3.21)	(2.94)	(2.87)	(2.08)	(2.88)
4 week	SR	1	0.77	1.03	0.95	0.93	0.67	0.93
	Return	0.003*	0.005	0.008*	0.006	0.008	0.016	0.008
	t-stats	(1.71)	(1.56)	(1.83)	(0.98)	(0.89)	(1.51)	(0.71)
5 week	SR	0.55	0.5	0.59	0.32	0.29	0.49	0.23
	Return	0.002	0.006*	0.006	0.008	0.006	0.008	-0.005
	t-stats	(1.37)	(1.82)	(1.37)	(1.16)	(0.83)	(0.85)	(-0.34)
6 week	SR	0.44	0.59	0.44	0.38	0.27	0.27	-0.11
	Return	-0.001	0.003	0.007	0.004	0.007	0.001	0.016
	t-stats	(-0.36)	(0.9)	(1.6)	(0.69)	(0.89)	(0.08)	(1.37)
7 week	SR	-0.12	0.29	0.52	0.22	0.29	0.03	0.44
	Return	-0.001	0.003	0.001	0.002	0.004	0.008	0.012
	t-stats	(-0.38)	(1.13)	(0.32)	(0.41)	(0.53)	(0.94)	(0.98)
8 week	SR	-0.12	0.37	0.1	0.13	0.17	0.3	0.32
	Return	0.002	0.003	0.005	0.005	0.006	0.008	0.005
	t-stats	(1.62)	(1.17)	(1.25)	(0.91)	(0.75)	(1.09)	(0.55)
	SR	0.53	0.38	0.4	0.29	0.24	0.35	0.18
Panel C: Independent Double-Sorting Information discreteness Momentum (IDZ proxy)								
Formation Period		Holding period (Days)						
		1	2	3	4	5	6	7
4 day	Return	0.006***	0.01***	0.011**	0.021***	0.021**	0.015	0.033***
	t-stats	(3.82)	(3.17)	(2.57)	(3.34)	(2.54)	(1.58)	(2.73)
	SR	1.24	1.02	0.83	1.08	0.82	0.51	0.88
5 day	Return	0.005***	0.012***	0.019***	0.027***	0.023**	0.026**	0.034**
	t-stats	(2.87)	(3.41)	(3.1)	(3.06)	(2.53)	(2.1)	(2.56)
	SR	0.93	1.1	1	0.99	0.82	0.68	0.83
6 day	Return	0.004***	0.009***	0.018***	0.022***	0.019**	0.023**	0.038***
	t-stats	(2.74)	(2.87)	(3.67)	(2.79)	(2.48)	(2.34)	(2.67)
	SR	0.89	0.93	1.18	0.9	0.8	0.75	0.86
7 day	Return	0.005**	0.008**	0.013**	0.024***	0.024***	0.014	0.05***
	t-stats	(2.51)	(2.37)	(2.3)	(3.04)	(2.74)	(1.31)	(3.45)
	SR	0.81	0.77	0.74	0.98	0.89	0.42	1.11
2 week	Return	0.007***	0.014***	0.023***	0.032***	0.032***	0.035***	0.06***
	t-stats	(3.88)	(3.95)	(3.54)	(5.24)	(4.15)	(3.66)	(4.15)
	SR	1.25	1.28	1.14	1.69	1.34	1.17	1.34
3 week	Return	0.006***	0.01***	0.019***	0.021***	0.032***	0.033***	0.039***
	t-stats	(3.1)	(2.82)	(3.36)	(2.75)	(3.35)	(3.36)	(3.03)
	SR	1	0.91	1.08	0.89	1.08	1.08	0.98
4 week	Return	0.002	0.003	0.005	0.003	0.007	0.008	0.01
	t-stats	(1.44)	(1.0)	(1.03)	(0.39)	(0.96)	(0.8)	(0.79)
	SR	0.47	0.32	0.33	0.13	0.31	0.26	0.26
5 week	Return	0.002	0.005*	0.009*	0.015***	0.007	0.003	0.011
	t-stats	(1.42)	(1.65)	(1.78)	(2.59)	(0.99)	(0.25)	(1.03)
	SR	0.46	0.53	0.57	0.84	0.32	0.08	0.33
6 week	Return	0.001	0.004	0.002	0.001	-0.004	-0.014	0.005

	t-stats	(0.86)	(1.23)	(0.38)	(0.15)	(-0.37)	(-0.79)	(0.53)
	SR	0.28	0.4	0.12	0.05	-0.12	-0.25	0.17
7 week	Return	0.002	0.005*	0.006	0.005	0.009	0.006	0.006
	t-stats	(1.54)	(1.74)	(1.38)	(0.86)	(1.16)	(0.64)	(0.54)
	SR	0.5	0.56	0.45	0.28	0.37	0.21	0.17
8 week	Return	0.004***	0.006**	0.013***	0.013**	0.012	0.02**	0.016
	t-stats	(2.65)	(2.19)	(3.13)	(2.33)	(1.56)	(2.44)	(1.34)
	SR	0.86	0.71	1.01	0.75	0.5	0.78	0.43

Tables 4 and 5 reveal two critical differences between cryptocurrency and equity markets. First, unlike equities-where winning/losing stocks sustain trends for extended periods (Da *et al.*, 2014)-cryptocurrency momentum persists over markedly shorter horizons. Second, IDMOM exhibits higher volatility than *c_mom*, evidenced by its lower Sharpe ratios (SR) despite higher mean returns (MR). For instance, IDMOM achieves an SR of 1.26 (MR: 2.3%) with a 2-week formation and 4-day holding period (Table 4, Panel A), whereas *c_mom* under identical parameters yields a 16% higher SR (1.47) despite a 15% lower MR (1.96%), as reported in Table 6, highlighting the IDMOM's stronger return potential but with a greater risk component. This inverse relationship indicates that IDMOM's enhanced returns are associated with increased volatility-under a 2-week formation period, its SR even falls below 1 when the holding period extends to 6 days.

3.3 Performance Comparison

To provide a benchmark for evaluating the stylized momentum strategies, we construct conventional momentum (*c_mom*) portfolios following the same methodology. Table 6 presents the performance of conventional momentum portfolios. A robust momentum premium is evident across nearly all tested formation and holding periods. All portfolios generate positive mean returns (MR), with strategies employing formation periods of 3 days to 6 weeks delivering significant returns regardless of holding period. The strongest performance occurs for a 2-week formation period: Peak MR of 4.51% (7-day holding period), Highest Sharpe Ratio (SR) of 1.47 (4-day holding period). We observe a steady rise in mean returns (MR) as holding periods lengthen from 1 to 7 days. In contrast, the Sharpe ratio (SR) exhibits no monotonic trend: its

maximum value only occurs at 7-day holding period for portfolios with 6-day formation period. This divergence implies that while extended holding periods amplify raw returns, they also introduce incremental risk, eroding risk-adjusted performance. These results align with the values reported in earlier studies (e.g., Liu *et al.* 2022), who find that formation periods of 2–3 weeks combined with 1-week holding periods generate the strongest momentum premium⁵.

Table 6 Performance of Conventional Momentum Portfolios: This table reports the performance of portfolios constructed using the conventional momentum strategy with a 1-day formation gap between the formation and holding periods. Portfolios are formed by sorting cryptocurrencies into quintiles based on cumulative past returns over various formation periods (1 to 7 days and 2 to 8 weeks). We report the mean holding-period return (MR), the corresponding t-statistic, and the annualized Sharpe ratio (SR). Bold figures indicate statistically significant positive returns at the 10%, 5%, or 1% levels, denoted by *, **, and *, respectively.

Formation Period		Holding Periods (Days)						
		1	2	3	4	5	6	7
1 day	Return	0.001	0.001	0.006*	0.008*	0.006	0.012*	0.011
	t-stats	(0.7)	(0.42)	(1.93)	(1.77)	(1.28)	(1.83)	(1.02)
	SR	0.23	0.14	0.62	0.57	0.42	0.59	0.33
2 day	Return	0.003**	0.006**	0.007**	0.012***	0.015**	0.01	0.023*
	t-stats	(2.15)	(2.22)	(2.04)	(2.89)	(2.46)	(1.52)	(1.81)
	SR	0.7	0.72	0.66	0.93	0.79	0.49	0.58
3 day	Return	0.004***	0.008***	0.012***	0.021***	0.014**	0.016**	0.021***
	t-stats	(2.67)	(3.0)	(3.37)	(4.18)	(2.46)	(2.18)	(2.75)
	SR	0.86	0.97	1.09	1.35	0.8	0.7	0.89
4 day	Return	0.005***	0.009***	0.012***	0.017***	0.017***	0.018**	0.03**
	t-stats	(4.21)	(4.03)	(3.51)	(3.32)	(2.88)	(2.38)	(2.54)
	SR	1.36	1.3	1.13	1.07	0.93	0.76	0.82
5 day	Return	0.005***	0.009***	0.017***	0.018***	0.018***	0.033***	0.025**
	t-stats	(3.63)	(3.63)	(4.22)	(2.6)	(3.32)	(3.62)	(2.41)
	SR	1.17	1.17	1.36	0.84	1.07	1.16	0.78
6 day	Return	0.004***	0.008***	0.013***	0.013**	0.019**	0.021**	0.03***
	t-stats	(3.47)	(3.04)	(3.5)	(2.24)	(2.21)	(2.51)	(2.9)
	SR	1.12	0.98	1.13	0.72	0.72	0.81	0.94
7 day	Return	0.004***	0.008***	0.013***	0.018***	0.019***	0.017**	0.024**
	t-stats	(2.77)	(3.11)	(3.45)	(3.02)	(2.91)	(2.14)	(2.42)
	SR	0.9	1	1.11	0.97	0.94	0.69	0.78
2 week	Return	0.005***	0.011***	0.014***	0.02***	0.023***	0.028***	0.045***
	t-stats	(4.08)	(4.34)	(3.88)	(4.54)	(3.85)	(4.05)	(4.53)
	SR	1.32	1.4	1.25	1.47	1.25	1.3	1.46
3 week	Return	0.005***	0.009***	0.013***	0.019***	0.022***	0.023***	0.028***
	t-stats	(4.4)	(3.94)	(4.22)	(4.27)	(3.94)	(3.53)	(3.24)
	SR	1.42	1.27	1.36	1.38	1.27	1.13	1.05
4 week	Return	0.004***	0.008***	0.011***	0.013***	0.012**	0.02***	0.015*
	t-stats	(3.78)	(3.76)	(3.51)	(3.08)	(2.11)	(2.98)	(1.96)
	SR	1.22	1.21	1.13	0.99	0.68	0.96	0.63

⁵ The findings presented here are for a 1-day formation gap. In Online Appendix Table OA1, we show that the results hold for no formation gap.

5 week	Return	0.002**	0.006***	0.01***	0.013***	0.011*	0.012	0.019**
	t-stats	(2.25)	(2.83)	(3.0)	(3.0)	(1.81)	(1.62)	(2.27)
	SR	0.73	0.91	0.97	0.97	0.58	0.52	0.73
6 week	Return	0.002*	0.004*	0.006*	0.008*	0.01*	0.008	0.019**
	t-stats	(1.84)	(1.81)	(1.81)	(1.83)	(1.75)	(1.2)	(2.43)
	SR	0.6	0.59	0.58	0.59	0.57	0.39	0.78
7 week	Return	0.002	0.004*	0.008**	0.01**	0.012**	0.008	0.012
	t-stats	(1.37)	(1.78)	(2.51)	(2.3)	(2.02)	(1.25)	(1.57)
	SR	0.44	0.57	0.81	0.74	0.65	0.4	0.51
8 week	Return	0.002*	0.003	0.006*	0.006	0.009	0.012*	0.011
	t-stats	(1.68)	(1.28)	(1.84)	(1.45)	(1.62)	(1.95)	(1.35)
	SR	0.54	0.41	0.59	0.47	0.52	0.62	0.44

Table 7 evaluates three momentum strategies (conventional, residual, and information discreteness momentum) in cryptocurrency markets by analyzing the percentage of statistically significant positive returns (1% level) across formation periods. Residual momentum dominates overall, with 71.43% of returns being significant-far exceeding conventional and information discreteness momentum (both ~48%). While residual momentum strengthens with longer formation periods (5–8 weeks), information discreteness momentum peaks in intermediate horizons (2–4 weeks), a pattern unaffected by sorting methodology (sequential/independent). Conventional momentum aligns with information discreteness momentum in its intermediate-period efficacy (2–4 weeks) but diverges from residual momentum, which thrives in extended horizons. These results underscore residual momentum’s unique advantage in adapting to longer formation periods in cryptocurrency markets, contrasting with the narrower optimal windows of conventional and ID strategies.

Table 7 Percentage of Significant Momentum Portfolio Returns: This table reports the percentage of statistically significant positive returns (at the 1% level) for conventional momentum, residual momentum, and information discreteness momentum strategies across all 94 combinations of formation and holding periods.

	Conventional Momentum	Residual Momentum		Continues Information Momentum					
		2factors	3factors	Sequential Sorting			Independent Sorting		
				ID	IDMAG	IDZ	ID	IDMAG	IDZ
All Combinations	48.98%	71.43%	69.39%	48.05%	27.27%	42.86%	48.05%	32.47%	32.47%
Formation = 1 day to 3 days	28.57%	14.29%	9.52%	NaN	NaN	NaN	NaN	NaN	NaN
Formation = 4 days to 7 days	71.43%	67.86%	64.29%	71.43%	32.14%	57.14%	53.57%	39.29%	57.14%
Formation = 2 weeks to 4 weeks	90.48%	95.24%	95.24%	66.67%	57.14%	66.67%	90.48%	66.67%	42.86%
Formation = 5 weeks to 8 weeks	10.71%	100.00%	100.00%	10.71%	0.00%	10.71%	10.71%	0.00%	0.00%

3.4 Alpha returns of stylized momentum

Having established the efficacy of stylized momentum strategies in cryptocurrency returns, we further assess their ability to generate statistically significant alphas within the Liu *et al.* (2022) 3-factor model. We select the optimal combination for each strategy based on the Sharpe ratio. Table 8 summarizes the 3-factor model regression results for both stylized momentum strategies. Critically, both strategies generate statistically significant alphas (1% level), confirming their excess returns persist even after accounting for systematic risk factors—a finding consistent with anomalous behavior unexplained by the model. Notably, both strategies exhibit significant exposure to the CMOM factor (1% level), underscoring their sensitivity to cryptocurrency-specific momentum effects. A key difference emerges in market factor (CMKT) exposure: the RMOM strategy shows a robust positive beta (0.227, 1% significance), aligning its returns with broader market movements, while the IDMOM strategy displays no significant CMKT linkage, isolating its performance from market trends. These results highlight the dual role of momentum in cryptocurrency markets—partly systematic (via CMKT/CMOM) and partly idiosyncratic (via persistent alphas).

Table 8 Alphas of Stylized Momentum Strategies: This table summarizes the regression results from the cryptocurrency three-factor model (CMKT, CSMB, CMOM) applied to the optimal residual momentum and information discreteness momentum portfolios, selected based on the highest Sharpe ratios. The regression model is defined as:

$$r_{p,t} = \alpha_p + \beta_{1,p}CMKT_t + \beta_{2,p}CSMB_t + \beta_{3,p}CMOM_t + \varepsilon_t$$

where $r_{p,t}$ represents the excess return of the momentum portfolio p on week t . Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. The best-performing setup is selected based on the highest annualized Sharpe ratio with a 7-day holding period.

	Alpha	t(alpha)	CMKT	t(CMKT)	CSMB	t(CSMB)	CMOM	t(CMOM)	R ²
<i>RMOM</i>	0.024***	(4.03)	0.227***	(4.20)	0.066	(1.61)	0.305***	(6.79)	0.131
<i>IDMOM</i>	0.056***	(3.83)	0.083	(0.62)	0.058	(0.58)	0.879***	(8)	0.121

4. Predictability and explanatory power as potential factor

This section evaluates whether the two stylized momentum strategies (Section 3)

possess predictive power over cryptocurrency characteristics. We first identify return predictors from the 24 characteristics defined in Liu *et al.* (2022), then construct factor models based on the stylized momentum strategies to test their ability to explain returns associated with these characteristics.

4.1 Cross-sectional return predictors

Following Liu *et al.* (2022), we compute 24 cryptocurrency characteristics derived from price, volume, and market capitalization. Weekly, we sort cryptocurrencies into quintile portfolios based on each characteristic and calculate their value-weighted returns over the subsequent week. To evaluate the predictability of each characteristic, we construct long-short portfolios by taking long positions in the highest quintile and shorting the lowest quintile, then analyze the resulting return spreads. We report the return spread for those characteristics demonstrating predictive power⁶ in Table 9.

Table 9 Cross-Sectional Predictability of Cryptocurrency Characteristics: Table 9 reports the mean quintile portfolio returns and High-Low portfolio returns for the 14 cross-sectional return predictors (out of the 24 used by Liu *et al.* (2022)) that yield significant High-Low portfolio returns in our sample. Returns are the weekly mean returns of value-weighted, weekly rebalanced portfolios. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Low	2	3	4	High	High-Low
Panel A: Size related characteristics						
MCAP	0.078*** (8.51)	0.038*** (5.23)	0.023*** (3.58)	0.015** (2.39)	0.012** (2.53)	-0.066*** (-8.89)
PRC	0.036*** (2.78)	0.031*** (2.79)	0.019*** (2.62)	0.004 (0.7)	0.011** (2.53)	-0.025** (-2.19)
MAXDPRC	0.035*** (2.68)	0.029*** (2.67)	0.019*** (2.59)	0.007 (1.12)	0.011** (2.51)	-0.023** (-2.08)
Panel B: Momentum related characteristics						
MOM ₁	0.004 (0.59)	0.004 (0.72)	0.011* (1.96)	0.029*** (2.98)	0.03*** (2.6)	0.026** (2.27)
MOM ₂	0.0 (0.01)	0.004 (0.58)	0.008 (1.34)	0.026*** (3.4)	0.037*** (3.74)	0.037*** (3.57)
MOM ₃	0.001 (0.13)	-0.001 (-0.11)	0.01 (1.55)	0.027*** (3.35)	0.034*** (3.93)	0.033*** (3.7)
MOM ₄	0.007 (0.92)	0.004 (0.67)	0.008 (1.5)	0.03*** (3.51)	0.023*** (3.09)	0.015* (1.95)
MOM ₄₋₁	0.001 (0.08)	0.008 (1.22)	0.01* (1.79)	0.024*** (2.93)	0.015** (2.12)	0.015** (2.09)
MOM ₅₀	0.02***	0.014**	0.016**	0.016***	0.009	-0.011*

⁶ The results of the characteristics demonstrating no predictive power (i.e. the high-low return is not significant) are shown in Online Appendix Table OA3.

	(3.15)	(2.41)	(2.46)	(2.73)	(1.43)	(-1.92)
Panel C: Volume related characteristics						
VOL	0.039*** (3.91)	0.023*** (3.35)	0.018*** (2.79)	0.019** (2.49)	0.012** (2.52)	-0.028*** (-3.05)
PRCVOL	0.036*** (3.25)	0.033*** (2.91)	0.027*** (3.4)	0.025*** (2.63)	0.011** (2.43)	-0.025*** (-2.65)
VOLSCALED	0.028** (2.57)	0.029** (2.53)	0.017** (2.28)	0.015* (1.95)	0.011** (2.48)	-0.017* (-1.81)
Panel D: Volatility related characteristics						
STDPRCVOL	0.033*** (3.07)	0.03*** (2.89)	0.026*** (3.23)	0.022** (2.49)	0.011** (2.44)	-0.022** (-2.44)
DAMIHUDD	0.011** (2.5)	0.021** (2.17)	0.032*** (3.87)	0.028** (2.54)	0.039*** (3.3)	0.028*** (2.67)

Liu *et al.* (2022) identified 10 predictive characteristics for cryptocurrency returns from a set of 24. Our study reveals an enhanced predictive capacity, with 14 characteristics demonstrating return predictability in our extended sample. This improvement stems from the inclusion of four additional predictors: MOM50, VOL, VOLSCALED, and DAMIHUDD. While our findings maintain consistency with Liu *et al.*'s directional patterns for long-short returns, we observe statistically significant nonzero returns for these characteristics. This discrepancy likely results from our extended sample period, which provides greater data volume and improved statistical power to detect significant relationships.

As can be seen in Panel A, the size-related characteristics such as market capitalization (MCAP), end of week price (PRC) and highest price of the week (MAXDPRC) all generate significantly negative long-short strategy returns. The greatest performance comes from the sorts on market capitalization, with the differential return between the highest and lowest quintiles being -6.64% and it is significantly different from zero at 1% level. The predicting power for the price and maximum price is similar and both generate long-short strategy returns that are around -2.5% with 5% significance levels.

In Panel B, we detail the outcomes for portfolios organized based on momentum-related predictors, including past returns over one, two, three, four, one-to-four, and fifty weeks. As the formation horizon for the momentum return extends from one week to two weeks, the performance of the long-short strategies improves, moving from 2.60%

to 3.65%. However, a further increase in the formation period leads to a decrease in returns, dropping to 3.30% for the three-week strategy, 1.53% for the four-week strategy, 1.47% for the one-to-four-week strategy, and ultimately turning negative for the 50-week strategy.

Panel C demonstrates that all tested volume-related characteristics have predictive power for future returns in cryptocurrency markets. Long coins with the lowest volume (VOL), price volume (PRCVOL), or scaled price volume (VOLSCALED) during the portfolio formation week, and short those with the highest values, can yield significant weekly returns of 1.72% to 2.75%.

In Panel D, we identify two effective volatility-related predictors: STDPRCVOL, which represents the log standard deviation of the price volume, and DAMIHUD, which calculates the average absolute daily return divided by price volume, during the portfolio formation week. The STDPRCVOL predictor achieves a return of -2.21% at a 5% significance level, while the DAMIHUD predictor delivers a return of 2.80% at a 1% significance level.

4.2 Explanatory power as a single factor

We examine that stylized momentum factors exhibit superior explanatory power for cryptocurrency portfolio returns compared to traditional market, size, and conventional momentum factors. We first consider the single factor model. We construct the residual momentum factors using the following steps. First, each week, we separate the coins into large and small groups using median market capitalization values from the preceding trading day. Second, within each size group, we sort coins into terciles (30%-40%-30%) based on cumulative residual returns (RMOM2 or RMOM3). We then construct value-weighted (VW) portfolio by long the highest 30% and short the lowest 30%. The factor return equals the aggregated return spread between long and short positions across both size groups. We use the identical steps for constructing information discreteness momentum factor⁷ (either independent or

⁷ Here we select the formation period that generate the best performance and one-week holding period to construct the factors. We use the Sharpe ratio as performance evaluation criteria.

sequential sorting on *ID* proxy). In total, we have four stylized momentum factors: $RESMOM_2, RESMOM_3, IDMOM_I$ and $IDMOM_S$). The procedure strictly follows Liu *et al.* (2022) to construct the conventional momentum factor.

Table 10 Single-Factor Explanatory Power of Stylized Momentum Factors: This table reports the regression results for single-factor models employing stylized momentum factors — residual momentum ($RESMOM_2, RESMOM_3$) and information discreteness momentum ($IDMOM_I, IDMOM_S$)—to explain High-Low portfolio returns for 14 significant return predictors. The regression models are:

$$R_t = \alpha + \beta_1 F_t + \varepsilon_t$$

where R_t is the portfolio return and F_t is the respective stylized momentum factor ($RESMOM_2, RESMOM_3, IDMOM_I, IDMOM_S$). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All stylized momentum factors are constructed using the same procedure as the CMOM factor of Liu *et al.* (2022). The t-statistics for α and β are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Panel A: $RMOM_2^{factor}$					
	α	$t(\alpha)$	β	$t(\beta)$	R^2
MCAP	-0.063***	(-8.29)	-0.154**	(-2.11)	0.009
PRC	-0.009	(-0.84)	-0.727***	(-6.84)	0.086
MAXDPRC	-0.008	(-0.70)	-0.734***	(-6.99)	0.09
MOM ₁	0.017	(1.47)	0.425***	(3.83)	0.029
MOM ₂	0.025**	(2.44)	0.552***	(5.67)	0.061
MOM ₃	0.023**	(2.57)	0.484***	(5.71)	0.062
MOM ₄	0.009	(1.15)	0.29***	(3.82)	0.029
MOM ₄₋₁	0.009	(1.22)	0.285***	(4.2)	0.034
MOM ₅₀	-0.012*	(-1.90)	0.024	(0.41)	0
VOL	-0.026***	(-2.82)	-0.068	(-0.77)	0.001
PRCVOL	-0.014	(-1.46)	-0.539***	(-5.98)	0.067
VOLSCALED	-0.009	(-0.90)	-0.403***	(-4.41)	0.038
STDPRCVOL	-0.012	(-1.31)	-0.487***	(-5.64)	0.06
DAMIHUDD	0.015	(1.45)	0.609***	(6.15)	0.071
Panel B: $RMOM_3^{factor}$					
	α	$t(\alpha)$	β	$t(\beta)$	R^2
MCAP	-0.062***	(-8.16)	-0.168**	(-2.39)	0.011
PRC	-0.011	(-0.98)	-0.562***	(-5.41)	0.056
MAXDPRC	-0.01	(-0.88)	-0.553***	(-5.38)	0.055
MOM ₁	0.015	(1.32)	0.443***	(4.15)	0.034
MOM ₂	0.025**	(2.45)	0.471***	(5)	0.048
MOM ₃	0.02**	(2.25)	0.549***	(6.83)	0.086
MOM ₄	0.009	(1.11)	0.266***	(3.63)	0.026
MOM ₄₋₁	0.007	(1.02)	0.31***	(4.77)	0.044
MOM ₅₀	-0.01	(-1.58)	-0.055	(-0.93)	0.002
VOL	-0.024***	(-2.64)	-0.129	(-1.51)	0.005
PRCVOL	-0.013	(-1.36)	-0.511***	(-5.88)	0.065
VOLSCALED	-0.009	(-0.96)	-0.329***	(-3.71)	0.027
STDPRCVOL	-0.01	(-1.15)	-0.484***	(-5.84)	0.064
DAMIHUDD	0.014	(1.37)	0.564***	(5.9)	0.065
Panel C: $IDMOM_I^{factor}$					
	α	$t(\alpha)$	β	$t(\beta)$	R^2
MCAP	-0.062***	(-8.19)	-0.093***	(-2.72)	0.015

PRC	-0.012	(-1.07)	-0.285***	(-5.60)	0.059
MAXDPRC	-0.011	(-0.98)	-0.276***	(-5.48)	0.057
MOM ₁	0.006	(0.53)	0.451***	(9.17)	0.145
MOM ₂	0.022**	(2.23)	0.318***	(7.03)	0.09
MOM ₃	0.019**	(2.23)	0.307***	(7.9)	0.112
MOM ₄	0.007	(0.87)	0.189***	(5.36)	0.055
MOM ₄₋₁	0.012*	(1.72)	0.053	(1.64)	0.005
MOM ₅₀	-0.01	(-1.64)	-0.025	(-0.89)	0.002
VOL	-0.026***	(-2.82)	-0.033	(-0.79)	0.001
PRCVOL	-0.012	(-1.34)	-0.283***	(-6.72)	0.083
VOLSCALED	-0.007	(-0.78)	-0.219***	(-5.12)	0.05
STDPRCVOL	-0.01	(-1.17)	-0.26***	(-6.45)	0.077
DAMIHUUD	0.014	(1.37)	0.311***	(6.69)	0.083
Panel D: $IDMOM_S^{factor}$					
	α	$t(\alpha)$	β	$t(\beta)$	R^2
MCAP	-0.064***	(-8.30)	-0.06*	(-1.65)	0.005
PRC	-0.012	(-1.03)	-0.282***	(-5.21)	0.052
MAXDPRC	-0.01	(-0.92)	-0.278***	(-5.19)	0.051
MOM ₁	0.002	(0.2)	0.51***	(9.91)	0.165
MOM ₂	0.02**	(2.04)	0.347***	(7.27)	0.096
MOM ₃	0.02**	(2.25)	0.284***	(6.8)	0.085
MOM ₄	0.008	(1.05)	0.15***	(3.96)	0.031
MOM ₄₋₁	0.011	(1.57)	0.073**	(2.13)	0.009
MOM ₅₀	-0.011*	(-1.76)	-0.008	(-0.26)	0
VOL	-0.027***	(-2.95)	-0.004	(-0.08)	0
PRCVOL	-0.015	(-1.55)	-0.224***	(-4.92)	0.046
VOLSCALED	-0.008	(-0.81)	-0.203***	(-4.45)	0.038
STDPRCVOL	-0.012	(-1.36)	-0.208***	(-4.78)	0.044
DAMIHUUD	0.013	(1.26)	0.32***	(6.49)	0.078

Table 10 (Panel A and B) presents findings that use the residual momentum factors ($RESMOM_2, RESMOM_3$) to explain the long-short returns of 14 predictive characteristics in cryptocurrency markets. Both $RESMOM_2, RESMOM_3$ factors exhibit similar efficacy in accounting for these characteristics' significant returns. Notably, most characteristics (excluding MOM50 and VOL) have statistically significant exposure to both $RESMOM_2, RESMOM_3$, with beta estimates ranging from -0.154 to -0.734 or 0.266 to 0.609. In the factor regression models, the inclusion of $RESMOM_2, RESMOM_3$ as factors renders the alphas statistically insignificant for 9 and 10 out of the 14 examined characteristics, respectively. However, the returns associated with certain characteristics, including MCAP, MOM2, MOM3, and VOL, remain unaccounted for despite significant exposure to the residual momentum factors.

The performances of the information discreteness momentum factors ($IDMOM_I$ and $IDMOM_S$) are detailed in Panels C and D of Table 10. These factors

exhibit similar behaviors, with most strategies (excluding MOM50 and VOL) having significant exposure to the information discreteness momentum factors. Beta estimates range from -0.06 to -0.285 or 0.073 to 0.451. Both factors can explain the significant returns associated with a highly overlapping set of 9 characteristics. However, the long-short returns from characteristics MCAP, MOM2, MOM3, and VOL remain significantly different from zero and are not explained by the information discreteness momentum factors⁸.

4.3 Explanatory power as multi-factors

We further investigate whether stylized momentum factors retain superior explanatory power in multifactor models. Specifically, we construct two-factor models incorporating four stylized momentum factors ($RESMOM_2, RESMOM_3$, $IDMOM_I$ and $IDMOM_S$) developed in Section 4.1 and compare their ability to explain excess returns from successful long-short strategies across 14 cryptocurrency characteristics against the three-factor model proposed by Liu *et al.* (2022).

Table 11 Performance of Multi-Factor Models: This table reports regression results for three multi-factor models used to explain the High–Low portfolio returns of the 14 return predictors that yield significant returns. Model (1) is a two-factor model using the residual momentum factor $RMOM_2^{factor}$ and the information discreteness momentum factor $IDMOM_I^{factor}$. Model (2) replaces $IDMOM_I^{factor}$ with $RMOM_3^{factor}$ and $IDMOM_I^{factor}$ with $IDMOM_S^{factor}$. Model (3) is the benchmark three-factor model constructed following Liu *et al.* (2022), which includes CMKT, CSMB, and CMOM. The regression specifications are as follows:

$$\begin{aligned} (1): R_t &= \alpha + \beta_1 RMOM_2^{factor} + \beta_2 IDMOM_I^{factor} + \varepsilon_t \\ (2): R_t &= \alpha + \beta_1 RMOM_3^{factor} + \beta_2 IDMOM_S^{factor} + \varepsilon_t \\ (3): R_t &= \alpha + \beta_1 CMKT_t + \beta_2 CSMB_t + \beta_3 CMOM_t + \varepsilon_t \end{aligned}$$

The t-statistics for α and each β coefficient are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All stylized momentum factors are constructed using the same procedure as CMOM in Liu *et al.* (2022).

		α	CMKT	CSMB	CMOM	$RMOM^{factor}$	$IDMOM^{factor}$	R^2
MCAP	(1)	-0.061***				-0.102	-0.078**	0.018
		(-7.92)				(-1.32)	(-2.16)	
	(2)	-0.061***				-0.145**	-0.036	0.013
		(-7.91)				(-1.96)	(-0.94)	

⁸ Regression results for the conventional factors—CMKT, CSMB, and CMOM—when used individually in one-factor models are reported in Online Appendix Table OA4. Compared to these benchmarks, the stylized momentum factors ($RESMOM_2, RESMOM_3$, $IDMOM_I$ and $IDMOM_S$) demonstrate superior explanatory power.

PRC	(3)	-0.015*** (-2.90)	0.016 (0.35)	-0.939*** (-27.05)	-0.017 (-0.44)			0.609
	(1)	-0.003 (-0.30)				-0.595*** (-5.38)	-0.196*** (-3.76)	0.111
	(2)	-0.004 (-0.39)				-0.433*** (-4.00)	-0.21*** (-3.73)	0.081
MAXDPRC	(3)	0.029*** (2.86)	-0.554*** (-6.00)	-0.872*** (-12.47)	0.091 (1.19)			0.308
	(1)	-0.002 (-0.18)				-0.61*** (-5.58)	-0.185*** (-3.58)	0.113
	(2)	-0.003 (-0.29)				-0.426*** (-3.97)	-0.207*** (-3.72)	0.081
MOM ₁	(3)	0.029*** (2.90)	-0.569*** (-6.20)	-0.846*** (-12.20)	0.109 (1.43)			0.304
	(1)	0.004 (0.34)				0.136 (1.24)	0.431*** (8.31)	0.147
	(2)	-0.0 (-0.01)				0.143 (1.36)	0.486*** (8.96)	0.168
MOM ₂	(3)	0.026** (2.27)	0.021 (0.19)	-0.072 (-0.89)	0.703*** (7.99)			0.114
	(1)	0.017* (1.68)				0.377*** (3.78)	0.261*** (5.56)	0.116
	(2)	0.016 (1.55)				0.287*** (2.98)	0.299*** (5.99)	0.112
MOM ₃	(3)	0.031*** (3.04)	-0.011 (-0.12)	0.047 (0.68)	0.742*** (9.76)			0.168
	(1)	0.015* (1.71)				0.308*** (3.59)	0.261*** (6.45)	0.134
	(2)	0.013 (1.48)				0.417*** (5.03)	0.215*** (4.99)	0.129
MOM ₄	(3)	0.027*** (3.13)	-0.017 (-0.22)	0.055 (0.93)	0.697*** (10.72)			0.197
	(1)	0.004 (0.53)				0.181** (2.31)	0.162*** (4.37)	0.065
	(2)	0.005 (0.64)				0.193** (2.52)	0.118*** (2.97)	0.043
MOM ₄₋₁	(3)	0.004 (0.57)	-0.121* (-1.76)	0.177*** (3.41)	0.566*** (9.92)			0.201
	(1)	0.008 (1.16)				0.277*** (3.87)	0.012 (0.35)	0.035
	(2)	0.006 (0.90)				0.295*** (4.30)	0.024 (0.68)	0.045
MOM ₅₀	(3)	0.01 (1.42)	-0.021 (-0.33)	0.054 (1.08)	0.378*** (6.93)			0.096
	(1)	-0.011* (-1.73)				0.048 (0.76)	-0.033 (-1.10)	0.003
	(2)	-0.01 (-1.58)				-0.056 (-0.89)	0.002 (0.07)	0.002
VOL	(3)	-0.01 (-1.46)	0.138** (2.34)	-0.068 (-1.52)	0.035 (0.69)			0.015
	(1)	-0.025*** (-2.71)				-0.051 (-0.55)	-0.025 (-0.57)	0.002
	(2)	-0.025*** (-2.67)				-0.141 (-1.57)	0.02 (0.43)	0.005
	(3)	-0.012 (-1.24)	0.104 (1.20)	-0.305*** (-4.65)	-0.024 (-0.33)			0.044

PRCVOL	(1)	-0.007 (-0.74)				-0.387*** (-4.18)	-0.225*** (-5.15)	0.114
	(2)	-0.008 (-0.83)				-0.415*** (-4.57)	-0.155*** (-3.29)	0.085
	(3)	0.028*** (3.52)	-0.23*** (-3.18)	-0.913*** (-16.70)	-0.085 (-1.41)			0.4
VOLSCALED	(1)	-0.003 (-0.34)				-0.285*** (-2.99)	-0.177*** (-3.94)	0.067
	(2)	-0.004 (-0.41)				-0.226** (-2.45)	-0.166*** (-3.45)	0.05
	(3)	0.026*** (2.92)	-0.309*** (-3.85)	-0.721*** (-11.91)	0.06 (0.91)			0.262
STDPRCVOL	(1)	-0.005 (-0.60)				-0.347*** (-3.90)	-0.208*** (-4.97)	0.105
	(2)	-0.006 (-0.65)				-0.397*** (-4.57)	-0.142*** (-3.15)	0.083
	(3)	0.025*** (3.09)	-0.255*** (-3.53)	-0.79*** (-14.43)	-0.076 (-1.27)			0.34
DAMIHUDD	(1)	0.008 (0.74)				0.445*** (4.37)	0.244*** (5.07)	0.117
	(2)	0.006 (0.61)				0.408*** (4.14)	0.252*** (4.92)	0.109
	(3)	-0.024*** (-2.64)	0.18** (2.14)	0.9*** (14.16)	0.183*** (2.62)			0.33

Table 11 summarizes the results. The four stylized momentum factors ($RESMOM_2$, $RESMOM_3$, $IDMOM_I$, and $IDMOM_S$), generate four possible two-factor combinations, each pairing one factor from the residual momentum and one from the information discreteness momentum. For brevity, we focus on the two extremes: Model 1 of $RESMOM_2$ and $IDMOM_I$ (least effective) and Model 2 of $RESMOM_3$ and $IDMOM_S$ (most effective), as shown in Table 11.

We focus on the significance of alphas to evaluate the effectiveness of the two-factor models in capturing the risk premium associated with specific characteristics. The results reveal a notable decline in alpha significance across most characteristics. Specifically, the number of characteristics exhibiting significant alphas ranges from 2 to 5 across the two-factor models. In the optimal two-factor model, none of the characteristics retain predictive power for future returns except MCAP and VOL. This contrasts with the three-factor model, where returns linked to 10 of the 14 characteristics remain statistically distinct from zero.

The results reveal three critical insights: First, both the least and most effective two-factor models explain significant alphas unresolved by three-factor model,

including size-related (PRC, MAXDPRC), momentum-related (MOM1, MOM4, MOM4-1), volume-related (VOL, PRCVOL, VOLSCALED), and volatility-related (STDPRCVOL, DAMIHUDD) characteristics. Second, for MOM2 and MOM3, the least effective two-factor model (Model 1) reduces alpha magnitude and significance compared to the three-factor, while the optimal two-factor model (Model 2) fully eliminates these alphas. Third, the three-factor model demonstrates unique strength in explaining MCAP and VOL-related returns due to its inclusion of the CSMB (cryptocurrency size) factor. Specifically, the alpha associated with the VOL characteristic becomes insignificant in the three-factor model, and the alpha related to the MCAP characteristic is significantly reduced compared to those in the two-factor models.

To ensure robustness, we replicate the analysis using Liu *et al.*'s (2022) 10 return predictors and matching their 2014-2020 timeframe (Table 12). The two-factor model combining $RESMOM_3$ and $IDMOM_S$ successfully explains the alphas of 9 out of 10 characteristics, emerging as the most effective combination. Only MCAP remains unexplained. Even the least effective model ($RESMOM_2$ and $IDMOM_I$) accounts for 7 characteristics, though the magnitudes and significance levels of MOM2 and MOM3 alphas are reduced. These results confirm the persistent explanatory power of stylized momentum factors across time horizons. The enduring excess returns linked to MCAP likely stem from its strong correlation with cryptocurrency market capitalization, a dimension not captured by momentum factors.

Table 12 Performance of Two-Factor Models Between 2014 and 2020: This table reports regression results for two-factor models using stylized momentum factors to explain the High–Low portfolio returns of the 14 return predictors that yield significant returns. Model (1) includes the residual momentum factor $RMOM_2^{factor}$ and the information discreteness momentum factor $IDMOM_I^{factor}$. Model (2) uses $RMOM_3^{factor}$ and $IDMOM_S^{factor}$. The sample period spans from January 2014 to July 2020, consistent with the sample window used by Liu *et al.* (2022). The regression specifications are:

$$(1): R_t = \alpha + \beta_1 RMOM_2^{factor}_t + \beta_2 IDMOM_I^{factor}_t + \varepsilon_t$$

$$(2): R_t = \alpha + \beta_1 RMOM_3^{factor}_t + \beta_2 IDMOM_S^{factor}_t + \varepsilon_t$$

The t-statistics for α and each β coefficient are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. All stylized momentum factors follow the same construction methodology as in Liu *et al.* (2022).

		Cons	t	$RMOM^{factor}$	t	$IDMOM^{factor}$	t	R2
MCAP	(1)	-0.075***	(-6.88)	-0.13	(-1.50)	-0.024	(-0.55)	0.009
	(2)	-0.073***	(-6.58)	-0.148*	(-1.73)	-0.034	(-0.79)	0.011
PRC	(1)	-0.014	(-0.90)	-0.388***	(-3.08)	-0.162**	(-2.53)	0.054
	(2)	-0.005	(-0.31)	-0.545***	(-4.43)	-0.191***	(-3.07)	0.081
MAXDPRC	(1)	-0.013	(-0.81)	-0.386***	(-3.08)	-0.144**	(-2.27)	0.05
	(2)	-0.004	(-0.23)	-0.537***	(-4.39)	-0.173***	(-2.80)	0.076
MOM ₁	(1)	0.009	(0.58)	0.076	(0.66)	0.573***	(9.65)	0.227
	(2)	-0.003	(-0.20)	0.409***	(3.60)	0.576***	(10.02)	0.255
MOM ₂	(1)	0.023*	(1.70)	0.161	(1.50)	0.428***	(7.86)	0.173
	(2)	0.012	(0.91)	0.438***	(4.21)	0.439***	(8.35)	0.209
MOM ₃	(1)	0.028**	(2.36)	0.224**	(2.41)	0.283***	(5.98)	0.125
	(2)	0.016	(1.36)	0.524***	(5.92)	0.298***	(6.66)	0.194
MOM ₄	(1)	0.003	(0.28)	0.32***	(3.99)	0.185***	(4.54)	0.116
	(2)	0.002	(0.17)	0.237***	(2.95)	0.211***	(5.20)	0.098
MOM ₄₋₁	(1)	0.009	(0.92)	0.236***	(3.11)	0.074*	(1.93)	0.045
	(2)	0.004	(0.44)	0.295***	(3.97)	0.092**	(2.46)	0.062
PRCVOL	(1)	-0.022	(-1.60)	-0.338***	(-3.15)	-0.108**	(-1.97)	0.047
	(2)	-0.012	(-0.90)	-0.515***	(-4.94)	-0.133**	(-2.52)	0.085
STDPRCVOL	(1)	-0.02	(-1.51)	-0.289***	(-2.80)	-0.093*	(-1.77)	0.037
	(2)	-0.01	(-0.76)	-0.496***	(-4.98)	-0.114**	(-2.25)	0.083

Our analysis reveals two critical insights: First, the stylized momentum factors - residual momentum and information discreteness momentum - demonstrate robust performance in explaining anomalous returns linked to cryptocurrency characteristics. Using the optimal combination ($RMOM_3^{factor}$ and $IDMOM_S^{factor}$ factors), our model accounts for abnormal returns associated with 12 of 14 characteristics across the full sample period (2014 - 2023), including the post-2020 structural market shift (see Blandin et al. 2020). Second, MCAP and VOL remain exceptions: VOL-related excess returns are fully explained by Liu *et al.*'s three-factor model, whereas MCAP persists as an unexplained anomaly even under this framework. This underscores MCAP's strong connection to cryptocurrency market capitalization, a dimension uncaptured by momentum-based factors.

5. Mechanism of stylized momentum factors

In this section, we investigate the underlying mechanisms responsible for the predictability of conventional and stylized momentum strategies, and explanatory power of their corresponding factors in cryptocurrency market. Our discussion distinguishes between underreaction and overreaction - two extensively documented sources of momentum in equity markets - to determine whether these behavioral

mechanisms hold in cryptocurrency markets.

The equity market's momentum effect originates from two competing behavioral mechanisms: underreaction, driven by delayed price adjustments due to investors' conservatism bias (slow belief updating; Barberis *et al.*, 1998), cognitive dissonance (ignoring contradictory information; Antoniou *et al.*, 2013), or heterogeneous information processing across investors, leading to gradual price incorporation (Hong and Stein, 1999)—particularly for assets with small, steady returns (Da *et al.*, 2014); and overreaction, where overconfidence and self-attribution bias (Daniel *et al.*, 1998) or limited attention combined with speculative trading (Peng and Xiong, 2006) amplify price trends, especially for high-visibility securities, as empirically validated by Hou *et al.* (2009). These dual frameworks—slow correction versus speculative overshooting—underscore the subtle origins of momentum.

5.1 Persistence of the momentum effects

To differentiate the underreaction and the overreaction explanations of the momentum effects, we begin with investigating the persistency of the momentum returns over long horizons given that the premia caused by overreaction will likely to reverse while that by underreaction will likely not. Following the methodology of Liu *et al.* (2022) and consistent with our factor model construction, we select the optimal strategy within each momentum group (residual or information discreteness momentum strategies) based on performance at the one-week holding period. For each group, we retain only the top-performing combination (formation/holding periods) to serve as the primary measure in subsequent analysis, ensuring comparability across strategies. Further, as shown before, the two residual momentum factors (i.e., $RESMOM_2$ or $RESMOM_3$) behave very similar to each other and so does the two information discreteness momentum factors (i.e., $IDMOM_I$ or $IDMOM_S$), we only select one from each group for brevity.

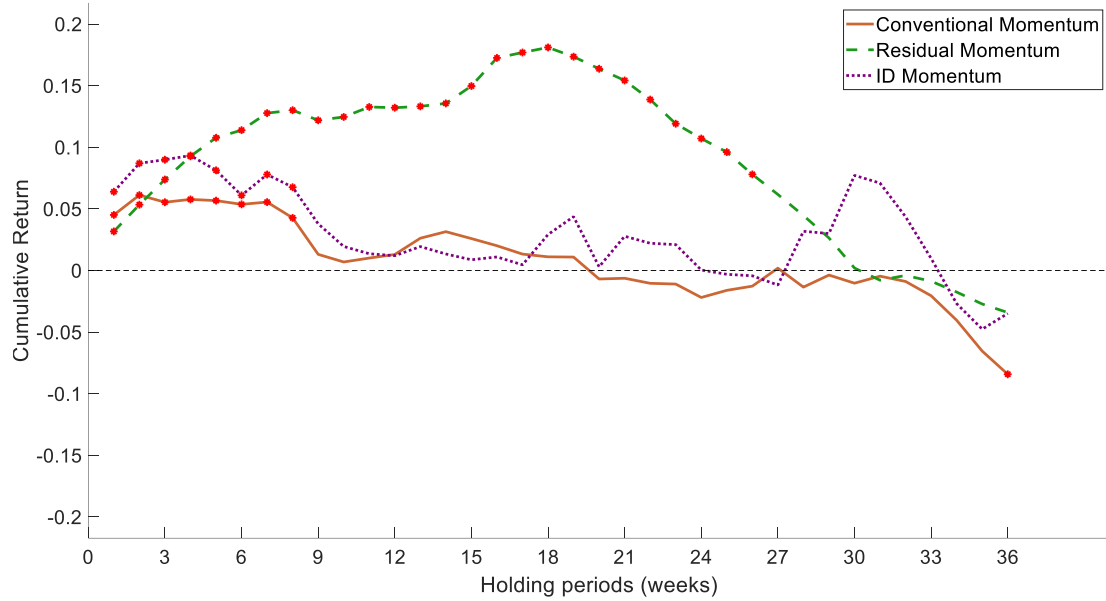


Figure 1 Cumulative Returns of Momentum Strategies Over Time: This figure shows the cumulative weekly returns from week 1 to week 36 following portfolio formation for the three momentum strategies: conventional momentum, residual momentum, and information discreteness momentum. All strategies are constructed using their optimal configurations, selected based on the highest Sharpe ratios. Asterisks (*) indicate weeks in which the weekly return is statistically significant at the 10% level or better. The x-axis represents weeks since formation; the y-axis shows cumulative returns.

Following previous literature (Jegadeesh and Titman, 1993; Medhat and Schmeling, 2021), for each selected strategy, we calculate the average cumulative sums of holding period returns over the 36 weeks period.⁹ In Figure 1, we report the cumulative values for the conventional momentum premium, the RMOM and the IDMOM premia between week 1 and week 36. The stars * on the lines indicate that relevant returns at that week have at least 10% statistical significance.

From Figure 1, we can see that the returns from the RMOM strategy continuous to increase when the investment horizon increases, and it only starts the downward trend from week 19 and the cumulative return does not turn negative until around week 30. By contrast, the reversal in the conventional momentum premium begins as early as week 8 and it also becomes statistically insignificant at this time. This contrasting pattern between the long-term performance of the *c_mom* and RMOM is similar to

⁹ Jegadeesh and Titman (1993) used a holding period of up to 36 months to examine the long-term persistency of conventional momentum strategy in the equity market. For the cryptocurrency market, we therefore use 36-week horizon as the long-term horizon. We find that the 36-week horizon is sufficient to demonstrate the post-formation pattern of strategy returns.

those in the equity market in which the c_mom reverses strongly while the RMOM continuous for years (Gutierrez and Pirinsky, 2007). It suggests that compared with the c_mom , the RMOM premium in our sample is more likely to be caused by investor underreaction. On the contrary, the c_mom in our sample is more likely to be caused by investor overreaction. This conjecture of the c_mom is also consistent with that in the Liu *et al.* (2022).

Similar to the c_mom , the return from the IDMOM also reverses quite rapidly. The turning point of the cumulative return starts in week 4, even earlier than that of the conventional momentum strategy. The cumulative return of this strategy also becomes statistically insignificant at week 8. Such finding is inconsistent with that of the equity market displayed in Da *et al.* (2014). In the equity market, the holding period return of the IDMOM remains to be significantly positive over a long horizon. The pattern of the post-formation return for the information discreteness momentum in the cryptocurrency market is more consistent with the overreaction rather than the underreaction explanation. This rapid mean reversion is consistent with the speculative episodes documented by Li, Shin, and Wang (2025), who show that retail-driven 'pump-and-dump' schemes lead to immediate price reversals as insiders transfer wealth from naive investors who reinforce their learning based on short-term price jumps.

5.2 Relationship between size, volume and the momentum returns

Investigating the relationship between momentum excess returns and cryptocurrency characteristics-particularly size (market capitalization) and trading volume, two measures central to momentum literature - provides critical insights into the drivers of cryptocurrency momentum effects. By conducting a cross-sectional analysis of momentum premia across coins stratified by size and volume, we isolate how these liquidity- and attention-driven attributes vary the strength and persistence of momentum returns, thereby testing competing behavioral explanations (e.g., underreaction vs. overreaction) in a market characterized by asymmetric information and speculative trading.

At each week, we divide our sample into two groups based on the median value of market capitalization or trading volume in the previous week.¹⁰ We then construct the conventional or stylized momentum strategy within each group. In Table 13, we report long-short returns for the different momentum strategies in sub-samples grouped by size or volume. In Figure 2, we plot the long-term performance of these momentum premia among coins with large size or high volume.

Table 13 Performance of Momentum Strategies Across Size and Volume Groups: This table reports the weekly performance of three momentum strategies: conventional momentum (*c_mom*), residual momentum (RMOM), and information discreteness momentum (IDMOM)—within different subsamples sorted by size and trading volume. Coins are first independently sorted into two groups based on their size or trading volume: above- and below-median. Within each subgroup, long-short portfolios are constructed following the procedures of each strategy. The reported returns are weekly mean returns of value-weighted, weekly rebalanced portfolios. T-statistics are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

	Size-sorted groups		Volume-sorted groups	
	Large Size	Small Size	High Volume	Low Volume
c_mom	0.041*** (4.67)	0.006 (0.67)	0.042*** (3.97)	0.027*** (2.89)
RMOM	0.03*** (5.0)	0.016* (1.89)	0.029*** (4.56)	0.04*** (3.36)
IDMOM	0.059*** (4.2)	0.028 (1.51)	0.051*** (3.29)	0.054*** (2.85)

¹⁰ Following Liu *et al.* (2022), we use the price volume as our trading volume measure.

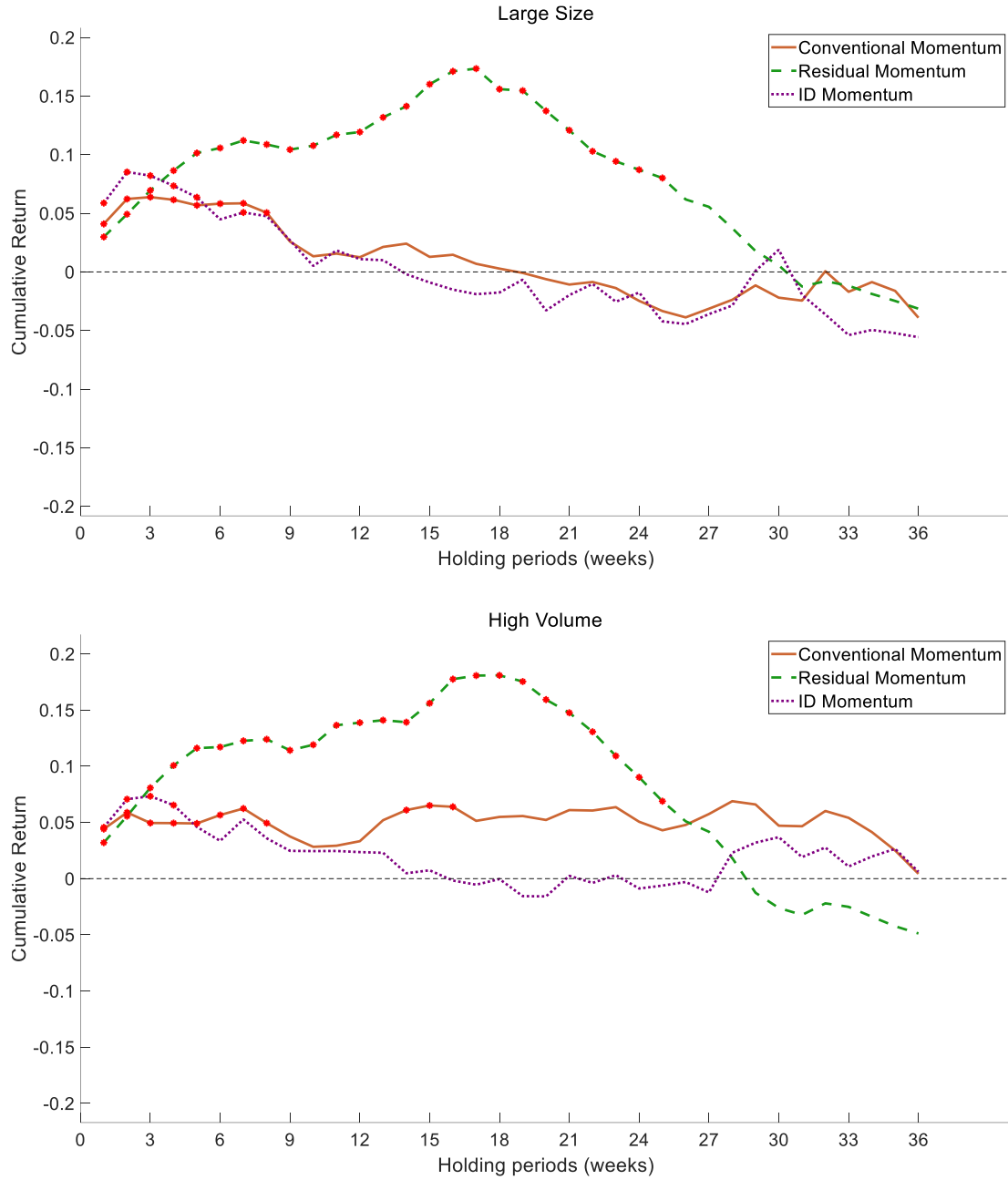


Figure 2 Momentum Return Persistence Among Large-Size and High-Volume Coins: This figure presents the 36-week cumulative post-formation returns for the conventional momentum, residual momentum, and information discreteness momentum strategies across two subsamples: (top) large-size cryptocurrencies and (bottom) high-volume cryptocurrencies. The large-size sample includes coins with above-median market capitalization at portfolio formation; the high-volume sample includes those with above-median trading volume over the prior 7 days. Asterisks (*) mark weeks with statistically significant returns at the 10% level or better.

Table 13 demonstrates that conventional momentum premia are markedly stronger in large-cap and high-volume cryptocurrencies compared to their small-cap and low-volume counterparts, consistent with Liu *et al.* (2022)'s evidence linking momentum

strength to investor attention (proxied by size and volume). Figure 2 further reveals a rapid reversal pattern in large-cap coins, aligning with the attention-driven overreaction hypothesis (Peng and Xiong, 2006). Among high-volume coins, while the reversal trend is less pronounced than in large-cap cohorts, premia diminish to statistical insignificance relatively quickly, mirroring the transient nature of attention-driven momentum. This asymmetry - swift correction in high-attention assets versus slower mean reversion in illiquid groups—supports the view that investor attention amplifies speculative overreaction in cryptocurrency markets, where continuous trading and retail participation exacerbate behavioral biases.

For the information discreteness momentum effect, Table 13 shows stronger returns in larger cryptocurrencies and those with high trading volume, though the difference between high- and low-volume groups is minor. Figure 2 reveals that in these larger, actively traded coins, the overall pattern of returns over time looks similar to the full market but reverses earlier - starting around weeks 2-3 - with returns fading to insignificance within 10 weeks. This quick reversal supports the idea that investors overreact when focusing too much on gradual price trends, unlike stock markets where slow price changes usually mean investors *underreact* (Da *et al.*, 2014).

We suggest that because cryptocurrency prices swing wildly and often, small, steady price changes stand out more in this environment. This aligns with the 'Trend Factor' proposed by Fieberg *et al.* (2025), who find that technical trend signals carry superior predictive power for the cross-section of returns. While their trend factor emphasizes risk-adjusted momentum, our IDMOM results suggest that the 'smoothness' of such trends (information discreteness) is a key behavioral trigger that leads to speculative overreaction among retail investors. These gradual trends - rare compared to sudden jumps-grab investors' attention more strongly, leading them to assume these trends will continue longer than they actually do. This overreaction creates short-lived returns that disappear quickly as attention shifts or less experienced traders sell their holdings. The difference between cryptocurrencies and stocks highlights how cryptocurrency's lack of clear fundamentals and heavy retail trading

activity make investors more prone to overreacting to unusual price patterns.

For residual momentum returns, we find that profits generated from trading on subtle, non-trending price patterns - are stronger in larger cryptocurrencies and those with high trading volume. Unlike conventional momentum, these returns persist over longer periods, as shown in Figure 2. This initially appears contradictory: long-term persistence aligns with underreaction theory, which posits that investors slowly absorb new information. However, underreaction is typically associated with smaller, less-traded assets (Hong and Stein, 1999), not the large, liquid ones observed here.

This paradox mirrors findings in equity markets. Medhat and Schmeling (2021) demonstrate that short-term momentum in stocks also concentrates in large, liquid companies. They explain this through two mechanisms. First, bounded rationality means traders often fail to infer hidden information from prices, leading to underreaction even in widely followed assets. Second, large, liquid assets experience fewer distortions from temporary trading activity, such as sudden liquidity-driven sell-offs (Campbell et al., 1993). This allows underreaction-driven momentum to dominate over time, as transient price pressures reverse less frequently in these assets.

In cryptocurrency markets, residual momentum isolates subtle price shifts obscured by market noise. These signals are harder to detect than raw price trends, causing investors to underreact - particularly in large, liquid coins where liquidity buffers against short-term distortions. This creates a unique subtle momentum effect: less noticeable price patterns in heavily traded assets generate stronger, longer-lasting returns. The cryptocurrency market's structure amplifies this phenomenon. Unlike stocks, cryptocurrencies lack fundamentals like earnings to anchor prices, magnifying underreaction to technical signals. Furthermore, Babiak and Bianchi (2025) demonstrate that systematic mispricing is pervasive in cryptocurrencies and is often captured by coin-specific characteristics. Their finding that mispricing delivers significant alpha across different liquidity tiers supports our evidence that RMOM can persist even in large, liquid assets where behavioral frictions - rather than just limits to arbitrage - dominate price formation. Additionally, retail traders - who dominate

cryptocurrency markets - are more prone to overlook subtle residual trends. Extreme volatility further masks gradual shifts, making residual patterns both harder to identify and more impactful once recognized.

These dynamics explain why cryptocurrency residual momentum defies traditional theories. The market's emerging nature, retail dominance, and volatility create conditions where underreaction manifests unexpectedly in large, liquid assets. This underscores the importance of studying cryptocurrency through a behavioral lens, as its structure transforms conventional financial theories into unique, amplified phenomena.

In summary, our findings highlight that both conventional and information discreteness momentum effects in cryptocurrency markets primarily stem from investor overreaction, which intensifies with higher investor attention (proxied by size and volume). The superior performance of information discreteness momentum strategies (Section 3.3) suggests cryptocurrency investors exhibit stronger overreaction to gradual, incremental price changes-contrasting sharply with equity markets, where such patterns reflect underreaction (Da *et al.*, 2014). This divergence underscores cryptocurrency's unique behavioral dynamics. Paradoxically, despite overreacting to price trends, investors underreact to coin-specific fundamental information, revealing a layered inefficiency in decentralized markets where speculative price responses coexist with neglect of idiosyncratic signals.¹¹ This dual-mechanism framework extends the growing consensus in the literature (e.g., Babiak and Bianchi, 2025; Fieberg et al., 2025) that cryptocurrency returns are a complex blend of systematic trend-following and pervasive mispricing. By identifying how information structure (residual vs. discrete) dictates the direction of behavioral bias, we provide a more granular map of the inefficiencies in decentralized digital markets.

6. Robustness analysis

This section evaluates the robustness of the baseline momentum strategies

¹¹ Online Appendix Figure OA1 presents the long-term performance for the small size and low volume groups, confirming our earlier conclusion as discussed in the main text.

introduced in Sections 3 and 4, focusing on their real-world practicality and sustained profitability under varying market conditions. We perform a battery of empirical tests.

6.1 Subsample analysis

Our sample data covers the periods from January 2014 to August 2023, extending the sample period studied by Liu *et al.* (2022) - which ended in July 2020 - by over three years. This extended timeframe allows us to evaluate momentum strategies across two distinct eras: the earlier "retail-dominated" phase (2014–2020) and the post-2020 period marked by growing institutional adoption (e.g., Bitcoin futures ETFs), stricter regulations (e.g., MiCA in the EU), the rise of stablecoins like USDT and USDC, and the rapid growth of decentralized finance (DeFi) platforms. Additionally, Bitcoin's block reward halving in 2016 and 2020 reduced mining incentives, altering supply dynamics (Blandin et al. 2020). These structural shifts raise two questions: First, did the momentum strategies identified by Liu *et al.* (2022) retain their profitability in the post-2020 environment? Second, given that our extended sample still spans fewer than ten years—a short window for an emerging, volatile asset class - how reliable are conclusions drawn from such limited data? While our results provide insights, the cryptocurrency market's youth and constant evolution necessitate caution when generalizing findings, as its risk-return patterns may still be stabilizing.

To evaluate whether the momentum strategies remain robust amid structural market shifts, we divide the sample period into two intervals: the **pre-2020 era** (January 2014–July 2020), aligning with Liu *et al.* (2022), and the **post-2020 era** (August 2020–August 2023), characterized by institutionalization and regulatory evolution. This division allows us to test whether the strategies' profitability persisted after the market's inflection point in 2020. For both sub-periods, we calculate three key metrics: the mean holding-period return (Return), its statistical significance (t-statistics), and the annualized Sharpe ratio (SR), which adjusts returns for volatility. Results are summarized in Table 14.

Table 14 Performance of the Momentum Strategies in in Pre- and Post-2020 Periods: This table presents the

performance of the stylized momentum strategies across two subsample periods: January 2014 to July 2020 and August 2020 to August 2023. Each strategy is evaluated under its optimal configuration, defined by the highest annualized Sharpe ratio. The reported returns are weekly means of value-weighted, weekly rebalanced long-short portfolios. Sharpe ratios are annualized. T-statistics are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

		Jan 2014-Jul 2020	Aug 2020-Aug 2023
RMOM	Return	0.039***	0.015**
	t-stats	(4.84)	(2.4)
	SR	1.89	1.37
IDMOM	Return	0.081***	0.027***
	t-stats	(3.94)	(2.83)
	SR	1.54	1.62

Both strategies demonstrate stronger performance in the pre-2020 sub-period, with higher mean returns and Sharpe ratios. However, they retain economically meaningful profitability and robust risk-adjusted returns (Sharpe ratios > 1) in the post-2020 era. For the RMOM strategy, the average monthly return declines from 3.94% (2014–2020) to 1.51% (2020–2023), though its Sharpe ratio shows only a modest reduction from 1.89 to 1.37. The IDMOM strategy experiences a sharper drop in raw returns, falling from 8.10% to 2.74%, yet remains statistically significant post-2020. Notably, its Sharpe ratio improves from 1.54 to 1.62, reflecting a substantial reduction in portfolio volatility after mid-2020.

These results highlight two key insights: Resilience to structural shifts: Despite market maturation - marked by institutional participation, regulatory changes, and DeFi growth - both strategies retain alpha-generating capacity, with Sharpe ratios consistently exceeding 1. Risk dynamics divergence: While residual momentum's return erosion aligns with rising market efficiency, IDMOM's enhanced Sharpe ratio suggests improved stability, likely due to reduced speculative noise as institutional traders entered the market.

In summary, the stylized momentum strategies exhibit enduring efficacy even amid the cryptocurrency market's post-2020 transformation. Their sustained risk-adjusted performance underscores their adaptability to evolving market structures.

6.2 The impact of transaction cost

A critical concern for the feasibility and profitability of stylized momentum strategies lies in their vulnerability to transaction costs. These strategies, which require weekly portfolio rebalancing, face amplified trading expenses due to the high turnover inherent in cryptocurrency markets. Recent research by Han *et al.* (2024) estimates an average transaction cost of 15 basis points (bps) on Binance, the largest cryptocurrency exchange by trading volume. However, actual costs can vary significantly across three dimensions: *platform*, *asset type*, and *market timing*. For instance, centralized exchanges like Coinbase offer tiered fee structures that favor institutional traders, while decentralized platforms (e.g., Uniswap) often incur higher slippage. Similarly, trading highly liquid assets like Bitcoin may cost less than 5 bps, whereas small-cap altcoins could exceed 50 bps due to thinner order books. Market volatility further compounds these costs—spreads widen sharply during events like the 2022 Terra/Luna collapse, disproportionately impacting retail traders.

To address this uncertainty, we simulate net returns across a broad transaction cost range, ranging from 1 bp (reflecting optimized institutional execution) to 30 bps (capturing worst-case scenarios for illiquid assets or retail traders). This approach ensures our analysis remains robust across diverse trading environments, from calm market conditions to periods of extreme volatility. By stress-testing profitability against these thresholds, we quantify how transaction costs erode returns and determine the breakeven point for strategy viability.

Table 15 compares raw returns with net returns adjusted for transaction costs across a range of scenarios. Even at 15 basis points (bps)—the estimated average cost on Binance—both strategies retain approximately 80% to 90% of their raw returns, with adjusted returns remaining statistically significant. At the upper-bound 30 bps threshold, which simulates worst-case scenarios (e.g., trading illiquid altcoins during volatility), the strategies demonstrate notable resilience. For instance, the RMOM strategy preserves over 60% of its raw return, while IDMOM shows similar robustness.

Table 15 The Impacts of Transaction Costs on the Momentum Strategy Return: This table reports the net weekly returns of the optimal stylized momentum strategies after adjusting for transaction costs ranging from 1 to 30 basis

points (bps). Raw returns represent gross portfolio performance, while adjusted returns simulate costs faced by different trader types. Strategies are based on the highest Sharpe ratio configurations. All returns are value-weighted and weekly rebalanced. Sharpe ratios are annualized. T-statistics are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

		Raw Return	1bps	5bps	10bps	15bps	20bps	25bps	30bps
RMOM	Return	0.032***	0.031***	0.03***	0.028***	0.026***	0.024***	0.022***	0.020***
	t-stats	(5.35)	(5.28)	(5.01)	(4.67)	(4.33)	(4)	(3.66)	(3.32)
	SR	1.73	1.7	1.62	1.51	1.4	1.29	1.18	1.07
IDMOM	Return	0.064***	0.063***	0.062***	0.06***	0.058***	0.056***	0.054***	0.052***
	t-stats	(4.44)	(4.41)	(4.3)	(4.16)	(4.02)	(3.89)	(3.75)	(3.61)
	SR	1.43	1.43	1.39	1.34	1.3	1.25	1.21	1.16

These results highlight two critical insights: Cost resilience: Weekly rebalancing, while costly, does not erode the core profitability of momentum strategies. Even under punitive transaction costs, the strategies retain economically meaningful returns. Market adaptability: The cryptocurrency market’s structural features—such as high liquidity for major coins and 24/7 trading—mitigate cost impacts compared to traditional markets, where similar strategies might falter.

In summary, Table 15 underscores the robustness of stylized momentum strategies in cryptocurrency markets. Despite transaction costs, their risk-adjusted returns remain compelling, suggesting their viability even for cost-sensitive traders.

6.3 The impact of short sale constraint

A structural constraint in cryptocurrency markets is the limited availability of short-selling mechanisms for most coins - particularly smaller altcoins - due to fragmented liquidity, regulatory barriers, and lack of institutional infrastructure. This raises practical concerns: if short positions are inaccessible, momentum strategies must rely exclusively on long portfolios, which could dilute profitability. To quantify this risk, Table 16 decomposes the performance of each strategy into its long and short components, alongside the long portfolio’s contribution ratio (the proportion of total returns attributable to long positions).

Table 16 The Contribution of the Long Portfolios on the Strategy Performance: This table decomposes the performance of the optimal stylized momentum strategies into their long and short components. Reported values include the weekly mean returns and corresponding t-statistics of each leg. The final column shows the contribution

of the long leg as a proportion of the total long-short portfolio return. Strategies are selected based on configurations with the highest annualized Sharpe ratios. All portfolios are value-weighted and weekly rebalanced. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Long		Short		Long side contribution %
	Return	t-stats	Return	t-stats	
RMOM	0.028***	(3.74)	-0.004	(-0.78)	87.30%
IDMOM	0.057***	(3.98)	-0.007	(-0.96)	88.45%

From Table 16, we can see that the profitability of the RMOM and IDMOM strategies stem mostly from the portfolios of the long side, with 87.3% and 88.45% of the long-short returns contributed by the long portfolio, respectively. Additionally, the returns of their long portfolios are significant at the 1% level, while those of the short portfolios are not statistically significant.

The results reveal two critical insights: Long-driven profitability - this asymmetry suggests that even without shorting, the strategies retain substantial alpha from long exposure alone. Market inefficiency - the outsized long contributions align with cryptocurrency markets' inherent momentum bias, where retail-driven speculation amplifies upward price trends more readily than corrections. These findings imply that while short constraints pose a theoretical challenge, the long portfolio's dominance - coupled with cryptocurrency's volatility asymmetry - preserves strategy viability. Traders unable to short could replicate results using derivatives (e.g., futures for broad exposure) or focus solely on long positions, albeit with reduced but still significant returns.

7. Conclusion

This study provides a comprehensive examination of momentum dynamics in cryptocurrency markets, analyzing their profitability, explanatory power, and underlying behavioral mechanisms over a transformative decade (2014–2023). By adapting equity-market frameworks to the unique microstructure of digital assets—characterized by 24/7 trading and retail-driven liquidity—we demonstrate that stylized momentum factors, specifically **Residual Momentum (RMOM)** and **Information**

Discreteness (IDMOM), are fundamental drivers of the cross-section of cryptocurrency returns. Our findings persist across various market regimes, institutional adoption phases, and rigorous robustness checks, including transaction costs and short-sale constraints.

The central contribution of this research lies in disentangling the concurrent behavioral channels that govern cryptocurrency pricing. Our evidence of a behavioral duality—where underreaction and overreaction coexist—provides a granular micro-level explanation for the systematic mispricing components identified by Babiak and Bianchi (2025). We uncover a striking **behavioral duality**: while RMOM exhibits sustained profitability consistent with **investor underreaction** to idiosyncratic signals, IDMOM generates transient returns that reverse rapidly, signaling a **speculative overreaction** to the structure of information arrival. This distinction challenges the "one-size-fits-all" behavioral explanations prevalent in earlier literature. In particular, the transformation of the "frog-in-the-pan" effect—from a signal of underreaction in equities to an indicator of "flash-in-the-pan" overreaction in cryptocurrencies—highlights a fundamental cross-market divergence in how investors process continuous versus discrete information.

Furthermore, our stylized two-factor model demonstrates superior explanatory power in the cryptocurrency return space. By capturing the premiums associated with 12 out of 14 prominent coin characteristics, we provide evidence that residual returns and information discreteness are not mere anomalies but are central to the risk-return framework of digital assets. The persistence of these effects, even as the market matured post-2020 with increased institutional participation and regulatory oversight, underscores the structural nature of these inefficiencies. While the market has evolved, the psychological frictions—ranging from limited attention to speculative herding—remain deeply embedded in the decentralized trading ecosystem.

From a practical perspective, our results offer a blueprint for systematic trading in cryptocurrency. The resilience of RMOM, which derives the majority of its alpha from long positions, provides a viable strategy even in the presence of fragmented liquidity

and short-selling barriers. However, the high volatility and rapid mean reversion of IDMOM caution against passive trend-following, suggesting that opportunistic trading in this space requires a sophisticated understanding of investor attention cycles.

In conclusion, this paper bridges the gap between traditional asset pricing theory and the idiosyncratic nature of cryptocurrency markets. We show that these markets reward strategies that can successfully navigate the tension between slow information diffusion and rapid speculative bursts. As the digital asset class continues to integrate with global financial systems, our findings provide a replicable framework for understanding the evolving boundaries of market efficiency and the persistent role of human behavior in shaping asset valuations. Future research may build upon this by exploring the causal links between decentralized governance structures and the long-term evolution of these momentum dynamics.

Reference

- Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31–56. [https://doi.org/10.1016/S1386-4181\(01\)00024-6](https://doi.org/10.1016/S1386-4181(01)00024-6)
- Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *The Review of Financial Studies*, 28(1), 33–72. <https://doi.org/10.1093/rfs/hhu059>
- Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259–299. <https://doi.org/10.1111/j.1540-6261.2006.00836.x>
- Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, 48(1), 245–275. <https://doi.org/10.1017/S0022109012000692>
- Babiak, M., & Bianchi, D. (2025). Mispricing and risk compensation in cryptocurrency returns. *Journal of Financial and Quantitative Analysis*. Advance online publication. <https://doi.org/10.1017/S0022109025102329>
- Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2), 427–446. <https://doi.org/10.1016/j.jfineco.2010.08.014>
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18. [https://doi.org/10.1016/0304-405X\(81\)90018-0](https://doi.org/10.1016/0304-405X(81)90018-0)
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307–343. [https://doi.org/10.1016/S0304-405X\(98\)00027-0](https://doi.org/10.1016/S0304-405X(98)00027-0)
- Barry, C. B., & Brown, S. J. (1984). Differential information and the small firm effect. *Journal of Financial Economics*, 13(2), 283–294. [https://doi.org/10.1016/0304-405X\(84\)90026-6](https://doi.org/10.1016/0304-405X(84)90026-6)
- Blandin, A., Pieters, G., Wu, Y., Eisermann, T., Dek, A., Taylor, S., & Njoki, D. (2020). *3rd global cryptoasset benchmarking study*. Cambridge Centre for Alternative Finance, University of Cambridge Judge Business School. <https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/publications/3rd-global-cryptoasset-benchmarking-study/>
- Blitz, D., Huij, J., & Martens, M. (2011). Residual momentum. *Journal of Empirical Finance*, 18(3), 506–521. <https://doi.org/10.1016/j.jempfin.2011.01.003>
- Cai, C. X., & Zhao, R. (2024). Salience theory and cryptocurrency returns. *Journal of Banking & Finance*, 159, 107052. <https://doi.org/10.1016/j.jbankfin.2023.107052>
- Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics*, 108(4), 905–939. <https://doi.org/10.2307/2118454>
- Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics*, 59(1), 3–32. [https://doi.org/10.1016/S0304-405X\(00\)00080-5](https://doi.org/10.1016/S0304-405X(00)00080-5)
- Da, Z., Gurun, U. G., & Warachka, M. (2014). Frog in the pan: Continuous information and

- momentum. *The Review of Financial Studies*, 27(7), 2171–2218. <https://doi.org/10.1093/rfs/hhu003>
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), 1839–1885. <https://doi.org/10.1111/0022-1082.00077>
- De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793–805. <https://doi.org/10.1111/j.1540-6261.1985.tb05004.x>
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636. <https://doi.org/10.1086/260061>
- Fieberg, C., Liedtke, G., Poddig, T., Walker, T., & Zaremba, A. (2025). A trend factor for the cross section of cryptocurrency returns. *Journal of Financial and Quantitative Analysis*, 60(7), 3116–3153. <https://doi.org/10.1017/S0022109024000747>
- George, T. J., & Hwang, C.-Y. (2004). The 52-week high and momentum investing. *The Journal of Finance*, 59(5), 2145–2176. <https://doi.org/10.1111/j.1540-6261.2004.00695.x>
- Gutierrez, R. C., & Prinsky, C. A. (2007). Momentum, reversal, and the trading behaviors of institutions. *Journal of Financial Markets*, 10(1), 48–75. <https://doi.org/10.1016/j.finmar.2006.09.002>
- Hackethal, A., Hanspal, T., Lammer, D. M., & Rink, K. (2022). The characteristics and portfolio behavior of Bitcoin investors: Evidence from indirect cryptocurrency investments. *Review of Finance*, 26(4), 855–898. <https://doi.org/10.1093/rof/rfab034>
- Han, C., Kang, B., & Ryu, J. (2023). Time-series and cross-sectional momentum in the cryptocurrency market: A comprehensive analysis under realistic assumptions. *SSRN*. <https://doi.org/10.2139/ssrn.4675565>
- Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, 55(1), 265–295. <https://doi.org/10.1111/0022-1082.00206>
- Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6), 2143–2184. <https://doi.org/10.1111/0022-1082.00184>
- Hou, K., Peng, L., & Xiong, W. (2009). A tale of two anomalies: The implications of investor attention for price and earnings momentum [Working paper]. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.976394>
- Hou, K., & Moskowitz, T. J. (2005). Market frictions, price delay, and the cross section of expected returns. *The Review of Financial Studies*, 18(3), 981–1020. <https://doi.org/10.1093/rfs/hhi023>
- Huang, S., Lee, C. M. C., Song, Y., & Xiang, H. (2022). A frog in every pan: Information discreteness and the lead-lag returns puzzle. *Journal of Financial Economics*, 145(2, Part A), 83–102. <https://doi.org/10.1016/j.jfineco.2021.10.011>
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65–91. <https://doi.org/10.1111/j.1540-6261.1993.tb04702.x>
- Kozlowski, S. E., Puleo, M. R., & Zhou, J. (2021). Cryptocurrency return reversals. *Applied Economics Letters*, 28(11), 887–893. <https://doi.org/10.1080/13504851.2020.1784831>
- Li, T., Shin, D., & Wang, B. (2025). Cryptocurrency pump-and-dump schemes. *Journal of*

- Financial and Quantitative Analysis*, 60(8), 3622–3659.
<https://doi.org/10.1017/S0022109025000201>
- Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, 77(2), 1133–1177. <https://doi.org/10.1111/jofi.13119>
- Medhat, M., & Schmeling, M. (2022). Short-term momentum. *The Review of Financial Studies*, 35(3), 1480–1526. <https://doi.org/10.1093/rfs/hhab055>
- Miller, M. H., & Scholes, M. S. (1982). Dividends and taxes: Some empirical evidence. *Journal of Political Economy*, 90(6), 1118–1141. <https://doi.org/10.1086/261114>
- Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, 80(3), 563–602.
<https://doi.org/10.1016/j.jfineco.2005.05.003>
- Shen, D., Urquhart, A., & Wang, P. (2020). A three-factor pricing model for cryptocurrencies. *Finance Research Letters*, 34, 101248. <https://doi.org/10.1016/j.frl.2019.07.021>
- Zaremba, A., Bilgin, M. H., Long, H., Mercik, A., & Szczygielski, J. J. (2021). Up or down? Short-term reversal, momentum, and liquidity effects in cryptocurrency markets. *International Review of Financial Analysis*, 78, 101908.
<https://doi.org/10.1016/j.irfa.2021.101908>