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Up or down? Short-term reversal, momentum, and liquidity effects in cryptocurrency markets

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ABSTRACT

We demonstrate a new powerful predictive signal for cryptocurrency returns: the last day's return. Based on daily prices of more than 3600 coins, we document that the cryptocurrencies with low last day's return significantly outperform their counterparts with high last day's return. The effect is confirmed by a battery of cross-sectional tests and portfolio sorts, and is not subsumed by a broad range of other return predictors. We argue that the daily reversals result from the illiquidity of the vast majority of traded cryptocurrencies. In consequence, the pattern is cross-sectionally dependent on liquidity, and the handful of largest and most tradeable coins exhibit daily momentum rather than a reversal. Our findings help to reconcile earlier conflicting evidence on return persistence in cryptocurrency markets.

1. Introduction

Past prices are a mine of return predictors. A cornucopia of studies demonstrates that signals such as momentum or reversal can drive prices across many different assets (Asness, Moskowitz, & Pedersen, 2013; Cooper, Mitrache, & Priestley, 2020; Ilmanen, Israel, Moskowitz, Thapar, & Wang, 2019; Zaremba, Long, & Karathanasopoulos, 2019). Hence, it should not come as a surprise that the emergence of a new asset class—cryptocurrencies—spurred a proliferation of similar research.[1] Numerous papers have attempted to document the momentum effect in cryptocurrencies (e.g., Grobys & Sapkota, 2019; Tzouvanas, Kizys, & Tsend-Ayush, 2020; Yang, 2019).

Importantly, since cryptocurrencies are a fresh and young asset class, momentum studies still lack uniform sample selection and testing methodologies. The sample sizes vary from just several to hundreds of coins, and the sorting periods range from just several weeks to multiple months. Hence the results are also far from uniform. For instance, whereas Shen, Urquhart, and Wang (2020), Li, Zhang, Xiong, and Wang (2019), and Borgards and Czudaj (2020) provide evidence of strong reversal effects, Tzouvanas et al. (2020) and Yang (2019) argue that cryptocurrencies demonstrate momentum. The conflicting evidence calls for introducing some structure and order into momentum studies that would help to reconcile the earlier findings.

This study adds to the cryptocurrency anomaly literature by documenting and investigating a new powerful pattern in the cross-section of returns: the daily returns reversal. By doing so, we also help to explain

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[1] For comprehensive review of research on cryptocurrencies, see Batten, Corbet, and Lucey (2020).

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the earlier contradictory findings on the momentum effect in cryptocurrencies across different sorting periods and asset universes. To this end, we examine returns on over 3600 cryptocurrencies for the years 2015–2021. We apply cross-sectional regressions as well as univariate and bivariate sorts to demonstrate and explain the astounding reversal anomaly.

We begin by examining the cross-sectional dependence between current cryptocurrency performance and past returns over the different estimation periods. We demonstrate that one particular period stands out remarkably as the essential driver of the reversal effect: the most recent day. The last day's return is a formidable negative return predictor in the cross-section of returns, and its significance is incomparable to that of any known cryptocurrency anomaly. The coins with the highest last day's return significantly underperform the coins with the lowest last day's return. The effect is confirmed in a battery of cross-sectional and time-series tests, and it is not subsumed by other prominent return predictors, such as beta, idiosyncratic volatility, size, medium- and long-term returns, seasonality, liquidity, turnover, and various tail risk measures. Importantly, the daily reversal is an independent anomaly not explained by the weekly reversals in returns discovered by Li et al. (2019) or Shen et al. (2020). Finally, the anomaly holds across different functional and technical categories of cryptocurrency assets.

Having established the daily reversal phenomenon, we focus on the role of size. Remarkably, some of the earlier studies (e.g., Grobys & Sapkota, 2019; Tzouvanas et al., 2020) focused on the limited samples of the largest cryptocurrencies, and document the momentum effect rather than a reversal. We demonstrate that the direction of the return predictability depends on the capitalization of the cryptocurrency. The vast majority of the cryptocurrencies display the daily reversal pattern. Nonetheless, a small fraction—approximately 2%—of the biggest cryptocurrencies does not display any visible reversal effect. Importantly, from the economic perspective, this handful of coins exhibiting return continuation is undeniably more significant than all the remaining cryptocurrencies. This 2% of the largest names correspond to more than 90% of the total market capitalization of the cryptocurrency markets.

Finally, we discuss the potential sources of the short-term reversal effect and the discrepancy between the behavior of small and big coins. We argue that the phenomenon stems from cross-sectionally time-varying liquidity. Specifically, the reversal may stem from two mechanisms: bid-ask bounce (Boudoukh, Richardson, & Whitelaw, 1994; Conrad, Gultekin, & Kaul, 1997; Hasbrouck, 1991; Jegadeesh & Titman, 1995a; Keim, 1989; Mech, 1993) and temporary price deviations following liquidity shocks (Grossman & Miller, 1988; Jegadeesh & Titman, 1995b; Pastor & Stambaugh, 2003). For example, a recent study of equity markets by Medhat and Schmeling (2020) documents that the short-run reversal in equities is present only in low-turnover stocks, while the high-turnover shares display short-term momentum.

Consistently with this, we demonstrate that the cryptocurrency market value is closely linked to its liquidity. The small and medium cryptocurrencies are characterized by remarkably higher Amihud's (2002) illiquidity ratios and bid-ask spreads. Hence while the majority of coins display the short-term (daily) reversal effect, a small fraction of most liquid cryptocurrencies exhibit momentum. This cross-sectional dependence on liquidity is confirmed by convincing evidence coming from both portfolio sorts and cross-sectional regressions. To conclude, in liquid cryptocurrencies, the dominant market force is momentum. Nevertheless, in the illiquid market segments, the microstructure issues and demand or supply shocks lead to the development of the short-term reversal effect, replacing the momentum pattern. This dissimilarity between liquid and illiquid cryptocurrencies explains how earlier articles that focused on the small sets of the most important coins found momentum, whereas others employing comprehensive samples pointed to a reversal.

Our study is most closely related to the rapidly growing asset pricing literature on the momentum and reversal patterns in cryptocurrency returns (Borgards & Czudaj, 2020; Grobys & Sapkota, 2019; Kosc, Sakowski, and Ślepaczuk 2019; Shen et al., 2020; Yang, 2019; Liu, Liang, & Cui, 2020; Liu, Tsyvinski, & Wu, 2019; Tzouvanas et al., 2020; Dong, Jiang, Liu, & Zhu, 2020). From a broader perspective, we also contribute to the literature on return predictability of cryptocurrency returns (Dong et al., 2020; Kraaijeveld & De Smedt, 2020; Grobys & Sapkota 2020; Caporale, Plastun, & A., 2019; Bouri, Lau, Lucey, & Roubaud, 2019; Wei, 2018; Corbet, Eraslan, Lucey, & Sensoy, 2019).

Notably, our findings are also consistent with the studies of momentum and reversal effects in other asset classes, such as equities (Asness et al., 2013; Blackburn & Cakici, 2017), currencies (Menkhoff, Sarno, Schmelinga, & Schrimpf, 2012; Tajaddini & Crack, 2012), fixed income (Jostova, Nikolova, Philipov, & Stahel, 2013; Zaremba & Czapkiewicz, 2017; Zaremba, Demir, Long, Szczygielski, & Vasenin, 2020), equity indices (Balvers & Wu, 2006; Malin & Bornholt, 2013), or commodities (Bianchi, Drew, & Fan, 2015). In particular, our findings closely match Medhat and Schmeling (2020), Chiang, Kirby, and Nie (2020), and Nagel (2012) who link short-term reversal effect is related with trading liquidity. We provide an out-of-sample confirmation of their findings by showing that, as in the stock market, liquid (illiquid) cryptocurrencies exhibit the (momentum) reversal effect. Also, Baltussen, van Bekkum, and Da (2019) associate the negative serial dependence in Exchange Traded Fund performance with financial market efficiency.

The remainder of the article proceeds as follows. Section 2 summarizes the literature review on the cross-sectional momentum and reversal effects in cryptocurrency markets. Section 3 presents data and variables. Section 4 discusses the basic empirical findings. Section 5 explores the essential role of size and illiquidity for return persistency in cryptocurrency markets. Finally, Section 6 concludes the study.

2. Related literature

While numerous studies have investigated momentum and price reversals in cryptocurrencies, the findings are often contradictory, with differing methodologies, samplings, and holding periods. Table 1 summarizes the major studies of momentum and reversal so far. Notably, we focus solely on studies examining pure momentum and reversal strategies, leaving aside articles examining different aspects of these phenomena, such as the studies of overreaction by Borgards and Czudaj (2020) and Caporale et al. (2019).

The study period is usually dictated by data availability. Therefore, it usually ends between 2017 (Kosc, Sakowski, and Slepaczuk 2019) and 2019 (e.g., Dong et al., 2020 or Li et al., 2019). While this aspect of sample construction may not seem relevant, it can potentially influence the results. Given that cryptocurrencies emerged only some years ago, these two years (more or less) of data may constitute a significant percentage of the entire study period.

The number of assets included in the sample ranges widely. While Shen et al. (2020) and Li et al. (2019) rely on samples of approximately 1800 cryptocurrencies, Dong et al. (2020) and Tzouvanas et al. (2020) concentrate on just 12 of the most significant names. Importantly, this minority of coins outweighs all the remaining "altcoins" in terms of economic importance, as they form the majority of the capitalization of the cryptocurrency market.

The selection of sorting periods also lacks consistency. Dong et al. (2020) and Grobys and Sapkota (2019) attempt to follow the seminal study of Jegadeesh and Titman (1993) and rank the assets on their returns ranging from 1 to 12 months. However, such an approach may be challenging for cryptocurrencies, which are a very young asset class with only several years of trading history. Hence, numerous other studies, such as Liu et al. (2019), Shen et al. (2020), and Tzouvanas et al. (2020) limit the study period to several weeks. Furthermore, Yang (2019) only focuses on daily ranking and sorting periods.

Given the noticeable variability in the methodological approach and sample construction, it should come as no surprise that the results are

Table 1
Major studies of the momentum and reversal effects in cryptocurrency markets.

Article	Study period	Research sample	Sorting period	Holding period	Results
Dong et al. (2020)	01/01/2015 to 30/04/2019	12	1–6 months	1 month	Past winners generate monthly returns between 0.17% and 4.65% higher than past losers, but the difference is statistically insignificant.
Grobys and Sapkota (2019)	01/01/2014 to 31/12/2018	143	1–12 months	1 month	Insignificant profits on the momentum strategy. Significant 1-month reversal effect (1-month holding, 1-month sorting) of up to 14.87%.
Kosc, Sakowski, and Ślepaczuk (2019)	12/05/2014 to 28/10/2017	1223	1 week	1 week	Annualized rate of return of 273.2% on cryptocurrencies with the highest return and 20.9% on cryptocurrencies with the lowest return.
Li et al. (2019)	01/01/2014 to 31/05/2019	1803	1 week	1 week	Losers significantly outperform winners by 4.45% to 28.27%, depending on the size quintile.
Liu et al. (2020)	07/08/2015 to 31/12/2018	78	1 week	1 week	Winner minus loser portfolio yields a highly significant 10.94% per month.
Liu et al. (2019)	07/08/2014 to 31/12/2018	1583	1, 2, 3, 4, 8, 16, 50, 100 weeks.	1 week	Long-short strategies for one, two, three, and four-week sorting periods generate excess returns of 2.7%, 3.3%, 4.1%, and 2.5%, respectively. Remainder not statistically significant.
Shen et al. (2020)	28/04/2013 to 31/03/2019	1786	1, 2, 3, and 4 weeks.	1, 2, 3, and 4 weeks.	Strong reversal effect for 1–2-week sorting period of up to 12.3% per month. Significant momentum effect for 4-week sorting period and 1-month holding periods.
Tzouvanas et al. (2020)	01/12/2015 to 29/01/2019	12	7, 15, 30 days	7, 15, 30 days.	7/7 long-short strategy is the most profitable, with weekly return of 19.396% (32.004%) for 12 (6) cryptocurrencies. Returns remain positive and significant after controlling for transaction costs.
Yang (2019)	21/03/2014 and 21/07/2018	63	Past 1, 3, 5, 7, and 14 days; returns between 1 and 2, 3–5, 3–7, 5–7, and 7–14 days.	1 day	Positive and significant returns on the majority of long-short momentum portfolios up to 0.63% daily.

The table summarizes the major studies of the momentum and reversal effects in cryptocurrency markets.

also not uniform. Some authors demonstrate sizeable momentum profits (Tzouvanas et al., 2020), while others point to remarkable reversal effects (e.g., Li et al., 2019 or Shen et al., 2020). In general, we noticed that the studies indicating some form of momentum usually rely on fewer assets than the papers documenting the reversal effect. This may suggest that the momentum effect is linked to the cryptocurrency size or liquidity.

Finally, only one study—by Yang (2019)—examines patterns of day-to-day return dependence. Interestingly, contrary to our work, the author finds evidence for momentum rather than a reversal effects. Notably, the article is based on a limited dataset of 23 core cryptocurrencies composed of 40 ERC20 tokens. This corresponds to the pattern that the investigations of more constrained asset universes are more likely to report momentum profits.

3. Data and variables

Following Grobys and Sapkota (2019), Zaremba et al. (2020), and Antonakakis, Chatziantoniou, and Gabauer (2019), we base our calculations on data from *https://coinmarketcap.com*. We retrieve prices, market values, and trading volumes all cryptocurrencies passing several basic conditions.[2] We require each coin to be traded on at least one public exchange, and meet the following basic criteria: 1) be based upon consensus algorithms, distributed ledgers, and peer-to-peer technology, 2) be publicly traded on at least one exchange, 3) have a functional website, and 4) have a public representative.

To ensure the quality of our sample, we apply several filters. First, we exclude cryptocurrencies-day observations with the missing return, volume, or market values. Also, we delete cases where a price equals zero, and we discard the cryptocurrencies with a price history shorter than 20 weeks. Finally, we winsorize all the log-returns exceeding 200% in absolute terms.[3] Notably, we do not control for size and liquidity in our filters. We will consider these issues separately in our tests.

Since our examinations are cross-sectional in nature, they need an ample number of cryptocurrencies per month. Hence we arbitrarily chose the start of the study period for returns on 1 January 2015, when the number of coins in the cross-section exceeds 150. Thus, our study period returns run from 1 January 2015 to 1 March 2021, but we also use earlier data, if necessary, to derive certain variables. Eventually, after applying all the adjustments and filters, our actual sample covers 3607 instruments and 2,700,925 daily return observations. The exact number of cryptocurrencies in the sample increases through time, as demonstrated in Fig. 1, and the average number of assets in the sample equals 1126.

Our data is retrieved in U.S. dollars. Consistently with that, the risk-free return is proxied by the daily T-Bill rate obtained from French (2020).

Our baseline return predictive variable is the daily lagged log-return (*LRET*) on day *t*-1, that is (Eq. 1):

$$LRET_{i,t} = ln\left(P_{i,t-1}\right) - ln\left(P_{i,t-2}\right) \tag{1}$$

where $P_{i,t-1}$ and $P_{i,t-1}$ are the prices of cryptocurrency *i* on days *t*-1 and *t*-2, respectively, and $LRET_{i,t}$ is the lagged return, our essential return predictor. Following our earlier reasoning and preliminary evidence, we

[2] If a cryptocurrency is listed on multiple exchanges, the crypto asset prices retrieved from https://coinmarketcap.com are volume-weighted averages of market pair prices from different exchanges. The rationale for using a volume-weighted average is that the high-volume markets tend to be more liquid and less prone to fluctuations. Therefore, the higher percentage of volume that is contributed from the pair, the more influence it has on the average price in our dataset. For additional details, please see https://support.coinmarketcap.com/hc/en-us/sections/360008888252-Metric-Methodologies."

[3] The employed data filters follow typical procedures in asset pricing literature. To assure the robustness of our findings, in unreported analyses, we relax these filters concerning data filtering. Specifically, we include the price observations with missing volume data. Furthermore, we fill in the missing price information with the most recent available values. Finally, we relax the filter on both maximum and minimum daily returns, testing alternative levels or no limits at all. None of these operations materially affect our findings.

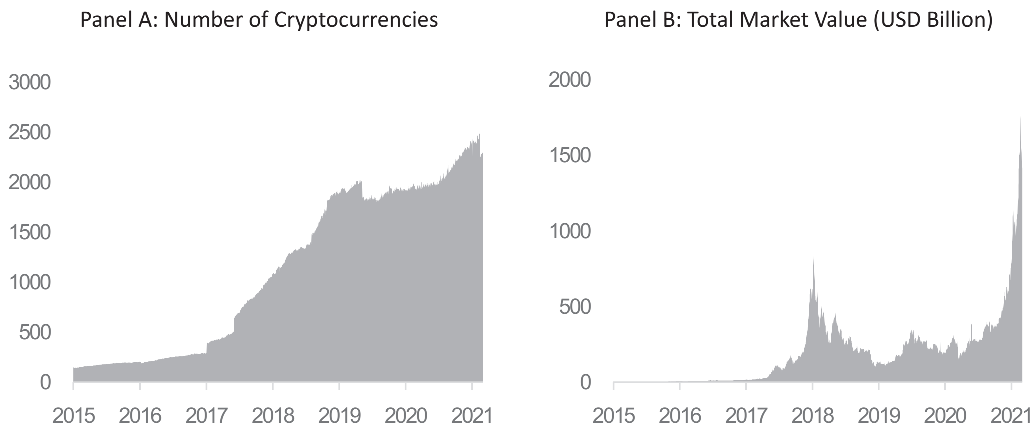


Fig. 1. Sample of Cryptocurrencies.
The figure presents the research sample of the cryptocurrencies. Panel A demonstrates the number of different cryptocurrencies, and Panel B displays their aggregate market value expressed in USD billions.
Panel A: Number of Cryptocurrencies.
Panel B: Total Market Value (USD Billion).

conjecture that *LRET* is negatively correlated with the next day's returns in the cross-section.

In addition to *LRET*, we also calculate several control variables that have been documented to potentially predict future cryptocurrency returns (see, e.g., Tzouvanas et al., 2020; Grobys & Sapkota, 2019; Liu et al., 2019; Liu & Tsyvinski, 2018; Liu et al., 2019; Poyser, 2019; Shen et al., 2020; Sovbetov, 2018; Zaremba et al., 2020). Notably, the counterparts of all the signals we use have been initially demonstrated to also explain the cross-section of equity returns. *MV* is the logarithm of the total market capitalization of the cryptocurrency on the previous day (Banz, 1981). Market beta (*BETA*) is the slope coefficient from the regression of the coin's excess returns on the excess returns on a value-weighted portfolio of all the cryptocurrencies estimated using a 20-week trailing period, and idiosyncratic volatility (*IVOL*) is the residual term from the same regression equation (Ang, Hodrick, Xing, & Zhang, 2006; Frazzini & Pedersen, 2014). The cross-sectional seasonality effect (*SEAS*) by Keloharju, Linnainmaa, and Nyberg (2016) is proxied by the average same-weekday log-return over the past 20 weeks. *ILLIQ* denotes the illiquidity ratio of Amihud (2002), i.e., the ratio of the absolute value of the price change to the dollar volume averaged over the past 20 weeks. The turnover ratio (*TURN*) is the ratio of daily dollar volume over total market capitalization averaged over the 20-week trailing period (Datar, Naik, & Radcliffe, 1998). Notably, Avramov, Chordia, and Goyal (2006) demonstrate that *ILLIQ* and *TURN* are two independent predictors capturing different phenomena and that turnover does necessarily reflect liquidity.

Last but not least, we also control for past returns that have been intensively explored in the cryptocurrency momentum literature. As we demonstrate in Section 2, different studies relied on various sorting periods for momentum, so we consider two separate return predictors. The short-term return (*STRET*) relates to short-term return relationships as in, e.g., Shen et al. (2020) or Li et al. (2019), and is calculated as the average daily log-return during the last week with the most recent day skipped to avoid overlap with *LRET*. On the other hand, the long-term return (*LTRET*) concerns long-run return relationships, similar to those studied in Liu, Dong et al. (2020) or Grobys and Sapkota (2019), and is calculated as the average daily log-return over the last 20 weeks with the most recent week excluded to avoid overlap with *STRET*.

Table 2 reports the basic statistical properties of the major variables used in this study, along with the daily returns, that is, the dependent variable in our tests. Notably, our main predictor, *LRET*, does not display any major correlation with other controls (explanatory variables). The only exception is the relationship with *STRET*, where the rank-based correlation coefficient amounts to −0.26. However, this should not be surprising as the major point of this article is that the daily returns tend to reverse in the cross-section.

4. Basic empirical findings

Several studies of the momentum and reversal effects in cryptocurrency returns have relied on different sorting periods varying from a few days to several months. Therefore, we begin our inquiry with a preliminary test examining the role of various ranking windows using cross-sectional regressions. Subsequently, we continue with rigorous univariate and bivariate-sorts, as well as cross-sectional regressions.

4.1. Preliminary test: return dependence over different periods

The sorting windows for momentum in the cryptocurrency literature range from a week to up to 12 months. Therefore, in our initial test, we explore the role of particular days and periods with cross-sectional regressions. Specifically, to have a broad overview of the magnitude of the cross-sectional relationship between current and past returns at different lgas, we replicate the exercise in Keloharju et al. (2016). For each day, we run the following regressions in the style of Fama and MacBeth (1973):

$$R_{i,t} = \gamma_{0,t} + \gamma_{1,t}\overline{R}_{i,t-1:t-k} + \varepsilon_{i,t} \tag{2}$$

$$R_{i,t} = \gamma_{0,t} + \gamma_{2,t}R_{i,t-k} + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the daily log-return on cryptocurrency *i* on day *t*; $\overline{R}_{i,t-1:t-k}$ is the average daily log-return from *t*-1 to *t*-*k*; $R_{i,t\text{-}k}$ is the daily-log return on cryptocurrency *i* on day *t*; $\gamma_{i,0}$, $\gamma_{i,1}$, and $\gamma_{i,1}$ are estimated regression parameters; and $\varepsilon_{i,t}$ is the residual term. The *k* parameter ranges from 1 to 365 days. In other words, Eq. (2) investigates the role of average returns on sorting periods *of different lengths*, while Eq. (3) explores the role of specific lagged days within these sorting periods. The results of these exercises are demonstrated in Fig. 2.

Fig. 2, Panel A, displays *t*-statistics corresponding with the slope coefficients for the average returns computed over different periods. The first most vivid observation is that the relationship is strongly negative over all the study periods. Our results findings are thus in line with, for example, Shen et al. (2020) and Kosc, Sakowski, and Ślepaczuk (2019), but contradict the results of Yang (2019) and Tzouvanas et al. (2020). The *t*-values are exceptionally high and, in all the instances exceed 3 in absolute terms. Nonetheless, a clear pattern in *t*-values emerges, and the relationship is the most powerful for the short sorting period and

Table 2
Statistical properties of major variables.

	R	LRET	BETA	MV	STRET	LTRET	IVOL	SEAS	ILLIQ	TURN
Panel A: Statistics Based on a Pooled Sample										
Average	−0.01	−0.01	0.79	173.51	0.00	0.00	−0.01	0.17	18.60	0.50
St. deviation	0.24	0.24	0.57	5384.44	0.07	0.01	0.14	0.09	2470.22	13.00
Skewness	−2.49	−2.49	−0.16	88.57	0.36	0.10	2.01	−4.88	139.51	48.15
Kurtosis	35.30	35.30	9.71	11,440.26	114.00	8.46	5.39	141.41	19,746.74	2473.43
1st quartile	−0.05	−0.05	0.52	0.10	−0.02	−0.01	0.07	−0.03	0.00	0.00
Median	0.00	0.00	0.82	0.84	0.00	0.00	0.12	0.00	0.00	0.02
3rd quartile	0.05	0.04	1.08	6.23	0.02	0.00	0.22	0.02	0.00	0.08
Panel B: Averages of Daily Statistics										
Average	0.00	0.00	0.83	131.71	0.00	0.00	0.16	−0.01	13.52	0.28
St. deviation	0.22	0.22	0.55	2819.90	0.06	0.01	0.12	0.08	395.01	5.20
Skewness	−1.41	−1.40	−0.15	28.11	0.19	−0.24	1.93	−2.32	16.01	17.23
Kurtosis	24.64	24.62	6.09	973.69	39.82	10.53	5.39	60.15	417.80	457.99
1st quartile	−0.05	−0.05	0.58	0.12	−0.02	0.00	0.08	−0.02	0.00	0.00
Median	0.00	0.00	0.85	0.99	0.00	0.00	0.13	0.00	0.00	0.02
3rd quartile	0.04	0.04	1.09	6.24	0.02	0.00	0.21	0.02	0.00	0.06
Panel C: Correlation Coefficients										
RET		−0.20	0.00	−0.03	−0.02	−0.01	−0.01	0.00	0.01	−0.01
LRET	−0.29		0.00	0.02	−0.15	−0.01	−0.01	0.00	0.01	−0.01
BETA	0.00	0.00		0.06	0.00	0.04	−0.01	0.01	−0.06	0.12
MV	0.00	0.00	0.01		0.04	0.17	−0.64	0.04	−0.83	0.18
STRET	−0.05	−0.26	0.00	0.00		−0.09	−0.01	0.07	0.01	−0.01
LTRET	0.00	−0.01	0.05	0.02	−0.12		0.05	0.17	−0.02	0.06
IVOL	−0.03	−0.02	0.01	−0.08	0.01	0.03		0.00	0.78	−0.23
SEAS	0.01	0.01	0.01	0.00	0.12	0.12	−0.11		−0.01	−0.47
ILLIQ	0.00	0.00	0.02	−0.02	0.01	0.01	0.34	−0.01		0.01
TURN	0.00	0.00	−0.02	−0.01	−0.01	−0.02	0.00	−0.03	0.00	

The table reports the statistical properties of the major variables used in this study: contemporaneous daily log-return (*R*) on day *t*; lagged daily log-return (*LRET*) on day *t*-1; beta (*BETA*) estimated as a slope coefficient on the market portfolio based on 20 weeks of daily data; the total market capitalization (*MV*) at *t*-1 (in USD 1,000,000); short-term return (*STRET*) calculated as total log-return over days *t*-7 to *t*-2; long-run return (*LTRET*) calculated as a trailing 20-week total log-return with the most recent week excluded; cross-sectional seasonality (*SEAS*), calculated as the average daily log-return on the same weekday over the past 20 weeks; idiosyncratic volatility (*IVOL*) calculated as the residual term from the regression of daily excess returns on the market portfolio; Amihud's (2002) illiquidity ratio (*ILLIQ*) estimated using 20 weeks of daily data; and turnover ratio (*TURN*), i.e., the ratio of daily dollar volume over total market capitalization averaged over the 20-week trailing period. The study period is from 1 January 2015 to 1 March 2021. Panel A presents the statistics based on a pooled sample, while Panel B shows the averages of daily statistics. Panel C demonstrates the daily averages of pair-wise correlation coefficients. The values below the diagonal are Pearson's product momentum coefficients, and the values above the diagonal are Spearman's rank-based coefficients.

relatively weaker for longer periods. When the estimation window is as short as a few days, the *t*-statistics fall even below −120. This suggests that the whole reversal phenomenon may be driven by these very few most recent dates. To explore this further, let us take a look at the role of specific lagged days in Fig. 2, Panel B.

When we examine the relationship between the past returns on different lagged days and future cryptocurrency performance, the picture becomes much clearer. We no longer see any reliable pattern for the majority of periods, but there is one day that vividly stands out: the most recent trading day (*LRET*). The *t*-statistic corresponding with the slope coefficient on *t*-1 exceeds −120 in absolute terms and is incomparable to any similar effect for other days. In other words, the lagged most recent trading day is an essential contributor to the reversal effect in cryptocurrency markets documented by Shen et al. (2020) and Kosc, Sakowski, and Ślepaczuk (2019), and is a remarkable driver of future performance in the cross-section.[4] Notably, this observation matches evidence from equity markets. For example, Nagel (2012) demonstrates a powerful one-day reversal effect in stock markets. Let us now see how robust it is and how it is related to other well-known cryptocurrency return predictors.

[4] To corroborate the essential role of the last day's return, we experiment with the methodology in Abedifar, Giudici, and Hashem (2017). Specifically, we run cross-sectional regressions on lagged returns that are orthogonalized with re-spect to return at other lags within the estimation period. The results of this exercise confirm the vital role of the most recent day, that leads to a powerful reversal effect in cryptocurrency markets.

4.2. *Portfolio sorts*

Having established the unique role of the last day's return, we continue with portfolio sorts. This exercise aims to explore further the predictive power of the last day's return (LRET) and check its reliability. To this end, each day, we sort all the cryptocurrencies on LRET into quintiles and form value-weighted and equal-weighted portfolios. Also, we form long-short strategies buying (selling) the quintiles of cryptocurrencies with the highest (lowest) LRET. The performance of these spread portfolios served as an acid test for any cross-sectional pattern in returns. We evaluate the performance of the portfolios with three different factor models:

$$R_{p,t} = \alpha_1 + \beta_{MKT} MKT_t^F + \varepsilon_{1,t} \tag{4}$$

$$R_{p,t} = \alpha_3 + \beta_{MKT} MKT_t^F + \beta_{MV} MV_t^F + \beta_{STRET} STRET_t^F + \varepsilon_{3,t} \tag{5}$$

$$\begin{aligned} R_{p,t} = \alpha_8 &+ \beta_{MKT} MKT_t^F + \beta_{MV} MV_t^F + \beta_{STRET} STRET_t^F + \beta_{LTRET} LTRET_t^F \\ &+ \beta_{SEAS} SEAS_t^F + \beta_{IVOL} IVOL_t^F + \beta_{IVOL} ILLIQ_t^F + \beta_{TURN} TURN_t^F + \varepsilon_{8,t} \end{aligned} \tag{6}$$

where $R_{p,t}$ is the excess return on portfolio *p* on day *t*; β_{MKT}, β_{MV}, β_{STRET}, β_{LTRET}, β_{SEAS}, β_{IVOL}, β_{ILLIQ}, and β_{TURN} are exposures to MKT^F, MV^F, $STRET^F$, $LTRET^F$, $SEAS^F$, $IVOL^F$, $ILLIQ^F$, and $TURN^F$ factors, respectively; α_1, α_3, are α_8 denote the abnormal returns (so-called "alphas"); and $\varepsilon_{1,t}$, $\varepsilon_{3,t}$, and $\varepsilon_{8,t}$ indicate the residual terms. MKT_t^F is the daily excess return on the market portfolio, calculated as the value-weighted portfolio. The remaining factor returns—MV_t^F, $STRET_t^F$, $LTRET_t^F$, $SEAS_t^F$, $IVOL_t^F$, $ILLIQ_t^F$, and $TURN_t^F$—reflect daily payoffs on long-long short portfolios buying the value-weighted quintile of stocks with the highest *STRET*, *SEAS*, or *ILLIQ* and the lowest *MV*, *LTRET*, *IVOL*, or *TURN*, and selling

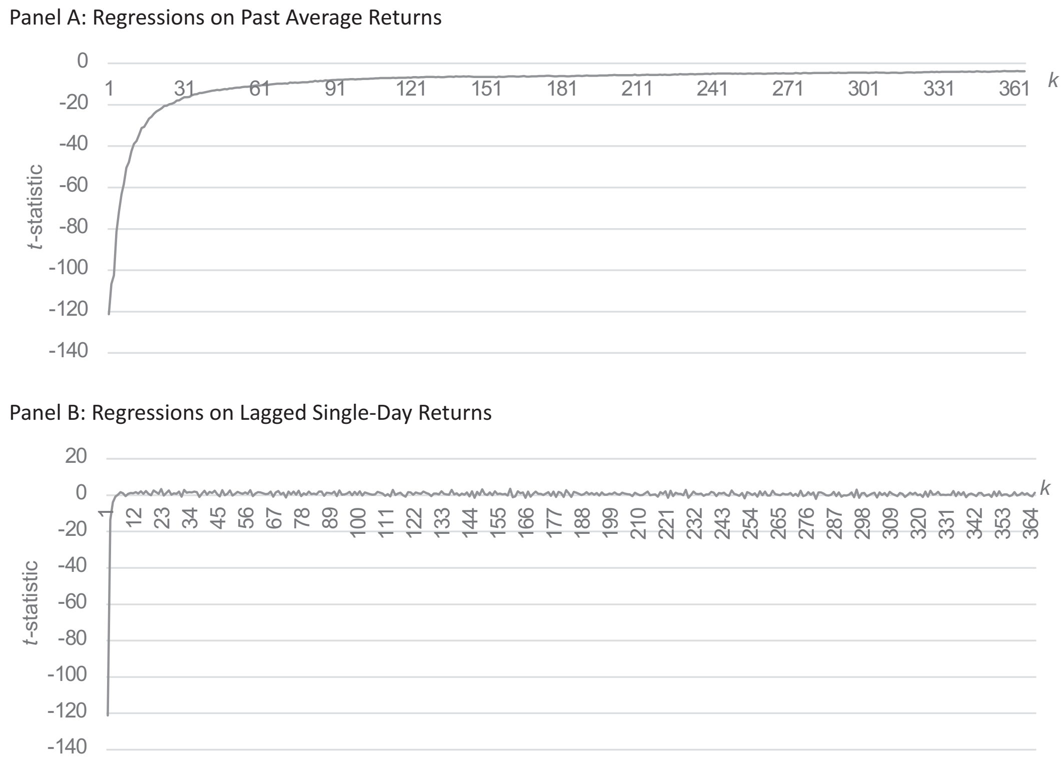


Fig. 2. Reversal Effects in Cryptocurrency Returns.

Panel A of the figure reports Newey-West (1987) *t*-statistics associated with average slope coefficients from daily cross-sectional regressions in the style of Fama and MacBeth (1973) of daily returns log-returns on past average log-returns on cryptocurrencies: $R_{i,t} = \gamma_{0,t} + \gamma_{1,t}\overline{R}_{i,t-1:t-k} + \varepsilon_{i,t}$

where $R_{i,t}$ is the daily log-return on cryptocurrency *i* on day *t*, $\overline{R}_{i,t-1:t-k}$ is the average daily log-return from *t*-1 to *t*-*k*. Panel B shows the slope coefficients from the regression of daily log-returns on past single-day returns: $R_{i,\ t} = \gamma_{0,\ t} + \gamma_{2,\ t}R_{i,\ t-k} + \varepsilon_{i,\ t}$

where $R_{i,t-k}$ is the daily-log return on cryptocurrency *i* on day *t*. $\gamma_{i,0}$, $\gamma_{i,1}$, and $\gamma_{i,1}$ are estimated regression parameters, and $\varepsilon_{i,t}$ is the residual term. The *k* parameter, ranging from 1 to 365 days, is indicated on the horizontal axis. The study period is from 1 January 2015 to 1 March 2021.

Panel A: Regressions on Past Average Returns.

Panel B: Regressions on Lagged Single-Day Returns.

the quintile of stocks with the lowest *STRET*, *SEAS*, or *ILLIQ* and highest *MV*, *LTRET*, *ILLIQ*, or *TURN*.

Note that instead of bivariate or trivariate sorts, characteristic for popular factor models (see, e.g., Hou, Mo, Xue, & Zhang, 2019), we opt for simple univariate sorts in factor construction. This is aimed at ensuring consistency in factor design with the construction of the examined portfolios. In this way, we mitigate the risk that any abnormal returns would be due to portfolio formation approaches and the rebalancing process rather than to the underlying return predictive signal. The primary statistical properties of all our asset pricing factors are demonstrated in Table A1 in the Internet Appendix, and Fig. A1 displays their cumulative returns.

The one-factor model (4) covers only the market risk and conceptually corresponds to the Capital Asset Pricing Model (Sharpe, 1964). The model (5) corresponds with the three-factor model of Shen et al. (2020), and encompasses the market, size, and short-term reversal risk factors. Finally, the broad model (6) encompasses all the established return patterns in cryptocurrency markets outlined in Section 3. Notably, the model (6) nests the models (5) and (6), so we use it as our default evaluation tool.

For robustness and to provide further insights, we supplement the above-described examinations with two additional tests: the GRS test by Gibbons, Ross, and Shanken (1989), and the monotonic relationship (MR) test by Patton and Timmermann (2010). The first of these tests check whether all the alphas in the cross-section are simultaneously equal to zero. The second test pursues a simulation-based framework to assert whether there is a monotonic relationship in the cross-section of portfolio returns linked to *LRET*.

Table 3 demonstrates the performance of the quintile portfolios from univariate sorts. Let us first focus on the value-weighted portfolios presented in Panel A. The portfolio of cryptocurrencies with the highest *LRET* procures a mean daily excess return of −0.67%, while the portfolio with the lowest *LRET* delivers an average daily return of 2.29%. Consequently, the return on the long-short portfolio produces an exceptionally high (in absolute terms) and extremely significant negative return of −2.96%. Furthermore, the effect is significant even after we apply all the different asset pricing models, and the alphas range from −2.96% to −2.99%. The cross-sectional pattern in returns is also confirmed by the GRS test, though the *p*-values from the MR test of Patton and Timmermann (2010) point to a lack of clear monotonic relationship in the cross-section of returns. Indeed, a closer look at the performance of the five adjacent portfolios reveals that the abnormal performance is driven in particular by extreme returns on the top and bottom portfolios.

Table 3, Panel B, reports analogous results for the equal-weighted portfolios. The cross-sectional pattern, in this case, is even more compelling. The long-short portfolio return amounts to −12.99% daily on average and is associated with a very high statistical significance. Again, the role of LRET remains significant even after the application of the different factor models and is confirmed by GRS tests.

Table 4 provides further insights into the performance of the portfolios from univariate sorts by demonstrating the exposures of the long-short portfolios to different cryptocurrency pricing factors. Notably, the spread portfolios do not display major significant exposure to the two

Table 3
Returns on portfolios from univariate sorts.

	Low	2	3	4	High	High-Low	GRS	MR
Panel A: Value-weighted portfolios								
μ	2.29***	0.13	0.23**	0.50***	−0.67**	−2.96***		0.8428
	(0.000)	*(0.107)*	*(0.005)*	*(0.000)*	*(0.001)*	*(0.000)*		
σ	9.83	6.05	4.12	5.24	8.94	12.28		
α_1	1.86***	−0.27*	−0.18***	0.07	−1.12***	−2.99***	0.0000***	0.8014
	(0.000)	*(0.006)*	*(0.000)*	*(0.171)*	*(0.000)*	*(0.000)*		
α_3	1.91***	−0.27*	−0.19***	0.07	−1.05***	−2.96***	0.0000***	0.8354
	(0.000)	*(0.006)*	*(0.000)*	*(0.159)*	*(0.000)*	*(0.000)*		
α_8	2.07***	−0.25*	−0.18***	0.06	−0.93***	−2.99***	0.0000***	0.6200
	(0.000)	*(0.008)*	*(0.000)*	*(0.190)*	*(0.000)*	*(0.000)*		
Panel B: Equal-weighted portfolios								
μ	9.69***	1.59***	1.60***	1.01***	−3.30***	−12.99***		0.0489*
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*		
σ	5.91	4.38	4.33	4.25	4.77	4.99		
α_1	9.24***	1.19***	1.21***	0.63***	−3.66***	−12.91***	0.0000***	0.2036
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*		
α_3	9.15***	1.12***	1.15***	0.55***	−3.77***	−12.92***	0.0000***	0.2049
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*		
α_8	9.17***	1.13***	1.16***	0.56***	−3.74***	−12.91***	0.0000***	0.2629
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*		

The table reports the performance of quintile portfolios from univariate sorts on the lagged daily return (*LRET*). *Low* and *High* indicate the portfolios with the highest and lowest *LRET*, respectively, and *High-Low* denote the zero-investment strategy of buying (selling) the *High* (*Low*) portfolio. μ is the mean daily excess return and σ is their standard deviation. α_1, α_3, and α_8 are alphas from the one-, three-, and eight-factor models, respectively, as described by Eqs. (4)–(6). μ, σ, α_1, α_3, and α_8 are expressed in percentage terms. *GRS* is the *p*-value from the test of alpha equality by Gibbons et al. (1989) and *MR* indicates the tests of monotonic relationship by Patton and Timmermann (2010). The values in parentheses are *p*-values corresponding with bootstrap (for mean returns) and Newey-West (1987) adjusted (for alphas) *t*-statistics. The asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. The study period is from 1 January 2015 to 1 March 2021. *Panels A* and *B* present the results for value-weighted and equal-weighted portfolios, respectively.

Table 4
Factor exposure of spread portfolios formed on a lagged daily return.

	MKT^F	$SIZE^F$	$STRET^F$	$LTRET^F$	$SEAS^F$	$IVOL^F$	$ILLIQ^F$	$TURN^F$	R^2
Panel A: Value-weighted portfolios									
(1)	0.06								0.0000
	(0.214)								
(2)	0.05	−0.18	0.09						0.0219
	(0.256)	*(0.163)*	*(0.227)*						
(3)	0.10	−0.21	0.08	0.39**	0.00	0.04	0.01	−0.14	0.0803
	(0.104)	*(0.113)*	*(0.246)*	*(0.001)*	*(0.490)*	*(0.313)*	*(0.455)*	*(0.158)*	
Panel B: Equal-weighted portfolios									
(1)	−0.18***								0.0218
	(0.000)								
(2)	−0.18***	0.02	0.03						0.0214
	(0.000)	*(0.334)*	*(0.122)*						
(3)	−0.18***	0.01	0.03	0.03	−0.04	0.00	0.04*	−0.06	0.0241
	(0.000)	*(0.376)*	*(0.117)*	*(0.173)*	*(0.032)*	*(0.460)*	*(0.012)*	*(0.087)*	

The table reports the measures of exposure of the spread portfolio buying (selling) the quintile of cryptocurrencies with the highest (lowest) lagged daily return (*LRET*) to other factor portfolios, that is, the market risk (MKT^F), size (MV^F), short-term return ($STRET^F$), long-term return ($LTRET^F$), seasonality ($SEAS^F$), idiosyncratic risk ($IVOL^F$), illiquidity ($ILLIQ^F$), and turnover ($TURN^F$) factors. R^2 is the time-series adjusted coefficient of determination. Different specifications (1), (2), and (3) correspond with multifactor models (4), (5), and (6) described in Section 4.1. The numbers in parentheses are *p*-values corresponding with Newey-West (1987) adjusted *t*-statistics, and the asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. The study period is from 1 January 2015 to 1 March 2021. *Panels A* and *B* present the results for value-weighted and equal-weighted portfolios, respectively.

other factors that would be robust across the two different weighting schemes: equal-weighted and value-weighted. The value-weighted portfolios display some partial correlation with the *LTRET* returns, suggesting potential persistence in short-term return patterns. On the other hand, the equal-weighted portfolios display negative exposure to the market portfolio. This may be linked to the weighting scheme, as the equal-weighted portfolios accentuate small cryptocurrencies, while the market portfolio is predominantly driven by a low number of the largest coins. Also, the illiquidity coefficient is significantly positive, but at a relatively low level of significance.

For robustness, we examine the pattern represented in subperiods. To this end, we split our full study period into two equal subsamples: 1 January 2015 to 30 January 2018 and 31 January 2018 to 1 March 2021. Subsequently, we perform the univariate sorts within each of this subperiods. The test confirms the robustness of the observed reversal pattern, and the effect is highly significant in both the early and the late periods. For the sake of conciseness, we report these results only in Table A2 in the Internet Appendix.

Summing up the performance of the one-way sorted portfolios, our initial results confirm the striking and highly significant daily reversal pattern. Interestingly, the effect is remarkably stronger for equal-weighted than for value-weighted portfolios. This vivid difference is most likely driven by the role of size—the small cryptocurrencies are overly weighted in the equal-weighted portfolios relative to their actual market capitalization. We discuss this point in detail in Section 5.2.

4.3. Bivariate portfolio sorts

Having established the daily reversal effect in the cryptocurrency returns, we want to ascertain that it is an independent asset pricing phenomenon. In other words, we want to verify whether the *LRET* effect is not simply a manifestation of some other cryptocurrency anomaly. To this end, we perform two separate tests: bivariate sorts and multivariate cross-sectional regressions.

In the first of these two exercises, we perform two-way dependent sorts on control variables and *LRET* to check whether the daily reversal effect remains the same. Specifically, in the first pass, each day we rank all the cryptocurrencies in our sample on different control variables listed in Section 3—*BETA*, *MV*, *STRET*, *LTRET*, *SEAS*, *IVOL*, *ILLIQ*, and *TURN*—and sort them into tertiles. Subsequently, within each of these tertiles, we sort the coins on *LRET* to form three portfolios. Thus, we obtain $3 \times 3 = 9$ portfolios from two-way dependent sorts. In the final step, we calculate average returns on the *LRET*-tertile portfolios across different tertiles of the conditioning variables. We evaluate them with the eight-factor model (6), nesting models (4) and (5). For brevity, Table 5 reports only the results for equal-weighted portfolios. The outcomes for the value-weighted portfolios, which are qualitatively similar, though with lower statistical significance, are available upon request.

Clearly, none of the control variables can explain the *LRET* effects. The mean returns and alphas on the long-short portfolios from bivariate sorts remain negative and highly significant in all examined specifications. The high statistical significance for each of the conditioning sorts confirms that the *LRET* effect is an independent and robust pricing phenomenon and not just some other cryptocurrency anomaly in disguise.

4.4. Cross-sectional regressions

The bivariate sorts are a powerful tool with the clear benefits of being unitive and non-parametric, meaning that it does not impose any functional form on the relationship between returns and the sorting variables. Nevertheless, this method is not free of drawbacks. First, it may lead to information loss due to aggregating cryptocurrencies into portfolios. Second, the sorts cannot generally incorporate more than two or three explanatory variables. Therefore, following the view of Fama (2015) that both time-series and cross-sectional tests have their unique advantages, we supplement the two-way sorts with the regressions in the spirit of Fama and MacBeth (1973).

In this test, each day we run the regression of cryptocurrency returns on LRET and a set of control variables:

$$R_i = \lambda_0 + \lambda_{LRET} LRET_i + \sum_{j=1}^{J} \lambda_j K_i + \varepsilon_i \tag{7}$$

where the dependent variable R_i is the daily log-return on cryptocurrency *i*. $LRET_i$ is the lagged daily return at *t*-1, K_i denotes the set of control variables, ε_i is the residual term, and λ_0, λ_{LRET}, and λ_J are the estimated regression parameters. Hence, by estimating the average regression coefficient, we aim to ascertain that the predictive power of *LRET* is not explained by a combination of other predictors.

Importantly, in the baseline approach, we apply the cross-sectional regression not only to the log-returns but also, for the sake of robustness, we follow the arguments of Brennan, Chordia, and Subrahmanyam (1998) and replace the log-returns with risk-adjusted returns. Specifically, we obtain the risk-adjusted payoffs from rolling 20-week regressions on the *MKT* factor by utilizing the estimation method similar to Jacobs (2015).

Table 6 presents the results of the cross-sectional regressions. The essential takeaway from this exhibit is that the role of *LRET* remains negative and significant in all the specifications. Regardless of whether we consider multivariate or univariate regressions or whether we apply them to log-returns or risk-adjusted returns, the *p*-values are always close to zero, and the slope coefficient ranges from −0.29 to −0.34. To conclude, the Fama-MacBeth (1973) regressions provide strong evidence in support of the daily-reversal phenomenon.

In addition to *LRET*, Table 6 reveals several additional significant variables. In line with the findings of Zaremba et al. (2020), we observe the significant seasonality effect. Moreover, *TURN* correlates negatively with future returns, indicating that high-turnover portfolios underperform. Also, the phenomenon underlying the model of Shen et al. (2020) remaisin strong and significant. This includes the measures of past performance—*STRET* and *LTRET*. Notably, this indicates that not only the last day's return but also the earlier performance can predict future performance in the cross-section, although the statistical significance

Table 5
Performance portfolios from bivariate sorts.

	Panel A: Mean excess returns (μ)				Panel B: Eight-factor model alphas (α_8)			
	Low	Medium	High	High-Low	Low	Medium	High	High-Low
BETA	5.30***	1.23***	−1.42***	−6.72***	4.81***	0.78***	−1.89***	−6.69***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
MV	6.35***	1.60***	−1.61***	−7.97***	5.86***	1.16***	−2.06***	−7.92***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
STRET	6.56***	1.52***	−1.77***	−8.33***	6.07***	1.07***	−2.21***	−8.28***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
LTRET	6.13***	1.47***	−1.62***	−7.74***	5.62***	1.02***	−2.07***	−7.68***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
SEAS	6.44***	1.56***	−1.60***	−8.04***	5.94***	1.11***	−2.05***	−7.99***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
IVOL	5.18***	1.38***	−1.46***	−6.64***	4.69***	0.93***	−1.92***	−6.61***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
ILLIQ	3.39***	0.84***	−0.99***	−4.39***	2.92***	0.38***	−1.47***	−4.39***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
TURN	4.36***	0.99***	−1.23***	−5.59***	3.87***	0.54***	−1.70***	−5.57***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*

The table summarizes the performance of equal-weighted portfolios from bivariate sorts. In the first step, we sort the cryptocurrencies into tertiles based on different control variables indicated in the first column: beta (*BETA*), market value (*MV*), short-term return (*STRET*), long-term return (*LTRET*), seasonality (*SEAS*), idiosyncratic risk (*IVOL*), illiquidity (*ILLIQ*), and turnover ratio (*TURN*). In the second step, we sort the firms in each quintile into three portfolios formed on lagged daily return (*LRET*), obtaining $3 \times 3 = 9$ portfolios from two-way dependent sorts. The reported values are the mean excess returns (*Panel A*) and eight-factor model alphas (*Panel B*) on the LRET-tertile portfolios averaged across different tertiles of the conditioning variables. *High* (*Low*) indicates the tertile with the highest (lowest) *LRET* and *High-Low* denotes the return on the long-short portfolio buying (selling) the *High* (*Low*) tertile. The values in parentheses are *p*-values corresponding with bootstrap (for μ) and Newey-West (1987) adjusted (for α_8) *t*-statistics. The asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. μ and α_8 are reported in percentage terms. The sample period is from 1 January 2015 to 1 March 2021.

Table 6
Cross-sectional regressions.

	Panel A: Raw log-returns			Panel B: Risk-adjusted returns		
	(1)	(2)	(3)	(4)	(5)	(6)
LRET	−0.29***	−0.34***	−0.30***	−0.31***	−0.34***	−0.29***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
BETA		0.00	0.00		−0.01***	−0.01***
		(0.314)	*(0.377)*		*(0.000)*	*(0.000)*
MV		0.00	0.00		0.00***	0.00
		(0.204)	*(0.361)*		*(0.000)*	*(0.036)*
STRET		−0.49***	−0.36***		−0.48***	−0.34***
		(0.000)	*(0.000)*		*(0.000)*	*(0.000)*
LTRET			−0.34***			−0.61***
			(0.000)			*(0.000)*
SEAS			0.09***			0.07***
			(0.000)			*(0.000)*
IVOL			−0.04***			0.10***
			(0.000)			*(0.000)*
ILLIQ			0.36**			1.10***
			(0.004)			*(0.000)*
TURN			−0.01*			−0.02*
			(0.008)			*(0.008)*
$\overline{R^2}$	0.0939	0.1327	0.1488	0.0889	0.1221	0.1422
#Obs.	2,670,613	1,901,218	1,311,119	2,293,758	1,699,852	1,182,117

The table reports average slope coefficients from daily cross-sectional regressions in the style of Fama and MacBeth (1973): $R_i = \lambda_0 + \lambda_{LRET} LRET_i + \sum_{j=1}^{J} \lambda_j K_i + \varepsilon_i$.

where the dependent variable R_i is the daily log-return (*Panel A)* or daily risk-adjusted return (*Panel B*) on cryptocurrency *i. $LRET_i$* is the lagged daily return at *t*-1, K_i denotes the set of control variables, ε_i is the residual term, and λ_0, λ_{LRET}, and λ_J are the estimated regression parameters. The control variables encompass beta (*BETA*) estimated as a slope coefficient on the market portfolio based on 20 weeks of daily data; logarithm of the total market capitalization (*MV*) at *t*-1; short-term return (*STRET*) calculated as total log-return over days *t*-7 to *t*-2; long-run return (*LTRET*) calculated as a trailing 20-week total log-return with the most recent week excluded; cross-sectional seasonality (*SEAS*), calculated as the average daily log-return on the same weekday over the past 20 weeks; idiosyncratic volatility (*IVOL*) calculated as the residual term from the regression of daily excess returns on the market portfolio; Amihud's (2002) illiquidity ratio (*ILLIQ*) estimated using 20 weeks of daily data; and turnover ratio (*TURN*), i.e., the ratio of daily dollar volume over total market capitalization averaged over the 20-week trailing period. $\overline{R^2}$ is the average cross-sectional adjusted coefficient of determination. *#Obs.* is the total number of cryptocurrency-day observations. The numbers in parentheses are *p*-values corresponding with Newey-West (1987) adjusted *t*-statistics, and the asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. The study period is from 1 January 2015 to 1 March 2021.

and predictive abilities of *LRET* cannot be challenged. Taking the log-returns into consideration, *LRET* explains on average 9.39% of the cross-sectional variation in returns. Adding all the other variables together to the regression increases this average R^2 coefficient to only 14.88%.

4.5. Additional robustness checks

So far, all the analyses in Section 4 pointed to a substantial daily reversal effect in the cryptocurrency returns. To substantiate this conclusion further, we perform two additional robustness checks. First, we explore the interplay between the *LRET* effect and the tail risk in cryptocurrency markets. Second, we verify whether it holds across different types of cryptocurrencies.

To begin with the tail risk, we are interested in whether the daily reversal anomaly is not subsumed by the cross-sectional return patterns that are associated with tail risk. Furthermore, we want to know if it holds across different quintiles of tail risk measures. Therefore, we conduct two tests. To begin with, we conduct cross-sectional regressions, as in Section 4.4, but accounting also for tail risk measures. Specifically, we employ three different proxies for tail risk: extreme downside risk (*EDH*) of Harris, Nguyen, and Stoja (2019), extreme downside correlation (*EDC*) of Harris et al. (2019), and tail beta (*TBETA*) of Van Oord and Zhou (2016). The measures are estimated closely, following the implementation in Ahelegbey, Giudici, and Mojtahedi (2021) and Van Oord and Zhou (2016), and are based on twenty weeks of daily data. Second, we analyze portfolios from bivariate sorts on the tail risk measures and *LRET*. In particular, we run two-way dependent sorts into quintiles in a similar fashion to Section 4.3; ranking the stocks on *EDH*, *TBETA*, *EDC*, and subsequently on *LRET*. Both of these tests confirm the validity of our initial findings. The daily reversal effect remains robust, even after controlling for tail risk via cross-sectional analyses or quintile analyses. The details of the results of these exercises are summarized in Tables A3 and A4 of the Internet Appendix.

Next, we examine the daily reversal effect across different types of cryptocur-rencies in our sample. We want to ascertain that some particular class of coins does not drive the entire phenomenon. To this end, we group cryptocurrencies into seventeen popular functional and technical categories. We employ the classification by https://coinpaprika.com/ and focus our examination on the labels that are available for at least one hundred cryptocurrencies in our sample. Hence, we consider eleven functional categories (assets management, blockchain service, finance and banking, marketplace, mining, monetization, payments, platform, privacy and security, smart contracts, and trading and investing), and six technical classes (ETH token, masternode, premine, proof of stake, proof of work, scrypt). The detailed description of these cryptocurrency types is provided in Table A5 of the Internet Appendix. Subsequently, we replicate our baseline analyses within each of these categories; i.e., the portfolio sorts and cross-sectional regressions. The essential summary of this exercise is displayed in Table A6 in the Internet Appendix. To summarize, the daily reversal effect is not driven by any particular class of cryptocurrencies. The anomaly remains substantial across all the tested cryptocurrency categories.

5. Further insights: cross-sectional variation in the reversal effect

Having demonstrated a strong daily reversal effect in cryptocurrency returns, we now continue by providing further insights. This section focuses on two particular aspects. First, we document the vital role of cryptocurrency market value for the reversal pattern. Second, we examine the source of this relationship with liquidity effects.

5.1. Size effect in cryptocurrency return reversals

Our findings so far point to a powerful short-term reversal effect in cryptocurrency daily returns. Though these observations are in line with the conclusions of Shen et al. (2020) and Li et al. (2019), they contradict the findings in several other papers, such as Liu et al. (2019) or Tzouvanas et al. (2020). What is the source of the difference? How can we reconcile these findings?

The studies documenting momentum usually focus on the limited samples of the largest cryptocurrencies. Tzouvanas et al. (2020), examining the return patters within the 12 biggest coins, may just serve as an example. On the other hand, the papers demonstrating reversal rely on broader asset sets. For instance, Shen et al. (2020) investigate as many as 1700 coins. Remarkably, many of them are rather small in terms of market capitalization and have limited economic significance.

The differences in sample selection suggest that the results may be solidly influenced by the size segment of the cryptocurrency markets. Perhaps the return patterns in the large and small cryptocurrencies are not uniform. To explore this issue, we perform the following test. First, we sort all the cryptocurrencies in our sample based on their size (market value) into 50 quantiles. Subsequently, within each of these quantiles we run univariate Fama-MacBeth cross-sectional regressions following Eq. (8):

$$R_i = \lambda_0 + \lambda_{LRET} LRET_i + \varepsilon_i \tag{8}$$

where the dependent variable R_i is the daily log-return on cryptocurrency i, $LRET_i$ is the lagged daily return at t-1, ε_i is the residual term, and λ_0, λ_{LRET}, and λ_J are the estimated regression parameters. We want to see whether the slope coefficient on LRET depends on the capitalization quintile. In other words, we are interested in whether the daily reversal effect is equally strong for all the sizes of cryptocurrencies.

Fig. 3 displays slope coefficients along with the corresponding t-statistics across all the size classes of cryptocurrencies. The dependence is striking: the vast majority of small and medium cryptocurrencies are characterized by the reversal pattern. However, as the size of the coin increases, the pattern gradually becomes weaker, and, finally, for the 2% of the largest cryptocurrencies only, we observe a *positive* slope coefficient. In other words, while the small and medium cryptocurrencies display the reversal effect, the largest coins uncover the momentum.

Notably, while 2% of different coin names may seem a minuscule number, it does not reflect its true economic significance. Fig. 4 shows the structure of our sample of cryptocurrencies split by their size into Big cryptocurrencies, representing the top 2% in terms of market value, and Small cryptocurrencies, representing the bottom 98%. Our sample contains, on average, 1126 cryptocurrencies daily, which implies that only about 23 coins usually qualified as Big. Nonetheless, this handful of largest coins represent on average 94% percent of the market capitalization, and the remaining several hundred account for as little as 6% of the market value on average. In other words, while the reversal pattern is prevalent in the vast majority of the cryptocurrencies, this pattern is hardly significant from an economic standpoint. The largest coins, forming the significant majority of the capitalization of the entire market, show momentum.[5]

To scrutinize the momentum and reversal effects in cryptocurrencies, we implement portfolio sorts on *LRET* within the subsets of *Big* (top 2%) and *Small* (bottom 98%) coins. In other words, we first daily split the sample cross-sectionally by size, and then apply sorts into quintile portfolios on the previous day's return. The results of this exercise are demonstrated in Table 7.

The examination of the portfolios from the bivariate sorts on *MV* and *LRET* confirms our initial finding in Fig. 3. The small cryptocurrencies (Panel A) demonstrate a powerful reversal effect. The mean returns and alphas on the long-short portfolios are negative and significant for all the types of asset pricing models, as well as for both value-weighted and equal-weighted portfolios. On the other hand, the Big coins show absolutely no trace of the reversal effect (Panel B). The long-short value-weighted portfolio (Panel B.1) buying (selling) the assets with the top (bottom) *LRET* have a positive mean monthly return of 0.22% and a corresponding eight-factor alpha of the same magnitude. The results for the equal-weighted portfolios are qualitatively similar, demonstrating the average return on the long-short portfolio equalling 0.22% and an eight-factor model alpha of 0.25%.

For robustness, we verify the conclusions from Table 7 with cross-sectional regressions. In this check, we again divide the sample into the top 2% of the biggest cryptocurrencies and the remaining 98% of the asset universe. Next, within each of these subsets, we run cross-sectional regressions following Eq. (7). The results confirm that while 2% of the biggest cryptocurrencies display there is no negative relationship between returns and *LRET* in the cross-section, for the other 98% of coins, the slope coefficient is negative. For the sake of brevity, we do report the full details of this exercise only in Table A3 of the Internet Appendix.

Our findings so far are a step towards reconciling the earlier conflicting evidence on the momentum and reversal anomalies in the cryptocurrency markets. While the majority of the market displays a reversal effect, the handful of the biggest coins displays an opposite pattern. The obvious question that arises is: why? What is the source of this difference in the behavior of big and small coins?

5.2. Sources of the returns reversals: the role of liquidity

The small cryptocurrencies uncover a powerful return reversal phenomenon, which is not visible for the largest coins. The asset pricing literature usually links the short-term reversal effect with microstructural issues and the role of illiquidity (see, e.g., Cakici & Topyan, 2014 for a review).[6] There exist at least two stock market mechanisms that can lead to a short-term reversal in illiquid stocks. First, illiquid stocks are usually associated with a high bid-ask spread (Amihud & Mendelson, 1986; Chung & Zhang, 2014). Consistently with that, several authors (Boudoukh et al., 1994; Conrad et al., 1997; Hasbrouck, 1991; Jegadeesh & Titman, 1995a; Keim, 1989; Mech, 1993) document that microstructural issues lead prices to "bounce" between the bid and ask, which is manifested in autocorrelation in returns. Second, Grossman and Miller (1988), Jegadeesh and Titman (1995b), and Pastor and Stambaugh (2003) link the reversal with liquidity shocks. A significant and unexpected demand or supply pressure cannot be absorbed by the existing offer, temporarily moving the price away from the fundamentals. Once the liquidity improves, the prices return to their previous levels.

Notably, and consistently with that, two recent studies by Medhat and Schmeling (2020) and Chiang et al. (2020) argue that the short-term reversal is strongly dependent on stock turnover. Specifically, it drives the prices of low-turnover firms, while the big firms display a short-term momentum.

In line with the reasoning above, we conjecture that the momentum and reversal phenomena in cryptocurrencies stem from the cross-sectional variation in trading liquidity. Likewise, as in Medhat and Schmeling (2020), big cryptocurrencies are liquid, which in turn results in the development of the momentum effect. On the other hand, the vast

[5] For robustness, we replicate also the outcomes in Fig. 4 by applying the cross-sectional regressions to risk-adjusted returns instead of log-returns. This exercise yields no qualitative difference in the results. For details, see Figure A3 in the Internet Appendix.

[6] Alternatively, Shiller (1984), Stiglitz (1989), and Subrahmanyam (2005) argue that the profits from the short-term reversal strategy may be driven by investors' initial overreaction to new information. However, Kaul and Nimalendran (1990) and Cox and Peterson (1994) find no support for this hypothesis.

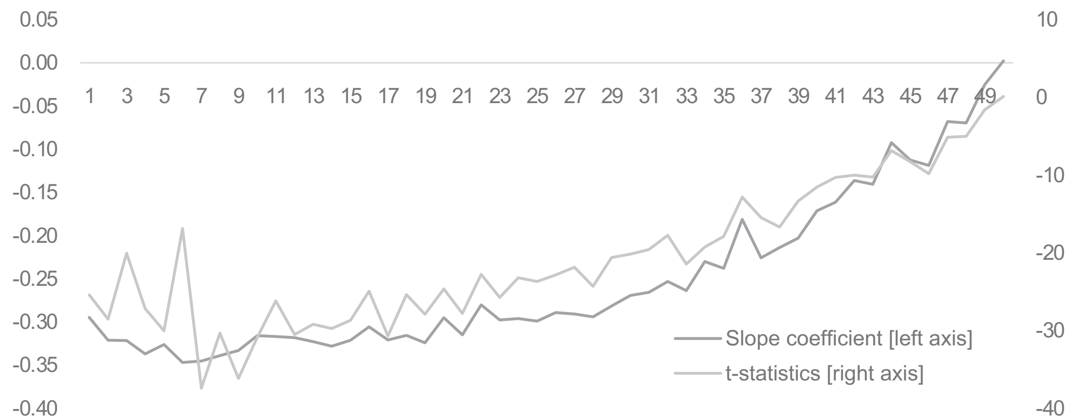
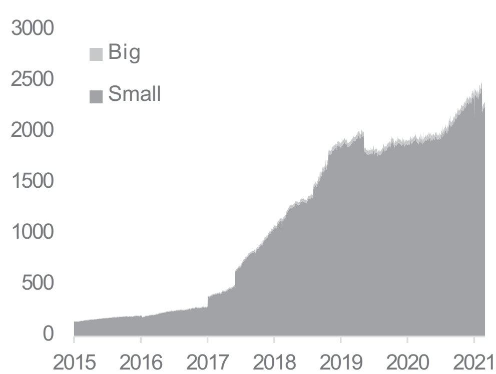


Fig. 3. Cross-Sectional Regressions across Different Size Classes.
Each day, we sort the cryptocurrencies into 50 equal subsets based on their market capitalization (MV) and apply cross-sectional regressions in the style of Fama and MacBeth (1973): $R_i = \lambda_0 + \lambda_{LRET} LRET_i + \varepsilon_i$,
where the dependent variable R_i is the daily log-return on cryptocurrency *i*, $LRET_i$ is the lagged daily return at $t - 1$, ε_i is the residual term, and λ_0, λ_{LRET}, and λ_J are the estimated regression parameters. The figure reports average slope coefficients from the regression in different size-sorted subsets along with the associated Newey-West (1987) adjusted *t*-statistics. The subset 1 (50) on the horizontal axis denotes the portfolio of the smallest (biggest) cryptocurrencies. The study period is from 1 January 2015 to 1 March 2021.



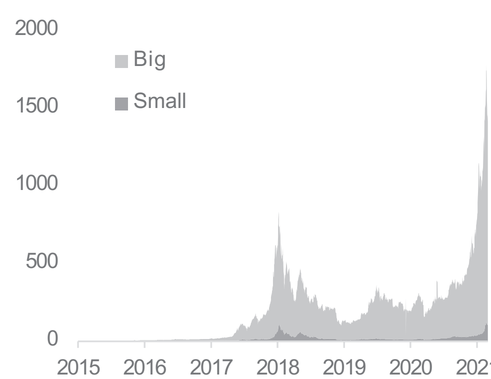


Fig. 4. Small and Big Cryptocurrencies in the Sample.
The figure presents the research sample of the cryptocurrencies split into 2% of the biggest cryptocurrencies in terms of their market capitalization (*Big*) and 98% of the smallest cryptocurrencies (*Small*). Panel A demonstrates the number of different cryptocurrencies, and Panel B displays their aggregate market value expressed in USD billions.
Panel A: Number of Cryptocurrencies
Panel B: Total Market Value (USD Billion).

majority of small and medium currencies are illiquid, so they display a reversal. This hypothesis yields two separate and testable implications. First, big stocks should be significantly more liquid than small stocks. Importantly, the lack of liquidity should be reflected in the bid-ask spread and price-impact measures, as these two features translate illiquidity into the reversal effect. Second, the liquidity-sorted portfolios should demonstrate an analogous (or even stronger) return pattern as with the size-sorted portfolios.

To verify these conjectures, we perform three separate exercises. First, we estimate price impact and bid-ask spread for different size-sorted portfolios. Second, we examine slope coefficients from regressions of cryptocurrency returns on *LRET* in different liquidity quantiles, similarly to Fig. 3. Finally, we compare the results of sorts in the most liquid and least liquid portfolios, as in Table 7.

To this end, we utilize two different liquidity measures. The price impact is already proxied by the illiquidity ratio (*ILLIQ*) of Amihud (2002). Notably, *ILLIQ* is one of the most popular and best-established illiquidity measures in the finance literature. In particular, in their literature survey, Ma, Anderson, and Marshall (2016) conclude that Amihud's measure is the best price impact proxy. The measurement of the bid-ask spread is less straightforward. To the best of our knowledge, high-quality and comprehensive data on bid-ask spreads are not publicly available for the universe of cryptocurrencies as broad as ours. Therefore, in line with the argumentation in Novy-Marx and Velikov (2016) that builds on Roll (1984), we estimate the bid-ask spread for day *t* as:

$$BAS = \sqrt{-cov(R_{t-1}; R_{t-2})} \tag{9}$$

where *BAS* denotes the percentage bid-ask spread, *cov* denotes the covariance function, and $R_{t\text{-}1}$ and $R_{t\text{-}2}$ are lagged cryptocurrency returns. Similarly, as for other variables, we estimate *BAS* with trailing 20-weeks of daily data.[7]

To examine cross-sectional liquidity patterns related to size, we first sort all the firms into 50 equally sized quantiles, analogously to earlier

[7] As noted by Harris (1990) and Hasbrouck (2009), estimations using equation (9) may be sometimes infeasible due to positive autocovariance between daily changes in prices. To cope with this problem, we replace positive autocovariance with zero.

Table 7
Returns on portfolios from univariate sorts in large and small cryptocurrencies.

	Low	2	3	4	High	High - Low	Low	2	3	4	High	High - Low
	Panel A: Small cryptocurrencies						Panel B: Big cryptocurrencies					
	Panel A.1: Value-weighted portfolios						*Panel B.1: Value-weighted portfolios*					
μ	2.59***	0.31**	0.18*	0.17	−1.26***	−3.84***	0.29	0.15	0.31**	0.55***	0.51**	0.22
	(0.000)	*(0.001)*	*(0.022)*	*(0.029)*	*(0.000)*	*(0.000)*	*(0.037)*	*(0.081)*	*(0.005)*	*(0.000)*	*(0.003)*	*(0.171)*
α_1	2.17***	−0.09	−0.21***	−0.22**	−1.67***	−3.85***	−0.14	−0.28***	−0.14	0.07	0.03	0.17
	(0.000)	*(0.082)*	*(0.000)*	*(0.005)*	*(0.000)*	*(0.000)*	*(0.184)*	*(0.000)*	*(0.030)*	*(0.205)*	*(0.412)*	*(0.223)*
α_3	2.15***	−0.13*	−0.26***	−0.27***	−1.78***	−3.94***	−0.07	−0.27***	−0.13	0.10	0.17	0.23
	(0.000)	*(0.014)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.342)*	*(0.000)*	*(0.048)*	*(0.137)*	*(0.134)*	*(0.151)*
α_8	2.22***	−0.11	−0.25***	−0.26**	−1.70***	−3.91***	−0.01	−0.26***	−0.12	0.09	0.20	0.22
	(0.000)	*(0.029)*	*(0.000)*	*(0.001)*	*(0.000)*	*(0.000)*	*(0.466)*	*(0.000)*	*(0.049)*	*(0.140)*	*(0.085)*	*(0.169)*
	Panel A.2: Equal-weighted portfolios						*Panel B.2: Equal-weighted portfolios*					
μ	9.77***	1.63***	1.65***	1.00***	−3.42***	−13.19***	0.18	0.17	0.29**	0.47***	0.40*	0.22
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.066)*	*(0.053)*	*(0.004)*	*(0.000)*	*(0.012)*	*(0.115)*
α_1	9.32***	1.23***	1.26***	0.61***	−3.79***	−13.11***	−0.25**	−0.25***	−0.18**	0.01	−0.04	0.21
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.003)*	*(0.000)*	*(0.004)*	*(0.474)*	*(0.386)*	*(0.110)*
α_3	9.23***	1.15***	1.19***	0.54***	−3.90***	−13.13***	−0.22*	−0.23***	−0.18*	0.01	0.05	0.27
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.009)*	*(0.000)*	*(0.006)*	*(0.442)*	*(0.370)*	*(0.063)*
α_8	9.25***	1.17***	1.21***	0.55***	−3.87***	−13.12***	−0.15	−0.22***	−0.17*	0.01	0.10	0.25
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.052)*	*(0.000)*	*(0.009)*	*(0.432)*	*(0.250)*	*(0.076)*

The table reports the performance of quintile portfolios from univariate sorts on the lagged daily return (*LRET*) in large and small cryptocurrencies. *Low* and *High* indicate the portfolios with the highest and lowest *LRET*, respectively, and *High-Low* denote the zero-investment strategy of buying (selling) the *High* (*Low*) portfolio. μ is the mean daily excess return. α_1, α_3, and α_8 are alphas from the one-, three-, and eight-factor models, respectively, as described by Eqs. (4)–(6). μ, α_1, α_3, and α_8 are expressed in percentage terms. The values in parentheses are *p*-values corresponding with bootstrap (for mean returns) and Newey-West (1987) adjusted (for alphas) *t*-statistics. The asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. The study period is from 1 January 2015 to 1 March 2021. *Panel A* shows the effects of the tests implemented in 98% of the smallest cryptocurrencies (in terms of the total capitalization), and *Panel B* focuses on 2% of the biggest cryptocurrencies. *Panels A.1* and *B.1* show value-weighted portfolios, and *Panels A.2* and *B.2* refer to equal-weighted portfolios.

tests. Then, we estimate the average *BAS* and *ILLIQ* within each of the quantiles.

Fig. 5 shows the average *ILLIQ* and *BAS* in differently sized quantiles. Undoubtedly, there is a solid and visible relationship between price impact and size and between bid-ask spread and size. The *ILLIQ* is relatively high for all the cryptocurrencies, but it decreases dramatically for the largest coins (Table 6, Panel A). This indicates that only the biggest cryptocurrencies can accommodate supply or demand shocks relatively easily, while all the rest are heavily affected. Notably, this observation is consistent also with Table 2, containing preliminary data statistics, which indicates that the average Spearman's rank-based cross-sectional correlation between *MV* and *ILLIQ* is −0.83. The variables point to the same conclusion: liquidity in cryptocurrencies goes hand in hand with their market capitalization.[8]

Fig. 5, Panel B, displays matching statistics for *BAS*. Again, the picture is very similar. The small-capitalization and medium-capitalization coins are characterized by very high bid-ask spreads, amounting to several percentages. Meanwhile, for the largest cryptocurrencies, the spreads decline to almost zero.

Having demonstrated the clear link between size and liquidity, we continue by examining the cross-sectional relationship between current returns and *LRET* in differently sized quintiles. We want to explore whether liquidity determines the momentum and reversal patterns in daily cryptocurrency returns. Therefore, in the first step, we sort all the firms into 50 equal quintiles based on inverted *ILLIQ* (1/*ILLIIQ*).[9] Next, within each of the quintiles, we run the cross-sectional regressions following Eq. (8). We aim to establish how the slope coefficient on *LRET* changes across different quintiles of stock market liquidity.

Indeed, in line with our conjectures, the liquidity level is an essential determinant of the relationship between past and future returns in cryptocurrencies (see Fig. 6). Across the vast majority of the predominantly illiquid cryptocurrencies, the relationship is strongly negative. However, for the largest coins, the slope coefficient turns *positive*. Moreover, the effect is very strong, and the *t*-statistics associated with slope coefficients are high. In other words, while we observe a reversal in the majority of coins, the handful of the biggest ones exhibit a powerful momentum.[10]

Finally, to explore this issue further, we continue with bivariate sorts. To achieve this, similarly to Table 6, each day we divide the sample by *ILLIQ* using the second percentile as the breakpoint. In other words, we qualify 2% of firms with the lowest *ILLIQ* as *liquid* and the remaining 98% as *illiquid*. In each of these subsets, we sort cryptocurrencies into five equal portfolios based on *LRET* and evaluate their performance using models (4) to (6). The results of this examination are presented in Table 8.

The illiquid cryptocurrencies (Panel A) show a strong daily reversal pattern. The long-short portfolios formed on *LRET* have high (in absolute terms) negative returns associated with *p*-values close to zero. Importantly, the results are significant even after applying one-, three-, and eight-factor models (4)–(6), and they continue to exhibit significant negative alphas for both value-weighted and equal-weighted portfolios.

Table 8, Panel B, concentrates on the top 2% of the most liquid cryptocurrencies. Notably, recall that this category is economically much more significant than all the remaining 98% of the coins. Again, in line with our conjectures, we see a significant daily momentum pattern. The value-weighted (Panel B.1) quintile of assets with the highest *LRET* outperforms the assets with the lowest *LRET* by 0.31% per month and is associated with a very high statistical significance. The eight-factor model alpha on the long-short portfolio equals 0.31%. The results for the equal-weighted portfolios (Panel B.2) are qualitatively consistent. The high *LRET* cryptocurrencies outperform the low *LRET* quintile by 0.18% per month, and the eight-factor model alphas amount to 0.20%.

To assure the robustness of our findings, we also examine the same phenomenon with multivariate cross-sectional regressions. We split the sample into the top 2% and bottom 98% in terms of market illiquidity

[8] Please note that Fig. 5, Panel A, shows logarithms of Amihud's ratios. The actual values resulted in a much bigger dispersion between small and big coins.

[9] We sort on *1/ILLIQ* rather than on *ILLIQ* to ensure consistency with the presentation in Fig. 4. Thanks to this operation, in both figures, the biggest/most liquid firms are on the right, and the smallest/least liquid coins are on the left.

[10] To ensure robustness, we also replicate the cross-sectional regressions using risk-adjusted returns instead of log-returns. The test produces consistent results, so, for brevity, we report them only in Figure A4 in the Internet Appendix.

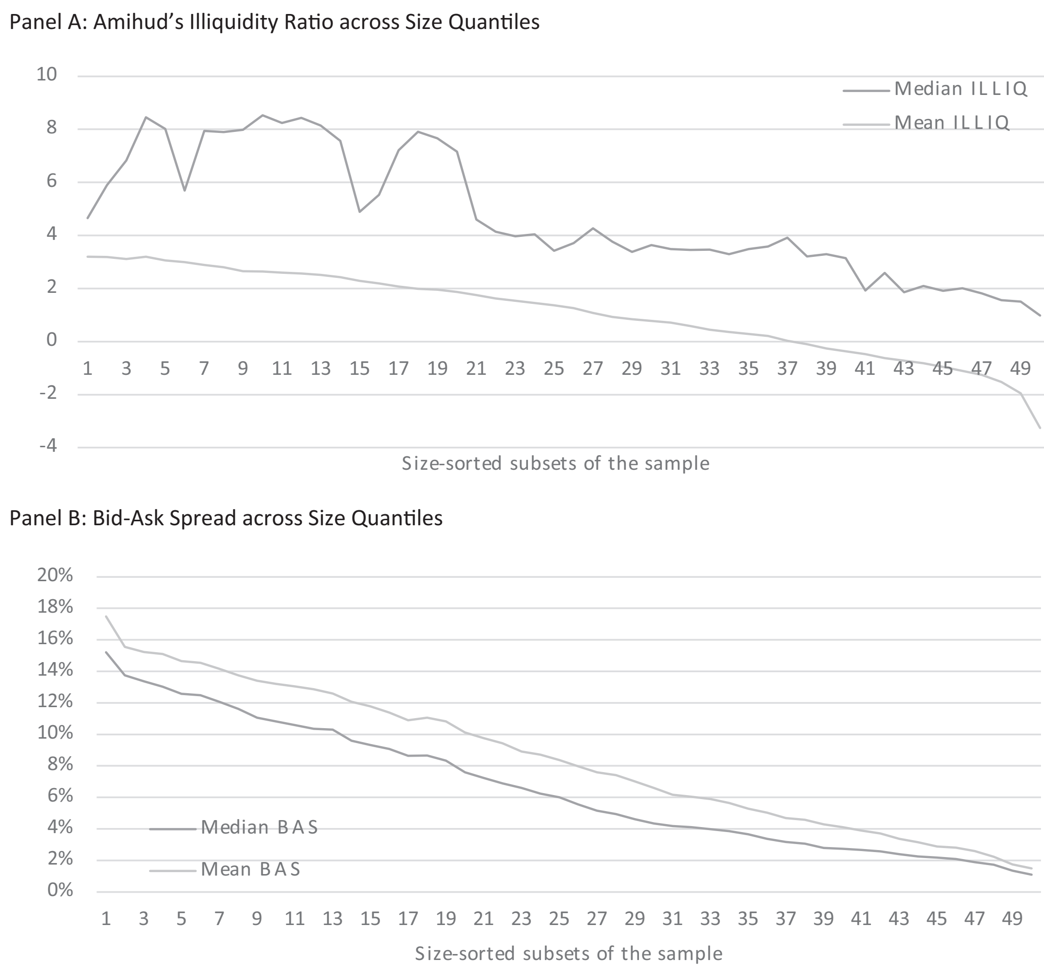


Fig. 5. Cryptocurrency Trading Liquidity across Different Size Quantiles.
The table presents the average levels of cryptocurrency liquidity across different size subsets. Each day, we rank all the cryptocurrencies in our sample on their market capitalization (*MV*) and sort them into 50 equal subsets containing 2% of the coins each. Panel A presents logarithms of the median and mean values of Amihud's (2002) illiquidity ratios (*ILLIQ*) for all the cryptocurrencies in the respective subsets, and Panel B presents the median and mean bid-ask spread (*BAS*). The subset 1 (50) on the horizontal axis denotes the portfolio of cryptocurrencies with the smallest (biggest) MV. *ILLIQ* is estimated using 20 weeks of daily data (divided by 1,000,000). *BAS* is estimated based on trailing 20 weeks of daily returns (R_t) using the formula $BAS = \sqrt{-cov(R_t, R_{t-1})}$. The study period is from 1 January 2015 to 1 March 2021.
Panel A: Amihud's Illiquidity Ratio across Size Quantiles.
Panel B: Bid-Ask Spread across Size Quantiles.

and apply cross-sectional Fama-MacBeth (1973) regressions similar to those in Table 6 in both subsamples. This additional test yields consistent results with sorts, showing a positive (negative) cross-sectional relationship between current returns in the cross-section and *LRET* in liquid (illiquid) cryptocurrencies. For brevity, we report these results in detail only in Table A4 of the Internet Appendix.

6. Concluding remarks

The study examines persistence in daily returns in cryptocurrency markets. We demonstrate a powerful short-term (one-day) reversal effect. The cryptocurrencies with low returns on the previous day strongly outperform cryptocurrencies with a high last day's return. The effect is confirmed by univariate and bivariate sorts, subperiod analysis, and cross-sectional regressions, and is not subsumed by popular asset price predictors, such as beta, market value, medium- and long-term past returns, seasonality, idiosyncratic volatility, illiquidity, and turnover.

Our further investigations reveal the essential role of size in the development of the reversal effect. We demonstrate that, contrary to the majority of different cryptocurrencies, 2% of the biggest coins exhibit momentum rather than reversal. Importantly, the remaining 98% of the market with reverting returns accounts for only a small fraction of the total market capitalization. The handful of cryptocurrencies, which make up more than 96% of the total market capitalization, shows no sign of reversal. This observation reconciles earlier conflicting findings on return patterns in cryptocurrency markets that relied on different samples.

Finally, we also discuss the sources of the daily reversal and discrepancy between the behavior of large and small cryptocurrencies. We argue that the effect is driven primarily by the liquidity effects. Small cryptocurrencies are less liquid. Hence, they suffer from demand and supply shocks that cannot be absorbed by liquidity, as well as exhibit a bid-ask bounce. Consistently with this, the illiquid cryptocurrencies display a daily reversal, while the liquid ones show a daily momentum.

Our findings provide new insights into asset pricing in cryptocurrency markets. They show that the cryptocurrencies exhibit similar return patterns as other asset classes such as equities, bonds, currencies, or commodities (see, e.g., Asness et al., 2013; Blackburn & Cakici, 2017; Tajaddini & Crack, 2012; Menkhoff et al., 2012; Jostova et al., 2013; Zaremba et al., 2020; Malin & Bornholt, 2013; Bianchi et al., 2015). We

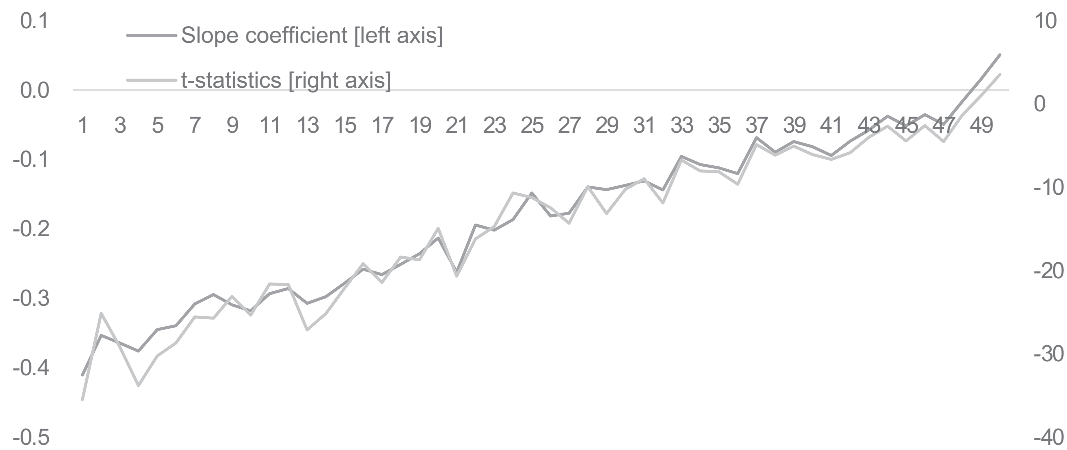


Fig. 6. Cross-Sectional Regressions across Different Liquidity Classes.
Each day, we sort the cryptocurrencies into 50 equal subsets based on their liquidity and measured with the inverted Amihud's (2002) illiquidity ratio (*1/ILLIQ*) and apply cross-sectional regressions in the style of Fama and MacBeth (1973): $R_i = \lambda_0 + \lambda_{LRET} LRET_i + \varepsilon_i$,
where the dependent variable R_i is the daily log-return on cryptocurrency *i*, $LRET_i$ is the lagged daily return at $t-1$, ε_i is the residual term, and λ_0, λ_{LRET}, and λ_J are the estimated regression parameters. The figure reports average slope coefficients from the regression in different liquidity-sorted subsets along with the associated Newey-West (1987) adjusted *t*-statistics. The subset 1 (50) on the horizontal axis denotes the portfolio of the least (most) liquid cryptocurrencies. The study period is from 1 January 2015 to 1 March 2021.

Table 8
Returns on portfolios from univariate sorts in liquid and illiquid cryptocurrencies.

	Low	2	3	4	High	High - Low	Low	2	3	4	High	High - Low
	Panel A: Illiquid cryptocurrencies						Panel B: Liquid cryptocurrencies					
	Panel A.1: Value-weighted portfolios						*Panel B.1: Value-weighted portfolios*					
μ	1.30***	0.19	0.24**	0.37**	−0.45**	−1.75***	0.13	0.22	0.17	0.31**	0.44***	0.31*
	(0.000)	*(0.026)*	*(0.004)*	*(0.001)*	*(0.002)*	*(0.000)*	*(0.081)*	*(0.034)*	*(0.044)*	*(0.002)*	*(0.000)*	*(0.007)*
α_1	0.90***	−0.22***	−0.17**	−0.06	−0.87***	−1.77***	−0.28***	−0.24**	−0.21**	−0.16	0.02	0.30**
	(0.000)	*(0.000)*	*(0.002)*	*(0.235)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.003)*	*(0.001)*	*(0.029)*	*(0.403)*	*(0.003)*
α_3	0.84***	−0.23***	−0.19***	−0.07	−0.95***	−1.79***	−0.26***	−0.25**	−0.21**	−0.16	0.06	0.32**
	(0.000)	*(0.000)*	*(0.000)*	*(0.187)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.001)*	*(0.025)*	*(0.260)*	*(0.002)*
α_8	0.90***	−0.23***	−0.18***	−0.08	−0.89***	−1.78***	−0.26***	−0.26**	−0.21**	−0.17*	0.05	0.31**
	(0.000)	*(0.000)*	*(0.000)*	*(0.175)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.001)*	*(0.013)*	*(0.276)*	*(0.003)*
	Panel A.2: Equal-weighted portfolios						*Panel B.2: Equal-weighted portfolios*					
μ	5.16***	1.00***	0.75***	0.48***	−1.97***	−7.12***	0.18	0.28*	0.16	0.28**	0.35***	0.18
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.030)*	*(0.006)*	*(0.043)*	*(0.004)*	*(0.000)*	*(0.064)*
α_1	4.72***	0.60***	0.35***	0.09	−2.35***	−7.06***	−0.21***	−0.17*	−0.21**	−0.14	−0.02	0.20*
	(0.000)	*(0.000)*	*(0.000)*	*(0.112)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.020)*	*(0.001)*	*(0.051)*	*(0.409)*	*(0.023)*
α_3	4.64***	0.53***	0.28***	0.01	−2.49***	−7.13***	−0.21***	−0.18*	−0.21**	−0.14	0.01	0.22*
	(0.000)	*(0.000)*	*(0.000)*	*(0.414)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.009)*	*(0.001)*	*(0.044)*	*(0.434)*	*(0.014)*
α_8	4.66***	0.55***	0.29***	0.02	−2.45***	−7.12***	−0.20**	−0.19*	−0.21**	−0.16*	0.00	0.20*
	(0.000)	*(0.000)*	*(0.000)*	*(0.369)*	*(0.000)*	*(0.000)*	*(0.001)*	*(0.006)*	*(0.001)*	*(0.019)*	*(0.485)*	*(0.025)*

The table reports the performance of quintile portfolios from univariate sorts on the lagged daily return (*LRET*) in large and small cryptocurrencies. *Low* and *High* indicate the portfolios with the highest and lowest *LRET*, respectively, and *High-Low* denote the zero-investment strategy of buying (selling) the *High* (*Low*) portfolio. μ is the mean daily excess return. α_1, α_3, and α_8 are alphas from the one-, three-, and eight-factor models, respectively, as described by Eqs. (4)–(6). μ, α_1, α_3, and α_8 are expressed in percentage terms. The values in parentheses are *p*-values corresponding with bootstrap (for mean returns) and Newey-West (1987) adjusted (for alphas) *t*-statistics. The asterisks *, **, and ***denote statistical significance at the 5%, 1%, and 0.1% levels, respectively. The study period is from 1 January 2015 to 1 March 2021. *Panel A* shows the effects of the tests implemented in 98% of the least liquid cryptocurrencies (in terms of Amihud's illiquidity ratio), and *Panel B* focuses on 2% of the biggest cryptocurrencies. *Panels A.1* and *B.1* show value-weighted portfolios, and *Panels A.2* and *B.2* refer to equal-weighted portfolios.

provide convincing evidence that both momentum and reversal drive commodity prices. Our findings corroborate the findings of Medhat and Schmeling (2020) and Chiang et al. (2020) that the existence of short-term momentum and reversal patterns strongly depend on trading liquidity.

Our study not only uncovers and explains new phenomena in the behavior of cryptocurrency prices, but may also lay foundations for efficient quantitative trading strategies. While the short-run reversal is prevalent in the vast majority of cryptocurrency returns, the practical implementation of reversal-based strategies may be challenging. The relatively small market value effectively limits potential profits. Investors should rather focus on the momentum effect, which drives the prices on the tradeable cryptocurrencies.

Future studies may concentrate on exploring the role of market capitalization and liquidity for other asset pricing anomalies in cryptocurrency markets. Perhaps other cross-sectional return patterns are also determined by size and illiquidity factors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2021.101908.

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