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Cryptocurrencies and the low volatility anomaly[☆]

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ABSTRACT

This study examines the low volatility anomaly in the cryptocurrency market. Constructing long-short portfolios for a sample of 1000 cryptocurrencies for the period April 28, 2013 – November 1, 2019, we find no evidence of a significant low volatility premium. This result is in contrast to the empirical findings from the equity, bond, and commodity markets and contributes to the debate on the efficiency of cryptocurrencies. In contrast to earlier studies, we find that the cryptocurrency market is far more efficient than expected, even after controlling for different sample sizes, rebalancing periods and / or portfolio construction methodologies.

1. Introduction

Stocks with high volatility should yield high expected return. This is one of the most fundamental principles in finance. However, a wide strand of empirical evidence has put this concept on trial, showing that in fact the opposite is true – Low volatility stocks has historically outperformed high volatility stocks.[1] Haugen and Heins (1975, 1972) were the first to document the lack of positive relationship between risk and return in the empirical cross-section of stock market returns. Later studies confirm these findings by demonstrating its robustness across regions (Ang et al., 2006; 2009; Peswani, 2017; Joshipura and Joshipura, 2016), asset classes (Frazzini and Pedersen, 2014), and alternative measures of risk (Chan et al., 1999; Clarke et al., 2006).

The question “what explains the cross-section of stock returns” is one of the most (if not the most) researched topics in the financial literature. For example, Banz (1981) introduced the size effect almost 40 years ago. Fama and French (1992) construct a three-factor model using size, value, and market, while Jegadeesh and Titman (1993) introduce monentum. Since then, a variety of factors, or “anomalies”, have been discovered, each of which contributes a little further to the understanding of stock market returns.

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[1] This phenomenon, often referred to as the ”Low Volatility Anomaly”, has remained an unresolved puzzle to thiss day. The most common explanation revolves around behavioral biases such as attention-grabbing bias, representativeness bias, overconfidence, and preference for lotteries (Blitz and Van Vliet, 2007; Baker et al., 2011). According to attention-grabbing bias, high-risk assets are more likely to experience extreme returns, thereby better catch the attention of investors, which in turn creates upward buying pressure (Barber and Odean, 2007). Representativeness bias and overconfidence, on the other hand, assume that investors are too optimistic about the stock’s future prospects, therefore overpaying for so-called growth stocks and generating lower future returns (Blitz et al., 2019). Finally, preference for lotteries refers to investors preferring stocks with lottery-like payoffs, i.e. high volatility and positively skewed stocks (Baker et al., 2011; Kumar, 2009). Alternative explanations include (1) investor constraints, (2) relative performance objectives, (3) agency issues, and (4) skewness preferences. For an overview, the reader is referred to (Blitz et al., 2019).

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Since the introduction of Bitcoin and other cryptocurrencies, academics and practitioners around the world are asking the same question they have been asking for decades about equities and other asset classes - what are the drivers (or factors) that explain cryptocurrency. This study is motivated by this long-standing question. More precisely, this study aims to answer the following question: “Can the low volatility factor explain the cross-section of cryptocurrency returns?”

Our work contributes to two strands of literature. First, it contributes to the broad literature on low volatility strategies by extending the results of Haugen and Heins (1972, 1975) and others for traditional financial markets to the cryptocurrency market. To the best of our knowledge, this study is the first to study this well-known phenomenon in the context of cryptocurrencies. Therefore, we significantly contribute to the empirical cryptocurrency pricing literature. Second, our findings contribute to the ongoing debate on the market efficiency of cryptocurrencies. While the vast majority of literature finds cryptocurrencies largely inefficient compared to other assets such as stocks, bonds, or gold (Al-Yahyaee et al., 2018; Burggraf et al., 2020; Urquhart, 2016; Zhang et al., 2018), we find evidence that cryptocurrencies are more efficient than earlier studies suggest, as we do not find any significant low volatility anomaly in the cryptocurrency market. These findings are consistent over different holding periods, sample sizes, and portfolio construction periods, ranging between 3 and 12 months.

It is worth mentioning that there are several other studies examining volatility in the cryptocurrency market. For example, Baur and Dimpfl (2018) analyze asymmetric volatility effects and find that cryptocurrencies have higher volatility after positive shocks than after negative shocks, pointing into the direction that cryptocurrencies may have different volatility characteristics than equity markets. Bouri et al. (2016) find a similar effect for Bitcoin (neglecting other cryptocurrencies) for the time before the Bitcoin price crash of 2013. They show that besides shocks, trading volume plays an important role in predicting volatility. In the same vein, Bouri et al. (2019) find a positive Granger-causal relationship between trading volume and daily volatility while Dyhrberg (2016) shows that bitcoin may be useful in risk management and ideal for risk averse investors in anticipation of negative shocks to the market. Katsiampa (2019) uses a Diagonal BEKK model to study the volatility dynamics of Bitcoin and Ether. The study provides evidence of interdependencies within the cryptocurrency market and that Ether can be an effective hedge against Bitcoin. Similarly, Bariviera (2017) show by studying the long-range dependence of Bitcoin return and volatility that daily return time-series become more efficient over time, while daily volatility exhibits long-range memory. Finally, Chen and Hafner (2019) develop a test for speculative bubbles in cryptocurrency markets based on sentiment. They argue that cryptocurrencies show characteristics of speculative bubbles and that volatility increases with negative sentiment. In summary, most of the previous literature focuses on the predictability of cryptocurrency volatility by applying GARCH or TARCH models. In our study, we flip the question around by asking whether volatility can predict differences in the cross-section of cryptocurrency returns.

The remainder of this study is structured as follows. Section 2 provides the data used in this study and introduces the portfolio construction methodology. Section 3 discusses the results. Section 4 concludes and discusses practical and regulatory consequences.

2. Data and methodology

Cryptocurrency closing prices quoted in reference to the USD for the top 1000 largest cryptocurrencies[2] by market capitalization are collected from Coinmarketcap[3] for the period April 28, 2013 – November 1, 2019 for a total of 2378 daily observations. The sample was cleaned for data errors and series with ten or less data points were dropped. All cryptocurrency returns are in logarithmic first differences. Table 1 reports descriptive statistics for the full sample as well as for each quintile based on average volatility.

We next construct our $J-K$ low volatility cryptocurrency portfolios following the methodology of Jegadeesh and Titman (2001). Therefore, we rank the cryptocurrencies in ascending order in any given month t based on their volatilities in the past J months and hold them for K months. In this study, we select cryptocurrencies based on their past 3, 6, 9, and 12 month volatility. Similarly, we consider holding periods of 3, 6, 9, and 12 months. Next, we sort the cryptocurrencies into ten deciles based on their J-month past volatilities and build ten equally-weighted portfolios. We then go long in the top decile (“Buy”) and short the bottom decile (“Sell”). The zero-cost portfolio (“Buy-sell”) consists of the winners minus losers portfolios. Finally, we close the position in period K and roll the strategy forward until the end of the sample period is reached. In addition, to avoid bid-ask spread, price pressure, and lagged reaction effects, as documented in Jegadeesh (1990), Jegadeesh and Titman (1993) and Lehmann (1990), we investigate a second set of strategies that skips a week between the portfolio formation period and the holding period. For each strategy, we only used cryptocurrencies for which data were available at the time of the formation of the portfolio.

3. Empirical results

Table 2 reports average returns of the 32 portfolio strategies. The returns of the buy strategies are positive and statistically significant, except for the 3-month/3-month strategy in Panel B (− 0.002), and the 6-month/3-month strategy in Panel A (− 0.003). The returns of the sell strategies are positive and significant, and interestingly, considerably larger than the returns of the buy strategies. As a result, the buy-sell strategies generate significant negative returns at the 1% level across all strategies. The 12-month/12-month buy-sell strategy yields the lowest return with a return of − 0.062 (t-statistic: − 4.56), while the 6-month/9-month strategy yields a return of − 0.299 (t-statistic: − 22.62). Fig. 1 illustrates portfolio performances, confirming that (i) buy and sell strategy returns are positive during all times, (ii) sell strategy returns are more positive than buy strategy returns, and (iii) buy-sell strategies

[2] The full sample of cryptocurrencies used in this study is provided upon request.

[3] https://coinmarketcap.com/.

Table 1
Descriptive statistics of daily logarithmic returns for the full sample and classified according to the volatility level .

Period	Quintile	Mean	SD	SR	Min	Max	Skew	Kurt
Full sample		−0.0031	0.123	−0.025	−0.735	0.852	0.505	19.80
Low volatility	1	−0.00063	0.012	−0.051	−0.057	0.059	0.052	2.034
	2	−0.00062	0.017	−0.037	−0.079	0.094	0.119	2.556
	3	−0.00067	0.020	−0.034	−0.109	0.127	0.139	3.314
	4	−0.00054	0.025	−0.022	−0.154	0.197	0.100	4.528
High volatility	5	−0.00059	0.048	−0.012	−0.334	0.345	0.096	10.37

Note: The table presents descriptive statistics for the 1000 cryptocurrency daily return data for the period April 28, 2013 November 1, 2019. Quintile 1 represents descriptive statistics for the least volatile cryptocurrencies, and quintile 5 for the most volatile cryptocurrencies in our sample. All statistics are calculated from cryptocurrency return data. Mean is the daily mean return, SD is the daily sample standard deviation, SR is Sharpe ratio, Skew is skewness, and Kurt is excess kurtosis. Annualized mean is -1.132, annualized SD is 2.350, and annualized SR is -0.482. We use an annualization factor of 365 days. The Jarque-Bera test of normality (H0: Skewness and excess kurtosis equal zero) and the augmented Dickey-Fuller test (H0: Unit root is present) are both rejected at the 1% level for all cryptocurrencies. All series are in logarithmic first differences.

Table 2
Low volatility portfolio returns .

		Panel A				Panel B			
J	K =	3	6	9	12	3	6	9	12
3	Buy	0.004	0.013	0.062	0.104	-0.002	0.009	0.058	0.103
		(0.38)	(0.85)	(3.20)	(4.51)	(−0.27)	(0.61)	(2.97)	(4.44)
3	Sell	0.128	0.213	0.309	0.387	0.115	0.209	0.306	0.381
		(8.48)	(11.30)	(12.64)	(14.66)	(7.79)	(11.14)	(12.52)	(14.56)
3	Buy-sell	−0.124	−0.200	−0.247	−0.283	−0.118	-0.199	−0.248	−0.278
		(−12.11)	(−17.78)	(−16.89)	(−19.64)	(−11.97)	(−17.89)	(−17.01)	(−19.24)
6	Buy	−0.003	0.018	0.061	0.143	0.000	0.020	0.066	0.151
		(−0.30)	(1.10)	(2.95)	(5.74)	(0.00)	(1.27)	(3.20)	(6.08)
6	Sell	0.108	0.241	0.360	0.415	0.107	0.252	0.366	0.417
		(6.67)	(10.91)	(13.30)	(13.30)	(6.78)	(11.52)	(13.56)	(13.46)
6	Buy-sell	−0.111	−0.223	−0.299	−0.272	−0.107	−0.232	−0.299	−0.265
		(−10.53)	(−18.73)	(−22.62)	(−15.34)	(−10.54)	(−19.95)	(−22.60)	(−15.26)
9	Buy	0.029	0.092	0.179	0.265	0.026	0.092	0.181	0.266
		(2.49)	(5.42)	(8.23)	(10.41)	(2.29)	(5.49)	(8.35)	(10.48)
9	Sell	0.117	0.325	0.382	0.449	0.122	0.334	0.380	0.453
		(6.92)	(14.01)	(12.42)	(13.67)	(7.28)	(14.46)	(12.39)	(14.03)
9	Buy-sell	−0.088	−0.233	−0.203	−0.184	−0.095	−0.241	−0.198	−0.187
		(−8.88)	(−21.33)	(−13.06)	(−12.10)	(−9.75)	(−21.81)	(−12.91)	(−12.70)
12	Buy	0.078	0.180	0.280	0.389	0.080	0.183	0.282	0.393
		(6.37)	(10.61)	(12.87)	(15.06)	(6.64)	(10.93)	(13.04)	(15.28)
12	Sell	0.199	0.300	0.389	0.464	0.199	0.295	0.390	0.456
		(11.29)	(11.33)	(12.87)	(13.93)	(11.41)	(11.11)	(13.02)	(13.72)
12	Buy-sell	−0.121	−0.120	−0.109	−0.075	−0.119	-0.111	−0.107	−0.062
		(−12.32)	(−8.07)	(−8.83)	(−5.49)	(−12.08)	(−7.48)	(−8.31)	(−4.56)

Note: The table reports average daily returns of low volatility portfolios based on a sample of 1000 cryptocurrencies for the period April 28, 2013 – November 1, 2019. Panel A presents portfolios formed immediately after the portfolio formation period, Panel B presents portfolios that skip one week between the portfolio formation and the holding period. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

yield negative returns across all strategies. Standard errors confirm that returns are statistically significantly different from zero. Earlier studies such as Roll (1983) suspect that long-short strategies yield different results in the month of January than in the remaining months of the year. Therefore, to test this conjecture and to eliminate potential seasonal patterns in the performance of the portfolios, we perform a subperiod analysis using time-series data from February through December. The results are reported in Table 3. Although the absolute numbers are slightly different, the directional relationship as well as the statistical significance of the results do not change. That is, the short strategies still achieves positive abnormal returns relative to the long strategies, and the return of the long-short strategy therefore is negative. Furthermore, it could be argued that the time-varying nature of the portfolio alters the results. While it is true that certain cryptocurrency "default" over time and new cryptocurrency are released, we strongly believe that this does not have a significant impact. There are two main reasons for this. First, our sample is very large, therefore, each single cryptocurrency contribues relative little to the overall portfolio performance. Second, using only cryptocurrencies that have existed over the whole sample period by artificially trimming the data would result in very small portfolios, which in turn would negatively affect the reliability of our empirical results.

The results suggest that popular low volatility strategies do not work in cryptocurrency markets, and even worse, generate negative return, thereby confirming a positive relation between risk and return. This provides important information on the efficiency

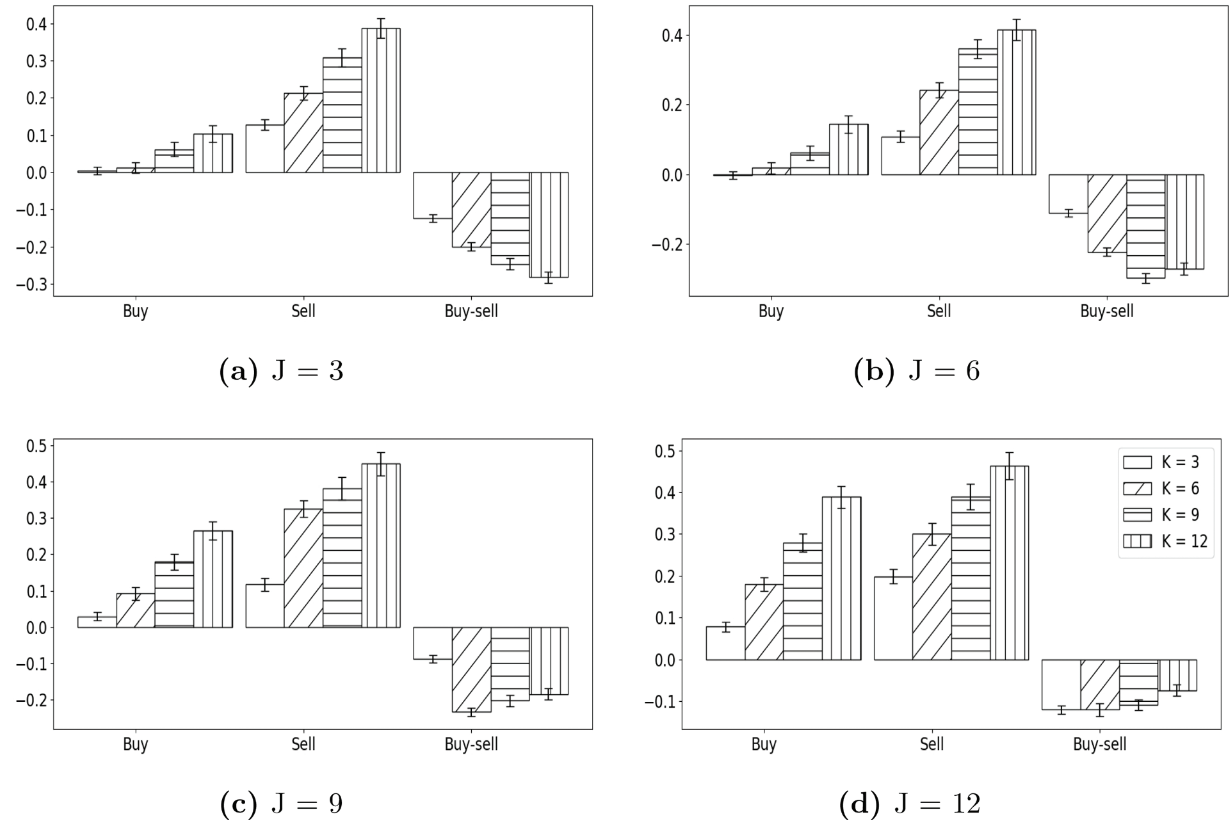

Fig. 1. Average low volatility $J - K$ portfolio returns. The figure illustrates portfolio returns for portfolios formed immediately after the portfolio formation period. The solid lines show standard errors of the mean.

of the cryptocurrency market, which has been labeled largely inefficient by many market participants.

The discrepancy between our results and those for traditional asset classes could be attributable to the uniqueness of the cryptocurrency market, and could be a combination of behavioral biases and the absence of large institutional investors. Therefore, the explanation for the disappearance of the low volatility anomaly could potentially follow the following causal chain. First, the capital asset pricing model (CAPM) assumes that investors only care about absolute return. In reality, institutional investors' mandates are often tied to beating the market, making low-volatility investments relatively unattractive for benchmark-relative investors because they involve high tracking error and lower expected return (Blitz and Van Vliet, 2007; Baker et al., 2011; Falkenstein, 2009). However, because the cryptocurrency market is dominated by retail investors and therefore by absolute-return oriented investors, the SML flattening as documented in Brennan et al. (2012) is less pronounced than in other markets. Second, profit-maximizing asset managers typically have an incentive to attract investor flows by investing in assets with high idiosyncratic volatility (Karceski, 2002; Baker and Haugen, 2012). This effect is reinforced by either small, young, or bad performing funds trying to attract capital by investing in more risky, lotterylike assets (Agarwal et al., 2018). Again, because institutional investors and asset managers are underrepresented in the cryptocurrency market, this agency issue documented for more mature market is less relevant. Third, investors prefer positively skewed, lotterylike payoffs (Blitz and Van Vliet, 2007; Ilmanen, 2012; Hsu and Chen, 2017). Because many investors participate in the stock market to gamble (Kumar, 2009), high-risk stocks typically yield very low returns (Barberis and Huang, 2008). Since the general cryptocurrency market is considered risky relative to the stock market, attraction to individual lottery investments is less severe, which keeps the risk-return relationship intact.

In order to ensure that our results are insensitive to our model specifications, we employ a large set of robustness tests. First, we use trimmed data that excludes the three most extreme returns of each series. Second, instead of using top and bottom deciles, we employ less concentrated strategies that buy the bottom 30% cryptocurrencies and sell the top 30% cryptocurrencies. Third, to address concerns that the results might be driven by small cryptocurrencies, we re-run our analysis using the largest 100 cryptocurrencies based on market capitalization. Across all robustness tests, the results remain consistent with our baseline model. The results are presented in Tables A.1–A.3 in the Appendix.

Lastly, the cryptocurrency market could possibly undergo several structural changes – institutional investors could enter the market, derivative products could be launched, or investors from certain countries could be prohibited from trading and investing in cryptocurrency. All this might influence the structure and efficiency of the cryptocurrency market. To test this hypothesis, we split

Table 3
Seasonal–adjusted low volatility portfolio returns .

		Panel A				Panel B			
	J	K = 3	6	9	12	3	6	9	12
3	Buy	0.021	0.050	0.072	0.150	0.020	0.049	0.071	0.150
		(1.93)	(3.18)	(3.60)	(6.34)	(1.84)	(3.09)	(3.56)	(6.31)
3	Sell	−0.107	−0.217	−0.331	−0.441	−0.107	−0.217	−0.332	−0.443
		(−7.58)	(−11.33)	(−13.42)	(−15.98)	(−7.66)	(−11.35)	(−13.44)	(−16.06)
3	Buy-sell	−0.086	−0.166	−0.260	−0.292	−0.088	-0.168	−0.261	−0.294
		(−8.87)	(−14.55)	(−18.59)	(−19.89)	(−9.10)	(−14.71)	(−18.76)	(−20.08)
6	Buy	0.037	0.065	0.122	0.225	0.037	0.064	0.122	0.225
		(3.15)	(3.81)	(5.59)	(8.80)	(3.15)	(3.81)	(5.62)	(8.82)
6	Sell	−0.104	−0.255	−0.354	−0.478	−0.104	−0.256	−0.355	−0.480
		(−6.47)	(−10.89)	(−11.45)	(−13.54)	(−6.48)	(−10.97)	(−11.48)	(−13.63)
6	Buy-sell	−0.067	−0.190	−0.232	−0.253	−0.067	−0.192	−0.232	−0.255
		(−6.53)	(−15.66)	(−13.69)	(−13.70)	(−6.56)	(−15.85)	(−13.70)	(−13.88)
9	Buy	0.044	0.139	0.236	0.356	0.044	0.139	0.236	0.357
		(3.45)	(7.74)	(10.22)	(13.25)	(3.48)	(7.76)	(10.24)	(13.28)
9	Sell	−0.150	−0.324	−0.403	−0.540	−0.151	−0.324	−0.404	−0.541
		(−8.81)	(−12.59)	(−12.37)	(−15.55)	(−8.93)	(−12.60)	(−12.43)	(−15.57)
9	Buy-sell	−0.106	−0.186	−0.167	−0.184	−0.108	−0.185	−0.168	−0.184
		(−11.76)	(−14.34)	(−11.27)	(−13.41)	(−12.00)	(−14.34)	(−11.40)	(−13.48)
12	Buy	0.102	0.219	0.325	0.465	0.102	0.218	0.325	0.465
		(8.08)	(12.48)	(14.38)	(17.30)	(8.07)	(12.47)	(14.40)	(17.32)
12	Sell	−0.162	−0.301	−0.430	−0.529	−0.161	−0.301	−0.429	−0.529
		(−7.90)	(−10.47)	(−13.15)	(−13.72)	(−7.83)	(−10.48)	(−13.13)	(−13.71)
12	Buy-sell	−0.059	−0.082	−0.105	−0.065	−0.059	-0.082	−0.104	−0.064
		(−4.60)	(−5.45)	(−7.18)	(−3.79)	(−4.51)	(−5.46)	(−7.09)	(−3.72)

Note: The table reports seasonal-adjusted average daily returns of low volatility portfolios based on a sample of 1000 cryptocurrencies for the period April 28, 2013 – November 1, 2019. To account for potential seasonal effects, the month of January has been removed from the sample. Panel A presents portfolios formed immediately after the portfolio formation period, Panel B presents portfolios that skip one week between the portfolio formation and the holding period. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

our sample into two periods using the China cryptocurrency ban policy in September 2017 as the cut-off point.[4] The results are provided in Table A.4 in the Appendix. Interestingly, while the results in the period before the ban remain the same, there is (albeit weak) evidence for some small low volatility premia after the Chinese government's ban. These are some very early indications that the efficiency of the market could change over time as more and more market participants enter or leave the market, providing new opportunities to harvest cryptocurrency factor premia.

4. Conclusion

In this study, we examined the low volatility anomaly for a sample of 1000 cryptocurrencies for the period April 28, 2013–November 1, 2019. Unlike earlier research for traditional asset classes, we cannot find evidence that this effect is present in cryptocurrency markets. While both buy and sell strategies generate positive returns, the zero-cost long-short strategy generates significant negative returns, even after controlling for different sample sizes, rebalancing periods, data preprocessing and portfolio construction methodologies. Potential explanations include agency issues, skewness preferences, and behavioral biases.

The results provide important information to a variety of stakeholders including investors, policymakers, and all aspect of society related to cryptocurrency market and contribute to the debate on the efficiency of cryptocurrency markets and whether the same anomalies that can be found in traditional financial markets are also present in cryptocurrencies. Our results indicate that cryptocurrencies are more efficient than expected, and that higher risk yields higher return. This has important practical implications. Specifically, market participants may use these results for portfolio allocation tasks. Policymakers could take this study as an indication that some rules that hold in traditional equity markets do not hold in cryptocurrency markets. This may have implementation for risk management regulation.

Our results provide some early evidence that factor premia could be time-dependent. Future research could further investigate the effect by testing whether this is consistent across different event breakpoints and alternative factors including size, value, and momentum. Lastly, alternative measures of (tail) risk, such as value at risk and maximum drawdown would be interesting fields of study.

[4] We thank an anonymous referee for this suggestion.

Author Statement

Herewith we confirm, that the manuscript is original, has not been previously published in its current or similar form and is not under review by another journal.

Appendix

Table A.1
Robustness test – low volatility portfolio returns for top 100 cryptocurrencies .

	J	K =	3	6	9	12
3	Buy		0.151	0.214	0.285	0.358
			(13.59)	(16.00)	(17.05)	(17.59)
3	Sell		0.199	0.469	0.659	0.749
			(9.34)	(15.22)	(17.99)	(17.96)
3	Buy-sell		−0.048	−0.255	−0.373	−0.390
			(−3.10)	(−12.08)	(−15.09)	(−15.44)
6	Buy		0.082	0.126	0.186	0.260
			(9.66)	(11.66)	(12.80)	(15.86)
6	Sell		0.217	0.454	0.606	0.751
			(10.45)	(15.63)	(16.73)	(16.86)
6	Buy-sell		−0.134	−0.328	−0.420	−0.490
			(−8.64)	(−15.10)	(−16.23)	(−15.43)
9	Buy		0.084	0.140	0.184	0.280
			(9.74)	(12.75)	(13.75)	(17.48)
9	Sell		0.241	0.496	0.679	0.862
			(10.34)	(14.75)	(15.39)	(16.00)
9	Buy-sell		−0.157	−0.355	−0.495	−0.582
			(−8.48)	(13.38)	(−14.25)	(−13.95)
12	Buy		0.060	0.148	0.218	0.255
			(8.18)	(13.94)	(16.57)	(17.02)
12	Sell		0.275	0.561	0.766	1.026
			(10.34)	(14.71)	(15.45)	(17.32)
12	Buy-sell		−0.214	−0.412	−0.548	−0.771
			(−9.30)	(−12.83)	(−13.54)	(−16.04)

Note: The table reports average daily returns of low volatility portfolios based on a sample of 100 cryptocurrencies for the period April 28, 2013 – November 1, 2019. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

Table A.2
Robustness test – low volatility portfolio returns for top / bottom 30% cryptocurrency quantiles .

	J	K =	3	6	9	12
3	Buy		0.008	0.006	0.027	0.085
			(0.68)	(0.33)	(1.14)	(3.11)
3	Sell		0.048	0.114	0.179	0.258
			(3.39)	(5.54)	(6.91)	(8.51)
3	Buy-sell		−0.039	−0.107	−0.152	−0.172
			(−7.35)	(−15.15)	(−18.23)	(−21.16)
6	Buy		−0.012	0.021	0.094	0.153
			(−1.02)	(1.12)	(3.87)	(5.29)
6	Sell		0.045	0.121	0.209	0.275
			(3.16)	(5.65)	(7.72)	(8.27)
6	Buy-sell		−0.058	−0.099	−0.114	−0.122
			(−12.27)	(−15.49)	(−12.48)	(−10.42)
9	Buy		0.026	0.090	0.159	0.253
			(2.15)	(5.01)	(6.80)	(8.96)
9	Sell		0.070	0.180	0.258	0.399
			(4.82)	(8.42)	(8.82)	(11.94)
9	Buy-sell		−0.044	−0.089	−0.098	−0.146
			(−7.95)	(−10.82)	(−7.87)	(−12.08)
12	Buy		0.052	0.124	0.225	0.338
			(4.20)	(6.77)	(9.39)	(11.85)
12	Sell		0.124	0.205	0.357	0.494
			(7.94)	(8.55)	(12.25)	(14.62)
12	Buy-sell		−0.071	−0.081	−0.131	−0.155
			(−9.52)	(−7.17)	(−12.81)	(−14.31)

Note: The table reports average daily returns of low volatility portfolios based on top / bottom 30% quantile cryptocurrency returns for the period April 28, 2013 – November 1, 2019. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

Table A.3
Robustness test – low volatility portfolio returns for trimmed cryptocurrency data .

	J	K =	3	6	9	12
3	Buy		0.004	0.011	0.064	0.101
			(0.48)	(0.83)	(3.65)	(4.83)
3	Sell		0.055	0.091	0.171	0.222
			(4.54)	(5.66)	(8.36)	(9.73)
3	Buy-sell		−0.051	−0.080	−0.106	−0.121
			(−5.77)	(−8.55)	(−9.77)	(−11.41)
6	Buy		−0.003	0.021	0.065	0.156
			(−0.40)	(1.49)	(3.52)	(15.86)
6	Sell		0.017	0.102	0.169	0.193
			(1.29)	(5.30)	(7.26)	(6.80)
6	Buy-sell		−0.021	−0.081	−0.103	−0.037
			(−2.39)	(−7.30)	(−8.61)	(−2.27)
9	Buy		0.041	0.084	0.182	0.258
			(3.94)	(5.60)	(9.32)	(11.30)
9	Sell		0.039	0.174	0.209	0.265
			(2.60)	(8.73)	(7.66)	(9.25)
9	Buy-sell		−0.002	−0.089	−0.026	−0.007
			(−0.23)	(−9.07)	(−1.80)	(−0.52)
12	Buy		0.045	0.142	0.248	0.335
			(4.09)	(9.31)	(12.50)	(14.50)
12	Sell		0.119	0.198	0.296	0.373
			(8.01)	(8.50)	(11.75)	(12.76)
12	Buy-sell		−0.073	−0.055	−0.047	−0.037
			(−8.10)	(−3.75)	(−4.29)	(−3.05)

Note: The table reports average daily returns of low volatility portfolios based on trimmed cryptocurrency data for the period April 28, 2013 – November 1, 2019. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

Table A.4
Low volatility portfolio returns before and after the ban of cryptocurrency in China .

		Panel A: Pre-cryptocurrency ban					Panel B: After-cryptocurrency ban			
	J	K =	3	6	9	12	3	6	9	12
3	Buy		0.070	0.083	0.097	0.066	-0.232	−0.353	−0.446	−0.531
			(5.26)	(4.59)	(4.77)	(3.45)	(−18.39)	(−19.17)	(−19.86)	(−21.40)
3	Sell		0.247	0.260	0.296	0.359	0.268	0.374	0.478	0.557
			(14.04)	(12.98)	(12.55)	(14.99)	(15.51)	(17.26)	(20.93)	(22.16)
3	Buy-sell		−0.178	−0.177	−0.199	−0.292	0.035	0.020	0.031	0.025
			(−12.66)	(−12.02)	(−10.54)	(−16.04)	(4.64)	(2.67)	(3.98)	(2.93)
6	Buy		0.070	0.106	0.079	0.090	−0.192	−0.272	−0.346	−0.347
			(4.93)	(5.16)	(3.83)	(4.81)	(−14.20)	(−13.53)	(−15.52)	(−18.18)
6	Sell		0.187	0.264	0.318	0.322	0.223	0.285	0.354	0.358
			(9.52)	(10.21)	(10.85)	(9.49)	(16.24)	(17.01)	(18.60)	(18.65)
6	Buy-sell		−0.117	−0.157	−0.239	−0.232	0.031	0.013	0.007	0.011
			(−8.46)	(−11.60)	(−13.86)	(−8.96)	(7.80)	(2.06)	(1.36)	(3.86)
9	Buy		0.125	0.190	0.203	0.224	−0.161	−0.187	−0.171	−0.193
			(7.95)	(9.00)	(9.89)	(11.58)	(−10.38)	(−8.81)	(−11.22)	(−14.69)
9	Sell		0.198	0.401	0.325	0.371	0.169	0.181	0.188	0.232
			(9.22)	(13.71)	(8.93)	(10.52)	(12.36)	(10.96)	(13.27)	(14.78)
9	Buy-sell		−0.073	−0.211	−0.212	−0.147	0.008	−0.006	0.016	0.039
			(−5.93)	(−14.96)	(−5.18)	(−6.24)	(1.39)	(−0.91)	(4.20)	(10.11)
12	Buy		0.188	0.299	0.324	0.359	−0.098	0.006	−0.016	−0.085
			(11.47)	(14.04)	(15.67)	(17.55)	(−5.87)	(0.44)	(−3.58)	(−9.07)
12	Sell		−0.333	−0.386	−0.402	−0.401	−0.113	−0.070	−0.129	−0.153
			(−14.33)	(−10.78)	(−11.94)	(−12.36)	(−7.18)	(−4.89)	(−12.69)	(−9.10)
12	Buy-sell		−0.144	−0.087	−0.078	−0.042	0.015	0.077	0.113	0.067
			(−10.55)	(−3.90)	(−4.10)	(−2.12)	(3.16)	(13.74)	(14.26)	(8.44)

Note: The table reports average daily returns of low volatility portfolios based on a sample of 1000 cryptocurrencies for two sample periods, the pre-cryptocurrency ban period (Panel A) and the after-cryptocurrency ban (Panel B) period by the Chinese government. The breakpoint date is September 1, 2017. All series are in logarithmic first differences. T-statistics are presented in parenthesis.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2020.101683 .

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