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Unravelling cross-sectional patterns in cryptocurrencies: a four-factor asset pricing model

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Abstract

Purpose – This paper examines the pricing effect of cross-sectional patterns in the cryptocurrency market, aiming to enhance the composition of asset pricing factors for a better explanation of cross-sectional variability in cryptocurrency returns.

Design/methodology/approach – The study utilizes data from 1,160 cryptocurrencies spanning over nine years, from January 2014 to December 2022, totalling 468 weeks. We obtain data for all cryptocurrencies using the application programming interface (API) provided by coinmarketcap.com and employ a well-established multifactor asset pricing methodology aimed at proposing an improved composition of cryptocurrency factors.

Findings – The findings of the study uncover a strong size effect, a distinctive reversal effect, and a significant premium for cryptocurrency illiquidity. Contrary to the prevailing views, the observed reversal effect challenges the established momentum effect, while the observed illiquidity premium appears not to be explained by the size effect or other cross-sectional patterns. In response to these insights, the study introduces a novel four-factor asset pricing model, comprising the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and crypto illiquidity factor (CIHML).

Originality/value – This paper contributes to the literature in three significant ways. Firstly, the comprehensive analysis of the cryptocurrency market from the perspective of empirical asset pricing enriches the available literature on cryptoasset pricing. Moving beyond the identified patterns of crypto market risk, crypto size effect and pervasive momentum effect in the market, our study advances the mostly used three-factor model with the reversal and illiquidity factors. The comparative evaluation of various combinations of three-factor, four-factor and five-factor models demonstrates the superior performance of the proposed four-factor model. Thirdly, the study identified a significant illiquidity premium in the cryptocurrency market.

Keywords Cryptocurrency, Asset pricing, Factor model, Size, Reversal, Illiquidity

Paper type Research article

1. Introduction

Since its emergence in 2009 as an open-source digital currency, Bitcoin has sparked the creation and launch of numerous cryptocurrencies built on blockchain technology (Liu, Liang, & Cui, 2020). Bitcoin holds the distinction of being the first decentralized blockchain-based cryptocurrency and continues to maintain its status as the most widely recognized and utilized coin in the cryptocurrency market (Li & Wang, 2017). In 2016, Bitcoin witnessed an impressive 122% surge in its price, followed by an astounding 1,360% increase in 2017 (Bouri,

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Shahzad, & Roubaud, 2019). The success of Bitcoin has inspired the creation of numerous alternative cryptocurrencies, such as Litecoin, Dogecoin and Ethereum, among others (Ammous, 2018). The cryptocurrency market operates in a completely decentralized manner, which contributes to its inherent volatility and susceptibility to massive speculative price bubbles (Yermack, 2015).

Many studies have attempted to examine the potential factors influencing cryptocurrency returns. Phillips and Gorse (2018) confirmed that online activities, including Google searches and Wikipedia queries, have a long-term positive association with cryptocurrency returns. The reason is that the increased interest in, and the number of searches on, cryptocurrency created the growth of cryptocurrency demand, including purchasing, methods of payment and transaction needs (Bakas, Magkonis, & Oh, 2022). In addition, Teker, Teker, and Ozyesil (2020) assess how the changes in gold and oil prices affect the various cryptocurrency movements during the period from 2017 to 2019. The empirical results reveal a co-integration relationship only between Tether, gold and oil prices. This is supported by Nakagawa and Sakemoto (2021), who investigated the relationship between cryptocurrency expected returns and macroeconomic fundamentals. The results suggest that a few macroeconomic factors are not sufficient in capturing the change in cryptocurrency returns; in contrast, the common factors are strongly associated with cryptocurrency expected returns. The rationale is that investors employ a lot of macroeconomic indicators for their investment decisions. Furthermore, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) also found evidence that the dynamics of cryptocurrencies are relatively isolated from a variety of other financial assets, indicating that it is practically impossible to construct effective cryptocurrency factors based on external information from other types of financial markets.

A substantial body of literature has focused on identifying common factors influencing cryptocurrency returns. Jia, Goodell, and Shen (2022) introduced a three-factor pricing model consisting of market, size and momentum factors, which outperforms the cryptocurrency CAPM and demonstrates greater explanatory power than the findings of Shen, Urquhart, and Wang (2020). This is supported by Liu *et al.* (2020), who documented that the three-factor model, including market, size and momentum factors, captures the cross-sectional variation in average cryptocurrency returns. In addition, Wang and Chong (2021) used the Fama–MacBeth method to investigate the cryptocurrency pricing factors, including cryptocurrency size, momentum and value-to-growth, taking cryptocurrency's unique coin-to-token as a proxy for value-to-growth. The results indicate that the three-factor model constructed with significant factors can explain most of the cryptocurrency excess returns. Additionally, Shahzad, Bouri, Ahmad, Naeem, and Vo (2021) incorporate the contagion risk factor into the three-factor pricing model, demonstrating that the four-factor pricing model provides an improved explanatory power compared to both the cryptocurrency CAPM and the three-factor model.

Similarly, Kakushadze (2019) employed a four-factor model and found that the momentum factor had the strongest influence on predicting crypto-asset returns, outperforming size, volume and volatility. This aligns with the broader literature, as size and momentum are among the most extensively studied effects in both traditional and cryptocurrency asset pricing (Liu, Tsyvinski, & Wu, 2022). These findings raise an important question: Does the momentum strategy dominate other factors in predicting cryptocurrency returns? To address this, the present study applies a four-factor model incorporating crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and crypto illiquidity factor (CIHML) to explore cryptocurrency return patterns.

To analyse the cryptocurrency market from the perspective of empirical asset pricing, we studied a total of 1,160 cryptocurrencies over nine years, from January 2014 to December 2022. Unlike the well-established equity asset pricing literature, this study utilizes only cryptoasset prices and available market data for analysis. The initial results reveal a strong size effect, a notable short-term reversal effect and a significant risk premium for illiquid cryptos. Contrary to the existing literature on momentum effects (Asness, Moskowitz, & Pedersen, 2013; Carhart, 1997; Jegadeesh, & Titman, 1993; Sockin & Xiong, 2023), the observed reversal patterns in cross-sections of cryptos were persistently found across one-week, two-week, three-week and four-week momentum proxies. These intriguing results are consistent with the findings of Grobys and Sapkota (2019) and Shen *et al.* (2020) and provide evidence that the crypto market adjusts quickly. The identified illiquidity pattern, previously assumed to be captured by the size effect in the literature (Liu *et al.*, 2022), requires further testing for its distinct explanatory power in cross-sections of crypto returns. The observed negative price effect of investors' expected lottery-like payoffs from the crypto markets is in line with the results that have been observed in the equity market (Bali *et al.*, 2011; 2017). Additionally, the use of the S&P index variable, which aimed to investigate the impact of equity market performance on crypto market performance, did not reveal any significant relationship between the two markets.

The identified patterns in the study are further used to construct different asset pricing factors, such as the crypto market factor (CRm-Rf), the crypto size factor (CSMB), the crypto reversal factor (CLMW), the crypto illiquidity factor (CIHML), the lottery-like max factor (CLMH) and the stock market factor (CS&PF). These factors are then regressed against each other to verify their distinct explanatory power of cross-sectional variability. Especially, the test of their orthogonalized form ensures that the illiquidity effect is not being captured by the size effect or any other, for instance. The regression results demonstrate the significant explanatory power of individual factors that can be incorporated into any composition of asset pricing models to test their relative performance in explaining the cross-sectional variability of expected crypto returns. Further tests of the single-factor, three-factor and four-factor models indicate that the proposed four-factor model outperforms across all regression tests. These regression tests were conducted against the nine size and momentum portfolios, nine size and illiquidity portfolios, nine size and max portfolios and eight zero investment portfolios, which form the left-hand side of the regressions. The used GRS tests also confirm the comparatively superior performance of the four-factor model, which includes the crypto market factor (CRm-Rf), the crypto size factor (CSMB), the crypto reversal factor (CLMW) and the crypto illiquidity factor (CIHML).

This paper contributes to the literature in three significant ways. First, the comprehensive analysis of the cryptocurrency market from the perspective of empirical asset pricing enriches the available literature on cryptoasset pricing. Moving beyond the identified patterns of crypto market risk, crypto size effect and pervasive momentum effect in the market, our study advances the mostly used three-factor model with the reversal and illiquidity factors. The comparative evaluation of various combinations of three-factor and four-factor models demonstrates the superior performance of the proposed four-factor model, which includes market, size, reversal, and illiquidity factors. The study presents robust results across daily and weekly analyses and the different sample periods of the crypto market, offering a refined composition of the crypto asset pricing factors for an improved explanation of the cross-sectional variability in expected crypto returns. Second, in contrast to the pervasive momentum effect of the equity market, the findings of this paper support the existence of a reversal effect in the crypto market. Short-term reversals in crypto differ from equities, often arising due to extreme retail speculation, overreaction to news, and market manipulation (Cong, Li, Tang, & Yang, 2023). The price reversal effect is further amplified by momentum-driven liquidation in leveraged trading (Liu *et al.*, 2022), supporting its inclusion as a key pricing factor.

Third, the study identified a significant illiquidity premium in the cryptomarket. Unlike other studies that assume that the illiquidity premium is captured by the size effect, our study demonstrates a robust presence of the illiquidity effect in the cryptocurrency market. Influenced by exchange fragmentation, arbitrage inefficiencies, and liquidity mining incentives in decentralized finance (DeFi) (Gandal, Hamrick, Moore, & Oberman, 2018), the observed illiquidity in cryptocurrencies delivers excess returns due to execution risk and market inefficiencies (Bianchi, Babiak, & Dickerson, 2022).

The rest of the paper is structured as follows: Section two describes the data and methodology employed in the study. Section three presents the study's results and discusses the observed phenomena. The final section concludes the paper by summarizing the key findings, providing implications of the findings and outlining future research directions in the field.

2. Data and methodology

2.1 Data and sample period

The study utilizes data from 1,160 cryptocurrencies spanning over nine years, from January 2014 to December 2022, totalling 468 weeks. The dataset primarily includes daily and weekly closing prices, trading volumes and market capitalization of these cryptocurrencies, sourced from the Coin Market Cap website. This website serves as a prominent source of cryptocurrency price and volume, as noted by Liu *et al.* (2022). It compiles information from over 200 major cryptocurrency exchanges, providing daily data on metrics, such as opening and closing prices, high and low prices, trading volume and market capitalisation (in US dollars [US$]) for a wide range of active and discontinued cryptocurrencies.

We obtain data for all cryptocurrencies using the application programming interface (API) provided by this website <https://coinmarketcap.com/>, which reports the last traded price and trading volume over the past 24 hours. Subsequently, all historical cryptocurrency data were cleaned and processed by Python software. This process led to the exclusion of cryptocurrencies that lacked available data on liquidity and trading volume and those with a market capitalization of less than $1 million. This approach aligns with Liu *et al.* (2022), who also excluded coins with a market capitalization below this threshold.

The data were collected for the period from 1 January 2014 to 31 December 2022. The rationale for this period is that Liu *et al.* (2022) highlighted the availability of cryptocurrency trading volume data in the last week of 2013, with their sample period starting from the beginning of 2014. Another reason is the remarkable expansion of the cryptocurrency market, beginning in 2018, along with the onset of the COVID-19 pandemic in March 2020 and the regulatory actions taken by the Chinese government in May 2022 (Yang, Wang, Wu, Wu, & Zheng, 2023). In addition, Bitcoin halving events took place in 2016 and 2020, marking two complete Bitcoin cycles from 2014 to 2022. These events have had a notable impact on the cryptocurrency market (Singla, Singla, & Gupta, 2023). Furthermore, this sample period ensured sufficient data for our study's empirical analysis. We obtained daily and weekly yields of US three-month treasury bills serving as a proxy for the risk-free rate of return and daily and weekly closing prices of the S&P 500 index acting as a stock market proxy.

2.2 Methodology

Utilizing the above-discussed data, we employ the well-established multifactor asset pricing methodology (Carhart, 1997; Fama & French, 1996, 2015, 2018; Hou, Xue, & Zhang, 2015). The employed methodology is expected to propose a nested composition of cryptocurrency factors that can be used to explain the maximum cross-sectional variability of expected returns in the cryptocurrency market. To implement the chosen methodology, we follow certain steps, outlined as follows:

To begin, we compute daily and weekly excess returns for the cryptocurrencies. The returns are calculated using the logarithmic difference in prices from which daily and weekly yields of US three-month treasury bills are subtracted to derive the excess returns. These excess returns are then used to formulate various variables for the study.

Secondly, we calculate all the remaining variables essential for the study. We initiate the process by calculating the market beta. To calculate the beta, we constructed a value-weighted cryptocurrency market portfolio utilizing all 1,160 considered cryptocurrencies. The resulting proxy of the market portfolio provides the daily market return (Rm). Upon subtracting the proxy of the daily risk-free return (Rf) from this value, we derive the daily market excess return (Rm-Rf). We then regress the daily market excess return against the excess return of individual cryptocurrency, yielding the coefficient of the regression, known as beta – a proxy for market risk. The calculation of this beta is performed recursively using the daily excess returns of the past three months. Employing a rolling window estimation based on the data from the last three months, we calculate beta every week, continuing this process until the end of our study, which results in a beta time series of 468 weeks.

Thirdly, we calculate the different forms of momentum variables. We start with the calculation of one-week momentum, which is the average of the previous week's daily returns. Similarly, the two-week momentum is the average of the previous two weeks' daily returns. Three-week momentum is the average of the previous three weeks' daily returns, and the four-week momentum is the average of the previous four weeks' daily returns. The illiquidity (Illiq) of individual cryptocurrencies is obtained following the method outlined by Amihud (2002). It involves dividing the absolute values of daily returns by the total daily volume/turnover of the respective cryptocurrencies and then averaging these values over the previous week. The max variable represents the highest single-day return from the past week. S&P beta is calculated in a similar manner as beta for cryptocurrencies, but this time, S&P index returns are regressed against individual cryptocurrency returns. The size variable used in the study is the weekly market capitalization of the considered cryptocurrencies. Fourthly, we calculate univariate quantile portfolio returns to identify the existing patterns in the cryptocurrency market. Fifthly, we create bivariate sorted portfolios, using the independent sorting method to disentangle the price specifics of the obtained patterns. Based on the identified patterns, then we form factors that contribute to the composition of various crypto asset pricing models, which are then rigorously tested for robust explanatory power.

Finally, we assess the explanatory power of different combinations of asset pricing factors, aiming to identify the nested composition of the cryptoasset pricing model. The GRS test is employed to evaluate the absolute explanatory power of each asset pricing model. Additionally, multiple regression sets are run to test the relative performance of different combinations of asset pricing factors against various sets of constructed portfolios. To ensure the robustness of our results, we also conducted the same analysis using daily data and across different sample periods (before the COVID-19 period and the whole sample period). The following section of the study presents a descriptive analysis of the data and highlights the patterns identified in the cross-sections of cryptocurrency returns.

3. Preliminary analysis

As the primary aim of this research is to discern notable cross-sectional patterns that can contribute to the formulation of a comprehensive framework for pricing factors, this section begins with an exploration of descriptive statistics concerning the study variables. Subsequently, the following subsection in the preliminary insight section unveils the outcomes of univariate and bivariate analysis utilized for detecting the presence of cross-sectional patterns in cryptocurrency returns.

3.1 Descriptive statistics

Table 1 summarizes the descriptive statistics for the market capitalization and the trading volume of the cryptocurrencies used in the study. Panel A of the table presents statistics for the size (market capitalization) of the currencies, while panel B shows a year-wise descriptive of daily trading volume. The table reveals an incremental change in the number of available cryptocurrencies, which was just 20 in 2014 and then reached 526 by 2021, though it further reduced to 453 by the end of 2022. Panel A of the table presents a similar incremental change in the average size of the cryptocurrencies. This incremental change in the size also reflects the boom of the cryptocurrency market. However, the downturn of 2022 seems to have corrected

Table 1. Yearly distribution of cryptocurrencies

Year	Number of coins	Mean	Median	SD	Skewness	Kurtosis	25th Pctl	75th Pctl	Maximum
Panel A: Size distribution									
Market cap (mil)									
2014	20	3705.10	1.12	16363.58	4.13	15.05	0.60	17.31	73224.40
2015	34	1504.94	0.79	8717.23	5.57	29.03	0.11	3.08	50839.33
2016	45	2911.56	1.44	19342.56	6.48	40.02	0.11	5.63	129780.11
2017	113	11088.10	77.42	85639.92	9.70	95.73	13.75	534.56	886797.26
2018	294	7083.43	41.09	98791.89	16.71	280.69	5.32	159.12	1683049.32
2019	394	5456.79	11.75	96765.43	19.71	387.35	2.30	78.18	1919301.37
2020	490	7652.64	19.26	150437.57	22.02	483.56	1.85	150.18	3328469.95
2021	526	30761.44	57.45	577276.69	22.60	512.50	6.22	512.73	13191205.48
2022	453	24004.04	20.92	407238.74	20.82	436.27	2.46	325.96	8615479.45
Panel B: Volume distribution									
Trading volume (mil)									
2014	20	13.43	0.05	59.26	4.25	16.04	0.01	0.26	272.03
2015	34	11.79	0.01	72.21	5.92	33.03	0.00	0.03	445.18
2016	45	25.42	0.01	178.26	6.86	45.02	0.00	0.05	1260.72
2017	113	369.47	1.37	2890.98	9.71	97.91	0.10	17.50	31662.11
2018	294	274.42	0.72	4153.58	18.65	349.01	0.07	4.51	78640.42
2019	394	602.99	0.38	11148.21	21.54	465.35	0.02	4.94	242842.10
2020	490	851.29	0.61	19328.51	27.77	777.03	0.04	7.37	543751.37
2021	526	1,150.52	1.26	22863.28	29.43	889.27	0.05	11.14	695747.95
2022	453	943.77	0.32	18139.88	25.90	693.78	0.01	3.40	493158.90

Note(s): The table presents descriptive statistics for the market capitalization and trading volume of the analysed cryptocurrencies. Panel A presents specifics regarding the market capitalization of the considered cryptocurrencies, while Panel B provides descriptive statistics for trading volume. Columns of the table offer year-wise information for the number of coins, mean market capitalization, mean trading volume, median, standard deviation (SD), skewness, kurtosis, 25th percentile, 75th percentile and the maximum observed value for each year

Source(s): Authors' work

this increased valuation of cryptocurrencies to some extent. The panel also shows that the observed increased size of the cryptocurrencies has progressed with the increased level of standard deviation, more skewness and a fat-tail distribution of the crypto market capitalization.

3.2 Bivariate analysis

Consistent with the methods used to identify the existence of cross-sectional patterns in the stock market, we utilize both univariate and bivariate sorting techniques to construct independently sorted portfolios. We proceed to analyse the existing patterns within the cryptocurrency market, assessing the presence of size, momentum, market risk, illiquidity, max and S&P beta patterns in the expected returns of the cryptocurrencies. In the initial stage, we form univariate-sorted portfolios based on the cross-sectional characteristics of the selected cryptocurrencies to identify the prevailing return patterns. Building on these findings, we apply bivariate independent sorting techniques to construct portfolios that simultaneously capture multiple pricing patterns. This approach allows us to disentangle the joint effects of different identified patterns, providing a more nuanced understanding of cryptocurrency return dynamics. For brevity, the results of the univariate-sorted portfolios are presented in Appendix section of the study.

3.2.1 Size and momentum weighted portfolios. Table 2 presents the average weekly expected returns in excess of the weekly yield of the one-month treasury bill rate. The table comprises the four panels which show the joint impact of size and momentum variables across the different proxies of momentum variables (one-week momentum, two-week momentum, three-week momentum and four-week momentum). Panel A of the table presents the expected impact of the size and one-week momentum (Momemtum1) variable across the nine bivariate independent sorted portfolios. The first column of the Panel, labelled "Big", reveals the expected excess returns for a portfolio comprising the largest cryptocurrencies, which make up the top 33% in terms of market capitalization. Conversely, the fifth column in the panel depicts results for the portfolio consisting of the smallest cryptocurrencies, representing the bottom 33% in the analysis. The third column of the panel presents portfolio returns for mid-range cryptocurrencies. Additionally, the seventh column provides the average returns for portfolios of different sizes (big, medium and small), considering various momentum-based

Table 2. Size and momentum sorted nine bivariate (3 × 3) value-weighted portfolios

	Big	(*t*)	Medium	(*t*)	Small	(*t*)	Col average	(*t*)
Panel-A- Size/Momentum1								
Size/Momentum1								
High	1.09	(1.18)	3.71***	(2.45)	5.88***	(3.07)	3.56***	(3.07)
Medium	1.89**	(2.52)	3.12***	(2.91)	7.62***	(4.86)	4.21***	(4.51)
Low	0.53	(0.58)	6.70***	(6.16)	12.83***	(6.60)	6.68***	(6.45)
Row Average	1.17*	(1.67)	4.51***	(4.35)	8.78***	(6.45)		
Panel-B- Size/Momentum2								
Size/Momentum2								
High	1.11	(0.95)	3.93***	(2.81)	5.70***	(3.09)	3.58***	(3.05)
Medium	1.49**	(2.03)	4.19***	(3.67)	5.82***	(4.02)	3.84***	(4.02)
Low	−0.14	(-0.18)	6.32***	(4.76)	13.42***	(6.08)	6.53***	(6.11)
Row average	0.82	(1.10)	4.81***	(4.52)	8.31***	(6.32)		
Panel-C- Size/Momentum3								
Size/Momentum3								
High	1.56*	(1.88)	3.72***	(2.79)	7.71***	(3.78)	4.33***	(3.72)
Medium	1.06	(1.39)	3.57***	(3.14)	3.79***	(3.24)	2.80***	(3.44)
Low	0.69	(0.83)	6.14***	(5.07)	13.39***	(5.99)	6.74***	(6.21)
Row average	1.10	(1.60)	4.48***	(4.48)	8.29***	(6.25)		
Panel-D- Size/Momentum4								
Size/Momentum4								
High	1.05	(1.28)	3.80***	(2.83)	6.59***	(2.91)	3.81***	(3.25)
Medium	1.01	(1.35)	4.20***	(3.14)	3.98***	(3.42)	3.07***	(3.34)
Low	1.35	(1.53)	5.93***	(5.46)	12.76***	(7.50)	6.68***	(6.80)
Row average	1.14*	(1.65)	4.65***	(4.49)	7.78***	(5.77)		

Note(s): The table shows the average weekly excess returns for portfolios formed by the intersection of Size (market capitalization) and Momentum observed in the returns of the analysed cryptocurrencies. Market capitalization is used as a proxy for size, while Momentum is calculated as the average daily returns over the previous one to four weeks (Momentum1, Momentum2, Momentum3 and Momentum4). These variables are used to create bivariate sorted portfolios over eight years from January 2015 to December 2022, totalling 418 weeks. Each week, cryptocurrencies are divided into three Size groups (Small, Medium and Big) and three Momentum groups (Low, Medium and High) using 33% breakpoints. This results in nine value-weighted portfolios that combine Size and Momentum variables, illustrating the relationship between these characteristics and the one week ahead expected excess returns. Statistical significance is indicated by superscripts ***, ** and * for the 1, 5 and 10% levels, respectively

Source(s): Authors' work

classifications of cryptocurrencies. Next to each of these columns, you will find *t*-stat values that indicate the statistical significance of the obtained results.

Panel A of Table 2 reveals a notable weekly average excess return of 8.78% for the smallest quantile portfolio. However, this return substantially diminishes to 1.17% weekly for the largest quantile of sorted cryptocurrencies. This observed pattern is not limited to the average level; it persists across various rows of the panel, encompassing different quantiles of momentum-sorted cryptocurrencies. The substantial contrast in returns between the smallest and largest quantiles of size-sorted cryptocurrencies underscores the presence of a significant size effect in the cryptocurrency market. This phenomenon is consistently observed across all panels of Table 2.

Panel A of Appendix Table 2 [1] also highlights similar findings regarding the strong size effect. The univariate sorted quantile portfolios reveal a negative relationship between cryptocurrency market capitalization and expected excess returns. The results show that cryptocurrencies with high market capitalization have an average weekly expected excess return of 1.13%, which increases to 10.98% for those with the smallest market capitalization. This results in a size premium of 9.76% per week (*t*-stat = 5.78) for the low-high capitalization portfolio. Consistent with the established literature on size effects across various asset classes (Ang, Hodrick, Xing, & Zhang, 2006; Asness, Frazzini, Israel, Moskowitz, & Pedersen, 2018; Banz, 1981; Fama & French, 2015; Liu *et al.*, 2022), these findings affirm the robust existence of a size effect in the cryptocurrency market.

The rows within Panel A exhibit portfolio returns for cryptocurrencies organized by their return momentum. The initial row in Panel A showcases outcomes for the High quantile (top 33%) of momentum-sorted cryptocurrencies across various quantiles of size-sorted cryptocurrencies. The average excess return noted for the highest quantile of the momentum-sorted portfolio is 3.56% weekly, increasing to 6.68% per week when calculated for the lowest quantile of momentum-sorted cryptocurrencies. The independent sorting portfolio technique unveils distinct cross-sectional patterns in cryptoreturns. To further scrutinize these patterns, the second row illustrates outcomes for mid-momentum cryptocurrencies, revealing a return of 4.21%. This figure surpasses the 3.56% return for the highest quantile and falls short of the 6.68% return for the lowest quantile (the third row delineates portfolio returns for low-momentum cryptocurrencies constituting the bottom 33% of cryptos in terms of momentum). The sequential rise in average returns from the highest to lowest quantile unveils a gradual increase in returns from cryptocurrencies that performed well in the last week to those that have recently underperformed. These findings deviate from the observed momentum effects in various other asset classes, where higher momentum stock returns typically imply a higher expected return (Asness *et al.*, 2013; Liu *et al.*, 2022; Sockin & Xiong, 2023). In this case, however, the lowest momentum cryptos exhibit higher expected returns when compared to the highest momentum quantile cryptos.

Simultaneously, an intriguing sub-pattern emerges in Panel A, supporting the momentum effect among large-sized cryptocurrencies. This sub-pattern reveals that, in contrast to other columns, within the quantile of large-size cryptos, high-momentum cryptos yield higher returns (1.09%), while low-momentum cryptos yield lower returns (0.53%). However, this sub-pattern is not robust enough to significantly impact the overall existence of an opposing momentum effect in the cryptocurrency market for a one-week momentum effect.

The subsequent panels provide analogous information, with the only distinction being the manner in which data is presented row by row, transitioning from one-week momentum to two-week, three-week and four-week momentum in the other panels (Panel B for size and two-week momentum, Panel C for size and three-week momentum and Panel D for size and four-week momentum). Despite these variations, all panels endorse the same patterns as identified in Panel A. Additionally, the univariate sorted momentum quantile portfolios [2] show a consistent pattern of returns decreasing from lower quantile momentum portfolios to higher quantile portfolios across all momentum variable proxies (Momentum1, Momentum2, Momentum3 and Momentum4). Similar results were obtained across different sample periods.

The analysis conducted for the pre-COVID-19 period presents the same pattern, with higher returns for the low-momentum portfolio, gradually decreasing as the value of momentum increases from low- to high-momentum portfolios. The daily data analysis similarly yields the same reversal effect across different momentum proxies.

These intriguing results contrast with the well-established momentum effect observed across traditional asset classes, necessitating a detailed explanation of the observed reversal effect in the cryptocurrency market. The unique market microstructure of cryptocurrencies provides key insights into these contrasting results. Unlike traditional financial markets, cryptocurrency markets are highly fragmented, dominated by retail traders and exhibit limited institutional presence, leading to greater price inefficiencies (Auer, Farag, Lewrick, Orazem, & Zoss, 2023). The existing literature suggests that short-term reversals in crypto differ from equities, often arising due to extreme retail speculation, overreaction to news and coordinated market manipulation, such as pump-and-dump schemes (Cong *et al.*, 2023). Furthermore, the high-frequency nature of algorithmic and arbitrage trading within cryptomarkets contributes to sharp price fluctuations, increasing the likelihood of mean-reverting behaviour over short horizons.

Additionally, the reversal effect is amplified by momentum-driven liquidation in leveraged trading, particularly on exchanges offering perpetual futures with high leverage, where forced liquidations trigger cascading price reversals (Liu & Tsyvinski, 2021). The absence of centralized risk-management mechanisms, such as margin call regulations or trading halts, further exacerbates the intensity of these reversals. Moreover, liquidity constraints in cryptocurrency markets, especially for smaller coins, lead to exaggerated price movements that often revert as temporary demand shocks dissipate (Gandal *et al.*, 2018; Borri & Shakhnov, 2023). Taken together, these factors support the existence of a statistically and economically significant reversal effect in cryptocurrencies. Unlike traditional assets, where momentum effects are more persistent, the structural inefficiencies and behavioural biases inherent in crypto trading environments foster a distinct and pronounced short-term reversal effect, offering new insights into cryptocurrency return dynamics. Along with the discussed reversal effect, these results unequivocally highlight the robust presence of a size effect in the cryptocurrency market.

3.2.2 Size and other variable sorted portfolios. Moving further, we continue with the examination of market risk, illiquidity, S&P beta and max patterns in the expected returns of the cryptocurrency market. Table 3 presents results for the different combinations of other cross-sectional effects of cryptocurrencies. Panel A of Table 3 present results for the nine bivariate portfolios, which are formed based on the combination of size and cryptocurrency market risk (beta). The size-sorted portfolios in the panel revealed a negative relationship between the market capitalization of cryptocurrency and its expected return. The panel shows a weekly average excess return of 9.04% for the small-size portfolios, which decreases to 0.24% weekly as it is calculated for the big-size cryptocurrencies. The observed negative pattern in the panel is very consistent as it gradually decreases from 9.04% observed for the small-size quantile to 5.11% weekly for mid-size cryptos and the lowest (0.24%) for the big-size cryptos. Similar negative size effects are also observed for other panels (Panel B, Panel C, and Panel D) of Table 3.

The other variable utilized for sorting cryptocurrencies in panel A is market risk, denoted by beta. The results presented in Panel A, organized by rows, showcase the outcomes of portfolios sorted based on beta. The initial row in the panel (high) displays the portfolio returns for cryptocurrencies with the highest sensitivity (top 33% percentile) to market returns, yielding an average weekly return of 5.33%. However, the portfolio associated with high-beta cryptocurrencies and big market capitalization yields a statistically insignificant zero return. In contrast, the portfolio resulting from high beta and small-sized cryptocurrencies generates a whopping weekly excess return of 11.03%. This notable return difference between large and small-sized cryptocurrencies with high market beta underscores varying levels of risk sensitivity among investors. It emphasizes that investors perceive a set of cryptocurrencies

Table 3. Size and beta, size and illiquidity, size and S&P beta and size and max sorted nine bivariate (3 × 3) value-weighted portfolios

	Big	(*t*)	Medium	(*t*)	Small	(*t*)	Col average	(*t*)
Panel-A- Size/Beta								
Size/Beta								
High	−0.05	(−0.07)	5.02***	(4.30)	11.03***	(4.51)	5.33***	(4.74)
Medium	1.87**	(2.27)	3.62***	(3.64)	5.85***	(4.13)	3.78***	(4.09)
Low	−1.08	(0.95)	6.69***	(4.17)	10.24***	(5.85)	5.28***	(4.74)
Row Average	0.24	(0.35)	5.11***	(4.68)	9.04***	(6.57)		
Panel-B- Size/Illiq								
Size/Illiq								
High	−0.30	(−0.27)	5.42***	(4.41)	11.91***	(7.07)	5.68***	(5.90)
Medium	2.26**	(2.34)	5.47***	(4.04)	5.70***	(2.82)	4.48***	(3.96)
Low	1.13**	(2.01)	3.74***	(2.71)	6.21***	(4.69)	3.69***	(4.46)
Row average	1.03	(1.61)	4.88***	(4.53)	7.94***	(6.44)		
Panel-C- Size/S&P_Beta								
Size/S&P_Beta								
High	0.68	(0.77)	4.21***	(3.66)	9.94***	(5.07)	4.94***	(4.53)
Medium	0.82	(1.41)	4.05***	(2.87)	11.30***	(4.98)	5.39***	(4.95)
Low	1.85**	(2.12)	6.29***	(4.70)	7.84***	(5.38)	5.33***	(5.65)
Row average	1.12*	(1.74)	4.85***	(4.53)	9.69***	(6.97)		
Panel-D- Size/Max								
Size/Max								
High	−0.51	(−0.43)	4.17***	(3.23)	9.33***	(3.85)	4.33***	(3.600
Medium	1.87**	(2.22)	5.52***	(3.66)	5.45***	(3.35)	4.28***	(4.03)
Low	1.38**	(2.20)	4.89***	(4.41)	13.16***	(7.24)	6.48***	(6.85)
Row average	0.91	(1.26)	4.86***	(4.47)	9.31***	(7.03)		

Note(s): The table shows average weekly excess returns for portfolios formed based on different cross-sectional characteristics of cryptocurrencies. These portfolios are created using the combinations of Size and Market risk (Beta), Size and the Illiquidity variable (Illiq), Size and the sensitivity of cryptocurrency returns with the returns of the S&P 500 market index (S&P Beta) and Size and Max (proxy of lottery effect). Each week, cryptocurrencies are divided into three Size groups (Small, Medium and Big) and three groups for Beta, Illiq, S&P Beta or Max (Low, Medium and High) using 33% breakpoints. This results in nine value-weighted portfolios for each combination (Size-Beta, Size-Illiq, Size-S&P Beta and Size-Max). Market Risk (Beta) is calculated weekly by regressing daily cryptocurrency returns against market returns over the past three months. This calculation is achieved using a rolling window regression, and it reflects the market sensitivity of individual cryptocurrencies, as indicated by the regression coefficient of market returns. Illiquidity (Illiq) is measured using the Amihud (2002) method, which divides the absolute daily returns by the daily trading volume and averages this over the past week. S&P Beta is calculated similarly to Beta but uses the S&P 500 index returns instead. The Max value represents the highest one-day returns observed in the last week. Statistical significance is indicated by superscripts ***, ** and * for the 1, 5 and 10% levels, respectively

Source(s): Authors' work

belonging to the small size and high market beta category as high-risk investments, thereby expecting higher returns. Conversely, there is an absence of a risk premium for cryptocurrencies categorized as large-sized with higher market risk. A similar trend is observed among low-beta cryptocurrencies, providing an average weekly excess return of 5.28%. Although the average returns for the medium beta quantile portfolio are slightly lower (3.78%), they appear more evenly distributed across different combinations of size and market risk.

Panel B demonstrates a positive risk premium associated with the illiquidity variable. When examining portfolios sorted by different quantiles of illiquidity, the findings indicate a higher return for cryptocurrencies experiencing greater illiquidity, while liquid cryptocurrencies exhibit lower returns. The observed positive illiquidity premium starts at 3.69% weekly for the lowest quantile (bottom 33% percentile of cryptocurrencies), gradually increasing to 4.48% for the medium quantile of illiquidity-sorted cryptos and reaching its peak at 5.68% for the top quantile of sorted cryptos. The univariate sorted portfolios of cryptocurrency illiquidity [3] show similar results, with a 3.74% weekly excess return for the high-low zero investment quantile portfolios. This consistent upward trend in returns from the lowest to the highest quantile of illiquidity underscores the presence of a significant illiquidity premium in the cryptocurrency market. These findings align with the results of Bianchi and Babiak (2021), who attribute the illiquidity premium in crypto markets to execution risks, market inefficiencies and the costs associated with liquidity provision in fragmented trading environments. Moreover, concurrent research highlights that cryptocurrency illiquidity is primarily driven by exchange fragmentation, arbitrage inefficiencies and liquidity mining incentives in decentralized finance (DeFi) (Gandal *et al.*, 2018; Auer *et al.*, 2023). Unlike in equity markets, where illiquidity is often correlated with firm size, cryptocurrency illiquidity is not solely explained by market capitalization. Instead, it emerges from the unique microstructure of crypto markets, which includes liquidity dispersion across centralized and decentralized exchanges, variations in trading fees, algorithmic trading dynamics and the absence of uniform market-making mechanisms. Given these structural differences, illiquidity in cryptocurrency markets requires distinct compensation, as it represents a risk factor separate from conventional size effects observed in traditional finance.

In contrast, Panel C of the table diverges from Panel B, showing no significant impact of S&P beta on cryptoreturns. Despite expectations regarding the influence of the stock market on cryptomarket performance, the results from Panel C reveal no discernible existence of the hypothesized phenomenon. Returns calculated across different quantiles of S&P beta-sorted portfolios exhibit no significant variability.

Panel D of Table 3 present the results for size and max-sorted portfolios. Consistent with the observed size effect, the table provides further evidence of a statistically significant relationship between size and returns in the cryptocurrency market. Additionally, the results reveal a strong max effect across different quantiles of size portfolios, demonstrating that cryptocurrencies with higher maximum daily returns tend to underperform, while those with lower maximum returns generate higher average returns. Specifically, portfolios with high max characteristics yield an average weekly return of 3.14%, whereas low max portfolios exhibit a significantly higher return of 6.77%. These findings are consistent across univariate analyses, the pre-COVID sample period and daily data analysis, reinforcing the robustness of the observed patterns. These results align with the well-established lottery effect in equity markets (Bali *et al.*, 2011; 2017), suggesting that investors seeking lottery-like payoffs tend to overinvest in high-max cryptocurrencies, leading to subsequent overvaluation and lower realized returns. This phenomenon mirrors findings in traditional finance, where assets with extreme positive returns attract speculative demand but ultimately deliver subpar long-term performance.

4. Factor construction

Following the identification of prevalent patterns in cryptocurrency's expected returns, we construct factors grounded in these recognized patterns. The creation of these identified factors marks the second phase of the process, aimed at assessing their explanatory efficacy. These devised factors are subsequently employed in diverse combinations to elucidate the cross-sectional variations in cryptocurrency returns.

To form these factors, we employed a 2 × 3 sorting scheme for the variables under consideration. Guided by the identified patterns, we initially categorize the entire pool of cryptocurrencies into small- and large-sized companies based on the median of each crypto's market capitalization. Subsequently, each cryptocurrency is sorted into three categories, determined by the 33% percentile breakpoints of momentum, illiquidity, max and S&P beta, respectively. Table 3 provided in Appendix section of the study offers a more in-depth comprehension of our factor construction methodology.

4.1 Descriptive statistics for factor returns

Table 4 presents the summary statistics for factor returns. Employing the patterns identified in the previous step, we derived six factors: crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML), crypto max factor (CLMH) and the S&P factor (S&PF). In Panel A of the table, the cryptomarket factor exhibits a statistically significant weekly average excess return of 1.15% and a standard deviation of 10.46%. The crypto size factor records a 5.93% return (*t*-stat = 6.56) with a standard deviation of 15.31%. Notably, the CSMB factor, showcasing the highest return among the factors, underscores the considerable influence of crypto size on investment decisions. The crypto reversal factor, representing a difference between the average returns of lower-momentum and high-momentum cryptos, discloses a weekly excess return of 2.77% (*t*-stat = 2.74). This short-term reversal, contrasting the (Carhart, 1997) momentum premium, delineates the distinctive dynamics of the crypto market, highlighting a substantial opposite momentum premium of 2.77% weekly.

The crypto illiquidity factor in the table demonstrates a weekly average excess return of 2.30%. Aligned with existing literature, the identified premium for this factor underscores the compensation associated with investing in illiquid cryptos. Additionally, the crypto max factor (CLMH) – designed to capture the effect of investors' preference for lottery-like returns – yields a weekly excess return of 1.77%. While this return is not statistically significant at the 95% confidence level, it does achieve significance at the 90% level, suggesting a moderately robust relationship. Conversely, the table indicates no premium for the S&P factor. Despite

Table 4. Summary statistics for factor returns

	CRm-Rf	CSMB	CLMW	CIHML	CLMH	S&PF
Panel: A – Mean, standard deviation and t-statistic for monthly excess factor returns						
Descriptive						
Mean	1.15**	5.93***	2.77***	2.30**	1.77*	0.08
Std dev	10.46	15.31	21.66	19.04	21.01	19.15
t-stat	−2.05	−6.56	−2.74	−2.18	1.70	−0.08
Panel: B – Correlation						
Correlation						
CRm-Rf	*1*					
CSMB	−0.02	*1*				
CLMW	0.01	−0.15***	*1*			
CIHML	−0.09*	−0.06	−0.17***	*1*		
CLMH	0.01	−0.16***	0.18***	−0.31***	*1*	
S&PF	−0.03	−0.05	−0.27***	0.11**	−0.11**	*1*

Note(s): Table 4 provides summary statistics for weekly factor returns. In Panel A, the initial row discloses the weekly average excess returns for the created factor portfolios, computed by deducting the weekly yield of the 91 days US government treasury bills. The row presents excess returns for the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML), crypto max factor (CLMH) and crypto stock market factor (CS&PF). The second row in this panel illustrates the observed standard deviation of the portfolio returns, while the third row highlights the statistical significance of factor returns. Moving on to Panel B, the table showcases the extent of correlation among distinct factors. Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

Source(s): Authors' work

expectations of the stock market's role as an alternative investment avenue influencing crypto returns, the observed absence of a premium for risk caused by the stock market accentuates the lack of a discernible relationship between the two markets.

In Panel B of the table, the correlation levels among the variables are presented. Except for the correlation between the S&PF and CLMW factors and between the CLMH and CIHML, none of the relationships exhibit a correlation exceeding 20%. Consequently, the correlations unveiled in the panel do not indicate any substantial relationships among the variables, affirming the independence of their explanatory power for the cross-sectional of expected returns.

4.2 The factor redundancy test

To test whether the explanatory power of a factor can be explained by other factors or their combinations in regression, we conducted a factor redundancy test. The outcomes of this test are presented in Table 5. The initial regression aims to evaluate the explanatory power of the cryptomarket factor (CRm-Rf). It utilizes the value-weighted average excess return of the crypto market factor as the dependent variable, regressing it against a combination of the crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML), crypto max factor (CLMH) and the S&P beta factor (S&PF). The results reveal a statistically significant regression intercept of 1.47 (*t*-stat = 2.57) and insignificant

Table 5. Factor redundancy test

Redundant factors	Intercept	CRm-Rf	CSMB	CLMW	CIHML	CLMH	S&PF	R^2
Rm-Rf								
Coefficients	1.47***		−0.02	−0.01	−0.06*	−0.02	−0.02	0.01
(*t*-statistic)	(−2.57)		(−0.64)	(−0.26)	(−1.86)	(−0.68)	(−0.54)	
CSMB								
Coefficients	7.08***	−0.05		−0.11***	−0.07	−0.13***	−0.07*	0.06
(*t*-statistic)	(−9.39)	(−0.64)		(−3.07)	(−1.60)	(−3.40)	(−1.77)	
CLMW								
Coefficients	4.23***	−0.02	−0.20***		−0.12**	0.09*	−0.29***	0.13
(*t*-statistic)	(3.791)	(−0.26)	(−3.07)		(−2.10)	(1.73)	(−5.52)	
CIHML								
Coefficients	3.93***	−0.15*	−0.09	−0.09**		−0.36***	0.03	0.19
(*t*-statistic)	(4.174)	(−1.86)	(−1.60)	(−2.10)		(−8.78)	(0.68)	
CLMH								
Coefficients	3.95***	−0.06	−0.21***	0.08*	−0.43***		−0.05	0.21
(*t*-statistic)	(3.821)	(−0.68)	(−3.40)	(1.73)	(−8.78)		(−1.04)	
S&PF								
Coefficients	1.47	−0.05	−0.11*	−0.24***	0.04	−0.05		0.09
(*t*-statistic)	(1.439)	(−0.54)	(−1.77)	(−5.52)	(0.68)	(−1.04)		

Note(s): Table 5 illustrates the utilization of five factors in regression analysis to elucidate the average returns on the sixth factor. In the first row of the table, the factor being employed as the dependent variable in the regression is presented. The second row displays the coefficient values for the obtained regression intercepts and other variables used as independent variables in the regression. The third row indicates the statistical significance of the obtained coefficient values. This pattern repeats for each factor being individually tested in the table to assess their idiosyncratic explanatory power. Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

Source(s): Authors' work

coefficients for the other independent variables in the regression. The noteworthy intercept underscores the distinct explanatory power of the cryptomarket factor that is not explained by the other factors in the regression.

In the second regression, conducted to analyse the impact of the crypto size factor, the obtained regression intercept is the highest among the various regressions in the table. With a statistically significant intercept of 7.08 (*t*-stat = 9.39), this highlights the unique explanatory power of the crypto size factor. Similarly, the third regression, focusing on the crypto reversal factor, exhibits a statistically significant intercept, reinforcing the factor's unique explanatory power in the regression and maintaining the observed contradictory impact of momentum in the cryptocurrency market.

The regression for the crypto illiquidity factor also yields a significant intercept of 3.93 (*t*-stat = 4.17), emphasizing the unique contribution of CIHML to the cross-sectional variability of the expected return in the cryptocurrency market. Similar to the illiquidity factor, the crypto max factor also exhibits a statistically significant intercept (3.95, *t*-stat = 3.82), highlighting its distinct explanatory power in capturing the cross-sectional variation in expected cryptocurrency returns. In contrast, the S&P factor yields an insignificant regression intercept, aligning with its negligible impact observed throughout the analysis. This result suggests that the S&P factor provides little to no additional explanatory power, as its effects appear to be subsumed by other factors in the model. Given its consistently insignificant results, we opt to exclude the S&P factor from further analysis to enhance the model's efficiency and focus on more relevant risk factors in the cryptocurrency market.

5. Results and discussion

Now we shift our focus to our main objective, which is to assess the explanatory power of the different combinations of asset pricing factors obtained in the previous stage. We begin by extending the combination of the crypto market factor (CRm-Rf) and crypto size factor (CSMB) with the inclusion of the crypto reversal factor (CLMW), crypto illiquidity factor (CIHML) and the crypto max factor (CLMH) into three three-factor models, two four-factor models and one five-factor model.

5.1 Model summary

The employed extended asset pricing models are represented by Equations (1) – (6), respectively:

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CLMW_{,t} + \varepsilon_{i,t} \tag{1}$$

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CIHML_{,t} + \varepsilon_{i,t} \tag{2}$$

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CLMH_{,t} + \varepsilon_{i,t} \tag{3}$$

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CLMW_{,t} + CIHML_{,t} + \varepsilon_{i,t} \tag{4}$$

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CLMW_{,t} + CLMH_{,t} + \varepsilon_{i,t} \tag{5}$$

$$LHSP_{i,t} = CR_m - R_{f,t} + CSMB_{,t} + CLMW_{,t} + CIHML_{,t} + CLMH_{,t} + \varepsilon_{i,t} \tag{6}$$

Where $LHSP_{i,t}$ (left-hand side portfolio) is the individual portfolio return belonging to the nine size and momentum portfolios, nine size and illiquidity portfolios, nine size and max portfolios and eight zero investment portfolios. To simplify, the proposed asset pricing factors form the right-hand side of the regression against the six sets of left-hand side portfolios ($LHSP_{i,t}$): nine size and momentum portfolios (from Panel A of Table 2), nine size and illiquidity portfolios (from Panel B of Table 3), nine size and max portfolios (from Panel D of Table 3) and eight zero investment portfolios.

The eight zero-investment portfolios are constructed uniquely as arbitrage portfolios. They involve taking a long position in the top (bottom) 20% of cryptos and a simultaneous short position in the bottom (top) 20% of cryptos based on crypto beta values, market capitalization, one-week momentum, two-week momentum, three-week momentum, four-week momentum, illiquidity and max effect of crypto trading. These portfolios are self-financed, allowing for long or short positions based on identified patterns in the cross-section of cryptoreturns.

Following the methods used to evaluate the effectiveness of asset pricing models in the stock market, we conduct similar empirical tests to assess the explanatory power of the above-explained (Equations (1) – (6)) asset pricing models in the cryptocurrency market. We initiate this process by employing Gibbons, Ross, and Shanken (1989) (GRS test) in the next subsection.

5.2 The GRS tests

To assess the explanatory power of the proposed asset pricing models against the left-hand side portfolios, we employ the GRS statistic introduced by Gibbons *et al.* (1989). According to the GRS static, if a model can explain the total variability in the expected excess returns of the portfolios, the regression intercept should not be indifferent from zero. However, Table 6 reveals that the GRS test consistently rejects all the proposed models, indicating their incomplete explanatory power. The absolute intercept values obtained across all panels are significantly larger than the expected zero values, rejecting the null hypothesis that the model can explain the total variability of expected cryptocurrency returns. In short, the GRS test suggests that all our models fall short of providing a complete description of expected returns. Nevertheless, this aligns with our focus on the relative improvement in explanatory power among the factor combinations rather than achieving an all-encompassing explanatory model.

Across the different sets of portfolios, the GRS values for different regressions consistently show the lowest values for four-factor asset pricing models. Panel A records a GRS value of 4.72, Panel B exhibits a value of 2.96, Panel C presents a GRS value of 3.48 and Panel D shows the lowest value of 2.07 for their respective four-factor asset pricing models. Correspondingly, the intercept values for four-factor models (1.67, 1.83, 1.76 and 1.53) are the lowest in their respective panels. These outcomes highlight the superior performance of the nested composition of the four-factor asset pricing model, which includes the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and crypto illiquidity factor (CIHML).

Among the three three-factor models tested, the model incorporating CRm-Rf, CSMB and CLMW demonstrated superior performance than the other three-factor specifications. This finding highlights the significant role of the crypto reversal factor in enhancing the explanatory power of the asset pricing model. Similarly, among the four-factor models, the specification including CRm-Rf, CSMB, CLMW and CIHML consistently outperforms the alternative four-factor model across various regression analyses. This result underscores the greater explanatory power of the illiquidity factor compared to the max factor when assessing the cross-sectional variation in expected cryptocurrency returns.

5.3 Regression results

To enhance our comprehension of the effectiveness of the proposed models, we will now closely examine specific details related to regression intercepts. Utilizing the same portfolios as employed in the previously conducted GRS test, we aimed to evaluate the explanatory power of our three three-factor models, two four-factor models and one five-factor model. Unlike the GRS test, these regressions assess the performance of the proposed models against each portfolio within the various sets.

Table 6. GRS test summary

GRS tests	GRS	GRS *p*-value	A|αi|	A|αi|/A|ri|	A|αi|2/A|ri|2
Panel A: 9 Size–momentum portfolios					
CLMW	5.42***	0.00	1.79	0.59	0.35
CIHML	6.64***	0.00	2.36	0.77	0.67
CLMH	6.92***	0.00	2.16	0.71	0.67
CLMW and CIHML	4.72***	0.00	1.67	0.55	0.3
CLMW and CLMH	5.73***	0.00	1.87	0.61	0.37
CLMW, CIHML and CLMH	5.43***	0.00	1.88	0.62	0.39
Panel B: 9 Size–illiquidity portfolios					
CLMW	3.59***	0.00	2.02	0.78	0.58
CIHML	3.79***	0.00	2.06	0.80	0.62
CLMH	5.33***	0.00	2.36	0.91	0.85
CLMW and CIHML	2.96***	0.00	1.83	0.71	0.44
CLMW and CLMH	4.42***	0.00	2.15	0.83	0.65
CLMW, CIHML and CLMH	3.67***	0.00	2.05	0.79	0.57
Panel C: 9 Size–max portfolios					
CLMW	4.81***	0.00	1.82	0.58	0.53
CIHML	6.28***	0.00	1.87	0.63	0.69
CLMH	5.16***	0.00	2.23	0.75	0.68
CLMW and CIHML	3.48***	0.00	1.76	0.52	0.57
CLMW and CLMH	4.23***	0.00	1.91	0.64	0.50
CLMW, CIHML and CLMH	3.58***	0.00	1.83	0.62	0.45
Panel D: Zero-investment portfolios					
CLMW	3.00***	0.00	2.05	0.86	0.71
CIHML	2.15**	0.04	1.61	0.68	0.53
CLMH	2.10***	0.04	1.86	0.82	0.50
CLMW and CIHML	2.07***	0.00	1.53	0.64	0.7
CLMW and CLMH	2.98***	0.00	2.08	0.91	0.66
CLMW, CIHML and CLMH	2.80***	0.00	1.71	0.75	0.68

Note(s): The table assesses the ability of different three, four, and five-factor models to explain the weekly excess returns on 9 Size and Momentum sorted portfolios, 9 Size and Illiquidity sorted portfolios, 9 Size and Max sorted portfolios and eight zero-investment portfolios. Specifically, Panel A examines 9 Size-Momentum portfolios, Panel B focuses on 9 Size-Illiquidity portfolios, Panel C shows results for 9 Size-Max portfolios and Panel D considers eight zero-investment portfolios. For each set of 9 regressions, the table presents the factors that enhance CRm-Rf and CSMB in the regression model. It includes the GRS statistic, which tests whether the expected values of all 9 intercept estimates are zero. Furthermore, the table features the average absolute value of the intercepts (A|αi|), the ratio of the average absolute value of the intercept (αi) to the average absolute value of ri (A|αi|/A|ri|) and A|αi|2/A|ri|2, i.e. the average squared intercept over the average squared value of ri, adjusted for sampling error in both the numerator and denominator. Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

Source(s): Authors' work

5.3.1 Regression results for size and momentum portfolios. Table 7 displays regression results for the tested models across the nine size and momentum portfolios. In Panel A, the table showcases regression intercepts of the three-factor model, consisting of the CRm-Rf, CSMB and CLMW factor. The left-hand side of the panel provides the obtained intercept values, while the right-hand side reveals the statistical significance (t statistics) of the intercepts, enabling a comparison of the explanatory power of the models.

The initial intercept of the panel, representing the portfolio comprising large-size and high-momentum cryptos, exhibits an intercept of 1.38, albeit statistically insignificant. With few exceptions, most intercepts in the panel demonstrate statistically insignificant values for

Table 7. Regressions for nine value-weighted size–momentum portfolios

	α			$t(\alpha)$		
Size/ Momentum	Big	Medium	Small	Big	Medium	Small
Panel A: Three-factor intercepts: CRm-Rf, CSMB and CLMW						
High	1.38	0.02	1.04	(1.55)	(0.02)	(0.65)
Medium	0.60	0.76	2.94**	(1.44)	(0.91)	(1.98)
Low	−1.36*	3.79***	2.32	(−1.72)	(4.67)	(1.53)
Panel B: Three-factor intercepts: CRm-Rf, CSMB and CIHML						
High	0.47	−2.40*	−1.66	(0.51)	(−1.95)	(−0.99)
Medium	0.65	1.07	3.96***	(1.58)	(1.30)	(2.71)
Low	−0.64	4.23***	5.41***	(−0.79)	(5.16)	(3.08)
Panel C: Three-factor intercepts: CRm-Rf, CSMB and CLMH						
High	1.39	−0.89	−0.42	(1.59)	(−0.72)	(−0.25)
Medium	0.66	1.02	2.95**	(1.60)	(1.23)	(2.00)
Low	−0.68	4.51***	6.90***	(−0.83)	(5.47)	(4.06)
Panel D: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CIHML						
High	1.28	−0.61	0.61	(1.42)	(−0.52)	(0.38)
Medium	0.62	0.79	2.49**	(1.49)	(0.93)	(2.34)
Low	−1.53	3.50***	1.63	(−1.62)	(4.28)	(1.08)
Panel E: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CLMH						
High	1.92**	0.51	1.35	(2.22)	(0.43)	(0.84)
Medium	0.63	0.79	2.57*	(1.50)	(0.94)	(1.73)
Low	−1.34*	3.96***	3.76***	(−1.68)	(4.85)	(2.70)
Panel F: Five-factor intercepts: CRm-Rf, CSMB, CLMW, CIHML and CLMH						
High	2.20**	−0.07	0.93	(2.49)	(−0.06)	(0.57)
Medium	0.69	0.86	3.12***	(1.61)	(1.00)	(2.06)
Low	−1.58*	3.63***	3.85***	(−1.95)	(4.36)	(2.71)

Note(s): Table 7 displays the regression intercepts and their corresponding statistical significance for the 9 size and momentum portfolios. In Panel A of the table, intercepts are presented for the regression conducted using the 9 left-hand side portfolios, regressed against the proposed three-factor model consisting of CRm-Rf, CSMB and CLMW. Panel B showcases regression intercepts for another three-factor model, comprising CRm-Rf, CSMB and CIHML. Panel C showcases regression intercepts for the other three-factor model, comprising CRm-Rf, CSMB and CLMH. Moving on to Panel D, the table presents results for the four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto illiquidity factor (CIHML). Panel E in the table presents results for the other four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto max factor (CLMH). Finally, Panel F presents results for the five-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML) and the crypto max factor (CLMH)
Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

Source(s): Authors' work

different portfolios. Notably, statistically significant intercepts tend to have higher values. The portfolio comprising small-sized cryptocurrencies with the lowest momentum produces the highest intercept and the highest statistical significance in the panel. This indicates that the returns of this cryptocurrency combination are scarcely explained by the employed three-factor model. Similar inadequacies of the three-factor model are also observed in the cases of the small-size and medium-momentum portfolios as well as with the medium-size and lowest-momentum portfolios. Corresponding to the GRS test results, the subpar performance of the proposed model in Panel A indicates an incomplete explanation of the expected returns in the cryptomarket. However, it is crucial to emphasize that our goal is not to propose a comprehensive crypto asset pricing model; rather, we aim to identify the optimal combination of factors for an improved explanation of cross-sectional variability in expected crypto returns. To achieve this objective, we assess the relative performance of our other models in subsequent panels of the table.

Moving to Panel B presents intercepts of regression runs across the nine size and momentum portfolios against another three-factor model. The utilized asset pricing model in this panel extends the combination of the cryptomarket and cryptosize factors by incorporating the crypto illiquidity factor. On average, the intercepts obtained in this model are slightly higher than those in Panel A. Despite the statistical insignificance of the intercepts in Panel B, a comparison with the significant intercepts of Panel A, Panel B reveals slightly higher values for medium-size and low-momentum, small-size and medium momentum and small-size and low-momentum portfolios. The revealed intercept for medium size and low momentum portfolio is 4.23, the intercept for small size and medium momentum portfolio is 3.96 and for the small size and low momentum portfolio, Panel B presents an intercept of 5.41, which is slightly higher than the observed intercepts in Panel A.

Panel C presents the regression results for an alternative three-factor asset pricing model comprising CRm-Rf, CSMB and CLMH. The intercept values reported in this panel are the highest observed across all three-factor models when tested against the nine size-momentum portfolios. This finding raises questions about the explanatory power of the max factor (CLMH), as it is the only variable altered in this model specification. The results suggest that while the max factor contributes to the model, its ability to explain cross-sectional return variation may be limited, warranting further investigation into its role within cryptocurrency asset pricing frameworks.

Panel D of the table presents the regression results for the four-factor asset pricing model, which includes CRm-Rf, CSMB, CLMW and CIHML. Notably, the intercepts in Panel D are significantly lower compared to those observed in the other five panels. While the alternative factor model combinations in the table report three to five statistically significant intercepts, this four-factor model yields only two significant intercepts, and even these are lower in magnitude than those in the other specifications. Consistent with the GRS test results, the fewer significant intercepts and their lower values highlight the superior explanatory power of the four-factor model in capturing the return variation of the nine size-momentum portfolios. This finding reinforces the relative outperformance of the proposed four-factor model compared to alternative factor models, suggesting that the inclusion of CIHML enhances the model's ability to explain cross-sectional cryptocurrency returns more effectively.

Panel E presents a similar attempt to evaluate the explanatory power of an alternative four-factor model in capturing the cross-sectional variation in the expected returns for the nine size-momentum portfolios. This model, which includes CRm-Rf, CSMB, CLMW and CLMH, is regressed against the nine right-hand-side portfolios, with the corresponding regression intercepts reported in Panel E. The results indicate no improvement in explanatory power, as the obtained intercepts suggest a greater degree of unexplained cross-sectional variation in expected returns. These findings highlight the comparatively weaker explanatory role of the max factor (CLMH) relative to the illiquidity factor (CIHML), which demonstrated better performance in the previous four-factor specification.

The final panel, Panel F, presents the regression results for the five-factor model, incorporating all the considered factors. However, the findings do not indicate a convincing improvement in model performance. The intercept values in the five-factor model are both larger and more numerous than those observed in the other models, suggesting a higher degree of unexplained return variation. This suboptimal performance of the five-factor model, in contrast to the comparatively stronger performance of the four-factor model (CRm-Rf, CSMB, CLMW and CIHML), suggests that the latter represents the most efficient factor combination for explaining the cross-sectional variability in cryptocurrency returns. The results reinforce the notion that the proposed four-factor model provides a more parsimonious and effective framework for understanding return dynamics in the cryptocurrency market.

The next subsection evaluates the explanatory power of the employed crypto asset pricing models against a different set of nine value-weighted portfolios, which are formed based on size and illiquidity variables.

5.3.2 Regression results for nine value-weighted size-illiquidity portfolios. Table 8 presents the regression results for the nine size-illiquidity portfolios, following the same structure as Table 7. The portfolios are regressed against three three-factor models, two four-factor models and one five-factor model, with the corresponding intercepts reported in the respective panels.

Panel A displays the intercepts for the three-factor model, which includes the crypto market factor (CRm-Rf), crypto size factor (CSMB) and crypto reversal factor (CLMW). The

Table 8. Regressions for nine value-weight size–illiquidity portfolios

		α			$t(\alpha)$	
Size/ Illiquidity	Big	Medium	Small	Big	Medium	Small
Panel A: Three-factor intercepts: CRm-Rf, CSMB and CLMW						
High	0.60	2.10**	5.26***	(0.49)	(2.05)	(3.73)
Medium	1.55	1.42	−1.90	(1.66)	(1.48)	(−1.30)
Low	−0.01	2.05	2.35*	(−1.30)	(1.58)	(1.73)
Panel B: Three-factor intercepts: CRm-Rf, CSMB and CIHML						
High	−0.84	0.55	5.18***	(−0.78)	(0.61)	(3.84)
Medium	1.40	1.01	−2.76*	(1.52)	(1.06)	(−1.87)
Low	−0.01	2.50*	3.97***	(−0.78)	(1.94)	(3.20)
Panel C: Three-factor intercepts: CRm-Rf, CSMB and CLMH						
High	1.06	2.31**	7.49***	(0.88)	(2.31)	(5.48)
Medium	1.89**	1.02	−2.67*	(2.06)	(1.06)	(−1.81)
Low	−0.01	2.45*	2.35*	(−1.24)	(1.89)	(1.74)
Panel D: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CIHML						
High	−1.13	0.71	2.67***	(−1.03)	(0.77)	(2.78)
Medium	1.41	1.48	−1.73	(1.50)	(1.53)	(−1.16)
Low	−0.01	2.10	2.95***	(−1.01)	(1.61)	(3.11)
Panel E: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CLMH						
High	1.04	2.57**	6.35***	(0.85)	(2.55)	(4.76)
Medium	1.86**	1.38	−1.90	(2.00)	(1.43)	(−1.28)
Low	−0.01	2.12	2.10	(−1.44)	(1.62)	(1.54)
Panel F: Five-factor intercepts: CRm-Rf, CSMB, CLMW, CIHML and CLMH						
High	−1.28	0.80	4.77***	(−1.15)	(0.86)	(3.64)
Medium	1.90**	1.44	−1.62	(2.00)	(1.46)	(−1.07)
Low	−0.01	2.26*	4.37***	(−1.12)	(1.70)	(3.40)

Note(s): Table 8 displays the regression intercepts and their corresponding statistical significance for the 9 size and illiquidity portfolios. In Panel A of the table, intercepts are presented for the regression conducted using the 9 left-hand side portfolios, regressed against the proposed three-factor model consisting of CRm-Rf, CSMB and CLMW. Panel B showcases regression intercepts for another three-factor model, comprising CRm-Rf, CSMB and CIHML. Panel C showcases regression intercepts for the other three-factor model, comprising CRm-Rf, CSMB and CLMH. Moving on to Panel D, the table presents results for the four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto illiquidity factor (CIHML). Panel E in the table presents results for the other four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto max factor (CLMH). Finally, Panel F presents results for the five-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML) and the crypto max factor (CLMH) Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

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majority of intercept values in this panel are statistically insignificant, with only a few exceptions demonstrating significance. Similar to the limited explanatory power observed in Table 7 for small-size and low-momentum portfolios, these results suggest that the three-factor model struggles to explain the return variation in cryptocurrencies characterized by small size and high illiquidity as well as those with small size and low illiquidity. This finding highlights the challenges asset pricing models face in capturing extreme illiquidity conditions in the cryptocurrency market. Even in cases where intercepts are statistically significant, their values remain relatively high, signalling that the model leaves substantial unexplained return variation. Comparing this three-factor model to an alternative specification that replaces the reversal factor (CLMW) with the crypto illiquidity factor (CIHML), Panel A indicates relatively superior performance. However, Panel B, which reports the intercepts for the three-factor model incorporating CRm-Rf, CSMB and CIHML, displays higher intercept values, suggesting poorer model performance compared to the momentum-based three-factor model.

Among the remaining panels, Panel D demonstrated the strongest performance, corresponding to the four-factor model incorporating CRm-Rf, CSMB, CLMW and CIHML. The results in Panel D exhibit the smallest intercept values, with only two statistically significant intercepts, reinforcing the improved explanatory power of this four-factor model. Consistent with the findings in Table 7, these results suggest that the four-factor model provides the best fit for explaining the cross-sectional return dynamics of the nine-size-illiquidity portfolios, outperforming both the three-factor model, the alternative four-factor model and the extended five-factor model in the table.

5.3.3 Regression results for nine value-weighted size-max portfolios. Consistent with the previous regression tables, Table 9 presents regression results for the nine size-max portfolios. The six cryptoasset pricing models are regressed against the nine right-hand-side portfolios to evaluate their respective explanatory powers. The results across the different panels of Table 9 report the intercepts obtained from these regressions, highlighting the relative performance of each model.

Once again, the findings reinforce the superior performance of the four-factor cryptoasset pricing model, which includes CRm-Rf, CSMB, CLMW and CIHML. Panel D, which presents the results for the proposed four-factor model, identifies only two portfolios that remain unexplained by this combination of factors. Moreover, the intercept values in Panel D are the lowest observed compared to other panels, and the number of significant intercepts is also fewer than in alternative model specifications. These results further emphasize the robustness and relative explanatory power of the four-factor model in capturing the cross-sectional variation in cryptocurrency returns, particularly in size-max portfolios.

5.3.4 Regression results for eight zero-investment portfolios. Unlike the previous regression tables, Table 10 presents results for eight zero-investment portfolios. As described earlier, these arbitrage portfolios are constructed by simultaneously taking long and short positions in specific cryptocurrency quantiles, based on identified cross-sectional premiums in the market. These self-financed portfolios, which are particularly relevant for market participants, also serve as a valuable tool for assessing the relative performance of the proposed asset pricing models.

Panel A reports the results for the initial three-factor model (CRm-Rf, CSMB and CLMW). The findings indicate that only the size and max portfolios yield statistically significant intercepts, while all other portfolios remain insignificant. This pattern persists across the other panels, with each model failing to explain at least two of the zero-investment portfolios. However, Panel D, which corresponds to the proposed four-factor model (CRm-Rf, CSMB, CLMW and CIHML), exhibits only one significant intercept – that of the zero-investment size portfolio. Additionally, this intercept is notably lower in magnitude, accompanied by a proportional reduction in other intercept values across the panel.

The zero-investment-size portfolio, which initially produced an abnormal expected return of 5.59% per week, experienced a decline to 5.20% when adjusted for the three-factor model (CRm-Rf, CSMB and CIHML). The application of the four-factor model further reduces this

Table 9. Regressions for nine value-weight size–max portfolios

Size/ Max	α Big	 Medium	 Small	t(α) Big	 Medium	 Small
Panel A: Three-factor intercepts: CRm-Rf, CSMB and CLMW						
High	−0.61	1.15	0.45	(−0.54)	(1.03)	(0.22)
Medium	0.92	0.96	0.20	(1.45)	(0.91)	(0.14)
Low	0.50	2.78***	7.91***	(1.21)	(3.36)	(5.30)
Panel B: Three-factor intercepts: CRm-Rf, CSMB and CIHML						
High	−0.90	0.05	1.08	(−0.81)	(0.05)	(0.53)
Medium	0.89	0.17	−0.84	(1.41)	(0.16)	(−0.58)
Low	0.58	3.25***	9.07***	(1.40)	(3.91)	(6.09)
Panel C: Three-factor intercepts: CRm-Rf, CSMB and CLMH						
High	0.41	1.92*	5.36***	(0.40)	(1.85)	(3.08)
Medium	1.06*	0.01	−0.97	(1.68)	(0.01)	(−0.66)
Low	0.26	2.87***	7.25***	(0.66)	(3.48)	(5.13)
Panel D: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CIHML						
High	−0.72	0.33	−1.10	(−0.64)	(0.30)	(−0.55)
Medium	0.90	0.98	0.26	(1.41)	(0.92)	(0.18)
Low	0.49	1.80***	6.28***	(1.16)	(3.33)	(5.49)
Panel E: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CLMH						
High	0.36	2.08**	3.31**	(0.35)	(1.98)	(2.02)
Medium	1.05	0.70	−0.06	(1.64)	(0.66)	(−0.04)
Low	0.25	2.57***	6.81***	(0.62)	(3.09)	(4.78)
Panel F: Five-factor intercepts: CRm-Rf, CSMB, CLMW, CIHML and CLMH						
High	0.97	1.55	3.23*	(0.92)	(1.46)	(1.93)
Medium	1.12*	0.53	−0.17	(1.72)	(0.49)	(−0.12)
Low	0.02	2.41***	6.48***	(0.05)	(2.84)	(4.45)

Note(s): Table 9 displays the regression intercepts and their corresponding statistical significance for the 9 size and max portfolios. In Panel A of the table, intercepts are presented for the regression conducted using the 9 left-hand side portfolios, regressed against the proposed three-factor model consisting of CRm-Rf, CSMB and CLMW. Panel B showcases regression intercepts for another three-factor model, comprising CRm-Rf, CSMB and CIHML. Panel C showcases regression intercepts for the other three-factor model, comprising CRm-Rf, CSMB and CLMH. Moving on to Panel D, the table presents results for the four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto illiquidity factor (CIHML). Panel E in the table presents results for the other four-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and the crypto max factor (CLMH). Finally, Panel F presents results for the five-factor model on the right-hand side, comprised of the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW), crypto illiquidity factor (CIHML) and the crypto max factor (CLMH) Superscripts ***, ** and * correspond to statistical significance at the 1, 5 and 10% levels, respectively

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return to 4.34% per week, a substantial decrease that underscores the superior explanatory power of the four-factor model relative to other crypto asset pricing models. Additionally, the relative decline in intercept values in Panel D provides further evidence of the stronger performance of the four-factor model. These results reaffirm that the proposed four-factor model serves as a more comprehensive framework, effectively capturing the maximum variation in the expected returns within the cryptocurrency market.

Although the regression analysis also provides individual slope coefficients for each factor – potentially offering insights into their explanatory power for specific portfolio combinations – we have chosen not to include these coefficients for two primary reasons. First, our primary

Table 10. Regressions for zero-investment portfolios

Portfolios	Size	Momentum_ 1W	Momentum_ 2W	Momentum_ 3W	Momentum_ 4W	Beta	Illiquidity	Max
Panel A: Three-factor intercepts: CRm-Rf, CSMB and CLMW								
Intercept (α)	5.59***	−1.62	0.89	1.60	2.32	0.26	1.87	3.53*
t(α)	(3.38)	(−1.06)	(0.55)	(1.03)	(1.48)	(0.20)	(1.14)	(1.82)
Panel B: Three-factor intercepts: CRm-Rf, CSMB and CIHML								
Intercept (α)	5.20***	0.98	1.86	1.40	1.54	0.20	0.94	5.39***
t(α)	(3.16)	(0.60)	(1.13)	(0.92)	(1.01)	(0.16)	(0.62)	(2.84)
Panel C: Three-factor intercepts: CRm-Rf, CSMB and CLMH								
Intercept (α)	4.41***	−0.70	1.21	1.47	1.51	0.26	2.92*	1.49
t(α)	(2.66)	(−0.44)	(0.75)	(0.95)	(0.98)	(0.20)	(1.80)	(0.90)
Panel D: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CIHML								
Intercept (α)	4.34***	−1.64	0.45	0.72	1.54	0.29	−0.01	2.67
t(α)	(3.83)	(−1.06)	(0.28)	(0.46)	(0.99)	(0.22)	(−0.01)	(1.42)
Panel E: Four-factor intercepts: CRm-Rf, CSMB, CLMW and CLMH								
Intercept (α)	5.24***	−2.54*	0.32	1.19	1.77	0.31	2.40	1.23
t(α)	(3.16)	(−1.71)	(0.20)	(0.76)	(1.13)	(0.24)	(1.47)	(0.73)
Panel F: Five-factor intercepts: CRm-Rf, CSMB, CLMW, CIHML and CLMH								
Intercept (α)	6.12***	−3.32**	−0.83	−0.51	0.12	0.39	−0.08	1.12
t(α)	(3.63)	(−2.20)	(−0.51)	(−0.33)	(0.08)	(0.29)	(−0.05)	(0.65)

Note(s): Table 10 presents the regression intercepts and their corresponding statistical significance for eight zero-investment portfolios. Each panel consists of two rows: the first row reports the estimated intercept values, while the second row provides their respective *t*-statistics. Panel A displays regression intercepts obtained from regressing the eight left-hand side portfolios against a three-factor model incorporating CRm-Rf, CSMB and CLMW. Panel B presents regression intercepts for an alternative three-factor model, replacing CLMW with CIHML (i.e. CRm-Rf, CSMB and CIHML). Panel C shows results from another three-factor model, which includes CRm-Rf, CSMB and CLMH. Panel D reports results for a four-factor model on the right-hand side. Panel E provides results for an alternative four-factor model that includes CRm-Rf, CSMB, CLMW and CLMH. Panel F presents regression intercepts for a five-factor model that incorporates CRm-Rf, CSMB, CLMW, CIHML and CLMH. Statistical significance is denoted using superscripts: *** (1% significance level), ** (5% significance level) and * (10% significance level)

Source(s): Authors' work

focus is on the overall explanatory power of the model, rather than the individual contributions of each factor. This aligns with our central objective of developing a comprehensive factor model that explains the maximum variability in expected cryptocurrency returns. Second, including individual slope coefficients would require additional space, and given our emphasis on presenting the most relevant findings concisely, we have opted to exclude them.

The four-factor model demonstrates notable improvements in explanatory power across various portfolios, particularly for small-size, low-momentum cryptocurrencies and small-size, extreme-illiquidity cryptocurrencies. These portfolio combinations, which were previously insufficiently explained by other factor models, reveal persistent pricing anomalies unique to the cryptocurrency market. These anomalies appear to be driven by the unique microstructure of cryptocurrency markets, which differ fundamentally from traditional equities. Unlike traditional asset classes, cryptocurrency markets are highly speculative, dominated by retail traders and subject to rapid price swings fuelled by behavioural biases. Extreme retail speculation, overreaction to news and market manipulation contribute significantly to short-term price reversals (Cong *et al.*, 2023). Additionally, momentum-driven liquidation in leveraged trading further amplify price reversals, reinforcing its role as a key pricing factor in crypto markets (Liu *et al.*, 2022). The absence of centralized regulation, coupled with high leverage availability on cryptoexchanges, creates vulnerability to forced liquidations, leading to short-term price distortions and reversals.

Beyond the reversal effect, our findings highlight a distinct and robust illiquidity effect in the cryptocurrency market. While prior studies have assumed that illiquidity premiums are largely captured by the size effect, we provide evidence that illiquidity operates as an independent pricing factor. The unique structure of cryptocurrency markets, particularly exchange fragmentation, arbitrage inefficiencies and liquidity mining incentives in decentralized finance (DeFi) (Gandal *et al.*, 2018), plays a crucial role in driving systematic illiquidity risk. These inefficiencies contribute to execution risks and market frictions, leading to excess returns for illiquid assets (Bianchi *et al.*, 2022). Our identification of the unique illiquidity premium in the cryptocurrency market strengthens the explanatory power of the asset pricing model, suggesting that investors demand compensation for holding illiquid crypto assets due to the higher trading costs and liquidity constraints associated with them.

While statistically significant intercepts persist for small-size and extreme-illiquidity cryptocurrencies, suggesting some unexplained return variation, these effects may present opportunities for investors to exploit existing mispricing. From a research perspective, these unresolved anomalies highlight promising directions for future studies in cryptocurrency asset pricing. The proposed four-factor model partially addresses these challenges, demonstrating superior performance by integrating a combination of key risk factors: the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and crypto illiquidity factor (CIHML). These results suggest that the model provides a more effective framework for understanding cross-sectional return variation in the cryptocurrency market. Future research could further refine this approach by developing a fully nested cryptoasset pricing model, capturing additional structural and behavioural characteristics unique to the cryptocurrency market.

6. Conclusion

This study demonstrates that the cross-sections of cryptocurrencies can be effectively used to explain the cross-sectional variability in expected returns. Initially, the study identifies a significant size effect, a unique reversal effect and a premium for cryptocurrency illiquidity. Among these, the size effect is the most dominant, but the reversal effect, which challenges the notion of investor overreaction and suggests a rapidly adjusting and possibly more efficient cryptocurrency market, is particularly noteworthy. Contrary to the well-known momentum effect, these findings offer a new perspective that remains robust across various proxies for the momentum variable. Another notable discovery is the illiquidity premium, which is more pronounced in smaller cryptocurrencies, though it is not overshadowed by the size effect. Redundancy tests confirm that the effect of illiquidity on returns is independent of size and other factors.

Further tests of asset pricing models were rejected by GRS statistics. The GRS results indicate that no combination of constructed factor models fully explains the cross-sectional variability of cryptocurrency returns. However, these results, which reject all the used models, serve as a benchmark to measure the relative performance of the concerned asset pricing models. The results reveal that the four-factor model, which includes the crypto market factor (CRm-Rf), crypto size factor (CSMB), crypto reversal factor (CLMW) and crypto illiquidity factor (CIHML), outperforms other models in explaining cross-sectional variability. Additionally, supporting evidence from other regression analyses across various portfolio combinations (nine size and momentum portfolios, nine size and illiquidity portfolios, nine size and max portfolios and eight zero-investment portfolios) further underscores the superior performance of this four-factor model than the commonly referenced three-factor model and other combinations of factors in cryptocurrency asset pricing literature.

The results of the study are robust in their statistical significance and have been derived by testing different sample periods across different data frequencies and using the most appropriate methodologies from empirical asset pricing literature. However, it is crucial to emphasize that these results pertain to an emerging market – one that is still in its nascent stage and undergoing various developments. Unlike the well-established equity market, the cryptocurrency market's performance is subject to unique market microstructure issues, government regulations, and, most importantly, investor sentiments. The limited availability of data points and the short period of its existence add complexity, making it a particularly intriguing area of study.

The cryptocurrency market is a rapidly evolving sector that continues to undergo significant transformations (Whitford & Anderson, 2021). Its inherent volatility and growing integration into financial markets have drawn considerable attention from policymakers, regulators and investors. Understanding the pricing mechanisms of cryptoassets is essential, as cryptocurrencies have the potential to disrupt traditional financial systems. This study contributes to this understanding by identifying key risk factors that influence cryptocurrency returns and their broader implications for market participants and regulatory bodies.

The findings of this study offer valuable insights for investors and traders, particularly in the design of zero-investment arbitrage portfolio strategies. By leveraging the observed pricing anomalies – such as the reversal effect and illiquidity premium – investors can simultaneously take long and short positions, capitalizing on mispricing opportunities in the market. For instance, the constructed size factor yields a weekly excess return of 5.63% for a portfolio that goes long on small-cap cryptocurrencies and short on large-cap ones, translating to an annualized return of approximately 292%. Similarly, the reversal factor delivers a weekly excess return of 2.77% (about 144% annually) by taking long positions in the bottom 33% and short positions in the top 33% of momentum-ranked cryptocurrencies. An illiquidity premium is also evident, with a weekly excess return of 2.30% (around 120% annually) observed for portfolios that long the most illiquid and short the most liquid cryptocurrencies. While these factor returns have not been adjusted for transaction costs or other market frictions, the magnitude of the observed premiums suggests promising opportunities for investors. These results highlight the potential of factor-based investing in the cryptocurrency market and underscore the ability of such strategies to generate substantial returns with relatively low trading costs.

The observed patterns, particularly the reversal effect and illiquidity premium, underscore fundamental market inefficiencies and regulatory gaps in the cryptocurrency ecosystem. The high prevalence of speculative trading, lack of centralized oversight and fragmented liquidity create an environment that is vulnerable to market manipulation, price distortions and systemic risks. Our findings emphasize the need for regulatory interventions that can enhance market transparency, efficiency and standardization – without compromising the decentralized nature of cryptocurrencies. Policymakers should consider implementing liquidity requirements, improved disclosure standards for crypto exchanges and stronger anti-manipulation measures to reduce the risks associated with pump-and-dump schemes, wash trading and excessive leverage. These steps would improve price discovery and investor confidence, ultimately fostering a more stable and mature cryptocurrency market. Additionally, regulators should address the risks associated with high-illiquidity tokens, which are particularly susceptible to artificial price inflation due to large trades by dominant market players. Mandatory liquidity disclosures and enhanced surveillance mechanisms can help mitigate such risks, ensuring that reported trading volumes are authentic and reflective of actual market activity.

As cryptocurrencies continue to gain traction as alternative stores of value, their increasing adoption could diminish the effectiveness of traditional monetary policy tools, such as interest rate adjustments and money supply controls. Capital flows between fiat and crypto assets – especially during periods of economic uncertainty or inflationary pressure – could create new challenges for central banks. Given these shifts, monetary authorities should integrate cryptocurrency liquidity conditions into macroeconomic models and develop frameworks that account for the growing interplay between crypto and traditional financial markets. Policymakers must also assess whether the expansion of decentralized finance (DeFi) and stablecoins could disrupt traditional banking structures, altering the transmission mechanisms of monetary policy.

Despite the growing body of research, future studies should investigate the long-term behaviour of cryptocurrency returns, their relationship with traditional assets and the impact of regulatory changes on market dynamics. Furthermore, future research should aim to develop comprehensive models for predicting cryptocurrency returns, examine the impact of decentralized finance on traditional financial systems and explore the socioeconomic consequences of widespread cryptocurrency adoption. These effects will provide deeper insights for informed policymaking and foster a balanced regulatory environment that encourages innovation while protecting against systemic risks.

Notes

1. Appendix Table 2 displays the univariate sorted value-weighted quantile portfolios for Size, Market risk, Illiquidity, Max and Stock Market Risk. This supplementary analysis was performed to reinforce the findings from the bivariate sorted analysis concerning the identification of cross-sectional patterns in the cryptocurrency market.
2. Appendix Table 1 displays the univariate sorted value-weighted quantile portfolio returns for the different proxies of Momentum variable (Momentum1,2,3,4).
3. Panel C of Appendix Table 2 presents the univariate sorted value-weighted illiquidity quantile portfolios. This additional analysis was conducted to support the findings from the bivariate sorted analysis regarding the identification of the illiquidity premium in the cryptocurrency market.

Supplementary material

The supplementary material for this article can be found online.

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