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MAX momentum in the cryptocurrency market

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Abstract

This paper studies the MAX effect, the relationship between maximum daily returns and future returns in the cryptocurrency market. The cryptocurrency market is an ideal setting for the MAX effect due to its lottery-like features (i.e., large positive skewness). Contrary to findings in other markets, we demonstrate that cryptocurrencies with higher maximum daily returns tend to achieve higher returns in the future and call this the "MAX momentum" effect. We also find that the magnitude of the MAX momentum effect varies with market conditions, investor sentiment and the underpricing of cryptocurrencies. Additionally, this effect is robust to longer holding periods, different MAX measures and alternative sample selection criteria.

Keywords: Cryptocurrency; MAX effect; Momentum

1. Introduction

Cryptocurrencies, especially Bitcoin, have received a great deal of attention over the last decade from the media, governments, regulators and investors, who have been attracted by the investment potential of these new assets. The academic literature on cryptocurrencies has exploded in recent times, with studies documenting the hedging and diversification benefits (Corbet *et al.*, 2018b; Kajtazi and Moro, 2019; Platanakis and Urquhart, 2019; Urquhart and Zhang, 2019; Wang *et al.*, 2019), the existence of bubbles (Cheah and Fry, 2015; Corbet *et al.*, 2018a), the volatility dynamics (Borri, 2019; Jain *et al.*, 2019; Walther *et al.*, 2019; Shen *et al.*, 2020), arbitrage opportunities (Makarov and Schoar, 2020; Duan *et al.*, 2021), Bitcoin futures (Jalan *et al.*, 2021) and the criminality (Gandal *et al.*, 2018; Corbet *et al.*, 2019a; Foley *et al.*, 2019) of cryptocurrencies.[1] However, the trading potential of cryptocurrencies has received limited attention, with a couple of papers documenting the performance of technical trading rules (Detzel *et al.*; Gerritsen *et al.*, 2020; Hudson and Urquhart, 2020) and asset pricing within cryptocurrencies (Li *et al.*, 2019; Tzouvanas *et al.*, 2019; Liu *et al.*, 2021; Zhang and Li, 2021).

In this paper, we study the existence of the MAX effect in the cryptocurrency market. The MAX effect, referring to the anomaly that assets with high maximum daily returns perform poorly in the subsequent period, was first proposed by Bali *et al.* (2011). Specifically, by measuring a US stock's extreme return as the maximum daily return over the prior month (MAX), Bali *et al.* (2011) document a statistically significant relationship between month t MAX and month $t + 1$ stock returns. The MAX effect is also found to be economically significant, with a portfolio taking a long (short) position in the low (high) MAX stocks generating raw and risk-adjusted returns in excess of 1% per month. Bali *et al.* (2011) suggest that this effect is driven by investors' preference for lottery-like assets that are overpriced due to their high positive skewness.[2]

[1] For a complete review of the literature on cryptocurrencies, see Corbet *et al.* (2019b).
[2] Bali *et al.* (2014) confirm the MAX effect as a preference for lotteries.

Following Bali *et al.* (2011), a number of studies have explored the MAX effect in settings outside of the US. For instance, Walkshäusl (2014) finds pervasive evidence of a negative relationship between MAX and future returns for 11 European countries; however, Annaert *et al.* (2013) examine a sample of nearly 8,000 European companies and detect little evidence of a MAX effect. Zhong and Gray (2016) document a strong MAX effect in Australian equities and show, by using Stambaugh *et al.* (2015) methodology to classify the mispricing of stocks, that the MAX effect is concentrated amongst the most overpriced stocks and reverses amongst the most underpriced stocks. Also, Chan and Chui (2016) show significant evidence of the MAX effect in the Hong Kong market, while Nartea *et al.* (2017) confirm findings in the stock market of Mainland China.

In this paper, we extend the knowledge of the MAX effect by examining the MAX effect in cryptocurrencies. The cryptocurrency market offers a unique setting to explore the MAX effect since it is widely suggested that the cryptocurrency market is comparable to lottery stocks and that cryptocurrencies have large positive skewness (Chuen *et al.*, 2018; Hu *et al.*, 2019; Momtaz, 2020).[3] Fig. 1 presents a histogram of the skewness of over 2,500 cryptocurrencies, which clearly shows the positive skewness of the majority of cryptocurrencies. Further, Conlon and McGee (2019) study Bitcoin transaction data and show that the changes in gambling volume explain a significant portion of Bitcoin price movements before March 2016. Pelster *et al.* (2019) explore individual-level brokerage data and find that cryptocurrency investors simultaneously increase their risk-seeking behaviour in stocks where they increase the number of trades and the leverage, resulting in lower returns. And Lammer *et al.* (2019) analyze the administrative data of customers of a large German online bank and document that cryptocurrency investors are active traders, more prone to investment biases and hold risky portfolios. Therefore, there is evidence that investors in the cryptocurrency market exhibit strong lottery-like preferences and risk-seeking behaviour.

[3] Kenneth Rogoff suggests that cryptocurrencies are like lottery tickets that might pay off in the future. See https://www.theguardian.com/business/2018/dec/10/cryptocurrencies-bitcoin-kenneth-rogoff.

We study the MAX effect across cryptocurrencies to determine whether the MAX effect is prevalent in this new asset class and whether investors can take advantage of this anomaly when trading cryptocurrencies. Specifically, using a sample of large tradeable cryptocurrencies between 1st January 2014 and 30th June 2020, we study how cryptocurrencies with extreme returns in a certain month perform in the subsequent week. It is important to note that, unlike other studies, we report weekly returns rather than monthly returns because the cryptocurrency market has relatively short history and extremely high volatility (Dwyer, 2015; Klein *et al.*, 2018; Shen *et al.*, 2020). Thus, weekly returns offer greater estimation accuracy. We find, contrary to previous studies in traditional financial markets, the existence of a MAX momentum effect, where cryptocurrencies with the highest extreme returns in the previous month outperform cryptocurrencies with the smallest extreme returns in the previous month. This suggests a momentum effect in the cryptocurrency market in terms of extreme returns and contrasts those results of Grobys and Sapkota (2019) who find that the traditional momentum strategy of Jegadeesh and Titman (1993) yields insignificant results while Tzouvanas *et al.* (2019) show that momentum trading is only profitable in the short term for the largest twelve cryptocurrencies. We also find that the MAX momentum effect is not due to the cryptocurrency market characteristics and performs the best during market upturns. Moreover, this effect is also more prevalent during periods of low investor sentiment in the cryptocurrency market and is stronger for cryptocurrencies that are deemed the most underpriced. Besides, the MAX premium is independent of and higher than idiosyncratic volatility premium and skewness premium. Finally, we show that our results are robust to longer holding periods and different MAX measures and are not driven by the smallest cryptocurrencies.

Therefore, this study contributes to the literature in several important ways. First, by employing a universe of cryptocurrencies, we comprehensively examine the benefits of the well-known MAX effect in the cryptocurrency market. The media and investor interest in cryptocurrencies has grown vastly over the previous decade, and this paper investigates whether the extreme returns can be utilized to gain significant returns. Second, cryptocurrencies are known to be lottery-like financial instruments with large positive skewness, thereby suggesting that traditional investment strategies used with traditional assets, which are based on mean returns, may not be appropriate. We find that, contrary to findings in traditional markets, there is a significant MAX momentum effect where cryptocurrencies with extreme past returns continue to perform well in the future. Third, we show that the MAX momentum effect is stronger during market upturns and during periods of low investor sentiment, indicating the behavioural aspects of the MAX momentum effect. Fourth, we follow the mispricing method of Stambaugh *et al.* (2015) and find that the MAX momentum effect is strongest for the most underpriced cryptocurrencies, indicating that the mispricing of cryptocurrencies is a significant driver of the MAX momentum effect. Finally, our results are confirmed for longer holding periods and constraining our sample to cryptocurrencies with a market capitalization greater than 500,000 USD or with a trading history longer than two years, indicating that the MAX momentum effect is not only a short-term effect and not driven by choice of sample selection criteria.

The rest of this paper is organized as follows. Section 2 presents the data and variable construction, while Section 3 reports the main results. Section 4 shows how different factors affect our main findings. Section 5 provides some robustness analyses, while Section 6 summarizes our findings and provides conclusions.

2. Data and variable construction

2.1. Data Source

Unlike traditional financial assets, cryptocurrencies are traded on a number of exchanges which means that closing prices can vary depending on the exchange used to source the data. We collect data over the period of 1st January 2014 to 30th June 2020 from www.coinmarketcap.com, a leading source of trading information on cryptocurrencies where closing prices are constructed using a weighted combination of closing prices from all exchanges on which the asset traded.[4] We source daily closing prices of 2,805 cryptocurrencies listed on www.coinmarketcap.com and exclude any cryptocurrency with unavailability of market capitalization. Some small cryptocurrencies are of little liquidity. To avoid the contamination of these cryptocurrencies, we only include the largest 300 cryptocurrencies at the end of each week in our sample.[5]

2.2. Construction of key variables

The key variable of interest in this study is a cryptocurrency's maximum daily return over the past month (denoted MAX). Specifically, for cryptocurrency *i* in week *t*, $MAX(1)_{i,t} = \max(R_{i,d}), d = 1, \ldots, D_t$, where $R_{i,d}$ is cryptocurrency *i*'s return on day *d* and D_t is the number of trading days in the past one month as of the end of week *t*.[6] In the traditional MAX effect of Bali *et al.* (2011), the extreme return of the previous month has a significant relationship with returns in the next month. In our study, we examine the extreme return in the previous month and its relationship with returns in the following weeks, since our data period is constrained by the number of observations available.[7] Besides MAX(1), we also calculate MAX(2), MAX(3), MAX(4) and MAX(5) as the average of 2, 3, 4 and 5 highest daily returns in the past month (denoted MAX(N)).

In addition, we also incorporate other cryptocurrency characteristics that may affect the MAX-return relationship into our analyses. Specifically, by regressing the daily returns of each cryptocurrency on the value-weighted market returns during the past month, we

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[4] Although there are many sources of cryptocurrency prices, www.coinmarketcap.com offers the largest set of information on the universe of cryptocurrencies and has been used in many recent, influential studies such as Gandal *et al.* (2018), Antonakakis *et al.* (2019), Platanakis and Urquhart (2019), and Corbet *et al.* (2020) amongst others.

[5] We thank an anonymous for suggesting this selection criterion.

[6] Since cryptocurrencies trade 7 days a week, the number of trading days per month for cryptocurrencies is substantially higher than that for traditional stocks that close on weekends.

[7] The formation and the forecast periods of MAX can be at different frequency levels. For example, Cao and Han (2016) study the relationship between extreme positive returns and expected weekly returns by defining MAX(5) as the average of the five highest daily returns in a rolling window of the previous 30 calendar days. Hollstein *et al.* (2019) also use the average of the five highest daily returns during the previous year to predict the monthly returns.

control for the influence of market beta (*Beta*). We use the logarithm of market value (*Size*) and the logarithm of one plus price on the last day of each week (*Prc*) to deal with the size impact. The return of the previous week (*Mom*)[8] is employed to control for the momentum effect (Liu *et al.*, 2021). Following Amihud (2002), we define the illiquidity measure (*Illiq*) for each cryptocurrency as its absolute daily returns divided by the mean daily dollar trading volume in each week.

Panel A of Table 1 reports the descriptive statistics of our main variables of interest where the MAX mean returns, standard deviations and skewness monotonically decrease as the length of the MAX increases. The mean of beta is positive, with a value of 0.912. Consistent with the findings of Tzouvanas *et al.* (2019), the mean of momentum (0.052) is also positive. As expected, momentum and illiquidity have quite large standard deviations, indicating the large variation in our sample of cryptocurrencies. Besides, to further show the relationships between our main variables, we include the time-series averages of cross-sectional correlations in Panel B of Table 1. Consistent with our expectation, the correlations between different MAX measures are remarkably high, suggesting that they act as good substitutes for each other. Among the rest of the cryptocurrency characteristics, *Beta* and *Mom* have high positive correlations (exceeding 16%) with MAX measures, while *Size* and *Prc* are negatively correlated with MAX measures.

3. Empirical results

3.1. Single-sorted portfolio analysis

We first explore cryptocurrencies' MAX effect with the single-sorted portfolio analysis. To do so, we sort cryptocurrencies into decile portfolios based on the MAX(N) in the previous month. Table 2 reports the equal-weighted (Panel A) and value-weighted (Panel B) average excess returns and alphas (adjusted with value-weighted market excess returns) one week ahead of the portfolio formation period.[9] Portfolio "Low" comprises cryptocurrencies

[8] In an untabulated test, we calculate momentum over longer windows, i.e., 2, 3 and 4 weeks, and find no significant changes in our main conclusions.

[9] Alphas are calculated as the intercepts from a regression of weekly excess returns of a portfolio on value-

with the lowest MAX(N) in the previous month, while portfolio "High" comprises those with the highest MAX(N). Additionally, we include the excess return and alpha differences between portfolios High and Low in this table to better illustrate the extra profits investors can earn via buying cryptocurrencies in portfolio High and selling those in portfolio Low. Contradicting the findings in other markets, we find that there is a general monotonic increase in the excess return and alpha as we move from portfolio Low to portfolio High. Specifically, portfolios of cryptocurrencies with the highest extreme returns in the previous month tend to continue to outperform other cryptocurrencies in the future. This pattern is clearer when we examine the return differences between portfolios High and Low. In both the equal and value weighting schemes, buying portfolio High and selling portfolio Low generate significant excess returns and alphas. This indicates a momentum-like behaviour for cryptocurrencies, which is not found in traditional stocks where the literature reported a significant negative MAX effect. We name this positive MAX effect "MAX momentum."

Another noteworthy fact about Table 2 is that return measures are significantly positive for most cases in the equal weighting scheme but often insignificant for the value weighting scheme, implying that cryptocurrencies with relatively small market capitalization play a critical role in driving the positive MAX effect. Given that small cryptocurrencies usually have less liquidity and a small investor base, a concern arises: the MAX momentum effect could be caused by cryptocurrencies that are highly illiquid and seldom traded. To mitigate this concern, we report some important characteristics of the above cryptocurrency portfolios in Table 3. As expected, the average market capitalization, price and trading volume for portfolio High is the lowest among the 10 portfolios, suggesting that cryptocurrencies in portfolio High are small and not be preferred by investors. Additionally, the illiquidity of cryptocurrencies in portfolio High is also significantly larger than those in portfolio Low. Nevertheless, the difference in illiquidity is acceptable given

weighted market excess returns. The value-weighted market excess returns are the value-weighted returns of all the available cryptocurrencies minus the one-month Treasury bill rate. In a similar vein, the excess returns for each portfolio are weekly portfolio returns minus the one-month Treasury bill rate.

that the illiquidity of portfolio High is also 20 times the illiquidity of portfolio Low in the stock market (Bali *et al.*, 2011).

We also check the cross-sectional persistence of MAX by examining the average 4-week-ahead portfolio transition matrix for our cryptocurrencies in our sample. In particular, we show the average probability that a cryptocurrency in a decile (defined by the rows) in one week will be in another decile (defined by the columns) in the following 4 weeks. Typically, all probabilities presented in the matrix should be close to 10% if MAX evolves randomly. Put differently, the relative magnitude of MAX in one period should have no implication about the relative MAX values in the next period. However, as shown in Table 4, 34% of cryptocurrencies in the lowest MAX decile in a week continue to be in the lowest MAX decile 4 weeks later. Likewise, 41% of cryptocurrencies in the highest MAX decile in a week again appear in this decile 4 weeks later. Other probabilities on the diagonal of Table 4 are also larger than 10%, indicating that MAX is a persistent characteristic of cryptocurrencies. Besides, the fact that 41% of cryptocurrencies remain to be in the highest MAX decile is less striking than that in the stock market (Bali *et al.*, 2011), which also suggests that the MAX momentum effect is not merely determined by those small cryptocurrencies with little liquidity.

3.2. Double-sorted portfolio analysis

To examine this finding in more detail and to determine whether some characteristics of the cryptocurrencies are a driving factor of our previous findings, we conduct a double-sorted portfolio analysis where cryptocurrencies are first divided into quintiles based on a given cryptocurrency characteristic. Then the portfolios are categorized into additional quintiles based on MAX(N) in each cryptocurrency characteristic quintiles. Specifically, motivated by studies (e.g., Bali *et al.*, 2011) focusing on the MAX effect in other markets, we split cryptocurrencies into quintiles based on beta, size, momentum, illiquidity and price and then examine the MAX effect. This is important since our sample is large and contains quite a diverse set of cryptocurrencies and will enable us to determine whether certain cryptocurrency characteristics are driving our results. For brevity, each column in Panel A (Panel B) of Table 5 presents excess returns (alphas) averaged across the 5 quintiles for a given characteristic to produce quintile portfolios with dispersion in MAX but containing cryptocurrencies with different values of these characteristics.[10] Irrespective of the MAX length and controlled cryptocurrency characteristics, portfolios with the lowest MAX still achieve less excess returns or alphas than those with the highest MAX. Although compared with the results in Table 2, the return differences between portfolios high and low are less prominent, they are still positive and statistically significant across all different cryptocurrency characteristics. This suggests that our original results are not driven by certain cryptocurrency characteristics.

3.3. Fama-MacBeth regression analysis

So far, our analysis has studied the portfolio excess returns and alphas to be gained from the MAX momentum effect in cryptocurrencies. However, some information may be omitted from the previous portfolio analysis. Also, to examine more deeply the relationship between the MAX momentum effect and other cryptocurrency characteristics, we run Fama-MacBeth (1973) regressions on the variables described in Section 2. Table 6 presents the time-series averages of the slope coefficients from the cross-sectional regressions of one-week-ahead cryptocurrency excess returns on MAX(N) individually (in columns (1)-(10)) or jointly with other cryptocurrency characteristics (in columns (11)-(15)). In all columns, the coefficients of MAX(N) are all significantly positive at the 1% level or the 5% level, implying that the MAX momentum effect is not subsumed by other factors that may influence cryptocurrency returns. Regarding the control variables, the coefficients of *Beta*, *Size* and *Prc* are statistically significant when they are used to predict cryptocurrency returns singly, indicating that cryptocurrency returns are positively related to *Beta* but are negatively related to *Size* and *Price.* However, the significant coefficients of *Beta* and *Prc* disappear when incorporating other cryptocurrency characteristics into the

[10] We report the low and high excess returns and alphas but not the other deciles to conserve space. However, the full results are available upon request from the corresponding author.

regression. Therefore, our Fama-MacBeth (1973) regression results support our previous findings of the significant and positive relationship between the extreme returns in the previous month and the returns in the subsequent week.

4. Heterogeneity analysis

4.1. Market Conditions

According to An *et al.* (2020), the pattern that stocks with high MAX earn fewer profits than stocks with low MAX is more pronounced among stocks with prior losses but weaker or even reversed when stocks have prior gains. This suggests that the MAX effect is somewhat dependent on whether investors are in a gain or loss region relative to a reference point. Given that our findings contradict those in the stock market, it could be the case that the MAX momentum effect will be more pronounced when investors have gained profits.

Although the idea is straightforward, it is challenging to empirically test it because of the unavailability of cryptocurrency investors' data. A partial solution is to roughly examine the MAX effect during market upturns and downturns. Typically, investors are more likely to earn profits when the market performs well but lose money when the market performs badly. Therefore, we follow Makarov and Schoar (2020) and use the standard Hodrick–Prescott filter[11] to form a series of the smoothed log price of the cryptocurrency market index[12] at the weekly level and plot the time series of this smoothed log price and the actual log price in Fig. 2. Motivated by Makarov and Schoar (2020), we define buying pressure as the residual (or deviation) between the actual log market price and the smoothed log market price. Periods when the residual is positive are denoted the market upturns and otherwise are denoted the market downturns. We then repeat the single-sorted portfolio analysis during market upturns and downturns.

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[11] We thank an anonymous for recommending this method.

[12] The market index is a value-weighted index of the 300 largest cryptocurrencies. We set the price of this index to be 100 on January 1st 2014.

Table 7 reports the results. For market upturns, the excess return and alpha differences between portfolios High and Low are positive and statistically significant for all cases. In stark contrast, the differences between these two portfolios are insignificant for market downturns. These results confirm our conjecture that the MAX momentum effect in the cryptocurrency market is more pronounced when the market performs well (or when more investors have gained profits).

4.2. Investor sentiment

Another factor that influences the MAX effect is investor sentiment, where Fong and Toh (2014) show that when sentiment is high, investors are more optimistic about the future payoffs of high MAX assets than when sentiment is low. Hence, these assets are overpriced more seriously during high sentiment periods. A reasonable extension of this logic is that the MAX momentum effect should be stronger in low sentiment periods than in high sentiment periods for cryptocurrencies since we find a positive MAX effect so far in our analyses. Following Da *et al.* (2015), we employ Google search frequency of "cryptocurrency" as the sentiment proxy. A given month will be categorized into the high (low) sentiment period if its search frequency is higher (not higher) than the median of the corresponding year. We then re-estimate the analysis in Table 2 in both high and low sentiment periods. Table 8 reports the results, and we find clear evidence that the MAX momentum effect performs better during low sentiment periods. Specifically, in months with low sentiment, the strategy that buying cryptocurrencies with the highest MAX and selling cryptocurrencies with the lowest MAX effect gains significant excess returns and alphas across all MAX(N), while during high sentiment months, this strategy tends to generate positive but insignificant excess returns and alphas for most cases. Therefore, these results provide evidence that the MAX momentum effect varies with investor sentiment. Additionally, these results also indicate that investor sentiment has a significant impact on cryptocurrency returns, consistent with the previous findings of Urquhart (2018).

4.3. Mispricing degree

Zhong and Gray (2016) report a significant MAX effect in Australian equities and show that the MAX effect concentrates amongst the most overpriced stocks and actually reverses amongst the most underpriced stocks. We examine whether this is the case for cryptocurrencies by following Stambaugh *et al.* (2015) and ranking cryptocurrencies based on their mispricing. Since cryptocurrencies are a relatively new financial asset and the academic literature is still in its infancy, there has not been reported as many anomalies as in stocks. Therefore, we include two anomalies in our mispricing methodology, namely the size and momentum anomalies (Liu *et al.*, 2021). On a monthly basis, a percentile rank is assigned to each cryptocurrency for each anomaly variable. The lowest rank is associated with the highest expected return (most underpriced), and the overpriced cryptocurrency with the lowest expected return receives the highest rank. This leads to two rankings for each cryptocurrency. And the two rankings are then averaged to generate the cryptocurrency mispricing for that month, where the cryptocurrencies with the highest (lowest) composite rank are the most overpriced (underpriced). Given the mispricing index, cryptocurrencies are independently double-sorted into quintiles based on mispricing and MAX.[13]

According to Table 9, the MAX momentum effect is concentrated in the most underpriced cryptocurrencies, suggesting that underpriced cryptocurrencies are important components of the MAX momentum effect. Further, return differences between the most underpriced cryptocurrencies and those that are most overpriced generally increase with MAX. In particular, the excess return difference is only 0.036 when the maximum daily return is the lowest but 0.092 when the maximum daily return is the highest.

4.4. Idiosyncratic Volatility, Skewness, and MAX

Despite the striking empirical phenomenon, there could be alternative interpretations of the relationship between extreme returns and future returns. For example, plenty of

[13] For brevity, we only report the results using MAX(1).

evidence shows that idiosyncratic volatility can be priced into cross-sectional returns. Given the many similarities between MAX and idiosyncratic volatility (e.g., Bali *et al.*, 2011), there is a probability that the extreme positive return merely represents high idiosyncratic volatility? Another potential explanation is that the maximum return could proxy for skewness.

The set of tests in this subsection is used to attenuate these concerns. Specifically, we compute idiosyncratic volatility (*Ivolatiliy*) as the standard deviation of residuals from regressions of excess cryptocurrency returns on excess market returns during the past 4 weeks. Regarding the skewness measure, we employ co-skewness (*Coskewness*) and idiosyncratic skewness (*Iskewness*). The first one is the coefficient of the squared excess market return term when regressing daily excess cryptocurrency returns on the daily excess market returns and the squared daily excess market returns in the past 30 days. And *Iskewness* is the standard deviation of residuals from regressions of the daily excess cryptocurrency returns on the daily excess market returns and the squared daily excess market returns in the past month.

We first perform the double-sorted portfolio analysis with these three variables as the first-stage sorting variables and with MAX as the second-stage sorting variables. As shown in Panel A of Table 10, both the excess return and alpha differences between portfolios High and Low remain to be significantly positive for all MAX measures, indicating that idiosyncratic volatility and skewness cannot fully explain the positive relationship between MAX and cryptocurrency returns.

In addition, we also compare the premiums of idiosyncratic volatility, co-skewness and idiosyncratic skewness to that of MAX. To do so, we conduct the single-sorted portfolio analysis with the above variables, respectively. From Panel B of Table 10, we can observe that neither excess return differences nor alpha differences between portfolios High and Low are significant when using co-skewness or idiosyncratic skewness as the sorting variable. In contrast, these differences are significantly positive for idiosyncratic volatility. Recall that the premiums of MAX(N) range from 0.041 to 0.070 in Panel B of Table 2, the premiums of idiosyncratic volatility are relatively small.

5. Robustness checks

5.1. Controlling for other factors

In our baseline analysis, we controlled for market beta, size, momentum returns, illiquidity and price. However, trading volume might also have a relationship with the MAX effect. To ensure that our MAX returns in cryptocurrencies do not disappear when we include trading volume factors, we re-estimate the double-sorted portfolio analysis with some new variables.

Following Atilgan *et al.* (2020), we use three proxies to measure trading volume. The first variable is the abnormal trading volume (*Abvol*), which is calculated as the average dollar trading volume for a given cryptocurrency in the portfolio formation week after subtracting the average dollar trading volume of the past 4 weeks. Apart from abnormal trading volume, we also include two dummy variables *Vlow* and *Vhigh* to denote whether dollar trading volume of a given cryptocurrency on the last day of the portfolio formation week is among the lowest and highest 10% of its daily dollar trading volume over the prior 30 days.

The results of double-sorted analyses with these trading volume variables are shown in Table 11. We find that the MAX momentum effect is still positive and significant in all cases. The pattern indicates that the MAX momentum effect cannot be encompassed by the trading volume in the cryptocurrency market.

5.2. Different forecast and holding periods

Next, we investigate the presence of the MAX momentum effect for the shortened forecast period of one week. That is to say, we calculate MAX(N) as the average of N highest daily returns in the past week. Since there are totally 7 days in a week, we only report the results with MAX(1), MAX(2), and MAX(3) in Table 12.[14] According to Table 12, the MAX momentum effect still holds when we use one week as the forecast period. What is more, we also examine whether the MAX momentum effect can last for a long time by extending the holding period of one week through to 4 weeks. As shown in Table 13,[15] the MAX momentum effect still exists when we hold the portfolios for 2 to 3 weeks but disappears over the 4-week periods, implying that it is not a short-run effect but cannot last for a very long time.

5.3. Subsample of cryptocurrencies with other screens

In this study so far, we have employed the largest 300 cryptocurrencies to alleviate the concern that some small cryptocurrencies lacking liquidity could affect our results. However, it could be argued that the choice of the largest 300 cryptocurrencies is somewhat arbitrary. In this subsection, we re-estimate our analysis but with different sample selection criteria. In Panel A of Table 14, we only include the cryptocurrencies with a market capitalization greater than 500,000 dollars in the sample and reconduct the double-sorted portfolio analysis. The results support our previous findings of a significant MAX momentum effect in the cryptocurrency market. Furthermore, we exclude cryptocurrencies with trading history of less than two years.[16] As shown in Panel B of Table 14, we again find that the portfolio with high MAX earns significantly higher returns than the portfolio with low MAX in the future, which demonstrates that our results are not driven by the small or immature cryptocurrencies.

5.4. Modified MAX effect

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14 The single-sort analysis provides qualitatively very similar results. Thus, for this test and the rest of the robustness tests, we do not report them to conserve space, but the results in full are available upon request from the corresponding author.

15 For brevity, we only report results using MAX(1) in this table.

16 Cryptocurrencies must have at least 2 full years of trading data to ensure that the cryptocurrencies included in this study have long enough history to examine the MAX effect and that our results are not driven by immature cryptocurrencies.

In a recent paper, Hung and Yang (2018) propose a modified MAX measure to address the issue of homogeneous MAX across stocks in markets where returns are capped at the daily price limit, e.g., stock markets in China and Japan. Although there are no price limits in cryptocurrency markets, it is interesting to see whether the MAX momentum effect still holds with the modified MAX measure. Since the volatility of cryptocurrencies has been shown to be quite high (Dwyer, 2015; Klein *et al.*, 2018; Shen *et al.*, 2020) and returns of cryptocurrencies have a higher possibility to be negative, we modified the MAX measure in Hung and Yang (2018) by selecting a range of price limits and calculating the frequency of daily returns exceeding the threshold *P (P=10%,20%,…50%)* within the past month (MMAX(P)). We then repeat our baseline double-sorted portfolio analysis and report the results in Table 15. The value-weighted excess returns and alphas for high minus low portfolios are significantly positive for MMAX(P), supporting that the previous finding is not driven by certain MAX measure.

6. Conclusions

Motivated by findings of a significant role of extreme returns in the US stock market (Bali *et al.*, 2011), we investigate the existence of the effect in the cryptocurrency sphere, which is characterized by extreme returns. Cryptocurrencies are known to be highly volatile, possess high positive skewness, experience extreme returns and are widely suggested that the cryptocurrency market is comparable to lottery stocks. We find that cryptocurrencies with a high extreme return in the previous month continue to perform well in the future, while cryptocurrencies with a low extreme return in the past month do not perform well in subsequent periods. This is contrary to the MAX effect that has been found in many stock markets around the world and supports the literature which finds that cryptocurrency returns possess momentum and that investing in cryptocurrencies is similar to lottery stocks. We further show that the MAX momentum effect varies with market conditions and investor sentiment, where the returns are highest in market upturns and during periods of low investor sentiment. The MAX momentum effect is also stronger for the most underpriced of cryptocurrencies. We also demonstrate that this effect holds for longer holding periods and different MAX measures.

To sum, our paper significantly contributes to the cryptocurrency and MAX literature by showing the significant MAX momentum in cryptocurrencies, which should be of great interest to market participants and cryptocurrency enthusiasts alike.

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Table 1: Descriptive Statistics. In Panel A, we report the mean, standard deviation, the first and third quartiles, median, 5th and 95th percentiles and skewness of the MAX(N) as well as *Beta*, *Size*, *Mom*, *Illiq* and *Prc* in this table. MAX(N) is as the average of N (N=1,2,…,5) highest daily returns in the past one month as of the end of week *t*. *Beta* is obtained from regressing daily returns of each cryptocurrency on the value-weighted market returns during the past month. *Size* is the logarithm of market value. *Mom* is the return of the previous week. *Illiq* is the absolute daily return divided by the mean daily dollar trading volume in each week. *Prc* is the logarithm of one plus price in the last day of each week. In Panel B, we report the Pearson correlations among these variables.

Panel A: Descriptive statistics

	Mean	Std.	P5	P25	Median	P75	P95	Skewness
MAX(1)	0.415	1.726	0.059	0.121	0.205	0.385	1.186	56.288
MAX(2)	0.313	0.921	0.053	0.105	0.173	0.315	0.900	47.272
MAX(3)	0.259	0.641	0.047	0.093	0.151	0.271	0.741	42.244
MAX(4)	0.224	0.497	0.043	0.084	0.135	0.238	0.634	38.773
MAX(5)	0.199	0.408	0.040	0.076	0.122	0.215	0.557	36.299
Beta	0.912	1.932	-0.491	0.497	0.932	1.293	2.282	15.930
Size	15.848	3.265	9.571	13.758	16.617	17.828	20.370	-0.562
Mom	0.052	0.540	-0.314	-0.115	-0.005	0.111	0.549	32.295
Illiq	0.040	22.850	0.000	0.000	0.000	0.000	0.008	142.819
Prc	0.586	1.222	0.000	0.007	0.077	0.556	3.128	3.435

Panel B: Correlation matrix

	MAX(1)	MAX(2)	MAX(3)	MAX(4)	MAX(5)	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
MAX(1)	1.000									
MAX(2)	0.989	1.000								
MAX(3)	0.975	0.996	1.000							
MAX(4)	0.962	0.990	0.998	1.000						
MAX(5)	0.951	0.983	0.995	0.999	1.000					
Beta	0.173	0.173	0.171	0.170	0.168	1.000				
Size	-0.147	-0.192	-0.218	-0.236	-0.247	-0.003	1.000			
Mom	0.163	0.186	0.197	0.204	0.209	0.071	-0.024	1.000		
Illiq	0.006	0.008	0.010	0.011	0.012	0.010	-0.024	0.004	1.000	
Prc	-0.041	-0.053	-0.061	-0.066	-0.069	0.008	0.405	-0.005	-0.005	1.000

Table 2: Single-sorted Portfolios. This table shows the one-week-ahead equal-weighted (Panel A) and value-weighted (Panel B) excess returns (ER) and alphas (Alpha) of decile portfolios based on the average of N (N=1,2,…,5) highest daily returns within the past one month as of the end of week *t* (MAX(N)). Portfolio High (Low) comprises cryptocurrencies with the highest (lowest) MAX(N). Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
	ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha
Panel A: Equal-weighted										
Low	0.021**	0.001	0.016*	-0.005	0.017**	-0.004	0.017**	-0.003	0.016*	-0.004
	(2.307)	(0.101)	(1.845)	(-1.182)	(1.993)	(-0.898)	(2.016)	(-0.742)	(1.862)	(-0.982)
2	0.027**	0.002	0.032***	0.008	0.032***	0.008	0.030***	0.005	0.030***	0.005
	(2.526)	(0.420)	(2.964)	(1.140)	(3.065)	(1.229)	(2.757)	(0.787)	(2.761)	(0.804)
3	0.035***	0.012	0.034***	0.010	0.026**	-0.000	0.029**	0.002	0.028**	0.001
	(3.088)	(1.479)	(2.867)	(1.306)	(2.106)	(-0.020)	(2.465)	(0.320)	(2.393)	(0.206)
4	0.031***	0.007	0.034***	0.010	0.041***	0.017**	0.040***	0.016**	0.040***	0.016**
	(2.978)	(1.134)	(3.175)	(1.458)	(3.770)	(2.253)	(3.583)	(2.138)	(3.630)	(2.161)
5	0.041***	0.013*	0.033***	0.006	0.036***	0.010	0.039***	0.013*	0.041***	0.017*
	(3.351)	(1.866)	(2.774)	(0.907)	(2.908)	(1.379)	(3.069)	(1.745)	(3.153)	(1.903)
6	0.060***	0.032***	0.058***	0.030***	0.051***	0.025**	0.050***	0.023**	0.066***	0.037**
	(4.435)	(3.413)	(4.341)	(3.287)	(4.008)	(2.531)	(3.884)	(2.425)	(3.376)	(2.161)
7	0.056***	0.031***	0.059***	0.033***	0.073***	0.048***	0.070***	0.045***	0.052***	0.028***
	(4.290)	(3.235)	(4.273)	(3.266)	(3.661)	(2.684)	(3.830)	(2.832)	(4.050)	(3.040)
8	0.072***	0.046***	0.082***	0.056***	0.065***	0.041***	0.075***	0.049***	0.078***	0.052***
	(3.676)	(2.605)	(4.040)	(3.101)	(4.337)	(3.387)	(4.706)	(3.744)	(4.546)	(3.544)
9	0.074***	0.052***	0.065***	0.041***	0.074***	0.049***	0.064***	0.040***	0.068***	0.043***
	(4.133)	(3.411)	(4.861)	(4.304)	(5.183)	(4.634)	(4.509)	(3.883)	(4.543)	(4.160)
High	0.095***	0.070***	0.105***	0.081***	0.111***	0.085***	0.119***	0.094***	0.126***	0.098***
	(6.943)	(6.812)	(7.429)	(7.192)	(7.141)	(7.245)	(7.394)	(7.530)	(7.489)	(7.810)
High-Low	0.074***	0.069***	0.089***	0.086***	0.094***	0.089***	0.102***	0.097***	0.109***	0.103***
	(6.150)	(5.949)	(7.889)	(7.504)	(7.754)	(7.551)	(7.809)	(7.653)	(8.086)	(7.944)
Panel B: Value-weighted										
Low	0.007	-0.008***	0.005	-0.011***	0.008	-0.009***	0.009	-0.008***	0.010*	-0.007***
	(1.286)	(-2.975)	(0.881)	(-4.621)	(1.435)	(-4.250)	(1.528)	(-3.852)	(1.671)	(-3.326)
2	0.015	-0.009*	0.018*	-0.006	0.012	-0.011**	0.010	-0.012**	0.012	-0.012**
	(1.497)	(-1.731)	(1.699)	(-1.201)	(1.352)	(-2.051)	(1.235)	(-2.136)	(1.361)	(-2.355)
3	0.007	-0.013*	0.011	-0.012*	0.015	-0.009	0.015	-0.009	0.015	-0.007
	(0.711)	(-1.715)	(1.020)	(-1.703)	(1.308)	(-1.096)	(1.385)	(-1.128)	(1.389)	(-0.967)
4	0.031**	0.005	0.014	-0.011	0.030	-0.001	0.026*	-0.002	0.019	-0.011
	(2.115)	(0.485)	(1.083)	(-1.292)	(1.572)	(-0.134)	(1.744)	(-0.223)	(1.228)	(-1.195)
5	0.007	-0.014	0.020	-0.010	0.018	-0.010	0.022	-0.006	0.025*	-0.001
	(0.593)	(-1.506)	(1.191)	(-1.007)	(1.022)	(-1.068)	(1.283)	(-0.656)	(1.698)	(-0.100)
6	0.030**	0.001	0.032	-0.002	0.016	-0.010	0.013	-0.015*	0.015	-0.012
	(2.095)	(0.089)	(1.603)	(-0.209)	(1.307)	(-1.059)	(1.005)	(-1.664)	(1.120)	(-1.342)
7	0.030	-0.004	0.014	-0.008	0.014	-0.008	0.015	-0.013	0.016	-0.007
	(1.409)	(-0.382)	(1.146)	(-0.742)	(1.092)	(-0.829)	(1.013)	(-1.529)	(1.345)	(-0.710)
8	0.008	-0.016	0.031	0.005	0.017	-0.007	0.019	-0.003	0.016	-0.007
	(0.507)	(-1.140)	(1.515)	(0.271)	(1.217)	(-0.609)	(1.279)	(-0.254)	(1.099)	(-0.596)
9	0.020	-0.002	0.026	-0.002	0.017	-0.005	0.015	-0.010	0.010	-0.014
	(1.299)	(-0.180)	(1.396)	(-0.162)	(1.100)	(-0.351)	(0.953)	(-0.814)	(0.620)	(-1.227)
High	0.059***	0.032*	0.062***	0.035**	0.064***	0.036*	0.071***	0.047**	0.080***	0.055**
	(3.157)	(1.866)	(3.327)	(2.019)	(3.089)	(1.926)	(3.433)	(2.324)	(3.532)	(2.487)
High-Low	0.052***	0.041**	0.057***	0.046***	0.055***	0.044**	0.062***	0.055***	0.070***	0.062***
	(2.919)	(2.283)	(3.217)	(2.593)	(2.934)	(2.384)	(3.261)	(2.718)	(3.323)	(2.809)

Table 3: Mean Values for Cryptocurrencies Sorted by MAX. This table shows the mean value of some important characteristics of decile portfolios formed every week by sorting cryptocurrencies based on the highest daily returns within the past one month as of the end of each week. Portfolio High (Low) comprises cryptocurrencies with the highest (lowest) MAX(N). *Volume* is the daily dollar trading volume of cryptocurrencies. The definitions of other variables are the same as those in Table 1. Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Volume*
Low	0.613***	16.514***	-0.025***	0.004***	0.827***	13.192***
	(49.812)	(172.021)	(-5.243)	(3.814)	(30.331)	(141.372)
2	0.782***	15.747***	-0.019***	0.013**	0.518***	12.481***
	(53.255)	(134.622)	(-3.109)	(2.054)	(25.841)	(99.791)
3	0.841***	15.541***	-0.006	0.017***	0.460***	12.139***
	(56.358)	(124.053)	(-0.898)	(2.767)	(21.330)	(95.207)
4	0.866***	15.226***	0.009	0.019***	0.436***	11.680***
	(48.369)	(113.564)	(1.211)	(4.299)	(17.681)	(89.444)
5	0.889***	14.882***	0.011	0.022***	0.312***	11.208***
	(54.834)	(106.740)	(1.505)	(3.290)	(18.881)	(88.575)
6	0.902***	14.622***	0.038***	0.032***	0.311***	10.876***
	(50.030)	(99.026)	(4.279)	(3.899)	(11.403)	(86.960)
7	0.943***	14.483***	0.059***	0.035***	0.260***	10.414***
	(50.182)	(95.835)	(6.090)	(3.892)	(13.318)	(87.343)
8	0.971***	14.227***	0.082***	0.054**	0.219***	10.048***
	(41.508)	(90.426)	(7.447)	(2.163)	(16.826)	(86.704)
9	1.045***	13.906***	0.120***	0.064***	0.175***	9.851***
	(42.703)	(83.114)	(9.123)	(3.155)	(19.653)	(89.053)
High	1.135***	13.541***	0.287***	0.080***	0.162***	9.438***
	(21.352)	(73.634)	(6.880)	(2.976)	(9.355)	(80.297)
High-Low	0.521***	-2.973***	0.312***	0.075***	-0.665***	-3.754***
	(9.534)	(-27.015)	(7.610)	(2.964)	(-23.608)	(-37.364)

Table 4: Transition Matrix. This table presents transition probabilities for MAX(1) at a lag of 4 weeks between January 2014 and June 2020. At each week, all cryptocurrencies are sorted into deciles based on an ascending ordering of MAX(1). The procedure is repeated after 4 weeks. Portfolio High (Low) comprises cryptocurrencies with the highest (lowest) MAX(1). For each MAX(1) decile in the week *t*, the percentage of cryptocurrencies that fall into each of the week *t + 4* MAX(1) decile is calculated. Then the time-series averages of these transition probabilities are presented. Each row corresponds to a different week *t* MAX(1) portfolio and each column corresponds to a different week *t + 4* MAX(1) portfolio.

	Low	2	3	4	5	6	7	8	9	High
Low	**34.126**	15.330	11.483	9.383	7.621	6.256	5.257	4.420	3.392	2.731
2	15.616	**18.261**	15.449	13.101	10.174	8.790	6.696	5.507	3.746	2.659
3	12.065	15.612	**15.088**	13.715	11.658	9.797	8.155	6.468	4.404	3.038
4	9.949	13.331	13.767	**13.847**	12.567	10.516	9.200	7.745	5.898	3.178
5	7.500	11.180	12.204	12.974	**13.417**	12.117	10.636	8.843	6.912	4.218
6	6.478	9.321	10.591	10.870	13.096	**13.669**	12.266	9.996	8.248	5.465
7	5.337	7.343	8.652	9.762	11.445	13.070	**14.319**	12.335	10.556	7.182
8	4.152	5.406	6.947	7.810	9.395	10.575	13.968	**16.696**	14.749	10.302
9	2.985	3.704	4.593	5.815	7.111	9.200	11.570	15.370	**22.215**	17.437
High	2.554	2.502	2.509	3.872	4.691	5.860	7.840	11.540	17.854	**40.779**

Table 5: Double-sorted Portfolios. This table shows the one-week-ahead equal-weighted and value-weighted excess returns (Panel A) and alphas (Panel B) of double-sorted portfolios. We first form quintile portfolios every week based on a given characteristic (*Beta*, *Size*, *Mom*, *Illiq* and *Prc*) and then form quintile portfolios based on MAX(N) (N=1,2,…,5) in each characteristic quintile. The ways of calculating these variables are the same as those in Table 1. Portfolio High (Low) is the combined portfolio of cryptocurrencies with the highest (lowest) MAX(N) in each characteristic decile. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Excess returns of double-sorted portfolios

		Equal-weighted					Value-weighted				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
MAX(1)	Low	0.029***	0.025***	0.022**	0.047***	0.032***	0.015**	0.022**	0.013*	0.025***	0.015
		(3.099)	(2.936)	(2.333)	(4.289)	(2.893)	(2.025)	(2.434)	(1.715)	(3.115)	(1.407)
	High	0.079***	0.060***	0.078***	0.125***	0.072***	0.052**	0.046***	0.053**	0.063***	0.071***
		(7.523)	(3.891)	(4.763)	(6.691)	(6.417)	(2.483)	(2.863)	(2.468)	(3.660)	(2.904)
	High-Low	0.050***	0.035**	0.056***	0.078***	0.041***	0.037***	0.024**	0.039**	0.038**	0.056**
		(4.129)	(2.189)	(4.553)	(4.608)	(3.491)	(2.633)	(2.196)	(2.003)	(2.241)	(2.353)
MAX(2)	Low	0.029***	0.028***	0.022**	0.042***	0.030***	0.021**	0.020**	0.014*	0.027***	0.015
		(3.100)	(2.768)	(2.440)	(3.925)	(2.710)	(2.588)	(2.263)	(1.736)	(3.121)	(1.356)
	High	0.074***	0.062***	0.079***	0.122***	0.078***	0.050**	0.048***	0.054**	0.061***	0.073***
		(7.523)	(3.991)	(4.767)	(6.607)	(6.394)	(2.333)	(2.935)	(2.520)	(3.565)	(2.893)
	High-Low	0.045***	0.034***	0.057***	0.080***	0.048***	0.030**	0.028**	0.040**	0.034*	0.058**
		(4.124)	(2.896)	(4.565)	(4.707)	(3.542)	(2.422)	(2.006)	(2.053)	(1.914)	(2.338)
MAX(3)	Low	0.030***	0.032***	0.020**	0.043***	0.030***	0.022**	0.019**	0.012	0.029***	0.016
		(3.062)	(2.719)	(2.152)	(4.051)	(2.785)	(2.508)	(2.188)	(1.474)	(3.280)	(1.428)
	High	0.088***	0.071***	0.082***	0.127***	0.089***	0.054***	0.051***	0.056**	0.058***	0.071***
		(8.071)	(4.132)	(4.960)	(6.572)	(6.622)	(3.038)	(3.075)	(2.461)	(3.383)	(2.877)
	High-Low	0.059***	0.039***	0.061***	0.084***	0.059***	0.032**	0.032**	0.044**	0.029***	0.056**
		(4.488)	(2.728)	(4.912)	(4.784)	(3.924)	(2.200)	(2.123)	(1.995)	(2.639)	(2.279)
MAX(4)	Low	0.030***	0.033***	0.018*	0.044***	0.031***	0.021**	0.020**	0.009	0.028***	0.015
		(3.020)	(2.833)	(1.931)	(4.039)	(2.711)	(2.335)	(2.251)	(1.111)	(3.142)	(1.401)
	High	0.083***	0.075***	0.081***	0.131***	0.085***	0.054***	0.050***	0.054**	0.057***	0.068***
		(7.877)	(4.400)	(4.847)	(6.970)	(6.895)	(2.991)	(3.122)	(2.382)	(3.398)	(2.750)
	High-Low	0.053***	0.042***	0.062***	0.088***	0.055***	0.033**	0.030**	0.045**	0.029***	0.054**
		(4.234)	(2.932)	(5.012)	(5.078)	(3.192)	(2.264)	(2.032)	(2.038)	(2.638)	(2.166)
MAX(5)	Low	0.032***	0.033***	0.019**	0.045***	0.031***	0.022**	0.021**	0.010	0.030***	0.015
		(3.154)	(2.887)	(1.968)	(4.097)	(2.761)	(2.384)	(2.358)	(1.176)	(3.200)	(1.425)
	High	0.088***	0.081***	0.080***	0.136***	0.089***	0.055***	0.050***	0.052**	0.059***	0.073***
		(8.022)	(4.514)	(4.824)	(7.255)	(7.054)	(3.059)	(3.152)	(2.310)	(3.547)	(2.960)
	High-Low	0.056***	0.047***	0.062***	0.091***	0.058***	0.033**	0.030*	0.042*	0.029*	0.058**
		(4.212)	(2.976)	(4.950)	(5.080)	(3.322)	(2.288)	(1.949)	(1.939)	(1.659)	(2.338)

Panel B: Alphas of double-sorted portfolios.

		Equal-weighted					Value-weighted				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
MAX(1)	Low	0.007	0.014	0.000	0.024***	0.008	-0.005	0.003	-0.006	0.009*	-0.007
		(1.498)	(1.624)	(0.112)	(3.752)	(1.544)	(-1.471)	(0.528)	(-1.452)	(1.959)	(-1.444)
	High	0.051***	0.034***	0.053***	0.096***	0.053***	0.011	0.021*	0.028	0.047***	0.052**
		(4.072)	(3.028)	(3.988)	(6.479)	(4.000)	(1.189)	(1.664)	(1.472)	(3.007)	(2.313)
	High-Low	0.044***	0.020**	0.053***	0.072***	0.045***	0.017**	0.018**	0.034**	0.038**	0.059***
		(4.971)	(2.343)	(4.303)	(4.408)	(5.418)	(2.106)	(2.406)	(2.273)	(2.287)	(2.591)
MAX(2)	Low	0.006	0.007	0.001	0.019***	0.005	0.000	0.001	-0.006	0.010*	-0.007
		(1.384)	(1.295)	(0.271)	(3.104)	(1.099)	(0.023)	(0.192)	(-1.442)	(1.833)	(-1.280)
	High	0.047***	0.036***	0.055***	0.094***	0.058***	0.011	0.024*	0.030	0.046***	0.054**
		(4.049)	(3.055)	(4.026)	(6.364)	(4.040)	(1.093)	(1.779)	(1.572)	(2.923)	(2.316)
	High-Low	0.040***	0.029**	0.053***	0.075***	0.053***	0.011**	0.023*	0.036**	0.036**	0.061**
		(4.999)	(2.508)	(4.311)	(4.593)	(5.571)	(2.067)	(1.652)	(2.302)	(2.121)	(2.578)
MAX(3)	Low	0.006	0.010	-0.001	0.021***	0.006	0.001	-0.000	-0.008*	0.011**	-0.007
		(1.359)	(1.254)	(-0.248)	(3.317)	(1.258)	(0.141)	(-0.109)	(-1.836)	(2.123)	(-1.410)
	High	0.052***	0.044***	0.058***	0.100***	0.060***	0.017*	0.027*	0.032	0.043***	0.054**
		(4.495)	(3.375)	(4.224)	(6.499)	(4.474)	(1.808)	(1.938)	(1.546)	(2.737)	(2.329)
	High-Low	0.046***	0.034**	0.060***	0.079***	0.054***	0.016***	0.027*	0.041**	0.032*	0.061***
		(4.481)	(2.488)	(4.679)	(4.809)	(6.023)	(2.616)	(1.831)	(2.484)	(1.893)	(2.616)
MAX(4)	Low	0.006	0.012	-0.003	0.021***	0.006	-0.001	0.000	-0.011**	0.011*	-0.007
		(1.362)	(1.385)	(-0.664)	(3.310)	(1.212)	(-0.120)	(0.048)	(-2.458)	(1.945)	(-1.472)
	High	0.057***	0.049***	0.057***	0.105***	0.067***	0.016*	0.027*	0.031	0.043***	0.052**
		(4.365)	(3.627)	(4.135)	(6.917)	(4.786)	(1.765)	(1.955)	(1.474)	(2.760)	(2.221)
	High-Low	0.050***	0.038***	0.060***	0.084***	0.060***	0.016***	0.027**	0.042**	0.032*	0.059**
		(4.205)	(2.683)	(4.763)	(5.095)	(6.302)	(2.693)	(2.158)	(2.346)	(1.925)	(2.497)
MAX(5)	Low	0.008	0.012	-0.003	0.022***	0.006	-0.000	0.001	-0.011**	0.012**	-0.007
		(1.608)	(1.462)	(-0.600)	(3.363)	(1.270)	(-0.016)	(0.267)	(-2.485)	(2.045)	(-1.424)
	High	0.062***	0.055***	0.056***	0.110***	0.070***	0.017*	0.028*	0.029	0.045***	0.057**
		(4.469)	(3.676)	(4.125)	(6.712)	(4.974)	(1.828)	(1.962)	(1.401)	(2.931)	(2.455)
	High-Low	0.054***	0.042***	0.059***	0.088***	0.063***	0.017***	0.026**	0.040**	0.033**	0.064***
		(4.161)	(2.728)	(4.716)	(4.907)	(4.472)	(2.714)	(2.288)	(2.464)	(1.984)	(2.729)

Table 6: Fama-MacBeth Regressions. This table shows results from Fama-MacBeth (1973) regressions of one-week-ahead returns on MAX(N) (N=1,2,…,5) and various cryptocurrency characteristics, which include *Beta*, *Size*, *Mom*, *Illiq* and *Prc*. The ways of calculating these variables are the same as those in Table 1. Coefficients and adjusted R^2 are the time-series averages from weekly cross-sectional regressions. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MAX(1)	0.071***										0.052**				
	(2.803)										(2.073)				
MAX(2)		0.086***										0.067**			
		(3.036)										(2.341)			
MAX(3)			0.099***										0.077**		
			(3.471)										(2.564)		
MAX(4)				0.115***										0.089**	
				(3.438)										(2.539)	
MAX(5)					0.126***										0.097***
					(5.575)										(5.022)
Beta						0.019*					0.009	0.009	0.009	0.009	0.008
						(1.869)					(1.214)	(1.186)	(1.108)	(1.108)	(1.047)
Size							-0.022***				-0.011***	-0.011***	-0.012***	-0.011***	-0.013***
							(-7.661)				(-4.377)	(-4.199)	(-5.835)	(-5.213)	(-5.641)
Mom								0.023			0.018	0.028	0.034	0.029	0.040
								(0.596)			(0.785)	(1.132)	(1.234)	(1.179)	(1.304)
Illiq									8.624		18.962	18.092	16.469	16.303	18.165
									(1.040)		(1.008)	(0.984)	(1.081)	(1.054)	(1.075)
Prc										-0.019***	-0.001	-0.000	-0.000	-0.000	-0.001
										(-7.743)	(-0.386)	(-0.184)	(-0.190)	(-0.095)	(-0.406)
Intercept	0.022	0.012	0.014	0.009	0.017	0.048***	0.363***	0.063***	0.057***	0.073***	0.166***	0.150***	0.166***	0.155***	0.186***
	(1.301)	(0.693)	(0.865)	(0.504)	(1.318)	(2.853)	(7.396)	(4.679)	(4.219)	(4.693)	(3.207)	(2.850)	(3.868)	(3.396)	(4.600)
Adj.R^2	2.68%	2.82%	2.92%	3.05%	2.96%	1.39%	1.55%	1.20%	2.20%	0.34%	8.33%	8.34%	8.17%	8.47%	8.37%

Table 7: Market Conditions. This table shows the one-week-ahead value-weighted excess returns (ER) and alphas (Alpha) of portfolios with the highest MAX(N) and lowest MAX(N)(N=1,2,…,5) as well as their differences in different periods for market upturns and market downturns. Specifically, we define the residual between the actual log market price and the smoothed log market price formed by the standard Hodrick–Prescott filter as the buying pressure. Periods when the buying pressure is positive are classified as the market upturn and otherwise are classified as the market downturn. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

		MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
		ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha
Upturns	Low	0.027***	-0.004	0.026***	-0.008***	0.031***	-0.006**	0.032***	-0.005	0.033***	-0.004
		(3.503)	(-1.104)	(3.423)	(-2.890)	(3.680)	(-2.256)	(3.825)	(-1.632)	(3.828)	(-1.472)
	High	0.101***	0.052**	0.093***	0.042**	0.096***	0.047**	0.103***	0.055**	0.117***	0.062**
		(3.802)	(2.522)	(3.651)	(2.425)	(3.300)	(2.477)	(3.270)	(2.322)	(3.281)	(2.335)
	High-Low	0.074***	0.056**	0.067**	0.051*	0.066**	0.053*	0.071**	0.060**	0.084**	0.067**
		(2.739)	(2.206)	(2.585)	(1.706)	(2.343)	(1.655)	(2.347)	(2.416)	(2.453)	(2.421)
Downturns	Low	-0.011	-0.011*	-0.015**	-0.015***	-0.012*	-0.013**	-0.013*	-0.013**	-0.011	-0.012**
		(-1.473)	(-1.848)	(-2.127)	(-2.902)	(-1.718)	(-2.439)	(-1.763)	(-2.501)	(-1.571)	(-2.226)
	High	0.021	0.020	0.034	0.033	0.034	0.033	0.041	0.041	0.045	0.044
		(0.845)	(0.922)	(1.325)	(1.416)	(1.236)	(1.319)	(1.480)	(1.519)	(1.609)	(1.648)
	High-Low	0.031	0.031	0.048	0.048	0.046	0.045	0.054	0.054	0.056	0.056
		(0.846)	(0.888)	(1.489)	(1.526)	(1.342)	(1.379)	(1.522)	(1.522)	(1.595)	(1.592)

Table 8: Investor Sentiment. This table reports the one-week-ahead value-weighted excess returns (ER) and alphas (Alpha) of portfolios with the highest MAX(N) and lowest MAX(N) (N=1,2,…,5) as well as their differences when investor sentiment is high or low. We define high (low) sentiment periods as months whose Google search frequency of "cryptocurrency" is higher (not higher) than the median of the corresponding year. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

		MAX(1)		MAX(2)		MAX(3)		MAX(4)		MAX(5)	
		ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha	ER	Alpha
	Low	0.017	-0.010*	0.013	-0.015***	0.020	-0.010***	0.022*	-0.009**	0.024*	-0.007**
		(1.253)	(-1.798)	(1.057)	(-3.365)	(1.616)	(-3.287)	(1.758)	(-2.411)	(1.885)	(-1.977)
High sentiment	High	0.028	-0.007	0.030	-0.003	0.042	0.006	0.084**	0.049	0.100**	0.061
		(1.196)	(-0.260)	(1.241)	(-0.098)	(1.352)	(0.212)	(2.284)	(1.302)	(2.284)	(1.358)
	High-Low	0.011	0.004	0.017	0.012	0.022	0.016	0.063*	0.057	0.076*	0.067
		(0.460)	(0.135)	(0.698)	(0.430)	(0.831)	(0.582)	(1.931)	(1.510)	(1.926)	(1.496)
	Low	0.002	-0.008**	0.000	-0.010***	0.002	-0.009***	0.002	-0.009***	0.002	-0.008***
		(0.385)	(-2.346)	(0.065)	(-3.695)	(0.293)	(-3.312)	(0.281)	(-3.319)	(0.383)	(-3.036)
Low sentiment	High	0.077***	0.054**	0.081***	0.057**	0.076***	0.053**	0.063***	0.046*	0.068***	0.051**
		(2.918)	(2.387)	(2.940)	(2.365)	(2.726)	(2.097)	(2.622)	(1.925)	(2.733)	(2.058)
	High-Low	0.075***	0.062***	0.080***	0.067***	0.074***	0.062**	0.062***	0.055**	0.066***	0.059**
		(2.951)	(2.653)	(3.115)	(2.773)	(2.811)	(2.439)	(2.633)	(2.288)	(2.704)	(2.382)

Table 9: Mispricing and MAX Momentum. This table shows the one-week-ahead value-weighted excess returns (in Panel A) and alphas (in Panel B) of quintile portfolios sorted by the mispricing index and MAX(1). The mispricing index is the average of ranks for each cryptocurrency based on size and momentum anomaly. Portfolio High (Low) comprises cryptocurrencies with the highest (lowest) MAX(1). Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Value-weighted excess returns

	Low	2	3	4	High	High-Low
Most underpriced	0.049***	0.053***	0.078***	0.129***	0.124***	0.074**
	(3.578)	(3.411)	(4.351)	(4.526)	(3.202)	(2.094)
2	0.005	0.021	0.020	0.035**	0.029	0.024*
	(0.548)	(1.407)	(1.461)	(2.050)	(1.617)	(1.705)
3	0.007	0.001	0.001	0.014	0.014	0.007
	(0.610)	(0.091)	(0.102)	(0.751)	(0.866)	(0.424)
4	0.008	0.014	0.002	0.030*	0.072	0.064
	(0.870)	(1.374)	(0.245)	(1.879)	(1.248)	(1.104)
Most overpriced	0.014*	0.014	0.034**	0.040*	0.031*	0.018
	(1.905)	(1.485)	(2.171)	(1.871)	(1.861)	(1.256)
Underpriced - overpriced	0.036***	0.039***	0.044**	0.089**	0.092***	
	(2.804)	(2.991)	(2.476)	(2.511)	(2.656)	

Panel B: Value-weighted alphas

	Low	2	3	4	High	High-Low
Most underpriced	0.028**	0.032**	0.055***	0.114***	0.096**	0.068**
	(2.307)	(2.284)	(3.202)	(3.837)	(2.469)	(2.027)
2	-0.015**	-0.006	-0.003	0.012	0.005	0.020
	(-2.305)	(-0.567)	(-0.278)	(0.768)	(0.305)	(1.339)
3	-0.017**	-0.021***	-0.024**	-0.015	-0.003	0.014
	(-2.279)	(-2.860)	(-2.561)	(-1.419)	(-0.170)	(0.815)
4	-0.009	-0.010	-0.020***	0.001	0.036	0.045
	(-0.971)	(-1.356)	(-2.905)	(0.050)	(0.669)	(0.815)
Most overpriced	-0.004	-0.009	0.005	0.013	0.003	0.008
	(-1.131)	(-1.633)	(0.545)	(0.744)	(0.291)	(0.606)
Underpriced - overpriced	0.032***	0.041***	0.050***	0.101***	0.093**	
	(2.616)	(3.222)	(2.762)	(2.808)	(2.505)	

Table 10: Idiosyncratic Volatility, Skewness and MAX Momentum. This table shows whether the relationship between MAX and cryptocurrency returns depends on idiosyncratic volatility and skewness. *Ivolatiliy* is the standard deviation of residuals from regressions of excess cryptocurrency returns on excess market returns during the past 4 weeks. *Coskewness* is the coefficient of the squared excess market return term when regressing daily excess cryptocurrency returns on the daily excess market returns and the squared daily excess market returns in the past 30 days. And *Iskewness* is the standard deviation of residuals from regressions of the daily excess cryptocurrency returns on the daily excess market returns and the squared daily excess market returns in the past month. Panel A reports the results of double-sorted portfolio analyses with *Ivolatility*, *Coskewness* and *Iskewness* as the first-stage sorting variables. Panel B reports the results of single-sorted portfolio analyses with *Ivolatility*, *Coskewness* and *Iskewness* as the sorting variables. Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Double-sorted portfolio analysis with *Ivolatility*, *Coskewness* and *Iskewness*

		ER			Alpha		
		Ivolatility	*Coskewness*	*Iskewness*	*Ivolatility*	*Coskewness*	*Iskewness*
	Low	0.021***	0.031***	0.016*	0.002***	0.009*	-0.004
		(3.767)	(2.913)	(1.826)	(3.227)	(1.942)	(-0.926)
MAX(1)	High	0.055***	0.054***	0.072***	0.033**	0.040***	0.057***
		(3.198)	(3.798)	(3.753)	(2.272)	(3.086)	(3.180)
	High-Low	0.034**	0.023**	0.057***	0.032**	0.031**	0.061***
		(2.329)	(1.988)	(3.037)	(2.158)	(2.348)	(3.397)
	Low	0.020***	0.030***	0.016*	0.004**	0.008	-0.003
		(3.421)	(2.751)	(1.879)	(2.571)	(1.525)	(-0.771)
MAX(2)	High	0.053***	0.057***	0.068***	0.032**	0.043***	0.054***
		(3.235)	(3.993)	(3.545)	(2.206)	(3.257)	(2.998)
	High-Low	0.033**	0.028**	0.052***	0.028**	0.035***	0.058***
		(2.075)	(2.004)	(2.745)	(2.249)	(2.674)	(3.177)
	Low	0.023***	0.029***	0.019**	0.005***	0.007	0.000
		(3.534)	(2.598)	(2.199)	(2.747)	(1.236)	(0.056)
MAX(3)	High	0.057***	0.057***	0.070***	0.036***	0.043***	0.056***
		(3.492)	(3.903)	(3.592)	(2.605)	(3.178)	(3.028)
	High-Low	0.034**	0.027*	0.051***	0.031**	0.036**	0.055***
		(2.130)	(1.780)	(2.629)	(2.329)	(2.564)	(3.008)
	Low	0.023***	0.025**	0.019**	0.007***	0.005	-0.000
		(3.659)	(2.421)	(2.193)	(2.908)	(0.817)	(-0.026)
MAX(4)	High	0.058***	0.058***	0.069***	0.037***	0.043***	0.054***
		(3.525)	(3.969)	(3.528)	(2.713)	(3.192)	(2.965)
	High-Low	0.034**	0.032**	0.050**	0.030**	0.039***	0.055***
		(2.179)	(2.144)	(2.572)	(2.226)	(2.762)	(2.960)
	Low	0.021***	0.025**	0.021**	0.004**	0.005	0.001
		(3.520)	(2.511)	(2.174)	(2.457)	(0.939)	(0.207)
MAX(5)	High	0.059***	0.059***	0.070***	0.037***	0.045***	0.057***
		(3.452)	(3.680)	(3.639)	(2.594)	(3.064)	(3.127)
	High-Low	0.038**	0.033**	0.049**	0.034**	0.040***	0.056***
		(2.408)	(2.148)	(2.493)	(2.178)	(2.714)	(3.047)

Panel B: Single-sorted portfolio analysis with *Ivolatility*, *Coskewness* and *Iskewness*

	Ivolatility		*Coskewness*		*Iskewness*	
	ER	Alpha	ER	Alpha	ER	Alpha
Low	0.009*	-0.009***	0.029*	0.010	0.010	-0.012***
	(1.652)	(-4.535)	(1.753)	(0.585)	(1.148)	(-2.991)
2	0.019	-0.006	0.021	-0.002	0.008	-0.014***
	(1.557)	(-0.756)	(1.538)	(-0.172)	(0.815)	(-2.619)
3	0.018	-0.007	0.020	-0.006	0.018*	-0.005
	(1.369)	(-0.781)	(1.403)	(-0.543)	(1.702)	(-0.885)
4	0.023*	-0.005	0.001	-0.022***	0.020*	-0.003
	(1.700)	(-0.586)	(0.092)	(-3.478)	(1.653)	(-0.331)
5	0.013	-0.011	0.020*	-0.005	0.035**	0.013
	(1.051)	(-1.255)	(1.741)	(-0.822)	(2.533)	(1.070)
6	0.008	-0.014	0.012	-0.007	0.029	0.009
	(0.644)	(-1.413)	(1.541)	(-1.394)	(1.418)	(0.459)
7	0.012	-0.010	0.026*	0.001	0.009	-0.011
	(0.915)	(-0.931)	(1.935)	(0.178)	(0.914)	(-1.567)
8	0.021	-0.005	0.007	-0.013*	0.011	-0.016
	(1.250)	(-0.379)	(0.617)	(-1.661)	(0.714)	(-1.502)
9	0.034	0.012	0.030	0.002	0.020	-0.009
	(1.121)	(0.421)	(1.647)	(0.202)	(1.478)	(-0.931)
High	0.041***	0.019*	0.033	-0.012	0.023	-0.008
	(2.606)	(1.684)	(1.219)	(-0.915)	(1.085)	(-0.672)
High-Low	0.031**	0.027**	0.003	-0.022	0.013	0.004
	(2.350)	(2.071)	(0.107)	(-1.016)	(0.660)	(0.275)

Table 11: Trading Volume and MAX Momentum. This table shows results of double-sorted portfolio analyses with trading volume variables being the first-stage sorting criterion. *Abvol* is calculated as the average dollar trading volume for a given cryptocurrency in the portfolio formation week after subtracting the average dollar trading volume of the past 4 weeks. *Vlow* and *Vhigh* denote whether dollar trading volume of a given cryptocurrency on the last day of the portfolio formation week is among the lowest and highest 10% of its daily dollar trading volume over the prior 30 days. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

		ER			Alpha		
		Abvol	*Vhigh*	*Vlow*	*Abvol*	*Vhigh*	*Vlow*
	Low	0.019**	0.015	0.012	0.002	-0.004	-0.006
		(2.063)	(1.603)	(1.368)	(0.288)	(-0.886)	(-1.297)
MAX(1)	High	0.064***	0.044***	0.034***	0.048***	0.023***	0.015***
		(3.290)	(4.204)	(3.687)	(2.664)	(3.193)	(2.682)
	High-Low	0.045**	0.029**	0.023**	0.047**	0.027***	0.021***
		(2.285)	(2.150)	(2.079)	(2.465)	(3.096)	(3.341)
	Low	0.020**	0.015	0.012	0.002	-0.004	-0.006
		(2.138)	(1.604)	(1.411)	(0.419)	(-0.806)	(-1.228)
MAX(2)	High	0.061***	0.044***	0.035***	0.046**	0.023***	0.016***
		(3.148)	(4.267)	(3.769)	(2.516)	(3.249)	(2.806)
	High-Low	0.041**	0.029**	0.023**	0.044**	0.027***	0.022***
		(2.102)	(1.993)	(2.448)	(2.304)	(3.085)	(3.326)
	Low	0.015*	0.016	0.013	-0.002	-0.004	-0.006
		(1.905)	(1.637)	(1.488)	(-0.465)	(-0.784)	(-1.150)
MAX(3)	High	0.068***	0.048***	0.040***	0.053***	0.026***	0.022***
		(3.509)	(4.491)	(4.179)	(2.914)	(3.626)	(3.379)
	High-Low	0.053***	0.032**	0.027**	0.055***	0.030***	0.027***
		(2.730)	(1.977)	(2.012)	(2.951)	(3.406)	(4.476)
	Low	0.015*	0.014	0.012	-0.002	-0.005	-0.007
		(1.834)	(1.506)	(1.368)	(-0.520)	(-1.043)	(-1.347)
MAX(4)	High	0.071***	0.047***	0.037***	0.056***	0.026***	0.019***
		(3.593)	(4.392)	(3.886)	(3.021)	(3.566)	(3.061)
	High-Low	0.056***	0.033**	0.025*	0.058***	0.031***	0.025***
		(2.814)	(2.068)	(1.909)	(3.060)	(3.589)	(4.339)
	Low	0.015*	0.014	0.011	-0.002	-0.005	-0.007
		(1.889)	(1.487)	(1.336)	(-0.447)	(-1.040)	(-1.446)
MAX(5)	High	0.068***	0.049***	0.043***	0.054***	0.029***	0.027***
		(3.500)	(4.367)	(4.188)	(2.933)	(3.557)	(3.443)
	High-Low	0.054***	0.035**	0.032**	0.056***	0.034***	0.033***
		(2.711)	(2.326)	(2.196)	(2.954)	(4.059)	(4.371)

Table 12: Double-sorted MAX Portfolios for the One-week Forecast Period. This table shows the one-week-ahead equal-weighted and value-weighted excess returns (ER) and alphas (Alpha) of double-sorted portfolios. We first form quintile portfolios every week based on a given characteristic (*Beta*, *Size*, *Mom*, *Illiq* and *Prc*) and then form quintile portfolios based on the average of N (N=1,2,3) highest daily returns within the past week (MAX(N)) in each characteristic quintile. The ways of calculating these variables are the same as those in Table 1. Portfolio High (Low) is the combined portfolio of cryptocurrencies with the highest (lowest) MAX(N) in each characteristic decile. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

		ER					Alpha				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
MAX(1)	Low	0.013	0.022**	0.009	0.024***	0.015	-0.007*	0.003	-0.010*	0.016**	-0.008*
		(1.473)	(2.419)	(1.130)	(3.277)	(1.353)	(-1.719)	(0.469)	(-1.950)	(2.077)	(-1.726)
	High	0.049***	0.062***	0.044**	0.063***	0.078***	0.031***	0.038***	0.017	0.047***	0.056**
		(3.905)	(3.688)	(2.356)	(3.596)	(2.806)	(2.821)	(2.887)	(1.145)	(2.964)	(2.231)
	High-Low	0.036***	0.040***	0.035**	0.040**	0.063**	0.038***	0.035***	0.027**	0.031**	0.064**
		(3.339)	(2.787)	(2.292)	(2.385)	(2.415)	(3.668)	(2.600)	(1.971)	(1.983)	(2.564)
MAX(2)	Low	0.006	0.024***	0.007	0.027***	0.014	-0.013***	0.006	-0.012***	0.020***	-0.011**
		(0.729)	(2.735)	(0.855)	(3.828)	(1.120)	(-3.590)	(0.976)	(-2.666)	(2.943)	(-2.067)
	High	0.059***	0.056***	0.047**	0.060***	0.076***	0.041**	0.032**	0.021	0.045***	0.057**
		(2.816)	(3.417)	(2.493)	(3.268)	(2.830)	(2.116)	(2.485)	(1.343)	(2.638)	(2.300)
	High-Low	0.054***	0.031**	0.040**	0.033**	0.062**	0.054***	0.026**	0.033**	0.025**	0.068***
		(2.677)	(2.258)	(2.468)	(2.148)	(2.355)	(2.796)	(2.030)	(2.219)	(2.129)	(2.704)
MAX(3)	Low	0.002	0.020**	0.004	0.022***	0.012	-0.017***	0.002	-0.015***	0.015**	-0.012**
		(0.296)	(2.209)	(0.515)	(3.204)	(1.043)	(-4.155)	(0.298)	(-3.131)	(2.067)	(-2.335)
	High	0.045***	0.058***	0.048***	0.060***	0.069***	0.027***	0.035***	0.023	0.045***	0.050**
		(3.958)	(3.585)	(2.651)	(3.541)	(2.636)	(2.777)	(2.744)	(1.474)	(2.891)	(2.081)
	High-Low	0.043***	0.038***	0.044***	0.038**	0.057**	0.044***	0.033**	0.038***	0.030**	0.063**
		(4.327)	(2.787)	(2.878)	(2.508)	(2.185)	(4.272)	(2.525)	(2.647)	(2.176)	(2.526)

Table 13: Double-sorted MAX Portfolios over the Longer Periods. This table shows the two-week-ahead (Panel A), three-week-ahead (Panel B) and four-week-ahead (Panel C) value-weighted excess returns (ER) and alphas (Alpha) of double-sorted portfolios. We first form quintile portfolios every week based on a given characteristic (*Beta*, *Size*, *Mom*, *Illiq* and *Prc*) and then form quintile portfolios based on the average of N (N=1,2,3) highest daily returns within the past week (MAX(N)) in each characteristic quintile. The ways of calculating these variables are the same as those in Table 1. Portfolio High (Low) is the combined portfolio of cryptocurrencies with the highest (lowest) MAX(N) in each characteristic decile. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	ER					Alpha				
	Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
Panel A: Holding for 2 weeks										
Low	0.037**	0.047**	0.028*	0.054***	0.043	0.014	0.024**	0.006	0.037***	0.013
	(2.296)	(2.404)	(1.701)	(3.388)	(1.642)	(1.478)	(2.071)	(0.551)	(3.337)	(0.920)
High	0.075***	0.083***	0.074**	0.113***	0.112***	0.052***	0.057**	0.048**	0.096***	0.087***
	(3.065)	(2.598)	(2.567)	(3.416)	(3.377)	(2.735)	(2.098)	(2.020)	(3.179)	(3.205)
High-Low	0.038**	0.035**	0.045**	0.059**	0.069**	0.038**	0.034**	0.042**	0.059**	0.074***
	(2.143)	(2.058)	(2.416)	(2.189)	(2.259)	(2.320)	(1.989)	(2.190)	(2.045)	(2.769)
Panel B: Holding for 3 weeks										
Low	0.059**	0.088***	0.050**	0.092***	0.094**	0.029*	0.057***	0.022	0.069***	0.046*
	(2.300)	(2.680)	(2.037)	(3.527)	(1.969)	(1.882)	(2.605)	(1.350)	(3.769)	(1.836)
High	0.098***	0.104***	0.111***	0.140***	0.164***	0.067**	0.069**	0.077**	0.119***	0.126***
	(2.739)	(2.675)	(2.776)	(3.890)	(3.421)	(2.461)	(2.353)	(2.336)	(3.737)	(3.529)
High-Low	0.039*	0.016*	0.061**	0.047*	0.070*	0.038*	0.012*	0.054**	0.050*	0.080**
	(1.801)	(1.711)	(2.435)	(1.863)	(1.752)	(1.787)	(1.682)	(2.172)	(1.781)	(2.560)
Panel C: Holding for 4 weeks										
Low	0.091**	0.100***	0.077**	0.142***	0.164**	0.056**	0.067**	0.042*	0.110***	0.096**
	(2.511)	(2.627)	(2.197)	(3.606)	(2.108)	(2.407)	(2.475)	(1.786)	(4.021)	(2.280)
High	0.138***	0.139***	0.178***	0.210***	0.219***	0.095**	0.097***	0.131***	0.181***	0.173***
	(2.690)	(2.882)	(2.924)	(3.199)	(3.186)	(2.503)	(3.085)	(2.689)	(3.021)	(3.118)
High-Low	0.047	0.039	0.101**	0.068	0.055	0.038	0.030	0.089**	0.072	0.077
	(1.426)	(1.300)	(2.540)	(1.075)	(0.900)	(1.287)	(1.322)	(2.340)	(1.179)	(1.570)

Table 14: Double-sorted MAX Portfolios with Other Filters. This table shows the one-week-ahead value-weighted excess returns (ER) and alphas (Alpha) of double-sorted portfolios with alternative sample selection criteria. In Panel A, we include cryptocurrencies whose market capitalization is larger than 500,000 dollars in our sample. In Panel B, we include cryptocurrencies whose trading history is larger than 2 years. Newey-West (1987) adjusted t-statistics are presented in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Market capitalization of greater than 500, 000 dollars

		ER					Alpha				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
MAX(1)	Low	0.015*	0.013*	0.010	0.024***	0.021*	-0.006	-0.001	-0.006	0.007	-0.002
		(1.756)	(1.749)	(1.382)	(2.688)	(1.769)	(-1.400)	(-0.229)	(-1.630)	(1.419)	(-0.345)
	High	0.055***	0.045***	0.037***	0.039***	0.043***	0.017***	0.015	0.010	0.028***	0.023**
		(4.075)	(2.850)	(2.607)	(4.533)	(3.246)	(3.702)	(1.605)	(1.201)	(4.969)	(2.589)
	High-Low	0.040***	0.033***	0.027***	0.015**	0.022**	0.023***	0.016**	0.017**	0.021***	0.025**
		(3.529)	(2.958)	(2.709)	(2.202)	(2.000)	(4.527)	(2.191)	(2.079)	(3.480)	(2.533)
MAX(2)	Low	0.016*	0.013*	0.010	0.027***	0.022*	-0.005	-0.000	-0.007	0.009*	-0.002
		(1.831)	(1.745)	(1.345)	(2.880)	(1.727)	(-1.280)	(-0.066)	(-1.605)	(1.749)	(-0.276)
	High	0.055***	0.045***	0.044***	0.040***	0.043***	0.017***	0.026*	0.013	0.029***	0.023***
		(4.211)	(2.883)	(2.684)	(4.661)	(3.253)	(3.801)	(1.747)	(1.551)	(5.133)	(2.597)
	High-Low	0.040***	0.032***	0.034***	0.013*	0.021**	0.022***	0.027**	0.020**	0.020***	0.025**
		(3.427)	(2.922)	(2.850)	(1.861)	(2.177)	(4.632)	(2.440)	(2.382)	(3.204)	(2.379)
MAX(3)	Low	0.015*	0.012*	0.009	0.027***	0.020	-0.006	-0.001	-0.007*	0.009*	-0.003
		(1.735)	(1.710)	(1.258)	(2.870)	(1.605)	(-1.508)	(-0.321)	(-1.652)	(1.809)	(-0.593)
	High	0.055***	0.045***	0.041***	0.040***	0.044***	0.018***	0.017*	0.013	0.029***	0.024***
		(4.269)	(2.970)	(2.697)	(4.671)	(3.299)	(3.939)	(1.848)	(1.484)	(5.120)	(2.655)
	High-Low	0.040***	0.033***	0.031***	0.012*	0.023**	0.024***	0.019**	0.020**	0.020***	0.027***
		(3.465)	(3.027)	(2.810)	(1.821)	(2.038)	(4.872)	(2.153)	(2.330)	(3.204)	(2.639)
MAX(4)	Low	0.014	0.012*	0.010	0.028***	0.020	-0.007*	-0.001	-0.007	0.010*	-0.003
		(1.596)	(1.687)	(1.277)	(2.849)	(1.612)	(-1.895)	(-0.323)	(-1.563)	(1.915)	(-0.619)
	High	0.055***	0.044***	0.041**	0.040***	0.043***	0.018***	0.016*	0.013	0.030***	0.023***
		(4.382)	(2.892)	(2.586)	(4.876)	(3.247)	(3.954)	(1.739)	(1.400)	(5.435)	(2.593)
	High-Low	0.041***	0.032***	0.030***	0.012**	0.023**	0.025***	0.017**	0.019**	0.020***	0.026***
		(3.468)	(3.060)	(2.671)	(2.146)	(2.042)	(5.330)	(2.156)	(2.196)	(3.413)	(2.686)
MAX(5)	Low	0.014	0.012*	0.009	0.028***	0.020*	-0.007*	-0.001	-0.008*	0.010*	-0.003
		(1.563)	(1.676)	(1.176)	(2.861)	(1.658)	(-1.826)	(-0.283)	(-1.880)	(1.957)	(-0.524)
	High	0.056***	0.045***	0.039**	0.040***	0.043***	0.020***	0.017*	0.012	0.030***	0.023***
		(4.665)	(2.987)	(2.551)	(4.937)	(3.252)	(4.274)	(1.874)	(1.338)	(5.495)	(2.600)
	High-Low	0.042***	0.032***	0.030***	0.012*	0.022**	0.027***	0.018**	0.020**	0.020***	0.026***
		(3.602)	(3.108)	(2.661)	(1.699)	(2.007)	(5.940)	(2.235)	(2.214)	(3.390)	(2.663)

Panel B: Trading history of longer than two years

		ER					Alpha				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
	Low	0.018*	0.028***	0.009	0.037***	0.021*	-0.004	0.010*	-0.011***	0.015***	-0.004
		(1.865)	(3.339)	(1.177)	(3.612)	(1.675)	(-1.005)	(1.905)	(-2.746)	(2.616)	(-0.731)
MAX(1)	High	0.058*	0.067***	0.079**	0.070***	0.060***	0.030	0.041***	0.055	0.054***	0.044***
		(1.759)	(4.106)	(2.209)	(3.461)	(3.312)	(0.679)	(3.291)	(1.557)	(2.775)	(2.753)
	High-Low	0.040**	0.039***	0.070**	0.033**	0.039**	0.034**	0.031**	0.065*	0.039*	0.048***
		(2.497)	(2.890)	(2.043)	(2.182)	(2.408)	(2.138)	(2.439)	(1.861)	(1.941)	(3.037)
	Low	0.020**	0.024***	0.011	0.032***	0.021*	-0.001	0.007	-0.008**	0.011*	-0.004
		(2.257)	(2.906)	(1.445)	(3.131)	(1.689)	(-0.272)	(1.302)	(-2.107)	(1.883)	(-0.578)
MAX(2)	High	0.052*	0.069***	0.086**	0.072***	0.066***	0.034	0.043***	0.062*	0.058***	0.049**
		(1.964)	(4.252)	(2.394)	(3.516)	(3.033)	(0.952)	(3.384)	(1.770)	(2.874)	(2.458)
	High-Low	0.032**	0.045***	0.075**	0.040**	0.045**	0.035**	0.036***	0.071**	0.047**	0.053***
		(2.142)	(3.311)	(2.174)	(2.040)	(2.188)	(1.979)	(2.841)	(2.007)	(2.250)	(2.620)
	Low	0.022**	0.023***	0.010	0.032***	0.021*	-0.001	0.005	-0.010***	0.009	-0.004
		(2.197)	(2.781)	(1.252)	(3.042)	(1.653)	(-0.332)	(1.082)	(-2.696)	(1.588)	(-0.669)
MAX(3)	High	0.052**	0.069***	0.088**	0.070***	0.078***	0.035	0.042***	0.066*	0.057***	0.060**
		(2.009)	(4.123)	(2.408)	(3.512)	(2.697)	(1.033)	(3.369)	(1.823)	(2.872)	(2.238)
	High-Low	0.031**	0.046***	0.078**	0.039**	0.057**	0.037**	0.036***	0.076**	0.048**	0.064**
		(2.151)	(3.409)	(2.213)	(2.032)	(2.014)	(2.041)	(2.945)	(2.116)	(2.341)	(2.358)
	Low	0.020**	0.023***	0.010	0.029***	0.019	-0.003	0.005	-0.011***	0.007	-0.006
		(2.027)	(2.742)	(1.177)	(2.981)	(1.518)	(-0.782)	(0.990)	(-2.757)	(1.324)	(-1.005)
MAX(4)	High	0.067*	0.095***	0.092**	0.073***	0.077***	0.030	0.069**	0.071*	0.060***	0.060**
		(1.823)	(2.878)	(2.537)	(3.809)	(2.676)	(1.209)	(2.155)	(1.948)	(3.190)	(2.226)
	High-Low	0.047**	0.073**	0.083**	0.045**	0.058**	0.033**	0.065**	0.081**	0.053***	0.066**
		(2.323)	(2.314)	(2.348)	(2.323)	(2.051)	(2.293)	(1.996)	(2.256)	(2.703)	(2.415)
	Low	0.022**	0.023***	0.009	0.027***	0.021*	-0.001	0.006	-0.011***	0.007	-0.004
		(2.200)	(2.922)	(1.114)	(2.922)	(1.664)	(-0.247)	(1.214)	(-2.748)	(1.240)	(-0.584)
MAX(5)	High	0.068*	0.113***	0.093**	0.107***	0.082***	0.032	0.088**	0.071*	0.096**	0.064**
		(1.895)	(3.107)	(2.567)	(2.763)	(2.760)	(1.316)	(2.537)	(1.963)	(2.391)	(2.336)
	High-Low	0.046**	0.090***	0.084**	0.080**	0.061**	0.033**	0.082**	0.082**	0.089**	0.068**
		(2.505)	(2.610)	(2.391)	(2.027)	(2.099)	(2.303)	(2.357)	(2.276)	(2.172)	(2.432)

Table 15: Double-sorted Modified MAX Portfolios. This table shows the one-week-ahead value-weighted excess returns (ER) and alphas (Alpha) of quintile portfolios based on the frequency of the daily returns exceeding the threshold *P (P=10%,20%,…,50%)* within the past one month as of the end of week *t* (*MMAX(P)*). Portfolio High (Low) comprises cryptocurrencies with the highest (lowest) (*MMAX(P)*). Newey-West (1987) adjusted t-statistics are reported in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

		ER					Alpha				
		Beta	*Size*	*Mom*	*Illiq*	*Prc*	*Beta*	*Size*	*Mom*	*Illiq*	*Prc*
	Low	0.018**	0.021**	0.014	0.029***	0.019	-0.002	-0.000	-0.008*	0.009**	-0.006
		(2.038)	(2.088)	(1.488)	(3.244)	(1.577)	(-0.382)	(-0.057)	(-1.706)	(2.323)	(-1.204)
MMAX(10%)	High	0.031**	0.054***	0.037***	0.048***	0.045***	0.015	0.033***	0.016	0.034***	0.028***
		(2.568)	(3.726)	(2.987)	(4.525)	(3.670)	(1.430)	(2.727)	(1.406)	(4.090)	(2.904)
	High-Low	0.013**	0.034***	0.022**	0.020**	0.026***	0.017*	0.033***	0.024**	0.025**	0.034***
		(2.264)	(3.108)	(2.302)	(2.269)	(2.817)	(1.689)	(3.053)	(2.376)	(2.037)	(3.997)
	Low	0.023**	0.028**	0.011	0.029***	0.024	0.002	0.005	-0.010**	0.011***	-0.004
		(2.508)	(2.535)	(1.312)	(4.431)	(1.591)	(0.479)	(0.802)	(-2.096)	(3.477)	(-0.640)
MMAX(20%)	High	0.037***	0.063***	0.034***	0.051***	0.046***	0.021**	0.040**	0.013	0.046***	0.031***
		(3.643)	(2.941)	(2.755)	(4.843)	(4.125)	(2.451)	(2.060)	(1.191)	(4.082)	(3.135)
	High-Low	0.014**	0.035*	0.023**	0.022**	0.022**	0.018**	0.035*	0.023**	0.035**	0.034***
		(2.476)	(1.815)	(2.422)	(2.265)	(2.513)	(2.028)	(1.665)	(2.347)	(2.234)	(3.450)
	Low	0.024**	0.031***	0.013	0.023***	0.019	0.002	0.010	-0.009*	0.004**	-0.005
		(2.386)	(3.045)	(1.426)	(3.370)	(1.625)	(0.441)	(1.529)	(-1.761)	(2.341)	(-0.753)
MMAX(30%)	High	0.036***	0.061***	0.041***	0.044***	0.040***	0.022**	0.037**	0.019	0.030***	0.025**
		(3.630)	(3.517)	(3.109)	(5.232)	(3.215)	(2.521)	(2.538)	(1.626)	(4.337)	(2.139)
	High-Low	0.013**	0.029*	0.028***	0.022**	0.021*	0.020**	0.028*	0.028***	0.026*	0.030***
		(2.261)	(1.929)	(2.740)	(2.217)	(1.832)	(2.190)	(1.880)	(2.692)	(1.808)	(2.747)
	Low	0.020**	0.031***	0.009	0.013***	0.024*	-0.002	0.010	-0.014**	0.005**	-0.001
		(2.135)	(3.181)	(0.975)	(3.721)	(1.778)	(-0.380)	(1.508)	(-2.570)	(2.560)	(-0.065)
MMAX(40%)	High	0.035***	0.064***	0.052***	0.044***	0.048***	0.019**	0.041**	0.025**	0.029***	0.021**
		(3.699)	(3.444)	(3.289)	(4.941)	(3.601)	(2.412)	(2.563)	(2.137)	(4.372)	(2.376)
	High-Low	0.015**	0.033*	0.043***	0.032**	0.023**	0.021**	0.031*	0.039***	0.024**	0.022**
		(2.285)	(1.952)	(3.747)	(2.397)	(2.125)	(2.552)	(1.868)	(3.649)	(2.252)	(2.237)
	Low	0.020**	0.041***	0.009	0.023***	0.025*	-0.003	0.018**	-0.015***	0.004**	-0.003
		(2.052)	(3.764)	(0.906)	(3.667)	(1.723)	(-0.563)	(2.350)	(-2.789)	(2.529)	(-0.325)
MMAX(50%)	High	0.041***	0.060***	0.036***	0.047***	0.063***	0.023***	0.039***	0.013	0.033***	0.047**
		(3.625)	(3.797)	(2.779)	(4.347)	(2.602)	(2.626)	(2.922)	(1.278)	(3.813)	(2.053)
	High-Low	0.022**	0.019**	0.028***	0.024**	0.038**	0.025***	0.021*	0.027***	0.028*	0.049**
		(2.203)	(2.411)	(3.018)	(2.329)	(2.452)	(2.611)	(1.858)	(3.095)	(1.842)	(2.061)

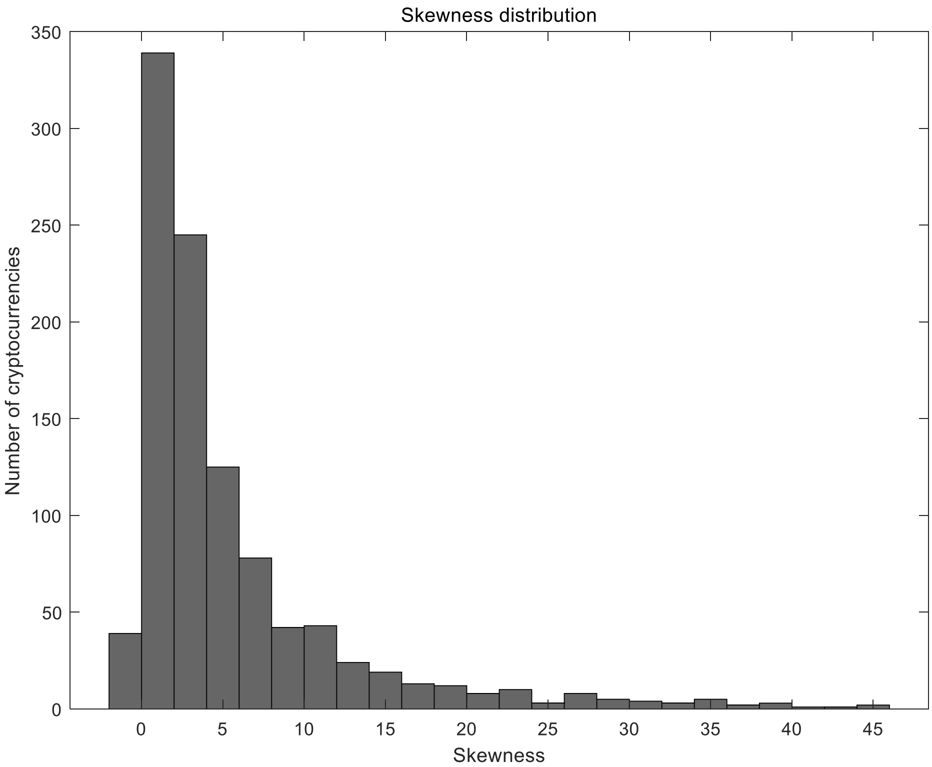

Fig. 1 Skewness distribution of cryptocurrencies

This figure shows the skewness distribution of cryptocurrencies in our sample during 2014.01-2020.06.

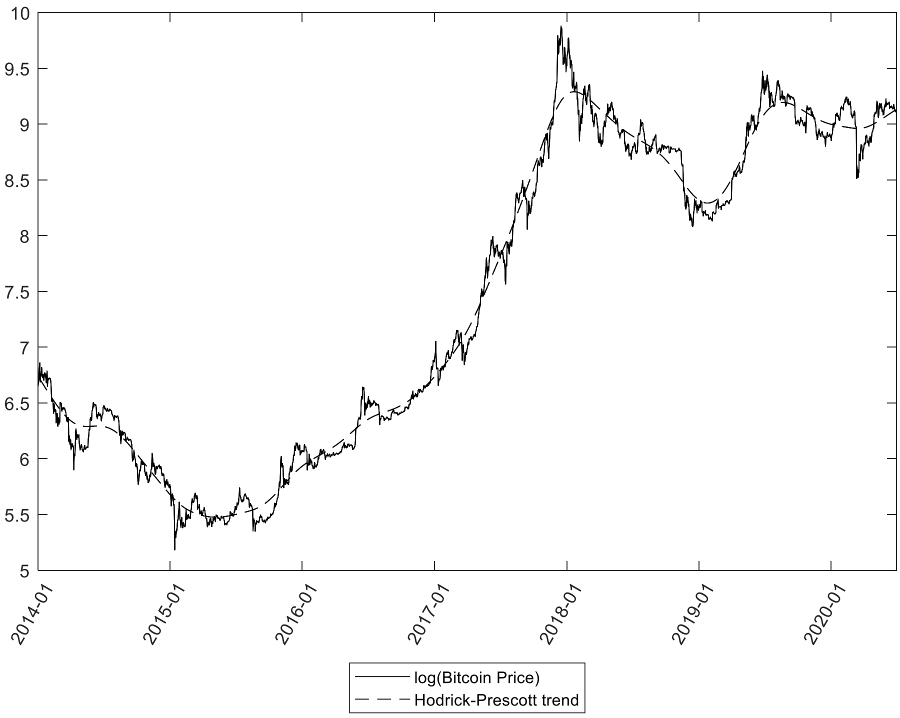

Fig. 2 Buying pressure

This figure plots the series of the smoothed log market price and the actual log market price of cryptocurrencies at the weekly level using the Hodrick–Prescott filter from January 2014 to June 2020.

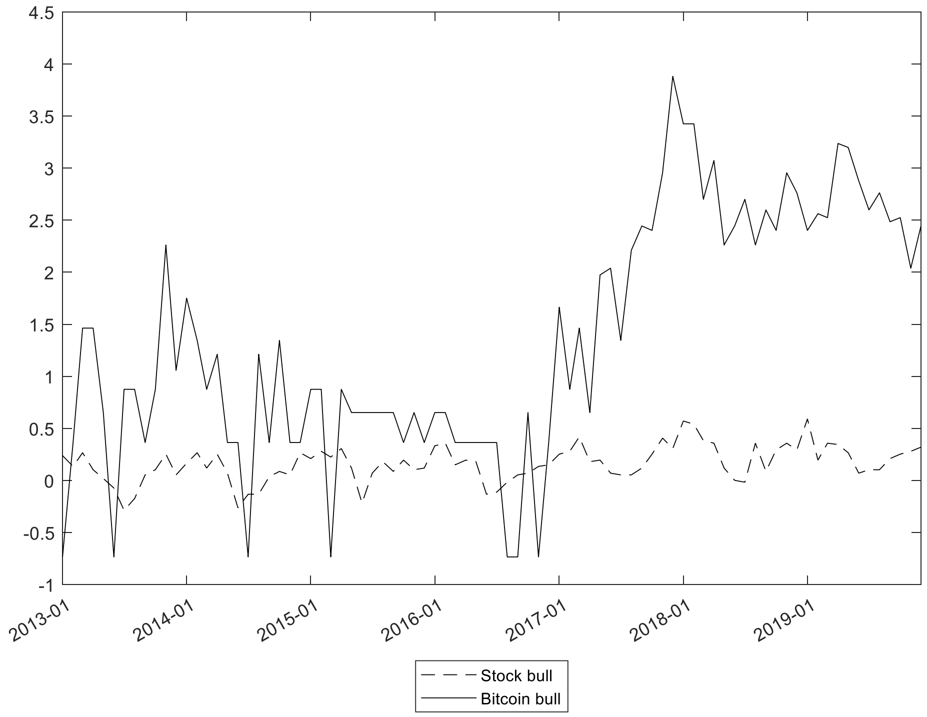

Fig. 3 Investor optimism in the cryptocurrency market and stock market

This figure displays the abnormal search frequencies of "Bitcoin bull" and "stock bull" in Google from January 1st, 2013 to December 31st, 2019. The abnormal search frequency is defined as the logarithm of search volume during a given month minus the logarithm of the mean value of search volume in 2012.