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Downside risk and the cross-section of cryptocurrency returns

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ABSTRACT

This paper investigates whether investors can earn higher profits by holding cryptocurrencies with higher downside risk. Both portfolio-level analyses and cryptocurrency-level cross-sectional regressions suggest a positive cross-sectional relation between downside risk and future returns in the cryptocurrency market. In addition to the risk-return tradeoff theory, the limits-to-arbitrage theory also has some explanatory power for these results. Moreover, we examine the source of downside risk premium, the existence of upside risk premium, as well as the intertemporal relation between downside risk and future returns. Collectively, our findings highlight the important role of downside risk in determining cryptocurrency prices.

1. Introduction

Since the whitepaper “Bitcoin: A Peer-to-Peer Electronic Cash System” released by Nakamoto (2008), cryptocurrencies have grown stunningly in popularity and mainstream adoption.[1] Till the end of December 2020, there are over 4000 cryptocurrencies with a total market capitalization of approximately 757 billion.[2] In the meantime, the wave of bubbles and crashes with unprecedented intensities has drawn public attention to the cryptocurrency market. A number of scholars, e.g., Liu et al. (2021) and Liu and Tsyvinski (2021), attempt to explore the determinants of cryptocurrency prices. However, largely absent from these inquiries is an analysis of cryptocurrencies' risk profile and how risk is related to their returns.[3]

It seems that cryptocurrencies are mainly regarded as investment instruments rather than alternative currencies (e.g., Baur et al. 2018, Corbet et al. 2019, Makarov and Schoar 2020, Griffin and Shams 2020), given the huge number of exchanges, the tremendous volume of daily trading, and the rapid emergence of crypto funds and Bitcoin futures. Nevertheless, several characteristics differentiate cryptocurrencies from traditional financial assets. First, unlike cash flows for stocks and bonds, the fundamental source of cryptocurrencies' intrinsic value is unclear (Detzel et al., 2020), despite heated debates and discussions (Biais et al., 2020; Bhambhwani et al., 2019; Cong et al., 2021; Liu et al., 2020; Sockin and Xiong, 2020). And there are also few, if any, publicly available signals (e.g., analyst reports and accounting statements) for reference, making cryptocurrencies hard to value. Second, there is currently little regulation on the trading of cryptocurrencies (Hossain, 2021), leaving them vulnerable to manipulation such as “pump-and-dump” schemes (Li et al., 2019) and useful in facilitating illegal trade (Foley et al., 2019). In contrast, most of the typical assets are subject to the centralized scrutiny of regulators. Moreover, individual investors are the major players in the cryptocurrency market. This is because barriers to entry are quite low. Anyone with a few bucks and an internet connection can start trading instantly.

Perhaps, the frequent booms and busts witnessed by the cryptocurrency market are due to the above features, making it comparable to a large casino (Ma and Tanizaki, 2019; Wang et al., 2019; Xu et al., 2019; Zhu et al., 2017). An example comes from Black Thursday (i.e., March 12, 2020), on which Bitcoin crashed by ap-

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[1] Up to 2019, 56% of the world's top 50 universities offer at least one course on crypto or blockchain, and the CFA has added topics on cryptocurrencies and blockchain as examinable material. Furthermore, according to a survey conducted by Harris Poll, about 11% of the U.S. residents own the major cryptocurrency: Bitcoin.

[2] At the end of 2020, the total market capitalization of all cryptocurrencies was 71 times as large as it was at the beginning of 2014. And at the middle of March 2021, the market capitalization was 170 times larger than that of 2014.

[3] The tail behavior of returns of five major cryptocurrencies has been studied by Gkillas and Katsiampa (2018). Although they also employ value-at-risk and expected shortfall as risk metrics, they only focus on five major cryptocurrencies and provide evidence on which cryptocurrency is the riskiest and which one is the least risky.

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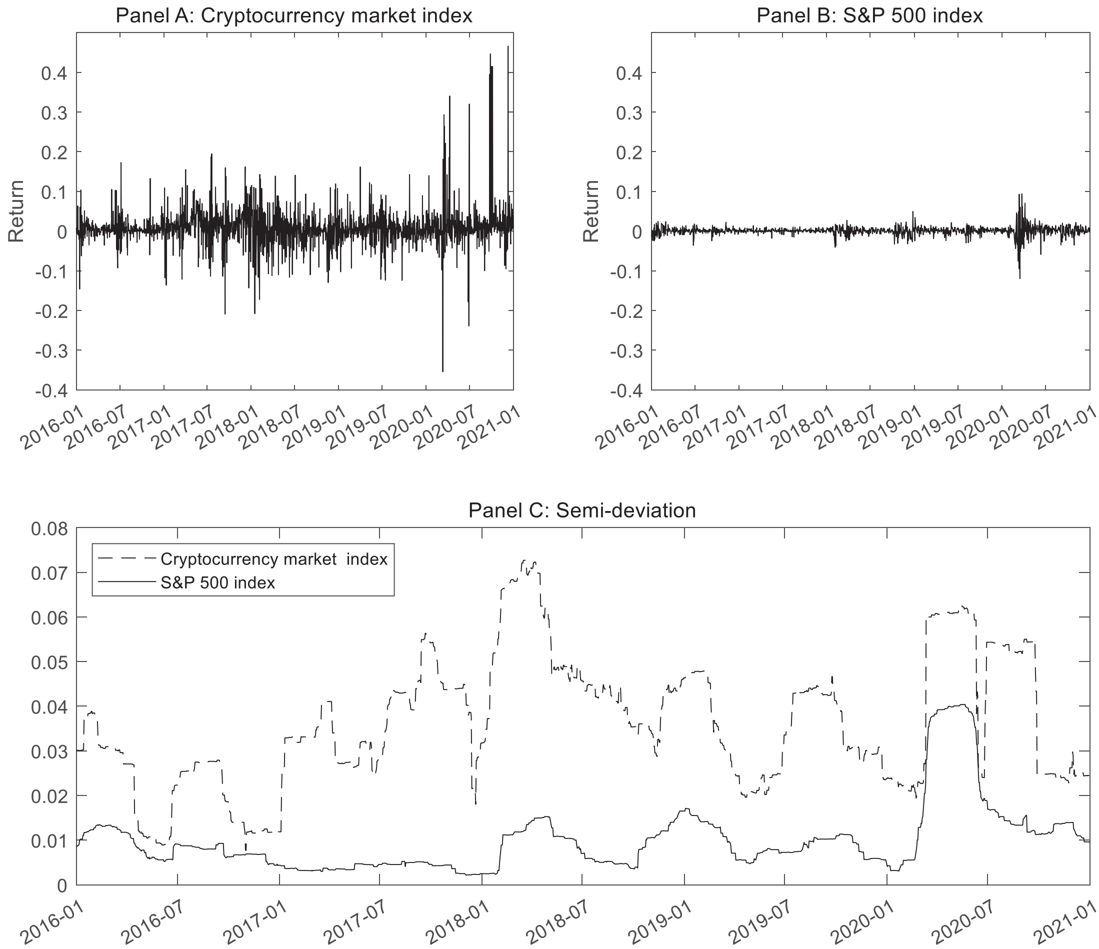

Fig. 1. Volatility of the cryptocurrency market and the stock market
This figure displays the returns and semi-deviation of the cryptocurrency market and the U.S. stock market. For the stock market, we employ the S and P 500 index. As for the cryptocurrency market, we use a value-weighted portfolio with all the sample cryptocurrencies as the market index. Panels A and B present the daily returns of the cryptocurrency market and the U.S. stock market, respectively. Panel C presents the semi-deviations (calculated in a three-month rolling window) of the cryptocurrency market and the stock market.

proximately 40%, and so did other cryptocurrencies.[4] We also plot the daily returns of the cryptocurrency market (Panel A) and the U.S. stock market (Panel B) as well as their semi-deviation (Panel C) in Fig. 1. It is evident that the cryptocurrency market suffers from greater volatility and downside risk than the stock market, which highlights the need for understanding the risk exposure of cryptocurrencies (Borri, 2019). Thus, in this paper, we try to ascertain how downside risk affects cryptocurrency returns.

Downside risk's impact on asset pricing has been recognized by academics for a long time. In his seminal paper, Roy (1952) puts forward that agents have different attitudes towards downside losses and upside gains. This view is then echoed by a series of studies. For instance, Markowitz (1952) claims that investors care more about the downside risk than the market risk and advocates the use of semi-variance in constructing portfolios. Likewise, the premise of loss aversion preferences proposed by Kahneman and Tversky (1979) and disappointment aversion preferences introduced by Gul (1991) is that investors dislike losses more than gains. Since losses are weighted more heavily than gains in investors' utility function, assets with higher downside risk should have higher expected returns than those with lower downside risk.

At first, scholars focus on the relation between downside or tail beta (usually referred to as the systematic downside risk) and future asset returns. Along with the increasing evidence showing that the portfolios of individual investors are not well diversified,[5] more attention is devoted to how unsystematic downside risk (also called idiosyncratic downside risk) is priced in the cross-section of asset returns. According to Lammer et al. (2019), compared to noncryptocurrency investors' portfolios, those of cryptocurrency investors are even less diversified and are more likely to consist of penny stocks and other investment vehicles with high idiosyncratic risk. Combined with the fact that most cryptocurrency investors only trade a small number of cryptocurrencies,[6] the underdiversification persists in the cryptocurrency market. Given that risk-averse investors typically require higher profits when holding assets with higher risk, we conjecture that cryptocurrencies with high idiosyncratic downside risk would have lower prices in compensation for the higher probability and magnitude of large losses. That is to say, higher returns should be realized from holding cryptocurrencies with high unsystematic downside risk. On the con-

[4] There are also huge crashes in the prices of other cryptocurrencies. For instance, Litecoin's price, Ethereum's price, and Ripple's price declined about 40%, 73%, and 46% on July 10, 2015, August 8, 2015, and April 3, 2017, respectively.

[5] The median number of stocks in individual investors' portfolios reported by Odean (1999) and Barber and Odean (2001) is 2 to 3. After examining a survey of fourteen million households, Polkovnichenko (2005) concludes that many households simultaneously invest in well-diversified funds and in poorly-diversified portfolios of stocks.

[6] According to Ante et al. (2020), on average, investors hold about 2 coins.

trary, if investors in the cryptocurrency market are merely risk-seekers (Conlon and McGee, 2019; Pelster et al., 2019), we should observe an insignificant or even a negative relation between downside risk and cryptocurrency expected returns.

Several risk metrics can be used to represent downside risk. Among them, value-at-risk, which estimates a decrease in the value of an asset at a given probability, is better suited for our setting. First, due to its easy calculation and wide applicability, it is typically used by firms and regulators in the financial industry to gage the amount of investment needed to cover possible losses. More importantly, value-at-risk measures the magnitude and probability of entity-level price crashes (i.e., the extreme downside risk), which could well reflect the extreme price movements in the cryptocurrency market. For these reasons, we use value-at-risk to detect the downside risk-return relation in the main analyses.

The univariate portfolio analysis shows a positive tradeoff between downside risk and returns in the cryptocurrency market. In particular, cryptocurrencies with higher downside risk tend to have higher future returns, while those with lower downside risk tend to have lower future returns. The excess return or alpha[7] difference between portfolios with the highest downside risk and the lowest downside risk is significantly positive regardless of equal weighting or value weighting. Meanwhile, by conducting the bivariate portfolio analysis and running Fama and MacBeth (1973) cross-sectional regressions, we demonstrate that this pattern persists after controlling for a series of cryptocurrency characteristics that may influence the cross-section of cryptocurrency returns.

To ensure that our results are not driven by issues like methodological choices, some influential observations, or a short sample, we run a battery of robustness checks. The first set of tests use other downside risk metrics, namely, expected shortfall, low partial moment, downside beta, and hybrid tail risk, as well as value-at-risk calculated over alternative windows. In the second set of tests, we replicate our analyses within samples obtained from different filters. Besides, we also address the short sample issue by breaking the sample into halves and extending the sample period. In all cases, our main results are not changed in any material ways.

Since all downside risk metrics are not a linear function of high-order moments of the return distribution, a natural question follows: where does the downside risk premium come from? Following Bai et al. (2019), we try to provide an answer by investigating whether high-order moments (volatility, skewness, and kurtosis) of cryptocurrency returns contribute to the predictive power of downside risk. Both the trivariate portfolio analysis and the Fama and MacBeth (1973) regression indicate that volatility plays a dominant role in explaining the relation between downside risk and future returns.

Another intriguing question to explore is whether there is a positive tradeoff between upside risk and future returns of cryptocurrencies. Motivated by Atilgan et al. (2020), we modify value-at-risk into a proxy for upside risk and perform the univariate portfolio analysis with this measure. Consistent with findings on downside risk, more excess returns will be realized by taking more upside risk. However, the bivariate portfolio analysis with both downside risk and upside risk metrics implies that the predictive power of upside risk is largely dependent on that of downside risk, while the predictive power of downside risk cannot be subsumed by that of upside risk.

Given that cryptocurrencies with higher downside risk are relatively small, volatile, and illiquid, we also test whether the limits-to-arbitrage theory explains our findings. For this purpose, we follow Atilgan et al. (2020) and conduct a bivariate independent-sort portfolio analysis based on a synthetic arbitrage index and value-at-risk. The positive relation between downside risk and future returns is more pronounced among cryptocurrencies that are costlier to arbitrage, confirming the role of limits-to-arbitrage in explaining our findings.

Finally, to advance the understanding of how downside risk determines cryptocurrency returns, we run time-series regressions to see whether the lagged value-at-risk can predict future returns of cryptocurrencies. For simplicity, we conduct these analyses at the market level and at the cryptocurrency level.[8] Somewhat surprisingly, nearly all regressions fail to identify a significant intertemporal relation between downside risk and one-week-ahead returns, which means that downside risk cannot serve as a reliable indicator of future returns from the time-series perspective.

To our knowledge, this is the first empirical research on how downside risk is priced in the cross-section of cryptocurrency returns. Hence, our contributions to the literature are mainly twofold. Notwithstanding the mixed empirical evidence on whether the tradeoff between downside risk and future returns is positive or negative, the significant relation between them has been found not only in the equity market (Ang et al., 2006; Atilgan et al., 2018; Farago and Tédongap, 2018, 2019; Atilgan et al., 2020) but also in the bond market (Bai et al., 2019), the foreign exchange market (Atanasov and Nitschka, 2014), the real estate market (Cheng, 2005), as well as the fund industry (Bali et al., 2007; Liang and Park, 2007). Our research expands the literature on downside risk by checking the downside risk premium in the cryptocurrency market.

On the other hand, we add to the literature on the predictability of cryptocurrency returns (Borri and Shakhnov, 2021; Liu et al., 2021). Although designed as a digital currency to facilitate peer-to-peer transactions (Foley et al., 2019), cryptocurrencies are mostly regarded as a new investment vehicle rather than a medium of exchange (Baur et al., 2018; Corbet et al., 2019; Li et al., 2019; Makarov and Schoar, 2020). Therefore, whether their returns can be analyzed with standard asset pricing tools has attracted interest from both scholars and practitioners (Liu et al., 2021). Previous studies have demonstrated that cryptocurrencies have no exposure to the common stock market and macroeconomic factors, as well as returns of currencies and commodities (Liu and Tsyvinski, 2021). However, factors specific to the cryptocurrency market (e.g., market return, size, momentum, MAX, idiosyncratic volatility, and liquidity) are useful in predicting cryptocurrency returns (Li et al., 2021; Liu et al., 2021; Zhang and Li, 2020, 2021). By confirming the existence of a positive relation between downside risk and future cryptocurrency returns, we introduce a new force that influences future returns of cryptocurrencies.[9] This conclusion may help understand the pricing of other "hard-to-value" assets (Detzel et al., 2020). Besides, our finding that investors can still earn higher compensation for taking higher downside risk contradicts the argument that cryptocurrency traders are simply risk-seekers (Conlon and McGee, 2019; Pelster et al., 2019).

This paper proceeds as follows. Section 2 describes the data and the main variables. Section 3 examines the cross-sectional relation between downside risk measured by value-at-risk and expected returns of cryptocurrencies. Section 4 conducts a battery of robustness checks. Section 5 investigates the source of downside risk premium, the role of upside risk in predicting future returns, the explanatory power of limits-to-arbitrage theory, and the

[7] The alpha is calculated with the cryptocurrency three-factor model proposed by Liu et al. (2021). Throughout the paper, when we mention the three-factor model, we refer to this cryptocurrency three-factor model.

[8] To better disentangle the intertemporal relation between downside risk and cryptocurrency returns, we conduct the cryptocurrency-level analysis with four leading cryptocurrencies.

[9] A recent study (Dobrynskaya, 2021) confirms our conclusion with different downside risk measures.

intertemporal relation between downside risk and future returns. And Section 6 concludes the paper.

2. Data and variables

2.1. Data and methodology

We collect trading data from Coinmarketcap.com, a leading source of cryptocurrency price and volume data that have been utilized by studies such as Gkillas and Katsiampa (2018) and Liu et al. (2021). Unlike Kaiko and Bitcoincharts.com, Coinmarketcap.com provides price data by taking the volume-weighted average of all prices reported in each market. Another benefit of using data from Coinmarketcap.com is that it lists both active and defunct cryptocurrencies, thus alleviating concerns about survivorship bias (Liu et al., 2021).

Our initial sample consists of all cryptocurrencies traded during the period of January 2016 to December 2020.[10] In order to be included in our final sample, a cryptocurrency must satisfy the criterion of having a market capitalization of more than 2 million dollars at the end of each week. We test the relation between downside risk and future cryptocurrency returns at a weekly frequency. The reason behind this is that weekly returns can offer improved estimation accuracy than monthly returns, whereas daily returns may introduce confounding microstructure problems such as bid-ask bounce and nonsynchronous trading. Thus, weekly returns seem to be a natural compromise. Additionally, to mitigate the concern that outliers bias our results, we winsorize all non-return variables each week at the 1% and 99% levels, following Liu et al. (2021).

According to previous literature (e.g., Bali et al. 2009, Atilgan et al. 2019 2020), several risk metrics can be used to measure downside risk. In the main analyses, we utilize value-at-risk (*VaR*) as the downside risk proxy to check the relation between downside risk and returns from the cross-sectional perspective. By definition, value-at-risk measures the decline in the value of an asset over a given period on a given probability level. In our setting, we calculate value-at-risk as the 5th percentile of daily cryptocurrency returns over the past 90 days as of the end of a given week and label it *5%VaR*. We choose a shorter period to calculate value-at-risk because compared with other classes of assets, the history of cryptocurrencies is relatively short and the price volatility of cryptocurrencies is relatively large. *5%VaR* is then multiplied by -1 so that higher values of *5%VaR* correspond to higher levels of downside risk. Besides, we also utilize *1%VaR*, which is -1 times the first percentile of daily cryptocurrency returns over the past 90 days as of the end of a given week. Since the results obtained with *1%VaR* are similar to those obtained with *5%VaR*, we report them in Table A1 of the online Appendix.

In addition to value-at-risk, we also exploit other downside risk metrics. The first one is expected shortfall (*ES*). Like value-at-risk, it also measures the extreme downside risk and is defined as the expectation of a loss when the loss is beyond a given probability level. In our setting, we use the average of observations that are less than or equal to the 5th (*5%ES*) or the 10th (*10%ES*) percentile of daily cryptocurrency returns during the past 90 days to denote expected shortfall.[11] In a similar vein to *1%VaR* and *5%VaR, 5%ES* and *10%ES* are also multiplied by -1.

The second measure is lower partial moment (*LPM*), which is constructed as the average value of squared negative deviations of daily returns from a target level (Price et al., 1982; Atilgan et al., 2019):

$$LPM_i = \int_{-\infty}^{l} (r_i - x_i)^2 f_i(r_i) dr, \tag{1}$$

where $f_i(\bullet)$ denotes the probability density function of returns for cryptocurrency *i*, r_i is the excess return of cryptocurrency *i*, x_i is the target level. In this paper, we use the 10th percentile (*10%LPM*) and the median (*50%LPM*) of the return distribution during the past 90 days as the target levels.

In addition to the above unsystematic downside risk measures, we also employ downside beta (β^-), which measures systematic downside risk, and hybrid covariance tail risk (*H-TCR*), which measures hybrid downside risk.

Initially proposed by Bawa and Lindenberg (1977) and then popularized by Ang et al. (2006), downside beta shows the sensitivity of a single asset's excess returns to the whole market's excess returns on days when the market's excess returns are less than a given threshold:

$$\beta_i^- = \frac{cov(r_{i,} r_m | r_m < x_m)}{var(r_m | r_m < x_m)}, \tag{2}$$

where r_i is the excess return of cryptocurrency *i*, r_m is the excess return of the cryptocurrency market,[12] and x_m is a threshold that can be replaced with different cutoffs such as the mean of market excess returns during the past 90 days (β_{mean}^-) and zero rate of return (β_0^-) (Ang et al., 2006; Atilgan et al., 2019).

Put forward by Bali et al. (2014), hybrid tail risk is the co-lower partial moment between an asset's extreme daily returns and the market's corresponding daily returns, conditional on the asset return being below a given threshold:

$$H - TCR_i = \{\mathrm{cov}(r_i - x_i)(r_m - x_m) | r_i < x_i\}, \tag{3}$$

where *x* denotes the return threshold either on the return distribution of cryptocurrency *i* or on the return distribution of market *m*, r_i is the excess return of cryptocurrency *i*, and r_m is the excess return of the cryptocurrency market. In this paper, we employ the 10th percentile (*10%H-TCR*) and the 20th percentile (*20%H-TCR*) of the return distribution during the past 90 days as the return thresholds.

Meanwhile, drawing on the literature on downside risk and cryptocurrencies (Atilgan et al., 2019, Atilgan et al., 2020; Liu and Tsyvinski, 2021), we derive other features that may influence the cross-sectional expected cryptocurrency returns. Market beta (*Beta*), calculated by regressing the daily returns of each cryptocurrency on the value-weighted market returns during the past 90 days in our setting, is the most well-known variable that affects asset pricing. Besides, it is demonstrated that there is a negative relation between market capitalization (*Size*) and future cryptocurrency returns. Thus, we use the logarithm of market value to control for the size impact. Furthermore, the momentum effect has also been verified in the cryptocurrency market. To alleviate its influence on the downside risk-return relation, we control for the cryptocurrency return in the previous week (*Mom*), following Liu et al. (2021). Simultaneously, motivated by Atilgan et al. (2020),

[10] The reason for beginning our sample in 2016 is to ensure a sufficient number of observations in the portfolio analysis.

[11] Since *1%VaR* and *1%ES* refer to the same value in the 90 days, we report the results with *5%ES* and *10%ES* instead of *1%ES* and *5%ES* being as the downside risk metrics.

[12] Since there is no well-accepted market index for cryptocurrencies, we follow Liu and Tsyvinski (2021) to calculate market returns as returns of a value-weighted portfolio with all sample cryptocurrencies. Throughout this paper, when we refer to market returns, we are referring to returns obtained by this method. And following Liu et al. (2021), the excess cryptocurrency market return is constructed as the difference between the cryptocurrency market index return and the risk-free rate that is measured as the one-month Treasury bill rate. For robustness, we also employ the return of CRIX proposed by Trimborn and Härdle (2018) and the return of CCI30 (https://cci30.com/) as the market return. The results remain essentially unchanged.

we deal with the potential effect of trading volume on cryptocurrency returns via both dummy variables (*Vhigh* and *Vlow*) and the continuous variable (*Abvol*). For a specific cryptocurrency, *Vhigh* (*Vlow*) equals one if its dollar trading volume on the last day of the portfolio formation week is among the highest (lowest) 10% of its daily dollar trading volume over the prior 49 trading days and zero otherwise. As for *Abvol*, we calculate it as the average logarithm of dollar trading volume for a given cryptocurrency in the portfolio formation week after subtracting the average logarithm of dollar trading volume of the past 12 weeks.

What is more, we control for other features that might influence future returns of cryptocurrencies. For instance, idiosyncratic volatility (*Ivol*) is computed as the standard deviation of residuals from regressions of excess cryptocurrency returns on excess market returns during the past 90 days. Following common practice, we estimate volatility (*Vol*) as the standard deviation of daily returns during the past 90 days. For each cryptocurrency, we follow Amihud (2002) and define the illiquidity measure (*Illiq*) as the absolute daily returns divided by the mean daily dollar trading volume for each week.[13] Co-skewness (*Coskew*) refers to 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 90 days. Also, due to cryptocurrency's lottery-like features, for each cryptocurrency, we use the average of five of the highest daily returns in the prior 4 weeks to control for *MAX*.

In addition, motivated by the findings of Liu et al. (2021), we also incorporate the following variables in our analyses: *Prc*, the logarithm of last day price in the portfolio formation week; *Maxdprc*, the logarithm of the maximum price of the portfolio formation week; *Prcvol*, the logarithm of average daily volume times price in the portfolio formation week; and *Stdprcvol*, the logarithm of the standard deviation of dollar volume in the portfolio formation week.

2.2. Summary statistics

We include the descriptive statistics of *5%VaR* and other features of cryptocurrencies in Panel A of Table 1, while those of other downside risk metrics are reported in Panel B of Table 1. To better present the cross-sectional distribution of these variables, we first calculate certain values of the cross-sectional distribution of a given variable for each week in the sample period and then report the time-series averages of the periodic cross-sectional values. The mean of *5%VaR* is 0.158, suggesting that for a typical cryptocurrency, there is a 5% likelihood that the average daily loss exceeds 15.8%. And there is a wide gap among *5%VaR* of different cryptocurrencies since the 5th percentile value is 0.067 while the 95th percentile value is 0.326. This is also the case for *1%VaR* and other downside risk metrics presented in Panel B. A plausible reason is that the cryptocurrency market is generally too volatile. Concerning other features, the differences between the 5th percentile and 95th percentile values for almost all of them are also quite sharp.

Moreover, we also include the time-series averages of cross-sectional correlations among the above variables in Table 2. An apparent trend of Panel A is that *5%VaR* has relatively high correlations with *Ivol* (0.729) and *MAX* (0.692). Another finding worth noting is the remarkably high correlation between *Ivol* and *MAX* (0.699), which conforms to findings in the stock market (Bali et al., 2011; Atilgan et al., 2020).

The correlations among different downside risk metrics are shown in Panel B. Consistent with our expectation, the correlation between *1%VaR* and *5%VaR* is 83.3%, indicating that these two value-at-risk metrics are highly correlated. Likewise, the correlations among unsystematic downside risk metrics are also relatively high. Besides, unsystematic downside risk metrics have a higher correlation with the hybrid tail risk than with the downside beta.

3. Empirical results

In this section, to investigate whether there is a tradeoff between downside risk and expected returns from the cross-sectional perspective, we conduct the univariate portfolio analysis, bivariate portfolio analysis, and Fama andMacBeth (1973) regression analysis with *5%VaR* representing downside risk.

3.1. Univariate portfolio analysis

We first examine the significance of a cross-sectional relation between value-at-risk, the metric for downside risk, and future cryptocurrency returns by using the univariate portfolio analysis. Specifically, for each week, we form decile portfolios by sorting cryptocurrencies based on their *5%VaR*, where portfolio 1 (also named as portfolio Low) contains cryptocurrencies with the lowest value-at-risk and portfolio 10 (also named as portfolio High) contains cryptocurrencies with the highest value-at-risk. We then calculate the time-series average (both equal-weighted and value-weighted) of one-week-ahead excess returns for each portfolio.[14] After that, to explore whether the excess return difference between the highest and lowest value-at-risk deciles can be explained by factors that capture the cross-sectional expected cryptocurrency returns, i.e., cryptocurrency market, size, and momentum factors,[15] we adjust excess returns with the three-factor model proposed by Liu et al. (2021).

Table 3 reports the results of univariate portfolio analysis by using *5%VaR* as the proxy for downside risk. For the equal-weighted portfolios, both the value and t-statistic of excess returns generally increase with *5%VaR*. The excess return of portfolio Low is 0.021, significant at the 5% level. In contrast, the excess return of portfolio High is the highest (0.095) among all portfolios, with a t-statistic of 5.353. If we adjust excess returns with the three-factor model, the alphas for most of the portfolios are negative. However, the alpha of portfolio High is 0.054 and statistically significant. A similar pattern can be observed among the value-weighted portfolios. The excess returns are higher among portfolios with higher *5%VaR* and are all significant at the conventional level. And the alphas in column (4) are also all negative except for portfolio High.[16]

To better illustrate the excess return and alpha differences between portfolios High and Low, we construct a zero-cost strategy by taking a long position in cryptocurrencies with the highest value-at-risk while taking a short position in cryptocurrencies with

[13] According to Brauneis et al. (2021), the Amihud (2002) illiquidity ratio performs well when estimating liquidity levels of cryptocurrencies.

[14] To obtain excess returns of each portfolio, we employ the one-month Treasury bill rate as the risk-free rate.

[15] These three factors are constructed as follows. The market factor (CMKT) refers to the cryptocurrency excess market return, which is calculated as the difference between the cryptocurrency market index return and the risk-free rate. For the cryptocurrency size factor (CSMB), each week, we split the cryptocurrencies into three size groups by market capitalization, i.e., the bottom 30%, the middle 40%, and the top 30%. We then form value-weighted portfolios for each of these three groups. Then, CSMB is calculated as the return difference between the small and the big size portfolios. The construction of the cryptocurrency momentum factor (CMOM) is based on the three-week momentum. Each week, we split the cryptocurrencies into three three-week momentum groups: the bottom 30%, the middle 40%, and the top 30%. Then, we form value-weighted portfolios for each of the three three-week momentum groups. CMOM is then measured as the return difference between the top and the bottom momentum portfolios.

[16] The fact that alphas are seldom significantly positive implies that only a small number of cryptocurrencies with relatively high downside risk can generate positive returns after taking into account the market, momentum, and size factors. Besides, these results are a good indication of the effectiveness of the three-factor model proposed by Liu et al. (2021).

Table 1
Summary statistics
This table reports the summary statistics for variables utilized in the main analyses. Panel A presents the summary statistics of *5%VaR* and a series of cryptocurrency characteristics that may influence the downside risk-return relation. *5%VaR* is the 5th percentile of daily returns in the past 90 days and then multiplied with −1. *Beta* is calculated by regressing daily returns of each cryptocurrency on the value-weighted market returns during the past 90 days. *Size* is the logarithm of cryptocurrency market value. *Mom* is the cryptocurrency return in the previous week. *Vhigh* and *Vlow* are two dummy variables, indicating whether the dollar trading volume for a given cryptocurrency on the last day of the portfolio formation week is among the highest or the lowest 10% of its daily dollar trading volume over the prior 49 trading days. *Abvol* is the difference between the average logarithm of dollar trading volume for a given cryptocurrency and the average logarithm of dollar trading volume of the past twelve weeks. *Ivol* is computed as the standard deviation of residuals from regressing excess cryptocurrency returns on excess market returns during the past 90 days. *Vol* is the standard deviation of daily returns during the past 90 days. *Illiq* is the absolute daily returns divided by the mean daily dollar trading volume for each week. *Coskew* 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 90 days. *MAX* is the average of five of the highest daily returns in the prior 4 weeks. *Prc* is the logarithm of last day price in the portfolio formation week. *Maxdprc* is the logarithm of the maximum price of the portfolio formation week. *Prcvol* is the logarithm of average daily volume times price in the portfolio formation week. *Stdprcvol* is the logarithm of the standard deviation of dollar volume in the portfolio formation week. Panel B shows the summary statistics of alternative measures for downside risk. *1%VaR* is the 1st percentile of daily returns in the past 90 days and then multiplied with −1. *5%ES* is −1 times the average of returns that are less than or equal to the 5th percentile of daily returns during the past 90 days. *10%ES* is −1 times the average of returns that are less than or equal to the 10th percentile of daily returns during the past 90 days. *10%LPM* is the average of squared negative deviations of daily returns from the 10th percentile of the return distribution during the past 90 days. *50%LPM* is the average of squared negative deviations of daily returns from the median of the return distribution during the past 90 day. β_0^- is the sensitivity of a single cryptocurrency's excess returns to the whole market's excess returns on days when the market's excess returns are less than zero in the past 90 days. β_{mean}^- is the sensitivity of a single cryptocurrency's excess returns to the whole market's excess returns on days when the market's excess returns are less than the mean of the distribution of market excess returns in the past 90 days. *10%H-TCR* is the covariance between cryptocurrency daily returns from the 10th percentile of the return distribution and market returns from the 10th percentile of the market return distribution when the cryptocurrency return is less than the 10th percentile of the return distribution during the past 90 days. *20%H-TCR* is the covariance between cryptocurrency daily returns from the 20th percentile of the return distribution and market returns from the 20th percentile of the market return distribution when the cryptocurrency return is less than the 20th percentile of the return distribution during the past 90 days. For each variable, we first calculate certain values of the cross-sectional distribution of a given variable for each week in the sample period and then report the time-series averages of the periodic cross-sectional values. All non-return variables are winsorized at the 1% and 99% levels. The sample period is from January 2016 to December 2020.

Panel A Summary statistics of *5%VaR* and other cryptocurrency characteristics

	Mean	Std.	P5	P25	Median	P75	P95
5%VaR	0.158	0.085	0.067	0.105	0.136	0.186	0.326
Beta	0.902	1.030	−0.090	0.594	0.880	1.170	1.903
Size	15.437	2.060	12.643	13.842	15.129	16.842	19.083
Mom	0.034	0.294	−0.274	−0.104	−0.013	0.099	0.481
Vhigh	0.099	0.179	0.000	0.000	0.000	0.011	0.812
Vlow	0.124	0.272	0.000	0.000	0.000	0.069	0.850
Abvol	−0.025	0.948	−1.474	−0.378	−0.024	0.358	1.401
Ivol	0.131	0.177	0.025	0.055	0.087	0.142	0.376
Vol	0.073	0.456	0.003	0.005	0.010	0.024	0.164
Illiq	0.011	0.239	0.000	0.000	0.000	0.000	0.007
Coskew	0.662	28.713	−15.058	−4.933	−1.622	1.842	18.902
MAX	0.206	0.244	0.050	0.091	0.138	0.225	0.559
Prc	0.391	0.899	0.000	0.010	0.062	0.311	1.884
Maxdprc	0.414	0.936	0.000	0.012	0.071	0.345	1.969
Prcvol	10.531	3.126	4.384	8.393	10.507	13.586	15.830
Stdprcvol	9.193	2.901	4.869	7.250	9.011	11.059	14.211

Panel B Summary statistics for alternative measures for downside risk

	Mean	Std.	P5	P25	Median	P75	P95
1%VaR	0.265	0.142	0.106	0.169	0.228	0.324	0.563
5%ES	0.192	0.126	0.060	0.131	0.174	0.239	0.405
10%ES	0.151	0.102	0.024	0.107	0.144	0.195	0.330
10%LPM	0.061	0.040	0.016	0.035	0.050	0.075	0.143
50%LPM	0.072	0.048	0.029	0.044	0.059	0.086	0.161
β_0^-	0.942	12.152	−3.019	0.444	1.045	1.579	4.965
β_{mean}^-	1.019	2.065	−1.331	0.550	0.988	1.410	3.401
10%H-TCR	0.008	0.007	0.003	0.005	0.006	0.008	0.019
20%H-TCR	0.004	0.004	0.001	0.002	0.003	0.004	0.009

the lowest value-at-risk.[17] The pattern that cryptocurrencies with higher downside risk earn higher returns than those with lower downside risk persists as the return differences between portfolios High and Low are significantly positive with t-statistics larger than 4.

Our findings are distinct from those of Atilgan et al. (2020), who document a negative cross-sectional relation between value-at-risk and future returns in the stock market. An explanation proposed by Atilgan et al. (2020) for their results is investor inattention. Specifically, given that left-tail risk is less tangible, average investors have difficulties in interpreting large negative price shocks and thereby underreact to left-tail events in the stock market. However, the frequent price crashes and the eye-catching return volatility of cryptocurrencies could make it hard for investors to ignore downside risk. Instead, they could overweight the occurrence probability of tail events when making investment decisions (Tversky and Kahneman, 1992). Also, Lammer et al. (2019) find that cryptocurrency investors are less sophisticated and are more prone to behavioral biases than noncryptocurrency investors. Considering that downside risk premium is primarily induced by investors' loss aversion (Ang et al., 2006; Bali et al., 2014; Atilgan et al., 2019, 2020), a type of investment bias, the positive relation between downside risk and cryptocurrency returns might be reasonable.

[17] We admit that short selling is not readily available in the cryptocurrency market. Nevertheless, the excess returns and alphas for all portfolios labeled "High" are significantly positive. And the absolute value of them is larger than that of portfolios labeled "Low." In other words, the profits from this zero-investment strategy are mainly driven by the long position. Hence, short-selling constraints have a limited impact on our conclusions.

Table 2
Correlation matrices
This table reports the correlation matrices for downside risk measures and other cryptocurrency characteristics. Panel A shows the correlation matrix for *5%VaR* and other cryptocurrency characteristics. Panel B presents the correlation matrix for different downside risk measures. The sample period is from January 2016 to December 2020.

Panel A Correlation matrix for *5%VaR* and other cryptocurrency characteristics

	5%VaR	Beta	Size	Mom	Vhigh	Vlow	Abvol	Ivol	Vol	Illiq	Coskew	MAX	Prc	Maxdprc	Prcvol	Stdprcvol
5%VaR	1.000															
Beta	0.076	1.000														
Size	−0.400	0.025	1.000													
Mom	0.051	−0.005	0.034	1.000												
Vhigh	−0.014	−0.006	0.036	0.051	1.000											
Vlow	−0.025	0.003	0.013	−0.076	−0.141	1.000										
Abvol	−0.013	−0.004	0.109	0.194	0.201	−0.250	1.000									
Ivol	0.729	0.054	−0.277	0.087	0.000	−0.028	0.055	1.000								
Vol	0.519	0.050	−0.137	0.069	0.000	−0.018	0.060	0.911	1.000							
Illiq	0.296	−0.006	−0.148	0.004	−0.015	0.016	−0.241	0.250	0.210	1.000						
Coskew	−0.005	0.066	−0.027	−0.014	0.009	−0.002	−0.022	−0.021	−0.037	−0.002	1.000					
MAX	0.692	0.057	−0.248	0.184	0.041	−0.073	0.124	0.699	0.560	0.282	−0.023	1.000				
Prc	−0.209	−0.003	0.460	0.011	0.007	−0.010	0.028	−0.142	−0.067	−0.029	0.014	−0.128	1.000			
Maxdprc	−0.205	−0.001	0.460	0.013	0.005	−0.009	0.030	−0.139	−0.065	−0.029	0.013	−0.124	0.927	1.000		
Prcvol	−0.484	0.014	0.803	0.037	0.077	−0.020	0.310	−0.331	−0.187	−0.320	−0.035	−0.312	0.340	0.339	1.000	
Stdprcvol	−0.442	0.013	0.778	0.050	0.122	−0.013	0.299	−0.297	−0.165	−0.266	−0.035	−0.259	0.342	0.342	0.903	1.000

Panel B Correlation matrix of measures for downside risk

	5%VaR	1%VaR	ES5%	10%ES	10%LPM	50%LPM	β_0^-	β_{mean}^-	10%H-TCR	20%H-TCR
5%VaR	1.000									
1%VaR	0.833	1.000								
5%ES	0.726	0.818	1.000							
10%ES	0.568	0.657	0.917	1.000						
10%LPM	0.669	0.893	0.731	0.582	1.000					
50%LPM	0.837	0.790	0.522	0.302	0.662	1.000				
β_0^-	0.040	0.034	0.020	0.011	0.027	0.011	1.000			
β_{mean}^-	0.039	0.038	0.010	−0.015	0.031	0.077	0.398	1.000		
10%H-TCR	0.637	0.494	0.270	0.085	0.353	0.781	0.065	0.240	1.000	
20%H-TCR	0.500	0.385	0.174	0.018	0.248	0.652	0.110	0.346	0.911	1.000

Table 3
Univariate portfolio analysis
This table reports excess returns and alphas (adjusted with the three-factor model proposed by Liu et al. (2021)) of different cryptocurrency deciles sorted based on *5%VaR* and formed on a weekly basis between January 2016 and December 2020. Portfolio Low is the portfolio of cryptocurrencies with the lowest *5%VaR*, while cryptocurrencies with the highest *5%VaR* comprise portfolio High. All equal-weighted and value-weighted excess returns and alphas are one week ahead of the portfolio formation period. Besides, we also include differences between portfolios High and Low in this table. Newey-West (1987) adjusted t-statistics are presented in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Equal-weighted Excess returns (1)	Alphas (2)	Value-weighted Excess returns (3)	Alphas (4)
Low	0.021**	−0.000	0.020**	−0.004
	(2.193)	(−0.056)	(2.102)	(−1.176)
2	0.022*	−0.007	0.020*	−0.009*
	(1.919)	(−1.257)	(1.850)	(−1.745)
3	0.023*	−0.005	0.020*	−0.009
	(1.963)	(−0.932)	(1.685)	(−1.646)
4	0.023**	−0.005	0.021*	−0.007
	(1.998)	(−0.752)	(1.765)	(−1.235)
5	0.031**	0.000	0.025**	−0.005
	(2.395)	(0.019)	(2.045)	(−0.669)
6	0.031**	0.001	0.026**	−0.003
	(2.519)	(0.121)	(2.258)	(−0.518)
7	0.026**	−0.001	0.021*	−0.006
	(2.092)	(−0.171)	(1.742)	(−0.775)
8	0.040*	0.010	0.031*	−0.001
	(1.944)	(0.580)	(1.748)	(−0.083)
9	0.045***	0.016*	0.033**	−0.000
	(3.222)	(1.761)	(2.470)	(−0.019)
High	0.095***	0.054***	0.075***	0.036***
	(5.353)	(6.123)	(4.311)	(4.408)
High-Low	0.074***	0.054***	0.055***	0.040***
	(6.211)	(7.060)	(4.866)	(5.625)

In view of the short-term predictive power of downside risk for returns, a natural question follows: can downside risk predicts returns in the long term? To offer an answer, we calculate weekly alphas from 2 to 12 weeks after the formation of portfolios.[18] According to Table 4, the predictive power of downside risk on cryptocurrency returns roughly holds over longer horizons. The alpha difference between portfolios High and Low remains significantly positive till 10 weeks after the portfolio formation. The same conclusion can be drawn from the results of excess return differences reported in Table A2 of the online Appendix.

To sum up, the univariate portfolio analysis shows that there is a significantly positive relation between downside risk and cryptocurrency future returns in both the short term and the long term.

3.2. Bivariate portfolio analysis

One potential concern with our findings is that the positive relation between downside risk and future returns may simply reflect other factors' impact on the cross-section of returns in the cryptocurrency market. To mitigate this concern, we derive some cryptocurrency characteristics from the literature on downside risk and cryptocurrencies, such as Liu et al. (2021) and Atilgan et al. (2020). To see which cryptocurrency attribute plays a role in determining the positive relation between downside risk and future returns, we again sort all cryptocurrencies into deciles based on their *5%VaR* on a weekly basis and then compute the time-series means of cross-sectional averages for different cryptocurrencies in each portfolio.

A set of coherent patterns emerges in Table 5. First, the mean *5%VaR* for portfolio Low is 0.031, while that for portfolio High is 0.370, which is consistent with the typical intuition that the cryptocurrency market is extremely volatile (Trimborn and Härdle, 2018). As mentioned earlier, Liu et al. (2021) point out that market return, size, and momentum are instrumental in generating the cross-section of expected returns in the cryptocurrency market. Consequently, in the following three columns, we check the average market beta, size, and momentum in different portfolios. The mean market betas for portfolios Low and High are 0.630 and 1.366, respectively. And the difference between them is significantly positive, implying that cryptocurrencies with higher value-at-risk are more affected by systematic risk. The results of size in different portfolios show that small cryptocurrencies typically have high value-at-risk. Meanwhile, cryptocurrencies with higher value-at-risk also have higher one-week lagged returns.

Additionally, there are some other noteworthy facts about Table 5. In particular, cryptocurrencies with low value-at-risk tend to have abnormally high or low trading volume. And they tend to be more liquid, less lottery-like, and have lower volatility and idiosyncratic volatility. However, unlike evidence from the stock market, we find no significant difference in co-skewness between portfolios Low and High. Considering that co-skewness is widely used to measure assets' own risk with regard to market risk and may impact the relation between downside risk and cryptocurrency return, we still include it in the subsequent analysis.

To rule out the possibility that some cryptocurrency features correlated with value-at-risk have a prominent influence on the cross-section of returns, we exploit two-stage sorts on various cryptocurrency characteristics and *5%VaR*. Specifically, each week, we first divide cryptocurrencies into quintiles based on a given cryptocurrency characteristic. And then, cryptocurrencies are sorted into additional quintiles based on *5%VaR* in each cryptocurrency characteristic quintile. Thus, for every cryptocurrency characteristic employed as the first-stage sort variable, there are a total of 25 portfolios. For brevity, we do not include returns for all 25 portfolios in Table 6. Instead, the return of portfolio Low refers to the average return across cryptocurrencies with the lowest value-at-risk in each cryptocurrency characteristic quintile. Likewise, the return of portfolio High refers to the average return across cryp-

[18] For brevity, portfolio returns presented in tables are value-weighted average returns of all cryptocurrencies in a given portfolio throughout this paper, unless otherwise specified.

Table 4
Long-term portfolio returns
This table shows the long-term return comparisons among cryptocurrency deciles sorted based on *5%VaR* and formed on a weekly basis from January 2014 to December 2020. We present the alphas (adjusted with the three-factor model proposed by Liu et al. (2021)) of value-weighted different portfolios. All alphas are 2–12 weeks ahead of the portfolio formation period. Besides, we also include differences between portfolios High and Low in this table. Newey-West (1987) adjusted t-statistics are presented in parentheses. $*$, $**$, and $***$ indicate the significance at the 10%, 5%, and 1% levels, respectively.

	$t+2$ (1)	$t+3$ (2)	$t+4$ (3)	$t+5$ (4)	$t+6$ (5)	$t+7$ (6)	$t+8$ (7)	$t+9$ (8)	$t+10$ (9)	$t+11$ (10)	$t+12$ (11)
Low	−0.006**	0.001	−0.004	−0.006**	−0.006*	−0.007**	−0.004	−0.007**	−0.006*	−0.005	−0.008**
	(−2.001)	(0.142)	(−1.061)	(−2.106)	(−1.922)	(−2.163)	(−1.335)	(−2.260)	(−1.867)	(−1.451)	(−2.528)
2	−0.008*	−0.010**	−0.009*	−0.009*	−0.009	−0.011**	−0.011**	−0.009*	−0.010**	−0.015***	−0.012***
	(−1.802)	(−2.241)	(−1.817)	(−1.844)	(−1.621)	(−1.970)	(−2.274)	(−1.705)	(−2.002)	(−3.496)	(−2.677)
3	−0.009	−0.008	−0.005	−0.008	−0.012**	−0.010*	−0.013**	−0.011*	−0.014***	−0.011**	−0.014***
	(−1.559)	(−1.370)	(−0.746)	(−1.289)	(−2.372)	(−1.674)	(−2.447)	(−1.957)	(−2.684)	(−2.064)	(−2.705)
4	−0.007	−0.009	−0.015***	−0.010*	−0.007	−0.007	−0.004	−0.007	−0.004	−0.006	−0.005
	(−1.145)	(−1.504)	(−2.707)	(−1.722)	(−1.230)	(−1.102)	(−0.650)	(−1.120)	(−0.793)	(−0.962)	(−0.793)
5	−0.002	−0.007	−0.004	−0.005	−0.003	−0.007	−0.006	−0.005	−0.001	−0.003	−0.009
	(−0.384)	(−1.096)	(−0.717)	(−0.788)	(−0.473)	(−1.258)	(−1.032)	(−0.887)	(−0.222)	(−0.589)	(−1.543)
6	−0.003	−0.008	−0.004	−0.005	−0.006	−0.005	−0.003	−0.000	−0.007	−0.006	−0.002
	(−0.457)	(−1.493)	(−0.600)	(−0.722)	(−0.940)	(−0.728)	(−0.382)	(−0.003)	(−1.120)	(−0.884)	(−0.332)
7	−0.009	−0.003	−0.003	−0.010*	−0.005	−0.006	−0.010	−0.010	−0.009	−0.004	−0.002
	(−1.087)	(−0.397)	(−0.519)	(−1.673)	(−0.806)	(−0.941)	(−1.510)	(−1.483)	(−1.356)	(−0.624)	(−0.234)
8	−0.002	−0.005	−0.008	−0.002	−0.000	−0.002	−0.003	0.000	0.001	0.003	0.004
	(−0.258)	(−0.627)	(−1.390)	(−0.305)	(−0.054)	(−0.296)	(−0.446)	(0.068)	(0.182)	(0.429)	(0.554)
9	0.002	−0.005	0.002	−0.003	−0.012*	0.001	0.005	0.004	−0.003	−0.009	−0.004
	(0.139)	(−0.728)	(0.221)	(−0.558)	(−1.947)	(0.098)	(0.618)	(0.458)	(−0.407)	(−1.566)	(−0.668)
High	0.025***	0.026***	0.019**	0.020**	0.015**	0.011**	0.012**	0.011	0.010	0.009	0.006
	(2.672)	(2.788)	(2.150)	(2.510)	(2.090)	(2.061)	(2.316)	(1.630)	(1.302)	(1.474)	(1.248)
High-Low	0.032***	0.025**	0.023**	0.026***	0.021**	0.018**	0.016**	0.018**	0.015*	0.015	0.013
	(3.661)	(2.327)	(2.255)	(3.512)	(2.353)	(2.026)	(2.136)	(1.989)	(1.763)	(1.612)	(1.449)

Table 5
Average portfolio characteristics
This table shows the time-series averages for *5%VaR* and other cryptocurrency characteristics for cryptocurrency deciles sorted based on *5%VaR* and formed on a weekly basis from January 2016 to December 2020. Portfolio Low is the portfolio of cryptocurrencies with the lowest *5%VaR*, while portfolio High is the portfolio of cryptocurrencies with the highest *5%VaR*. We also include all these characteristic differences between portfolios High and Low in this table. Newey-West (1987) adjusted t-statistics are presented in parentheses. ∗, ∗∗, and ∗∗∗ indicate the significance at the 10%, 5%, and 1% levels, respectively.

	5%VaR (1)	Beta (2)	Size (3)	Mom (4)	Vhigh (5)	Vlow (6)	Abvol (7)	Ivol (8)	Vol (9)	Illiq (10)	Coskew (11)	MAX (12)	Prc (13)	Maxdprc (14)	Prcvol (15)	Stdprcvol (16)
Low	0.031∗∗∗	0.630∗∗∗	16.862∗∗∗	0.023∗∗∗	0.101∗∗∗	0.117∗∗∗	0.021	0.063∗∗∗	0.084	0.001∗∗∗	5.985	0.071∗∗∗	1.107∗∗∗	1.161∗∗∗	11.541∗∗∗	10.622∗∗∗
	(3.670)	(13.985)	(281.711)	(3.679)	(12.941)	(16.211)	(0.821)	(22.191)	(1.353)	(4.526)	(0.904)	(33.731)	(39.769)	(40.839)	(141.086)	(87.758)
2	0.089∗∗∗	0.793∗∗∗	16.634∗∗∗	0.022∗∗∗	0.099∗∗∗	0.123∗∗∗	0.006	0.063∗∗∗	0.010∗∗∗	0.001∗∗∗	6.919	0.102∗∗∗	0.580∗∗∗	0.607∗∗∗	11.288∗∗∗	10.664∗∗∗
	(66.953)	(22.442)	(269.728)	(2.932)	(12.240)	(16.337)	(0.316)	(52.927)	(9.121)	(5.194)	(1.294)	(42.271)	(25.184)	(25.076)	(116.217)	(120.587)
3	0.105∗∗∗	0.868∗∗∗	15.993∗∗∗	0.028∗∗∗	0.096∗∗∗	0.127∗∗∗	0.011	0.075∗∗∗	0.011∗∗∗	0.002∗∗∗	−0.655	0.121∗∗∗	0.411∗∗∗	0.434∗∗∗	10.640∗∗∗	10.085∗∗∗
	(79.894)	(59.259)	(229.068)	(2.984)	(12.413)	(16.384)	(0.551)	(58.083)	(7.967)	(3.611)	(−1.607)	(45.432)	(22.605)	(22.413)	(99.939)	(104.095)
4	0.118∗∗∗	0.900∗∗∗	15.516∗∗∗	0.031∗∗∗	0.095∗∗∗	0.134∗∗∗	−0.016	0.089∗∗∗	0.017∗∗∗	0.002∗∗∗	−1.338	0.134∗∗∗	0.369∗∗∗	0.391∗∗∗	10.079∗∗∗	9.543∗∗∗
	(94.158)	(46.351)	(214.587)	(3.417)	(11.922)	(17.843)	(−0.810)	(61.058)	(13.247)	(4.009)	(−1.585)	(48.913)	(22.814)	(22.900)	(94.773)	(99.760)
5	0.131∗∗∗	0.921∗∗∗	15.195∗∗∗	0.032∗∗∗	0.098∗∗∗	0.127∗∗∗	−0.046∗∗	0.102∗∗∗	0.021∗∗∗	0.003∗∗∗	0.536	0.149∗∗∗	0.331∗∗∗	0.352∗∗∗	9.672∗∗∗	9.150∗∗∗
	(104.807)	(51.167)	(212.655)	(3.273)	(13.477)	(17.458)	(−2.002)	(61.373)	(4.976)	(3.218)	(0.587)	(48.718)	(20.302)	(20.326)	(90.983)	(93.461)
6	0.146∗∗∗	0.910∗∗∗	14.902∗∗∗	0.034∗∗∗	0.099∗∗∗	0.129∗∗∗	−0.026	0.127∗∗∗	0.071∗∗∗	0.003∗∗∗	0.278	0.169∗∗∗	0.298∗∗∗	0.318∗∗∗	9.273∗∗∗	8.820∗∗∗
	(116.510)	(28.539)	(212.777)	(3.496)	(13.556)	(16.421)	(−1.013)	(35.013)	(4.508)	(5.166)	(0.346)	(53.520)	(19.399)	(19.673)	(92.176)	(94.756)
7	0.165∗∗∗	0.861∗∗∗	14.685∗∗∗	0.046∗∗∗	0.096∗∗∗	0.123∗∗∗	−0.028	0.150∗∗∗	0.071∗∗∗	0.005∗∗∗	−2.738	0.199∗∗∗	0.245∗∗∗	0.264∗∗∗	8.852∗∗∗	8.511∗∗∗
	(121.683)	(19.116)	(252.362)	(4.393)	(12.945)	(18.152)	(−0.953)	(40.496)	(6.390)	(3.166)	(−0.512)	(45.866)	(18.860)	(19.244)	(106.298)	(107.306)
8	0.193∗∗∗	1.003∗∗∗	14.324∗∗∗	0.040∗∗∗	0.098∗∗∗	0.118∗∗∗	−0.074∗∗	0.179∗∗∗	0.131∗∗∗	0.009∗	−2.766	0.233∗∗∗	0.238∗∗∗	0.258∗∗∗	8.234∗∗∗	7.954∗∗∗
	(121.024)	(28.011)	(300.181)	(3.877)	(13.315)	(17.678)	(−2.358)	(43.195)	(3.324)	(1.691)	(−0.730)	(51.057)	(18.861)	(19.267)	(127.408)	(118.210)
9	0.237∗∗∗	0.897∗∗∗	13.978∗∗∗	0.061∗∗∗	0.099∗∗∗	0.114∗∗∗	−0.104∗∗∗	0.249∗∗∗	0.160∗∗∗	0.016	3.668	0.304∗∗∗	0.207∗∗∗	0.229∗∗∗	7.378∗∗∗	7.284∗∗∗
	(115.266)	(20.284)	(357.796)	(4.961)	(13.695)	(18.634)	(−3.284)	(40.533)	(9.613)	(1.596)	(0.676)	(45.171)	(17.660)	(18.246)	(117.936)	(109.110)
High	0.370∗∗∗	1.366∗∗∗	13.955∗∗∗	0.156∗∗∗	0.097∗∗∗	0.112∗∗∗	−0.024	0.463∗∗∗	0.395∗∗∗	0.058∗∗	−43.676	0.650∗∗∗	0.182∗∗∗	0.207∗∗∗	6.500∗∗∗	6.636∗∗∗
	(100.576)	(8.082)	(427.890)	(6.216)	(13.839)	(18.565)	(−0.535)	(43.033)	(9.041)	(2.177)	(−1.037)	(38.986)	(19.111)	(20.632)	(90.596)	(82.187)
High-Low	0.339∗∗∗	0.736∗∗∗	−2.907∗∗∗	0.133∗∗∗	−0.004∗∗∗	−0.005∗∗∗	−0.045	0.400∗∗∗	0.311∗∗∗	0.057∗∗	−49.661	0.579∗∗∗	−0.925∗∗∗	−0.954∗∗∗	−5.042∗∗∗	−3.986∗∗∗
	(38.760)	(4.378)	(−60.472)	(5.541)	(−4.550)	(−3.691)	(−1.124)	(39.839)	(3.413)	(2.107)	(−1.157)	(35.696)	(−35.201)	(−35.894)	(−67.333)	(−46.874)

Table 6
Bivariate portfolio analysis
This table reports the alphas (adjusted by the three-factor model proposed by Liu et al. (2021)) of value-weighted bivariate portfolios based on dependent double sorts of a series of cryptocurrency characteristics and *5%VaR* from January 2016 to December 2020. We first form quintile portfolios every week based on a given cryptocurrency characteristic. And then, we additionally form quintile portfolios based on *5%VaR* in each cryptocurrency characteristic quintile. Portfolio Low is the combined portfolio of cryptocurrencies with the lowest *5%VaR* in each cryptocurrency characteristic quintile, while portfolio High is the combined portfolio of cryptocurrencies with the highest *5%VaR* in each cryptocurrency characteristic quintile. The alpha differences between portfolios High and Low are also included in this table. Newey-West (1987) adjusted *t*-statistics are presented in parentheses. $*$, $**$, and $***$ indicate the significance at the 10%, 5%, and 1% levels, respectively.

	Beta (1)	Size (2)	Mom (3)	Vhigh (4)	Vlow (5)	Abvol (6)	Ivol (7)	Vol (8)	Illiq (9)	Coskew (10)	MAX (11)	Prc (12)	Maxdprc (13)	Prcvol (14)	Stdprcvol (15)
Low	−0.013***	−0.004	−0.013***	−0.028***	−0.029***	−0.017***	−0.020***	−0.014**	−0.006	−0.007*	−0.016***	−0.011**	−0.019***	−0.010*	−0.005
	(−4.061)	(−0.964)	(−3.303)	(−6.041)	(−6.532)	(−3.841)	(−3.038)	(−2.296)	(−0.882)	(−1.695)	(−3.132)	(−2.067)	(−3.187)	(−1.670)	(−1.054)
2	−0.021***	−0.013**	−0.020***	−0.010	−0.006	−0.017***	−0.021***	−0.027***	−0.016***	−0.024***	−0.023***	−0.023***	−0.018**	0.010	−0.007*
	(−3.739)	(−2.153)	(−3.483)	(−0.933)	(−0.591)	(−2.643)	(−3.509)	(−3.675)	(−2.846)	(−3.714)	(−3.448)	(−3.401)	(−2.586)	(0.702)	(−1.720)
3	−0.026***	−0.012	−0.027***	0.005	0.008	0.001	−0.019***	−0.010	−0.023***	−0.025***	−0.035***	−0.030***	−0.007	−0.005	−0.008
	(−3.741)	(−1.420)	(−3.972)	(0.887)	(1.640)	(0.114)	(−3.013)	(−1.421)	(−3.707)	(−3.029)	(−6.167)	(−3.996)	(−1.108)	(−0.685)	(−1.207)
4	−0.015	−0.049***	−0.038***	0.010**	0.009	−0.044***	−0.032***	−0.029***	−0.014	−0.018*	−0.023***	−0.040***	−0.007	−0.006	−0.000
	(−1.550)	(−3.482)	(−6.662)	(2.450)	(1.485)	(−3.702)	(−3.522)	(−2.748)	(−1.449)	(−1.876)	(−3.063)	(−6.445)	(−0.660)	(−0.716)	(−0.014)
High	0.007**	0.009*	0.012***	0.018***	0.025***	0.015**	0.005	0.003	0.005**	0.009**	0.012*	0.004**	0.023***	0.006	0.010*
	(2.265)	(1.802)	(2.727)	(3.376)	(3.142)	(2.511)	(1.509)	(1.337)	(2.009)	(2.150)	(1.917)	(2.334)	(4.317)	(1.396)	(1.758)
High-Low	0.020**	0.013**	0.025***	0.047***	0.054***	0.032***	0.024***	0.017**	0.011**	0.016**	0.028**	0.015**	0.042***	0.016**	0.015*
	(1.992)	(2.148)	(3.098)	(7.571)	(5.798)	(5.288)	(3.018)	(2.327)	(2.464)	(2.503)	(2.477)	(2.151)	(5.910)	(2.014)	(1.887)

tocurrencies with the highest value-at-risk in each cryptocurrency characteristic quintile.

Table 6 shows alphas of portfolios sorted first by a cryptocurrency characteristic and then by *5%VaR*. The alphas for most portfolios are negative. However, those of portfolio High are all positive, albeit insignificant for some cases. And regardless of the controlled features, the alpha differences between portfolios High and Low are all significantly positive. We find similar patterns from the excess return results reported in Table A3 of the online Appendix.

3.3. Fama-MacBeth regression analysis

So far, we have demonstrated that downside risk measured by *5%VaR* is a determinant of the cross-section of future returns at the portfolio level in the cryptocurrency market. Despite the advantage of being non-parametric,[19] the portfolio analysis has two obvious drawbacks (Bali et al., 2011). The first one is that via aggregation, the portfolio analysis omits a large amount of information in the cross-section. Another drawback is that it is much more difficult to control for multiple factors that affect returns simultaneously when conducting the portfolio analysis. The typical solution is to run Fama and MacBeth (1973) regressions. Therefore, to better gage the cross-sectional relation between downside risk and cryptocurrency returns, we use Fama and MacBeth (1973) regressions.

We calculate the time-series averages of the slope coefficients from the cross-sectional regressions of one-week-ahead cryptocurrency excess returns on *5%VaR* individually or jointly with other cryptocurrency features (namely *Beta, Size, Mom, Vhigh, Vlow, Abvol, Ivol, Vol, Illiq, Coskew, MAX, Prc, Maxprc, Prcvol*, and *Stdprcvol*). The results are presented in Table 7. In addition to slope coefficients and t-statistics, we also report the average adjusted R^2s over the sample period.

The significantly positive relation between value-at-risk and the cross-section of future cryptocurrency returns emerges clearly from the results of the univariate regression as the slope coefficient of *5%VaR* is 0.207 with a t-statistic of 5.132. In columns (2) - (16), we gradually add other cryptocurrency characteristics (one at a time) into the regression model. Although the t-statistics decline slightly (all larger than 2.8), the slope coefficients of *5%VaR*, ranging from 0.174 to 0.252, remain statistically positive.

Turning the focus to control variables, only a few, i.e., *Size, Mom, Vlow, Ivol*, and *Vol*, are statistically significant. These results imply that other cryptocurrency features cannot fully explain downside risk's predictive power on the cross-section of cryptocurrency returns. Put differently, downside risk contains valuable information distinct from information contained in such cryptocurrency characteristics as market beta, size, past returns, trading volume, idiosyncratic volatility, volatility, illiquidity, co-skewness, and lottery demand.[20]

4. Robustness checks

Although the pattern that cryptocurrencies with high downside risk will earn higher returns than those with low downside risk is clear, issues such as methodological choices and a small number of influential observations might drive our results. To address these concerns, we conduct an extensive set of checks to ensure that the positive relation between downside risk and cryptocurrency returns is robust to sensible alterations of our main setup.

4.1. Alternative downside risk metrics

The downside risk is the focal variable in our study. In addition to value-at-risk, other risk metrics such as expected shortfall, lower partial moment, downside beta, and hybrid tail risk can also be utilized to measure downside risk (Ang et al., 2006; Bali et al., 2014; Atilgan et al., 2019, 2020). If there exists a positive relation between downside risk and future cryptocurrency returns, analyses with other downside risk metrics should yield the same results. To test this prediction, we conduct the univariate portfolio analysis with alternative measures of downside risk and present the results in Table 8. [21]

Panel A reveals that return differences between portfolios with the highest *5%ES* or *10%ES* and the lowest *5%ES* or *10%ES* are also significantly positive. To be concrete, when portfolios are value-weighted, the excess return difference between portfolios with the highest *5%ES* (*10%ES*) and the lowest *5%ES* (*10%ES*) is 5.0% (5.2%) and significant at the 1% level. And the alpha difference between portfolios with the highest *5%ES* (*10%ES*) and the lowest *5%ES* (*10%ES*) is 4.0% (3.6%) with a t-statistic of 2.313 (2.153). Meanwhile, the results are more striking among the equal-weighted portfolios.

The results of Panel B portray a picture consistent with what we find in Table 3. Return differences between portfolios with the highest *10%LPM* or *50%LPM* and the lowest *10%LPM* or *50%LPM* are all significantly positive. This indicates that investors can earn higher profits by buying and holding cryptocurrencies with higher lower partial moment.

Panel C depicts the relation between downside beta and future cryptocurrency returns. Although return differences between portfolios High and Low decline in both value and significance when employing β_0^- or β_{mean}^- to measure downside risk, they are still significantly positive, providing further support to our main conclusion.[22]

Panel D shows how hybrid tail risk is priced in the cross-section of cryptocurrency returns. Consistent with findings of Bali et al. (2014) in the stock market, there is a significantly positive cross-sectional relation between hybrid tail risk and future returns in the cryptocurrency market as the portfolios with the highest *10%H-TCR* or *20%H-TCR* continues to earn higher returns than portfolios with the lowest *10%H-TCR* or *20%H-TCR*.

4.2. Alternative horizons

In the main analyses, we use the 5th percentile of daily returns over the past 90 days as the downside risk metric. Since the choice of 90 days seems arbitrary, we utilize windows of 180 and 360 days to recalculate value-at-risk and redo the univariate portfolio analysis. The results are shown in Table A5 of the online Appendix. The positive tradeoff between downside risk and future returns is quite clear from both excess return and alpha differences between portfolios High and Low when *5%VaR* is calculated over the windows of 180 days (Panel A) and 360 days (Panel B).

[19] Put differently, the main advantage of portfolio analysis is that there is no need to impose a functional form on the relation between downside risk and future returns.

[20] We also present a transition matrix in Table A4 of the online Appendix, i.e., the average probability of a cryptocurrency in one *5%VaR* decile (defined by the rows) in a week will be in another *5%VaR* decile (defined by the columns) in the subsequent 90 days. The results show that value-at-risk is relatively persistent, implying that downside risk is a reliable indicator and an inherent characteristic for cryptocurrencies.

[21] To conserve space, we only report the excess returns and alphas of portfolios High and Low as well as their differences in this table and tables hereafter.

[22] It is worth noting that this finding is inconsistent with findings in the stock market. For instance, Bali et al. (2014) detect no significant relation between downside beta and cross-section of stock returns. As mentioned before, a plausible reason is that cryptocurrency investors are more likely to be affected by behavioral biases such as loss aversion. Hence, they may require higher compensation for taking higher downside risk in the cryptocurrency market.

Table 7
Fama-MacBeth regression
This table shows the results from Fama and MacBeth 1973 cross-sectional regressions of one-week-ahead returns on *5%VaR* and a series of other cryptocurrency characteristics as control variables from January 2016 to December 2020. Coefficients and adjusted R^2 are the time-series averages from weekly Fama and MacBeth (1973) regressions. And the associated t-statistics in parentheses are adjusted with the Newey-West (1987) procedure. All non-return variables are winsorized at the 1% and 99% levels. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
5%VaR	0.207***	0.200***	0.180***	0.182***	0.185***	0.188***	0.174***	0.217***	0.238***	0.239***	0.242***	0.251***	0.252***	0.234***	0.246***	0.235***
	(5.132)	(5.116)	(4.239)	(4.460)	(4.671)	(4.655)	(4.611)	(3.154)	(3.587)	(3.485)	(3.378)	(3.303)	(3.341)	(3.153)	(3.179)	(2.897)
Beta		−0.007	−0.006	−0.009*	−0.010**	−0.011**	−0.010**	−0.009*	−0.010**	−0.007	−0.008*	−0.005	−0.007	−0.005	−0.003	−0.001
		(−1.542)	(−1.319)	(−1.890)	(−2.071)	(−2.249)	(−2.127)	(−1.876)	(−2.072)	(−1.457)	(−1.682)	(−1.214)	(−1.524)	(−0.924)	(−0.599)	(−0.121)
Size			−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004**	−0.004**
			(−3.144)	(−3.518)	(−3.660)	(−3.710)	(−3.254)	(−3.634)	(−4.636)	(−4.439)	(−4.318)	(−3.909)	(−3.737)	(−4.137)	(−2.030)	(−2.023)
Mom				0.027***	0.026**	0.026**	0.021*	0.020*	0.019*	0.023**	0.022**	0.025**	0.025**	0.025**	0.029***	0.028**
				(2.655)	(2.456)	(2.492)	(1.903)	(1.819)	(1.745)	(2.211)	(2.144)	(2.344)	(2.338)	(2.345)	(2.679)	(2.472)
Vhigh					−0.000	−0.002	0.000	−0.002	−0.005	−0.004	−0.005	−0.004	−0.005	0.001	0.004	0.003
					(−0.023)	(−0.262)	(0.005)	(−0.227)	(−0.620)	(−0.460)	(−0.632)	(−0.567)	(−0.589)	(0.136)	(0.417)	(0.333)
Vlow						−0.018***	−0.016***	−0.014**	−0.013**	−0.001	−0.001	−0.003	−0.004	−0.005	−0.005	−0.003
						(−2.785)	(−2.598)	(−2.320)	(−2.180)	(−0.092)	(−0.114)	(−0.305)	(−0.407)	(−0.474)	(−0.544)	(−0.289)
Abvol							0.001	0.003	0.005	0.006	0.007	0.006	0.005	0.005	0.003	0.004
							(0.211)	(0.746)	(1.100)	(1.414)	(1.619)	(1.216)	(1.091)	(1.135)	(0.624)	(0.829)
Ivol								−0.070	−0.414***	−0.410***	−0.431***	−0.351**	−0.397***	−0.354**	−0.362**	−0.316**
								(−1.017)	(−2.716)	(−2.802)	(−2.829)	(−2.333)	(−2.627)	(−2.328)	(−2.324)	(−1.989)
Vol									0.785**	0.773**	0.796**	0.594*	0.749**	0.700**	0.741**	0.691*
									(2.145)	(2.355)	(2.316)	(1.821)	(2.299)	(2.073)	(2.029)	(1.879)
Illiq										26.403*	23.442	20.454	18.195	24.678	27.603	33.663
										(1.672)	(1.645)	(1.505)	(1.337)	(1.200)	(1.162)	(1.389)
Coskew											0.000	0.001	0.001	0.001	0.000	0.000
											(0.467)	(0.871)	(0.970)	(0.871)	(0.759)	(0.468)
MAX												−0.015	−0.009	−0.017	−0.025	−0.036
												(−0.483)	(−0.273)	(−0.518)	(−0.747)	(−0.987)
Prc													0.001	0.042	0.048*	0.053**
													(0.466)	(1.508)	(1.783)	(1.970)
Maxdprc														−0.039	−0.045*	−0.049*
														(−1.464)	(−1.723)	(−1.893)
Prcvol															−0.001	0.002
															(−0.563)	(0.548)
Stdprcvol																−0.002
																(−0.794)
Intercept	−0.005	−0.000	0.041**	0.045**	0.047**	0.052***	0.047**	0.051***	0.084***	0.075***	0.077***	0.068***	0.072***	0.076***	0.073***	0.065***
	(−0.549)	(−0.030)	(2.233)	(2.401)	(2.544)	(2.671)	(2.372)	(2.607)	(4.030)	(3.538)	(3.550)	(3.135)	(3.641)	(3.825)	(3.335)	(2.809)
Adj.R^2	0.84%	1.67%	1.84%	3.02%	3.85%	3.62%	4.16%	5.07%	5.94%	6.97%	7.25%	8.26%	8.24%	8.17%	8.68%	9.16%

Table 8
Alternative downside risk measures
This table presents the results of the univariate portfolio analysis by using alternative downside risk measures. The sorting procedure is the same as that in Table 3. Panel A shows the results by using *5%ES* and *10%ES* as the downside risk metrics. Panel B shows the results by using *10%LPM* and *50%LPM* as the downside risk metrics. Panel C shows the results by using β_0^- and β_{mean}^- as the downside risk metrics. Panel D shows the results by using *10%H-TCR* and *20%H-TCR* as the downside risk metrics. In each panel, we include the excess returns and alphas (adjusted with the three-factor model proposed by Liu et al. (2021)) of equal-weighted and value-weighted portfolios. The excess return or alpha differences between portfolios High and Low are also presented in this table. The sample period is from January 2016 to December 2020. Newey-West (1987) adjusted t-statistics are presented in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A Expected shortfall								
	5%ES				10%ES			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	0.017**	−0.008	0.011	−0.012**	0.013**	−0.002	0.008*	−0.003
	(2.418)	(−1.181)	(1.371)	(−2.574)	(2.141)	(−0.130)	(1.742)	(−0.835)
High	0.080***	0.034**	0.061**	0.028**	0.079***	0.045***	0.059***	0.034**
	(4.869)	(2.010)	(2.473)	(1.996)	(4.799)	(3.543)	(4.149)	(1.974)
High-Low	0.063***	0.043***	0.050***	0.040**	0.066**	0.047**	0.052***	0.036**
	(5.280)	(2.928)	(3.070)	(2.313)	(2.535)	(2.017)	(2.749)	(2.153)

Panel B Lower partial moment								
	10%LPM				50%LPM			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	0.021**	0.009	0.010*	−0.006	0.019**	0.000	0.012*	−0.008
	(2.356)	(0.953)	(1.888)	(−1.256)	(2.543)	(0.033)	(1.888)	(−1.108)
High	0.095***	0.054***	0.062***	0.034*	0.090***	0.047***	0.070***	0.029**
	(6.762)	(5.438)	(4.341)	(1.844)	(6.743)	(4.758)	(4.547)	(2.554)
High-Low	0.074***	0.045***	0.052***	0.040**	0.071***	0.047***	0.058***	0.036***
	(4.001)	(3.038)	(3.558)	(2.384)	(5.548)	(5.191)	(5.291)	(3.001)

Panel C Downside beta								
	β_0^-				β_{mean}^-			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	0.022***	−0.007	0.005	−0.005*	0.026***	−0.001	0.008*	−0.005
	(2.755)	(−1.555)	(1.550)	(−1.842)	(2.853)	(−0.078)	(1.852)	(−0.966)
High	0.069***	0.026***	0.046***	0.023**	0.071***	0.020*	0.050**	0.015*
	(6.869)	(4.654)	(3.968)	(2.355)	(4.804)	(1.889)	(2.069)	(1.749)
High-Low	0.047***	0.032***	0.041**	0.028**	0.046***	0.021**	0.043**	0.020**
	(2.674)	(2.624)	(2.569)	(1.981)	(3.970)	(2.153)	(2.239)	(1.974)

Panel D H-TCR								
	10% H-TCR				20% H-TCR			
	Equal-weighted		Value-weighted		Equal-weighted		Value-weighted	
	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low	0.018**	−0.002	0.020**	−0.003	0.018**	−0.003	0.017*	−0.008**
	(2.087)	(−0.595)	(2.212)	(−0.710)	(2.001)	(−0.823)	(1.820)	(−2.165)
High	0.082***	0.042***	0.076***	0.038***	0.079***	0.041***	0.072***	0.029**
	(5.322)	(5.337)	(4.189)	(3.587)	(5.570)	(5.599)	(4.392)	(2.135)
High-Low	0.064***	0.045***	0.056***	0.040***	0.061***	0.044***	0.056***	0.037**
	(6.264)	(6.440)	(4.223)	(4.258)	(6.664)	(6.636)	(5.133)	(2.538)

4.3. Alternative screens

As mentioned earlier, we restrict our sample to cryptocurrencies that have market capitalization larger than 2 million dollars. In this section, we explore whether our findings still hold with alternative size screen and liquidity screen.

In Panel A of Table A6, a 3-million size screen is applied to the cryptocurrency sample. We repeat the univariate portfolio analysis with cryptocurrencies whose market capitalization is more than 3 million dollars at the end of each week. Compared with the results in Table 3, excess return and alpha differences between portfolios High and Low shrink to some extent. Nonetheless, these differences are still significant at the 1% level.

Given that characteristics associated with size and trading volume affect the relation between downside risk and cryptocurrency returns (as indicated in Tables 6 and 7), there is a concern that our conclusion could be driven by the liquidity of cryptocurrencies. To provide a response, we employ a liquidity screen by excluding cryptocurrencies whose liquidity (measured by the *Illiq*) is among the bottom 33% of the distribution for each week. The analysis results after applying this liquidity screen are reported in Panel B of Table A6. Similar to those in Panel A, the excess return and alpha differences become smaller. However, all of them remain significantly positive.

In a nutshell, these findings suggest that though size and liquidity indeed influence the predictive power of downside risk, they cannot fully determine the relation between downside risk and cryptocurrency returns.

4.4. Short sample

The short sample is a barrier difficult to overcome for studying cryptocurrencies (Liu and Tsyvinski, 2021). This issue is perhaps more severe since we start our sample from 2016 and end it in 2020 (i.e., 5 years of cryptocurrency data) to ensure a sufficient number of observations to do the portfolio analysis. To partially alleviate the short sample concern, we follow Liu and Tsyvinski (2021) and break the sample into halves to check whether our results are stable for these two subsamples. The results are presented in Panel A of Table A7 in the online Appendix. We find that the directions of all results are the same and the magnitude of all results are comparable for the first and second halves of the sample.

Another approach we take to address the short sample issue is to extend our sample period from 2016– 2020 to 2014–2020 and investigate whether there is any alter in our main conclusions. Given that there are a relatively small number of cryptocurrencies traded before 2016, instead of breaking the sample into deciles based on *5%VaR*, we group the sample cryptocurrencies into terciles based on *5%VaR*, following Liu and Tsyvinski (2021). As expected, the results from Panel B of Table A7 are similar to our previous findings, i.e., cryptocurrencies with higher downside risk generate higher returns in the future.

5. Additional analysis

Our results thus far demonstrate that downside risk is a reliable predictor of future cryptocurrency returns. However, several questions remain. For example, what is the source of this downside risk premium, is upside risk also useful in predicting future cryptocurrency returns, can the limits-to-arbitrage theory explain our findings, and is there any intertemporal relation between downside risk and future returns in the cryptocurrency market? In this section, we aim to provide answers to these questions.

5.1. Source of downside risk premium

Since measures used to represent downside risk are not linear functions of high-order moments of the return distribution, it seems worth exploring the phenomenon a bit further if only to help understand the source of this downside risk premium. Following Bai et al. (2019), we investigate whether the high-order moments of cryptocurrency returns, namely volatility (*Vol*), skewness (*Skew*), and kurtosis (*Kurt*), contribute to the predictive power of downside risk.

To do so, we estimate these three measures with a 90-day rolling window. After that, we first check the significance of the cross-sectional relations between them and cryptocurrencies' future returns by conducting the trivariate portfolio analysis. Specifically, to verify the contribution of volatility, we separate all cryptocurrencies into 27 portfolios by using a trivariate dependent sort on *Skew, Kurt*, and then *Vol*. For each sort, breakpoints are determined by the bottom 33% (Low), the middle 33% (Medium), and the top 33% (High). We then repeat the same process to determine the role of skewness and kurtosis. The results from these trivariate portfolio analyses are shown in Panel A of Table 9.

According to the first two columns, the excess return and alpha differences between portfolios High and Low are significantly positive when volatility is utilized as the third-stage sort variable. However, the significance of these differences diminishes when using skewness or kurtosis as the sort variable in the third stage, as shown in columns (3)–(6). Therefore, it seems that volatility premium is the primary source of the downside risk premium.

Next, we run Fama-MacBeth (1973) regressions to see whether volatility contributes the most in determining future cryptocurrency returns. As shown in Panel B of Table 9, only the slope coefficient of volatility is significant when it serves as the explanatory variable individually. Moreover, when we employ all of them to predict the returns of cryptocurrencies jointly, it is evident that both the slope coefficient (0.116) and t-statistic (3.591) of *Vol* are much larger than those of the other two high-order moments of cryptocurrency returns. After incorporating *Beta* and *Size* into the regression, the slope coefficients of *Skew* and *Kurt* are no longer significant. In contrast, the slope coefficient of *Vol* is still positive at the 1% significance level. Our findings collectively imply that volatility plays a dominant role in generating the downside risk premium.

5.2. Upside risk

Considering the role downside risk plays in determining the cross-section of future cryptocurrency returns, a reasonable extension is to test whether upside risk is also useful in predicting future returns.

Following Atilgan et al. (2020), we use *95%VaR* to denote the upside risk. Analogous to the definition of *5%VaR*, *95%VaR* is calculated as the 95th percentile of daily returns in the past 90 days for each cryptocurrency on a weekly basis. Since the value of *95%VaR* is often positive,[23] we do not multiply *95%VaR* with -1.

We first explore the relation between upside risk and cryptocurrency returns with the univariate portfolio analysis. According to Table A8 in the online Appendix, cryptocurrencies in the highest *95%VaR* decile achieve significantly higher excess returns and alphas than those in the lowest *95%VaR* decile, no matter in equal weighting scheme or value-weighting scheme. These findings indicate that investors can earn extra profits by taking upside risk.

However, the positive relation between upside risk and returns can be subsumed by the positive relation between downside risk and returns, as shown in Panel B. Specifically, return differences between portfolios High and Low disappear if we first sort cryptocurrencies into quintiles based on *5%VaR* and then on *95%VaR* (i.e., controlling for downside risk). In sharp contrast, the positive relation between downside risk and future cryptocurrency returns exists independently from the relation between upside risk and future cryptocurrency returns. The excess return and alpha differences between value-weighted portfolios High and Low are 2.8% (with a t-statistic of 3.236) and 1.9% (with a t-statistic of 2.877), respectively, when first utilizing *95%VaR* and then utilizing *5%VaR* as the sort variables.

5.3. Limits to arbitrage

As discussed earlier, our study is motivated by downside risk literature. Nevertheless, there could be another interpretation of our finding, i.e., limits to arbitrage.[24] This is because cryptocurrencies with higher downside risk are relatively small, volatile, and illiquid. The more direct evidence comes from the shrinks in return differences between portfolios High and Low when we use the value weighting scheme and employ a liquidity screen.

To test whether the limits-to-arbitrage theory can explain our findings, we follow Atilgan et al. (2020) and conduct a bivariate independent-sort portfolio analysis. Specifically, we first create an arbitrage index. Based on the previous literature (e.g., Atilgan et al. 2020, Brauneis et al. 2021), we employ the idiosyncratic volatility and the Amihud (2002) illiquidity ratio to measure the arbitrage costs. Since higher idiosyncratic volatility and illiquidity are associated with higher arbitrage costs, we sort cryptocurrencies in increasing order based on their idiosyncratic volatility and illiquidity. Each cryptocurrency is given the score of its decile rank for these two variables. And the arbitrage index is the sum of these scores with a higher value indicating

[23] This means that the larger the *95%VaR*, the higher the upside risk for a given cryptocurrency.

[24] We thank an anonymous referee for proposing this explanation.

Table 9
Source of downside risk premium
This table presents the source of downside risk premium. All cryptocurrencies in the sample are grouped into 27 value-weighted portfolios based on trivariate dependent sorts of volatility (*Vol*), skewness (*Skew*), and kurtosis (*Kurt*). All of these three measures are calculated with a 90-day rolling window. For each sort, breakpoints are determined by the bottom 33% (Low), the middle 33% (Medium), and the top 33% (High). We report the one-week-ahead average excess returns and alphas (adjusted by the three-factor model proposed by Liu et al. (2021)). Columns (1) and (2) show results of the trivariate dependent sort based on skewness, kurtosis, and then volatility. Columns (3) and (4) show results of the trivariate dependent sort based on kurtosis, volatility, and then skewness. Columns (5) and (6) show results of the trivariate dependent sort based on volatility, skewness, and then kurtosis. Panel B reports the average intercepts and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of one-week-ahead market excess returns on the volatility, skewness, and kurtosis with and without control variables. The last row presents the average adjusted R^2s. The sample period is from January 2016 to December 2020. Newey-West (1987) t-statistics are reported in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Panel A Trivariate portfolio analysis

	Vol		Skew		Kurt	
	Excess return	Alpha	Excess return	Alpha	Excess return	Alpha
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.021**	−0.014***	0.031***	−0.008	0.034***	−0.008
	(1.995)	(−3.939)	(2.785)	(−1.407)	(2.767)	(−1.198)
Medium	0.030**	−0.026***	0.037***	−0.024***	0.039***	−0.021***
	(2.476)	(−5.274)	(2.982)	(−4.687)	(3.099)	(−4.066)
High	0.050***	−0.002	0.033***	−0.011*	0.029***	−0.013***
	(3.786)	(−0.270)	(2.598)	(−1.783)	(2.615)	(−3.357)
High-Low	0.028***	0.012**	0.002	−0.003	−0.006	−0.005
	(5.212)	(2.071)	(0.326)	(−0.716)	(−1.340)	(−1.162)

Panel B Fama-MacBeth regressions

	(1)	(2)	(3)	(4)	(5)
Vol	0.087***			0.116***	0.148***
	(3.270)			(3.591)	(3.547)
Skew		0.003		0.009**	0.003
		(1.398)		(2.239)	(0.854)
Kurt			0.000	−0.003**	−0.002
			(−0.674)	(−2.138)	(−1.553)
Size					−0.009***
					(−8.167)
Beta					−0.007
					(−1.132)
Intercept	0.032**	0.031***	0.040***	0.035***	0.157***
	(2.571)	(2.673)	(2.795)	(3.225)	(6.901)
Adj.R^2	3.49%	1.18%	1.21%	5.38%	8.96%

costlier arbitrage for a cryptocurrency. After that, we independently sort cryptocurrencies into *5%VaR* and arbitrage index quintiles each week. According to Atilgan et al. (2020), assets that are costlier to arbitrage are more prone to mispricing. Hence, if the limits-to-arbitrage theory can explain our findings, we should observe that the return difference between portfolios with the highest *5%VaR* and with the lowest *5%VaR* is most striking among cryptocurrencies that are costlier to arbitrage. This is what we find in Table 10.[25]

However, despite the results in Table 10, the limits-to-arbitrage theory is insufficient to account for all our findings, as the positive relation between downside risk and cryptocurrency returns still exists after applying different size and liquidity screens.

5.4. Intertemporal relation

All the above analyses try to explore the relation between downside risk and returns from the cross-sectional perspective. Motivated by the intertemporal relation between downside risk and future returns in the stock market (Bali et al., 2009), we continue to detect whether a similar pattern exists in the cryptocurrency market.

To do so, we first perform the time-series regression at the market level. Specifically, we regress the value-weighted excess market returns on *5%VaR*, which is computed as the 5th percentile of daily excess market returns in the past 90 days at a weekly frequency, and the lagged excess market returns. Somewhat surprisingly, the slope coefficient of *5%VaR* is negative and insignificant in column (1) of Table A9, suggesting no significant intertemporal relation between value-at-risk and market future returns.

Table 10
Limits to arbitrage
This table shows results from the value-weighted bivariate portfolios based on independent double sorts of the arbitrage index and *5%VaR* from January 2016 to December 2020. To calculate the arbitrage index, cryptocurrencies are sorted each week into deciles according to their idiosyncratic volatility and illiquidity. Decile ranks are attributed to each stock increasing in their idiosyncratic volatility and illiquidity. The decile ranks for these attributes are then added together and a weekly arbitrage index that has a maximum value of 20 is constructed. The last row shows the differences of excess returns between *5%VaR* quintiles within each arbitrage index quintile. Newey-West (1987) adjusted *t*-statistics are presented in parentheses. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

	AI1	AI2	AI3	AI4	AI5
Low	0.016*	0.022*	0.027**	0.031*	0.035**
	(1.700)	(1.838)	(1.981)	(1.932)	(2.560)
2	0.021	0.020*	0.015	0.039**	0.036**
	(1.598)	(1.712)	(1.257)	(2.393)	(2.184)
3	0.014	0.019	0.027**	0.041***	0.043*
	(1.360)	(1.518)	(1.993)	(3.310)	(1.741)
4	0.013	0.015	0.029*	0.041	0.045**
	(1.296)	(1.507)	(1.879)	(1.381)	(2.325)
High	0.015	0.026	0.035	0.056***	0.079***
	(0.149)	(0.976)	(0.639)	(2.673)	(5.095)
High-Low	-0.001	0.004	0.008*	0.025**	0.044***
	(-0.705)	(1.391)	(1.794)	(2.377)	(3.443)

[25] Note that because of the short-selling constraints in the cryptocurrency market, this test is somewhat problematic regarding its economic sense. Notwithstanding the issue, this bivariate independent-sort portfolio analysis can still offer us some insights on how limits to arbitrage influence our results.

In a like manner, we also conduct cryptocurrency-level regression analyses with four leading cryptocurrencies, namely Bitcoin, Ethereum, Ripple, and Bitcoin Cash. In these regressions, we control for the potential effect of market excess returns and lagged excess returns on the predictive power of value-at-risk. According to columns (2)–(5), the slope coefficients of *5%VaR* are significant for Ethereum and Bitcoin Cash. However, the slope coefficient of *5%VaR* for Ethereum is negative, while the one for Bitcoin Cash is positive. And neither of the t-statistics in these cases is more than 2. Taken together, we conclude that there is no intertemporal relation between downside risk and future returns in the cryptocurrency market.

6. Conclusions

How downside risk affects asset pricing is an important question in financial economics. While extensive literature has dealt with this topic in various markets, no study in this field focuses on the cryptocurrency market, although this market suffers from big upswings and sudden downturns on a regular basis. In this paper, we undertake this task to explore the relation between downside risk and future cryptocurrency returns.

With the aid of portfolio analyses and Fama-MacBeth (1973) regressions, we demonstrate downside risk's role in determining the cross-section of returns in the cryptocurrency market. To be exact, we document a positive relation between downside risk and future cryptocurrency returns. This result is highly robust for controlling for a series of cryptocurrency characteristics, utilizing different downside risk metrics, employing different screens etc. Moreover, we verify that the downside premium mainly comes from volatility and that the upside risk's predictive power on future returns is dependent on the relation between downside risk and cryptocurrency returns. And in addition to the risk-return tradeoff theory, the limits-to-arbitrage theory can also explain some of the findings. Meanwhile, somewhat surprisingly, we find no significant intertemporal relation between downside risk and future returns in the cryptocurrency market.

Our conclusions complement the literature on downside risk and cryptocurrencies and have implications for pricing other assets that share similar characteristics (e.g., unregulated, extremely volatile, and lacking predictive information) with cryptocurrencies. Additionally, our finding that investors can still be compensated for taking higher downside risk contradicts the argument that cryptocurrency traders are simply risk-seekers (Conlon and McGee, 2019; Pelster et al., 2019).

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Wei Zhang: Resources, Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Yi Li:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Xiong Xiong:** Resources, Conceptualization, Writing – review & editing, Project administration, Funding acquisition. **Pengfei Wang:** Data curation, Writing – review & editing.

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Supplementary materials

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