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ARTICLE

Exploring the short-term momentum effect in the cryptocurrency market

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Abstract

This study explores the short-term momentum effect in the cryptocurrency market. Utilising a comprehensive cryptocurrency dataset and the portfolio construction methods of Fama and French (J Financ Econ 33:3–56, 1993) and Carhart (J Finance 52:57–82, 1997), we construct cryptocurrency portfolios and examine their performance. The main findings are: (1) the cryptocurrency market portfolio significantly outperforms major stock markets globally in terms of risk-adjusted return; (2) from an asset pricing perspective, short-term momentum effects are significantly priced in the cryptocurrency market, while size effects are controlled, suggesting that the short-term momentum effect explains variations in the returns of cryptocurrency portfolios; and (3) the portfolios constructed according to the short-term momentum effect do not outperform the cryptocurrency market portfolio.

Keywords Cryptocurrency · Bitcoin · Momentum · Asset pricing · Portfolio performance · Portfolio management · JEL classification: G11 · G12

JEL Classification G11 · G12

1 Introduction

Since the inception of Bitcoin in 2009, the cryptocurrency market has experienced dramatic price fluctuation and attracted significant investment. More than 3000 cryptocurrencies are traded on cryptocurrency exchanges, constituting a billion-dollar market (Aalborg et al. 2019). Cryptocurrencies are recognised as financial assets and securities in many countries around the world. They have emerged to form a

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new asset class, and are selected by hedge fund managers (Gurdus 2019, Pan 2019) and recommended as part of investors' portfolios (Gregoriou 2019).

In recent years, Bitcoin and other popular cryptocurrencies have garnered attention from both the general public and academic researchers. The popularity of these cryptocurrencies can be credited to the innovative technology, security, simplicity and transparency of this system (Urquhart 2016; Katsiampa 2017). As cryptocurrencies continue to evolve, their application and pricing have become prominent research issues for regulators, sophisticated investors and academics (Guo and Li 2017; Borri 2019), as there is lack of knowledge of this emerging and fast-changing market. For example, many well-known stock market effects and anomalies, such as the momentum effect (Carhart 1997) and the size effect (Fama and French 1992, 1993), have not been sufficiently investigated in the cryptocurrency market. We argue that stocks and cryptocurrencies are exchange-traded securities, so both asset classes should exhibit some commonalities. Therefore, well-known stock market effects, especially those closely related to price dynamics, may play important roles in the cryptocurrency market. Shen et al. (2019) is the first academic study exploring well-known stock market effects in the cryptocurrency market. Their study shows how the size and momentum effects are priced in cryptocurrency returns. However, the existing literature on these effects is far from sufficient to fully understand how they operate in the cryptocurrency context. To provide more insight, we explore a specific type of momentum effect in cryptocurrency markets.

Inspired and motivated by Shen et al. (2019), we investigate the short-term momentum effect in the cryptocurrency market, and in particular, short-term momentum effects over time intervals of 3 days, 7 days and 1 month. Studies of momentum effects in the cryptocurrency market are limited to Cheng et al. (2019), Grobys and Sapkota (2019) and Shen et al. (2019), which focus on monthly and week momentum effects. Hence, our study fills a gap in the literature by providing evidence on whether the short-term momentum effect is priced in the cryptocurrency market. Moreover, as our study focuses on short-term momentum effects over different time intervals, it provides systematic insights into which short-term momentum effect dominates others in cryptocurrency markets. Further, this paper also sheds light on how cryptocurrency market portfolios perform against major stock markets globally. Practically, our findings have strong implications for investor communities globally.

We construct a comprehensive cryptocurrency dataset that covers approximately 96.5 per cent of the global cryptocurrency market capitalisation for this study. Our analysis reveals several important and interesting findings. First, our market-level analysis shows that cryptocurrency market portfolios outperform the stock market portfolios in terms of risk-adjusted return, indicating that compensation for the same level of risk is larger in cryptocurrency markets than in stock markets. Second, we find that short-term momentum factors are significant in explaining cryptocurrency returns while controlling for the size effect. Third, none of the momentum portfolios generates positive and significant Jensen's alpha, indicating that the momentum portfolios underperform the cryptocurrency market portfolio after investors are compensated for the risks associated with the cryptocurrency market factor, the size factor and the short-term momentum factors.

The main empirical findings have three important practical implications for investors. First, cryptocurrency investors must be cautious when evaluating the performance of their cryptocurrency portfolios against benchmark portfolios, as our results indicate that expected returns of the cryptocurrency portfolios must be adjusted for size and momentum effects. This means size and momentum factors should be included in cryptocurrency performance evaluation models, because they are significant and powerful in capturing additional variations in cryptocurrency returns. Second, our results provide strong evidence to support the contention that better risk–return trade-off can be achieved in the cryptocurrency market than in the stock market, so cryptocurrencies should be considered as an alternative asset class for investors' portfolios.

Our study contributes to the literature by systematically investigating the momentum effect over short time intervals of 3 days, 7 days and 1 month. To the best of our knowledge, a systematic comparison of short-term momentum effects has never been done previously. There are limited numbers of studies in the area, but none of the existing studies has investigated the 3-day momentum effect and compared short-term momentum effects systematically. For example, Grobys and Sapkota (2019) examine medium to long-term momentum effects in the cryptocurrency markets based on 12-month, 6-month and 1-month timeframes; Shen et al. (2019) investigate the weekly momentum effect in the cryptocurrency market, which is the momentum effect over shortest interval documented in the literature to date. In addition, our study examines the short-term momentum effects from both asset pricing and portfolio management perspectives, and we find that cryptocurrencies can further improve the efficiency of investors' portfolios in terms of the risk–return trade-off.

The remainder of this paper is organised as follows. The next section reviews the relevant literature. Section 3 describes the data used for this study. Section 4 outlines the research methods. The empirical results are presented and discussed in Sect. 5. Section 6 summarises and concludes the study.

2 Literature review

2.1 Pricing and performance of cryptocurrencies

Values of cryptocurrencies are more challenging to determine than other asset classes. First, there is neither future cash-flow guarantee nor potential production of cash flow attached to cryptocurrencies (Tomaš and Švogor 2015), so discount cash flow models cannot be applied to value cryptocurrencies. Second, no government or reputable corporation has yet issued a cryptocurrency, so the value and legitimacy of cryptocurrencies are not guaranteed. Thus, both future cash flows and the risk of those cash flows are undeterminable for cryptocurrencies, which means that the proposition of discounted value (Miller and Modigliani 1961; Parker 1968) is not feasible.

Although precise values of cryptocurrencies are almost impossible to determine using discount cash-flow models, their returns can be explained using risk-factor models. The 'foundation' paper for stock market risk-factor models is Sharpe

(1964), which develops the theoretical framework of the capital asset pricing model (CAPM). Early studies suggest that CAPM fails to explain stock returns due to its over-simplified single-factor model and unrealistic assumptions. In the 1990s, researchers made important improvements to the single-factor model. For example, Fama and French (1993) develop a three-factor model by augmenting the singe-factor model with the size and book-to-market value factors; Carhart (1997) develops a four-factor model by adding a momentum factor to the Fama and French three-factor model; and more recently, Fama and French (2015) developed a five-factor model for the stock market. Although a large number of common risk factors have been identified and added to the existing risk factor models (Harvey et al. 2016), only marginal explanatory power can be observed by including more risk factors into asset pricing models. Among all the risk factors identified in different studies, market factor, size factor, book-to-market value factor and momentum factor are considered to be the indispensable risk factors for stocks. However, due to limited understanding and knowledge of cryptocurrencies, it is yet unclear what risk factors explain cryptocurrency returns. In contrast to the extensive stock market asset pricing literature, asset pricing studies on cryptocurrencies are still limited.

2.2 Size effect

Size effect in the stock market has been reported globally, and this effect has been detected and well documented for several decades. Banz (1981) first reports the role of the size effect in asset pricing literature and critiques the capital asset pricing model of Jensen (1968). Banz (1981) concludes that smaller firms outperform large firms in terms of risk-adjusted returns. Further evidence is provided by Keim (1983), who reveals a significant negative relationship between stock market capitalisation and abnormal return. Barry et al. (2002) investigate the size effect in 35 emerging equity markets, and find that a significant size effect can only be found when firm size is measured in relative, not absolute terms. Similarly, Hearn (2011) examines the size effect on cross-sectional expected returns through an investigation of the fluctuations in aggregate market size. In conclusion, in a wide variety of studies, the significance of size factor holds across markets, region and methodology applied.

2.3 Momentum effect

The momentum effect was first confirmed by De Bondt and Thaler (1985), DeBondt and Thaler (1987) and then Jegadeesh and Titman (1993) in the context of the overreaction hypothesis. The implication of contrarian momentum effect strategies (buying past loser and selling past winner) is expected to generate a positive abnormal return or significant Jensen's alpha. For a long time, the majority of academic findings suggested there is a momentum effect over a 3-year time horizon. However, these findings were conclusively challenged by Carhart (1997) using a momentum-augmented four-factor model. Carhart (1997) finds that the momentum factor works effectively as an explanatory variable for the returns of a wide range of financial securities when the momentum effect is measured over the past 12 months.

On the other hand, Bollen and Busse (2005) document an insignificant momentum effect when funds are ranked with 1-year returns, and in fact they find that superior performance is a short-lived phenomenon. However, when funds are ranked using Carhart's method and a 3-month momentum factor is applied to evaluate the performance of the funds, short-term outperformance persists. Fama and French (2012) study the international performance of stock returns and conclude there is underperformance of size, value and momentum portfolios compared with the broad market. In contrast, many studies support that positive alpha or abnormal returns are associated with momentum effect (Baker et al. 2010; Agarwal et al. 2013; Berk and van Binsbergen, 2015; and Pástor et al. 2015). Overall, the momentum effect has been investigated extensively in the stock markets, but the findings are still not conclusive.

2.4 Hypotheses

Inspired and motivated by Shen et al. (2019), this study further investigates the asset pricing roles of the short-term momentum effect constructed using cryptocurrency data. In the light of Shen et al. (2019) and Cheng et al. (2019), we investigate the short-term momentum effect, following the theoretical framework of modern portfolio theory and asset pricing models. The following hypothesis is developed to explore the role of the short-term momentum effect in the cryptocurrency market:

H1 The short-term momentum effect is significant in the cryptocurrency market.

Grobys and Sapkota (2019) report insignificant momentum effect in the cryptocurrency market using data from the period of January 2014–December 2018. Their study focuses on the monthly momentum effect, and the results are inconclusive, as momentum effects over shorter time intervals have not been examined. It is still inconclusive whether the short-term momentum effect exists in the cryptocurrency, and if so, whether or not short-term momentum strategies can generate significant abnormal returns. Thus, we develop the following hypothesis to examine whether or not short-term momentum strategies can generate significant abnormal returns utilizing the asset pricing models developed by Fama and French (1993) and Carhart (1997):

H2 The short-term momentum effect is significant in the cryptocurrency market.

3 Data

The sample selected for this study consists of the world's largest 100 cryptocurrencies according to their market capitalisation as of September 5th 2019. Major global stock market indices are selected as benchmarks when evaluating cryptocurrency market-level performance. The stock market indices are ASX200 (Australia), Hangseng Index—HIS (Hong Kong), FTSE (UK), S&P500 (US), DowJones (US), and

Nikkei225 (Japan). Stock market data are downloaded from Bloomberg. Cryptocurrencies data, including price, trading volume and market capitalisation, are obtained from the Coinmarketcap website. Our sample of 100 cryptocurrencies covers 96.5 per cent of total cryptocurrency market capitalisation as of September 5th 2019. The risk-free rate used in this paper is US 3-month Treasury Bill rate obtained from the central bank of the United States. The sample covers daily data from the period April 28th 2013 to September 5th 2019.

4 Methods

4.1 Cryptocurrency market versus stock markets

To explore the short-term momentum effect in the cryptocurrency market, a cryptocurrency market portfolio is constructed. To date, the literature is unclear as to how the cryptocurrency market portfolio performs compared with major stock market indices. In our analysis, we first explore the performance of the cryptocurrency market portfolio against the major stock market indices. To the best of our knowledge, this is the first study comparing the performance of a cryptocurrency market portfolio to those of stock market portfolios using a risk-adjusted performance measure. Sharpe ratio is employed as the performance evaluation measure. The specific methods are discussed below.

4.2 Equal and value-weighted cryptocurrency market portfolios

Equal-weighted and value-weighted cryptocurrency market portfolios are constructed to measure and evaluate cryptocurrency market performance. For the equal-weighted cryptocurrency market portfolio, every cryptocurrency contributes equal weight to this portfolio. For the value-weighted portfolio, the weights are determined by dividing the dollar value of each cryptocurrency in the sample by the total dollar value of the whole sample. The equal-weighted and value-weighted cryptocurrency market portfolios are rebalanced daily as the cryptocurrency prices fluctuate significantly on a daily basis.

4.3 Volatility measurement

Following Pozo (1992) and William Schwert (2002), this study utilises rolling standard deviation over a time interval of 30 days as a proxy for daily volatility. It is the standard deviation of daily return over the past 30-day period. Rolling standard deviation is calculated as:

$$\mathrm{SD}_t = \frac{\sum_{t-30}^{t} \left(R_t - \overline{R_t}\right)^2}{29}$$

where $\overline{R_t}$ is the mean return over the 30-day time interval from *t-30* to *t* (Pozo 1992, Hanley et al. 1993).

4.4 Sharpe ratio

Introduced by Sharpe in 1966 (1966), the Sharpe ratio measures the ability of a financial asset to generate an excess return when one extra unit of risk σ_p is taken. The Sharpe ratio is applied to compare the performance of the cryptocurrency market portfolio relative to stock market portfolios (Ledoit and Wolf 2008). The Sharpe ratio is calculated as the following:

$$\text{Sharpe ratio} = \frac{R_t - R_f}{\sigma_p},$$

where R_f is the risk-free rate which is proxied by the US 3-month Treasury Bill rate (Sharpe 1966).

4.5 The asset pricing models

4.5.1 Momentum effect and portfolio construction

In the momentum effect literature, Jegadeesh and Titman (1993) are the first to find a momentum effect in the stock market. Since the early 1990s, the momentum effect has been investigated extensively in the stock market. The literature on the momentum effect has been built up actively in stock markets and mutual funds, but there is a distinct lack of study in the cryptocurrency market.

We examine the short-term momentum effect by constructing short-term momentum portfolios/factors over time intervals of 3 days, 7 days and 1 month. The momentum portfolio is constructed in light of papers by Carhart (1997), Liu et al. (2016) and Hendricks et al. (1993). The reason we focus on the short-term momentum effect is because the cryptocurrency market is more volatile than the stock market (Zhang et al. 2018; Aalborg et al. 2019), so investors are expected to react rapidly to the rapid changes observed in the cryptocurrency market. Since the market is highly volatile and the price fluctuates extensively on a daily basis due to speculative trading activities and lack of regulation, the short-term momentum effect is expected to play a more important role in determining the cryptocurrency returns than long-term momentum.

The short-term momentum portfolios are constructed to capture short-term momentum effect. The following method is used to construct the portfolios: the cryptocurrencies are sorted into five portfolios according to their past returns. The top 20 per cent of cryptocurrencies in terms of past returns form the winner portfolio, i.e. portfolio 1, and the bottom 20 per cent of cryptocurrencies in terms of past returns form the loser portfolio, i.e. portfolio 5. This process is repeated every 3 days (3-day momentum), 1 week (7-day momentum) and 1 month (monthly momentum) to construct the momentum portfolios. They capture the momentum effects over short periods of 3 days, 7 days and 1 month respectively. The momentum factor (WML) is defined as the difference in the return between the winner portfolio and loser portfolio (Winner–Minus–Loser).

4.5.2 Size factor

Following the portfolio risk-mimicking approach of Fama and French (1993), cryptocurrencies are sorted into 5 portfolios (from the biggest to the smallest), at the beginning of each month, using their average market capitalisations of the previous month. The size factor is defined as the difference between the return of portfolio one (the large-cap portfolio) and the return of portfolio five (the small-cap portfolio). This method is also applied by Shen et al. (2019). The constructed size factor is denoted as BMS (big-minus-small).

4.5.3 Regression analysis

Regression analysis has been widely used to measure portfolio performance by estimating Jensen's alpha (Jensen 1968, Carhart 1997, Jensen et al. 1997, Fama and French 2015). In this study, the regression models consist of a cryptocurrency market portfolio, a cryptocurrency size factor and the short-term momentum factors. However, book values for cryptocurrencies do not exist, so the book-to-market equity ratios for cryptocurrencies cannot be estimated. Hence, the value versus growth factor of the Fama and French three-factor model is not included in the regression models.

A three-factor model is employed to examine the asset pricing roles of the short-term momentum factors and evaluate the performance of the momentum portfolios constructed on 3-day, 7-day and monthly momentum effects. The three-factor models consist of a cryptocurrency market factor, a momentum factor and a size factor. The equation is given below:

$$R_{it} - R_{ft} = \alpha_i + \beta_{mi}\left(R_{mt} - R_{ft}\right) + \beta_{\mathrm{BMS}i}\mathrm{BMS}_t + \beta_{\mathrm{WML}i}\mathrm{WML}_t + \varepsilon_{it}, \tag{2}$$

where R_{it} is portfolio i return on day t; R_{ft} is the risk-free rate on day t; R_{mt} is the value-weighted cryptocurrency market portfolio return on day t; BMS_t is the return of the size factor on day t; WML_t is the return of the 3-day, 7-day or monthly momentum factor on day t; ε_{it} is the error term.

5 Empirical results

5.1 Descriptive statistics

To gain more insights into the performance of the cryptocurrency market portfolio, equal-weighted and value-weighted cryptocurrency portfolios are constructed and the descriptive statistics for the equal-weighted and value-weighted cryptocurrency portfolios are provided in Table 1. The returns and rolling standard deviations are

Table 1 Descriptive statistics of the cryptocurrency market portfolios

	Portfolio return		Rolling standard deviation		High price		Low price		Market cap
	Equal - weighted	Value -weighted	Equal - weighted	Value -weighted	Equal - weighted	Value -weighted	Equal - weighted	Value -weighted	
Mean	0.077%	0.099%	1.895%	1.634%	79.033	2230.246	73.202	2112.707	23.818
Median	0.111%	0.109%	1.558%	1.481%	51.936	636.020	49.756	611.194	23.178
Standard deviation	2.269%	1.887%	1.591%	0.875%	75.218	2812.909	66.866	2629.988	1.802
Sample variance	0.051%	0.036%	0.025%	0.008%	5657.706	7,912,457.63	4471.030	6,916,839.02	3.246
Kurtosis	7.744	7.758	29.979	3.586	5.147	2.034	4.520	1.593	−1.303
Skewness	−0.110	−0.354	4.813	1.468	2.106	1.592	1.980	1.505	0.299
Range	31.258%	27.844%	12.772%	5.418%	454.970	15,024.576	397.667	14,347.868	6.833
Minimum	−13.111%	−11.936%	0.401%	0.315%	13.888	72.083	12.425	63.360	20.531
Maximum	18.147%	15.908%	13.173%	5.733%	468.858	15,096.659	410.093	14,411.228	27.364

Market cap is the natural logarithm of market capitalisation in US dollar value ($USD)

Columns 3 and 4 are the descriptive statistics of rolling standard deviation series

All the values reported in Table 1 are calculated using daily data used to evaluate the performance of the cryptocurrency market portfolio later. As shown in Table 1, there are two different types of standard deviation. The standard deviations of the portfolio returns throughout the sample period are reported in the first two columns. These values capture the dispersion in returns of cryptocurrency portfolios from April 28th 2013 to September 5th 2019. On the other hand, the standard deviation reported in columns 3 and 4 are the daily rolling standard deviations; they are calculated following the method discussed in Sect. 4.3.

In Table 1, it can be seen that the daily value-weighted return (0.099 per cent) is higher than the equal-weighted average daily return (0.077 per cent), which indicates that large market cap cryptocurrencies generate larger returns than small-cap cryptocurrencies over the sample period. The standard deviation of the returns for the value-weighted cryptocurrency market portfolio is lower than that of the equal-weighted portfolio. This result is interesting as the value-weighted cryptocurrency market portfolio generates higher returns at a relatively lower risk than the equal-weighted cryptocurrency market portfolio, indicating a better risk–return trade-off associated with the value-weighted cryptocurrency market portfolio compared with that of the equal-weighted portfolio. This finding also indicates that large-cap cryptocurrencies outperform small-cap cryptocurrencies. The equal-weighted cryptocurrency portfolio has lower minimum but higher maximum returns, which is consistent with the standard deviations of the returns of the portfolio, as the standard deviations indicate that small-cap cryptocurrencies are more volatile than large cryptocurrencies.

Table 2 shows the time series return, market cap and volatility of the equal-weighted and value-weighted cryptocurrency market portfolios. This table shows raw return, volatility and the aggregate market capitalisation of the equal-weighted and value-weighted cryptocurrency market portfolios across the sample period. The number of cryptocurrencies in each year over the sample period is also reported in Table 2. In general, the number of cryptocurrencies increases dramatically from 2013 to 2019, especially since 2017. Overall, throughout the sample period, the sample covers more than 90 per cent of the global cryptocurrency market in terms of market capitalisation.

In Table 2, it is interesting to see that average daily market cap for 2017 was \$121.44 billion, however, the end-year value is five times bigger at \$575.1 billion, showing an explosion in cryptocurrency valuation in 2017. The issuance of the stable coin Tether contributed to the price hike towards the end of 2017 (Griffin and Shams 2019). The daily mean returns for 2017 peaked at 0.569 per cent for the equal-weighed cryptocurrency market portfolio and 0.457 per cent for the value-weighted portfolio, suggesting that the price increase was much stronger for small-cap cryptocurrencies than large-cap cryptocurrencies in 2017. Except for 2017, statistics show that the value-weighted cryptocurrency portfolio had generated a higher return than the equal-weighted cryptocurrency market portfolio during the sample period.

The standard deviation of return for the value-weighted cryptocurrency market portfolio records the highest level in 2013. This was due to the Bitcoin price bubble that occurred at the end of 2013. From 2017 to 2018, the standard deviation was relatively high, due to the significant rise in prices of Bitcoin and other

Table 2 Time series return, market capitalisation and volatility

	Number of coins	Return		Market capitalisation		Percentage of coverage	Volatility	
		Equal -weighted	Value -weighted	End-year	Daily average	End-year	Standard deviation	Parkinson high-low
2013	4	0.257%	0.311%	10.0079	3.274,672	96.12%	0.024	0.059
2014	14	−0.093%	−0.087%	5.347,799	7.284454	97.56%	0.014	0.031
2015	17	−0.020%	0.023%	6.971306	4.424251	99.68%	0.013	0.028
2016	29	0.074%	0.109%	17.34373	10.52622	98.02%	0.008	0.041
2017	62	0.569%	0.457%	575.0903	121.4457	96.81%	0.018	0.040
2018	89	−0.243%	−0.177%	117.8441	282.1601	90.63%	0.020	0.035
2019	102	0.037%	0.136%	257.4371	197.4858	96.53%	0.016	0.030

Number of cryptocurrencies included in the sample at the end of each year

Market capitalisation is in billions of US dollar ($USD)

Standard deviation is the average daily rolling standard deviation throughout the year

Parkinson high-low volatility is the average daily Parkinson high-low volatilities throughout the year. $\text{Parkinson}_t = \sqrt{\frac{\frac{1}{4\ln 2}\sum_{t-30}^{t}\text{HL}_t^2}{30}}$;$\text{HL}_t = \ln\frac{H_t}{L_t}$

All the statistics are in daily frequency

cryptocurrencies. Furthermore, Chicago Board Options Exchange's closure of Bitcoin futures sent a negative signal to the market (Rooney 2019) leading to a significant price drop in the first half of 2019, which explains the high volatility observed in 2019. Another volatility measure, Parkinson high-low volatility, also shows consistent results.

5.2 Performance of the cryptocurrency market and stock markets

Table 3 shows the performances of the cryptocurrency market portfolios and the stock market indices. Over the sample period, the rolling standard deviation for the equal-weighted portfolio is higher than that of the value-weighted portfolio, however, they are both at a substantially higher level than the major stock markets. Interestingly, all the major stock markets underperform the cryptocurrency market portfolios in terms of Sharpe ratio. To be specific, for every one-unit increase in standard deviation, the equal-weighted (value-weighted) cryptocurrency market portfolio earns an extra 8.88 per cent (9.43 per cent) return. Since the Sharpe ratio for the equal-weighted cryptocurrency portfolio is less than that of the value-weighted cryptocurrency portfolio, this means that large-cap cryptocurrencies provide better risk–return trade-offs than small-cap cryptocurrencies.

Overall, the results reported in Table 3 show that the cryptocurrency market outperforms the stock market over the sample period. On average, with one extra unit of risk, cryptocurrency investors are compensated approximately three times better in terms of return than stock market investors. Consequently, despite this high-risk environment, the risk-adjusted return of the cryptocurrency market largely outweighs those of the stock markets.

Table 3 Performance of the cryptocurrency market portfolios versus stock market portfolios

	Sharpe ratio (%)	Standard deviation (%)
Equal-weighted cryptocurrency portfolio	8.88	1.898
Value-weighted cryptocurrency portfolio	9.43	1.640
ASX200	1.44	0.755
FTSE	−0.89	0.792
S&P500	5.19	0.757
HIS	1.85	1.029
Nikkei225	2.04	1.214
NASDAQ	6.31	0.923

Standard deviation is the average daily rolling standard deviation

All the statistics are in daily frequency

5.3 The cryptocurrency momentum portfolios

To investigate the short-term momentum effects, momentum portfolios are constructed over three-day, seven-day and monthly intervals. The methods used for momentum portfolio construction are discussed in more detail in Sect. 4.5.1.

The descriptive statistics and Sharpe ratios of the momentum portfolios are reported in Table 4. As shown in Table 4, the market cap of the cryptocurrencies is not associated with their past returns or momentum effect as there is no clear pattern in the market cap when moving across the momentum portfolios. However, across Panels A–C in Table 4, it can be seen that all the loser portfolios have the smallest cryptocurrencies in terms of market cap, indicating that the loser portfolios mainly consist of small-cap cryptocurrencies. Referring to the returns, there is no linear pattern when moving across the winner and loser portfolios. On the other hand, across Panels A to C, portfolio 1 (winner) and 5 (loser) have the highest level of risk than all the other portfolios. In general, portfolios 1 and 2 tend to have higher Sharpe ratios than other portfolios across Panels A to C. It means that portfolios 1 and 2 outperform the loser portfolios. Hence, the momentum effect is observed among the Sharpe ratios that are reported in Table 4.

Table 4 Descriptive statistics and Sharpe ratios of the cryptocurrency momentum portfolios

Portfolio	Market cap	Return (%)	Standard deviation (%)	Sharpe ratio (%)
Panel A: Three-day momentum				
1—Winner	21.074	0.135	2.947	2.8
2	21.561	0.151	2.366	4.0
3	21.569	−0.031	2.107	−0.9
4	21.107	0.033	2.427	0.1
5—Loser	20.325	0.078	2.858	3.5
Panel B: Weekly momentum				
1—Winner	28.968	0.146	2.864	5.3
2	29.321	0.090	2.335	1.9
3	29.119	0.059	2.156	2.4
4	28.784	0.036	2.395	-0.7
5—Loser	27.956	0.062	2.860	2.5
Panel C: Monthly momentum				
1—Winner	29.289	0.062	2.540	3.7
2	29.011	0.127	2.414	4.5
3	29.216	0.065	2.080	2.9
4	28.638	0.029	2.465	0
5—Loser	28.437	0.120	2.776	2.1

Market cap is the logarithm of average daily market capitalisation in dollar value ($USD)

All the statistics are in daily frequency

5.4 Asset pricing role of the momentum factors

In this section, we first investigate the asset pricing role of the short-term momentum factors; and second, the risk-adjusted performance of the momentum portfolios are evaluated using Jensen's alpha. Jensen's alpha is estimated using a regression model as described in Sect. 4.5.3. In the regression analysis, a cryptocurrency market factor, a cryptocurrency size factor and the momentum factors are included in the regression equations as explanatory variables. The daily portfolio excess returns serve as dependent variables in all the regression models. The cryptocurrency market factor is proxied by the excess return of value-weighted cryptocurrency market portfolio; the size factor (BMS) is included as a control variable in the analysis; the three-day momentum (WML_d) factor is proxied by the return difference in the winner and loser portfolio constructed by three-day momentum. Similarly, WML_w (WML_m) is the return difference between seven-day (monthly) momentum winner portfolio and loser portfolios.

Table 5 reports the correlation coefficients between the independent variables. High correlation is not detected among those variables. To be specific, the size factor barely has a linear relationship with the momentum factors as the correlation coefficients are −0.02901, −0.03449 and −0.07165. Furthermore, the cryptocurrency market return has no relationship with both size and momentum factors. Therefore, there is no multicollinearity concern if all the variables are presented in the same regression equation.

We first do a regression analysis using two explanatory variables, the cryptocurrency market factor and a short-term cryptocurrency momentum factor. The two-factor model is used as our base model for the regression analysis. Results obtained from the two-factor models are provided in Table 6. As seen in Table 6, four out of five coefficients of the momentum factor are significant in Panels A and B. Furthermore, three out of five coefficients of the momentum factor are significant in Panel C, indicating that the momentum factors explain the returns of the momentum portfolios. These findings confirm significant momentum effect in the cryptocurrency market, so that Hypothesis 1 is accepted.

Turning our attention to Jensen's alphas reported in Table 6, none of them are statistically significant. Those insignificant Jensen's alphas indicate that the momentum

Table 5 Correlation coefficients

	BMS	WML_d	WML_w	WML_m	$R_M - R_f$
BMS	1				
WML_d	−0.02901	1			
WML_w	−0.03449	0.299777	1		
WML_m	−0.07165	0.082691	0.219705	1	
$R_M - R_f$	0.02608	0.016591	−0.01712	0.029385	1

BMS is the size factor (Big-Minus-Small)

WML is the momentum factor (Winner-Minus-Loser) in 3-day, weekly and monthly timeframes

$R_M - R_f$ is the market risk premium

Table 6 Momentum effect – two-factor model

	1—Winner	2	3	4	5—Loser
Panel A: Three-day momentum					
α	−0.0001 (−0.32)	0.00077 (−1.76)	−0.0004 (−1.02)	−0.0005 (−1.20)	−0.0001 (−0.32)
$R_M - R_f$	0.998*** (−40.242)	0.999*** (−45.000)	0.961*** (−45.117)	0.977*** (−41.752)	0.998*** (−40.242)
WML_d	0.488*** (−40.667)	−0.0216* (2.012)	−0.0298** (2.893)	−0.0175 (1.549)	−0.512*** (42.667)
N	2033	2033	2030	2033	2033
Adj. R^2	0.620	0.500	0.501	0.462	0.624
Panel B: Weekly momentum					
α	7.36E−07 (−0.002)	−0.0000797 (0.194)	−0.0000485 (0.134)	−0.000904* (2.385)	0.000000736 (−0.002)
$R_M - R_f$	0.993*** (−40.697)	1.000*** (−41.494)	0.985*** (−46.244)	0.960*** (−43.243)	0.993*** (−40.697)
WML_w	0.456*** (−38.320)	−0.017 (1.487)	−0.044*** (4.252)	−0.037*** (3.398)	−0.544*** (45.714)
N	2027	2027	2027	2027	2027
Adj. R^2	0.602	0.461	0.518	0.482	0.656
Panel C: Monthly momentum					
α	0.00012 (−0.317)	−2.1E−05 (0.052)	−9.6E−06 (0.026)	−0.00083 (1.765)	0.00012 (−0.317)
$R_M - R_f$	0.983*** (−43.689)	1.020*** (−42.149)	0.967*** (−44.977)	1.001*** (−36.007)	0.983*** (−43.689)
WML_m	0.355*** (−30.603)	−0.020 (1.624)	−0.015 (1.036)	−0.109*** (7.622)	−0.645*** (55.603)
N	1984	1984	1984	1984	1984
Adj. R^2	0.596	0.472	0.504	0.403	0.710

t statistics in parentheses

*Indicates p value < 0.10, **indicates p value < 0.05, ***indicates p value < 0.01

Note: independent variables are market risk premium $R_M - R_f$ and momentum factor WML_d (panel A), WML_w (panel B), WML_m (panel C); dependent variable is 3-day, 7-day and monthly momentum portfolios return, respectively portfolios do not outperform the cryptocurrency market portfolio after investors are compensated for the risks associated with the cryptocurrency market, cryptocurrency size and the short-term momentum effects. In general, all the momentum portfolios, which capture 3-day, 7-day and monthly momentum effects, are unable to produce significant positive alpha. Hence, Hypothesis 2 is rejected. The coefficients of the market factor are all close to one and statistically significant, indicating that the variation in return of all portfolios has a close relationship with that of the value-weighted cryptocurrency market.

In conclusion, the results reported in Table 6 show strong evidence that the short-term momentum effect explains the returns of the momentum portfolios, but the portfolios constructed on the short-term momentum effect fail to generate superior risk-adjusted returns. Overall, the regression results suggest that short-term momentum effects are important from an asset pricing perspective. However, they are less important from a portfolio management perspective, because the momentum portfolios do not outperform the cryptocurrency market portfolio. This result is expected given the previous literature on the stock and mutual fund market, where Jensen (1968) states that “not only average fund performance but also individual fund performance is no better than that predicted from a mere random chance”.

Table 7 reports the regression results obtained from the three-factor models. In the three-factor models, the cryptocurrency size factor is included in the regressions as a control variable. Interestingly, there are only two out of 15 significant coefficients for the size factor across Panel A–C of Table 7. The two coefficients are significant at the 10 per cent level, which indicates very weak explanatory power of the size factor. Overall, the size factor does not explain much variation in the returns of the momentum portfolios. Inclusion of the size factor does not significantly alter the explanatory power of the momentum factors, except the coefficient of the monthly momentum factor for Portfolio 1 (Winner) and 5 (Loser) becomes insignificant in Table 7 compared with those reported in Table 6. This implies that the monthly momentum effect is not as stable as the shorter-term momentum effect, such as that observed in a three-day and seven-day period. A possible explanation is that volatility of the cryptocurrency market is much higher than that of the stock markets, so shorter-term momentum factors should be more effective in capturing cryptocurrency traders’ reactions to past price trends observed in the last 3–7 days.

6 Conclusions

Globally, cryptocurrencies have gained popularity in recent years and attracted much interest from investors and researchers due to their increasingly important role in the global financial system. To date, the complexities of this market have not been fully explored in the literature. Given the lack of cryptocurrency pricing and performance analysis studies, this study aims to explore the effect of short-term momentum in the cryptocurrency market from the perspective of asset pricing and portfolio management. This is the first study of its kind to investigate and compare short-term momentum effects, particularly 3-day, 7-day and monthly momentum effects, in the cryptocurrency market.

Table 7 Momentum effect – three-factor model

	1—Winner	2	3	4	5—Loser
Panel A: Three-day momentum					
α	9.8E−05 (−0.19)	0.00052 (−1.08)	0.00024 (−0.52)	−0.0006 (−1.30)	−0.0009 (−1.50)
$R_M - R_f$	0.989*** (−36.98)	1.090*** (−45.25)	1.066*** (−45.66)	1.051*** (−46.22)	1.067*** (−36.7)
BMS	−0.0178 (−0.75)	−0.0337 (−1.57)	−0.0076 (−0.37)	−0.0304 (−1.50)	0.0148 (−0.57)
WML_d	0.0779*** (−3.48)	0.0808*** (−4.01)	−0.0098 (−0.50)	−0.0796*** (−4.18)	−0.182*** (−7.47)
N	979	979	979	979	979
Adj. R^2	0.589	0.683	0.682	0.687	0.584
Panel B: Weekly momentum					
α	−0.0003 (−0.73)	0.00059 (−1.23)	0.00034 (−0.75)	−0.0005 (−1.07)	−0.0003 (−0.73)
$R_M - R_f$	1.020*** (−44.93)	1.095*** (−45.13)	1.060*** (−45.88)	1.037*** (−46.17)	1.020*** (−44.93)
BMS	−0.0041 (−0.20)	−0.0339 (−1.56)	−0.0108 (−0.52)	−0.0352* (−1.75)	−0.0041 (−0.20)
WML_w	0.426*** (−19.86)	−0.0274 (−1.19)	−0.0998*** (−4.57)	−0.136*** (−6.42)	−0.574*** (−26.75)
N	979	979	979	979	979
Adj. R^2	0.704	0.678	0.688	0.694	0.746
Panel C: Monthly momentum					
α	0.00013 (−0.25)	0.00051 (−1.07)	0.00018 (−0.39)	−0.0007 (−1.45)	−0.001 (−1.64)
$R_M - R_f$	0.995*** (−37.04)	1.100*** (−45.71)	1.070*** (−46.32)	1.047*** (−45.83)	1.054*** (−35.31)
BMS	−0.0182 (−0.76)	−0.0409* (−1.89)	−0.0162 (−0.78)	−0.0354 (−1.73)	0.0117 (−0.44)
WML_m	−0.0125 (−0.46)	−0.0958*** (−3.92)	−0.104*** (−4.45)	−0.0548*** (−2.36)	−0.0214 (−0.71)
N	979	979	979	979	979
Adj. R^2	0.584	0.683	0.688	0.683	0.56

t statistics in parentheses

*Indicates p value < 0.1, ** indicates p value < 0.05, *** indicates p value < 0.01

Note: independent variables are market risk premium $R_M - R_f$ and momentum factor WML_d (panel A), WML_w (panel B), WML_m (panel C); dependent variable is 3-day, weekly and monthly momentum portfolios return, respectively, numbered from 1—Winner to 5—Loser

In conclusion, we find that the large-cap cryptocurrencies outperform the small-cap cryptocurrencies, and the cryptocurrency market portfolio outperforms the stock market portfolios. We also find strong evidence that short-term momentum plays a crucial role in explaining the return of cryptocurrencies. This finding supports and extends the findings of Shen et al. (2019), who find that size and momentum are the significant variables in pricing cryptocurrencies. On the other hand, from a portfolio management perspective, the momentum portfolios do not generate significant and positive abnormal returns. For future research, researchers could investigate other candidates for cryptocurrency pricing models and other portfolio management strategies that may yield significant and positive abnormal returns.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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