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Cryptocurrencies’ Price Crash Risk and Crisis Sentiment

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ABSTRACT

We examine the effect of crisis sentiment on cryptocurrencies’ price crash risk. We show that cryptocurrencies’ price crash risk is positively related to the FEARS index, indicating that a higher crisis sentiment by investors increases cryptocurrencies’ price crash risk. Our findings advance the understanding of the consequences of investor sentiment on the cryptocurrency market.

Introduction

Since its moment of creation, about a decade ago, Bitcoin (Nakamoto, 2008) has attracted massive attention among both retail and institutional investors. This phenomenon has resulted in the introduction of other cryptocurrencies and the creation of a new ecosystem, more commonly known as the cryptocurrency market. Over the past few years, this new erratic system has managed to capture the attention of academia, resulting in a growing academic literature, focusing on various aspects of the cryptocurrency market (Corbet et al., 2019). Thus far, the main areas of interest have been the unusually high returns exhibited, along with the high volatility of the cryptocurrency market (Feng et al., 2017; Katsiampa, 2017). Furthermore, topics like market efficiency (Urquhart, 2016; Wei, 2018), hedging capabilities (Urquhart and Zhang, 2019; Conlon and McGee, 2020), asset pricing bubbles (Cheah and Fry, 2015; Corbet et al., 2017), herding behavior (Vidal-Tomás et al., 2018; Ballis and Drakos, 2019) and arbitrage opportunities (Krückeberg and Scholz, 2020) have been highly investigated by the research community. Finally, Edwards et al. (2019) highlighted the concerns that are likely to arise in this emerging asset class.

This study aims at contributing to the expanding literature around the cryptocurrency market by investigating whether investors’ crisis sentiment affects cryptocurrencies’ price crash risk. In particular, we utilize the top 23 cryptocurrencies (as of July 10, 2020), according to market capitalization, over a 6-year period, and we investigate whether the crisis sentiment affects cryptocurrencies’ price crash risk. These top 23 cryptocurrencies cover over 90% of the overall market. Our study contributes to the literature in several ways. First, we provide a new explanation for cryptocurrencies’ price crash risk. Although there are few published works on the determinants of cryptocurrencies’ price crash risk, there is no prior work attempting to directly link investors’ crisis sentiment with cryptocurrencies’ price crash risk. Second, in our study we document that investors’ crisis sentiment is related to irrational behavior and is positively associated with cryptocurrencies’ price crash risk, which constitutes an important complement to traditional explanations for assets’ price crash risk. Finally, our study adds to the growing literature on investor sentiment and its economic consequences (Da et al., 2015; López-Cabarcos et al., 2019; Fu et al., 2020).

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The rest of this paper is organized as follows. The next section presents the data, variables and methodology. Section 3 reports the empirical findings. Finally, Section 4 concludes.

Data, Variables and Methodology

Our initial dataset consists of daily data for the period from September 27, 2014 to June 27, 2020. We obtained data for the cryptocurrencies under scrutiny from www.cryptocompare.com. As dependent variable, we adopt two crash-risk metrics (NCSKEW and DUVOL) derived from the stock price crash literature, firstly proposed by Chen et al. (2001).

The first measure is the negative coefficient of skewness of the weekly returns of each cryptocurrency (NCSKEW). This measure is appropriate when returns are asymmetric, as manifested by negative skewness, and this fits the cryptocurrencies case given that many studies provide evidence that their returns are negatively skewed (see among others Urquhart, 2016; Chaim and Laurini, 2019). Hence, we calculate cryptocurrencies' price crash risk on a weekly interval, as the negative of the third moment of their daily returns, divided by the cubed standard deviation.

$$NCSKEW_{i,t} = \frac{-\left(n(n-1)^{3/2}\sum R_{i,t}^{3}\right)}{(n-1)(n-2)\left(\sum R_{i,t}^{2}\right)^{3/2}} \tag{1}$$

where n stands for the number of daily cryptocurrencies' returns, R is the daily return and i, t stand for cryptocurrency and time, respectively.

The second measure (DUVOL) is less sensitive to extreme returns, as it does not take into account the third moment. DUVOL is defined as follows:

$$\Delta GSVI_t^j = \ln\left(GSVI_t^j\right) - \ln\left(GSVI_{t-1}{}^j\right) \tag{2}$$

The elements n_u and n_d stand for the number of up and down daily returns within a week, respectively. Also, subscripts i, t stand for cryptocurrency and time, respectively. We separate all daily returns below (above) the daily mean return each day, thereby classifying each day as a "down'' ("up'') day. We then calculate the standard deviation for the down and up days separately. Finally, we calculate the log ratio of the standard deviation of the down days to the standard deviation of the up days.

Following the price crash risk literature (e.g., Jia, 2018; Kalyvas et al., 2020; Fu et al., 2020), we winsorize the variables at the 1st and 99th percentiles.

Following the methodology of Da et al. (2015), we employ (seven day) daily internet search volume data[1] (GSVI hereafter) extracted from the Google Trends database in order to construct the *Financial and Economic Attitudes Revealed by Search* (FEARS) index.

Letting j, t to denote the search term and time (days), we calculate the daily changes for each search term as follows:

$$\Delta GSVI_t^j = \ln\left(GSVI_t^j\right) - ln\left(GSVI_{t-1}{}^j\right) \tag{3}$$

Then, following Da et al. (2015) we proceed as follows: First, we winsorize each original ΔGSVI time series at the 5% level (2.5% in each tail) to remove any potential outliers. Then, also as in Baker and Wurgler (2006), each deseasonalized time series is scaled by its corresponding standard deviation to diminish heteroscedasticity. Defining ΔAGSVI as the adjusted deseasonalized, winsorized and standardized daily change for each search term j at period t, then the FEARS index reads as follows:

$$FEARS_t = \frac{1}{30}\sum_{j=1}^{30}\Delta AGSVI_t^j \tag{4}$$

According to Da et al. (2015), these specific GSVIs incorporated into the FEARS index are able to capture investors' crisis sentiment before it is entirely incorporated into the market.

We estimate both univariate and multivariate regression models. In the multivariate regression, we control for the following determinants:

(i) the US economic policy uncertainty index (EPUI) of Baker et al., (2016). This daily news-based indicator captures the general level of economic uncertainty in the US.
(ii) the CBOE implied volatility index (VIX), which measures the uncertainty in the US equity (source: Bloomberg).
(iii) the MSCI All Country World Index (MSCI) (source: Bloomberg).

Following Wu et al. (2019) and Kalyvas et al. (2020), we only employ potential determinants that are US-based due to US economy's prominent position in the financial markets around the world. All variables are expressed in percentage changes.

To examine the relationship between cryptocurrencies' price crash risk and investors' crisis sentiment, we employ the following univariate and multivariate econometric specifications:

[1] The main merit of employing internet search volume data for capturing public sentiment is that by doing so we are able to get insights on how agents actively seek information on their topics of interest (McLaren and Shanbhoge, 2011).

$$CrashRisk_{i,t} = a + \lambda_1 \times FEARS_t + u_{i,t} \quad (5)$$

$$CrashRisk_{i,t} = a + \lambda_1 \times FEARS_{t-1} + u_{i,t} \quad (6)$$

$$CrashRisk_{i,t} = a + \lambda_1 \times FEARS_t + \sum_{i=1}^{q} \gamma_i \times controls_t + u_{i,t} \quad (7)$$

$$CrashRisk_{i,t} = a + \lambda_1 \times FEARS_{t-1} + \sum_{i=1}^{q} \gamma_i \times controls_t + u_{i,t} \quad (8)$$

$$CrashRisk_{i,t} = a + \lambda_1 \times FEARS_{t-1} + \sum_{i=1}^{q} \gamma_i \times controls_{t-1} + u_{i,t} \quad (9)$$

In the above equations the dependent variable (*CrashRisk*) is measured by NCSKEW or DUVOL. The main explanatory variable is *FEARS* and the *controls* as discussed above. We estimate the above models with the Fixed Effects methodology with cluster robust standard errors (Wooldridge, 2010). We have also estimated our models with the Random Effects methodology and the results remained unaffected. However, the Hausman (1978) test suggested that Fixed Effects is the most appropriate methodology, and thus we only report the results of this method in the next section.

Table A1 in the Appendix reports the main descriptive statistics for each variable under scrutiny.

Results

In Table 1, we report the estimation results with NCSKEW being the main independent variable. We find that the FEARS index exerts a positive and statistically significant impact on the price crash risk of the cryptocurrencies. In other words, a higher FEARS index increases the so-called investors' crisis sentiment, which in turn increases cryptocurrencies' price crash risk. Our results suggest that a higher internet search intensity of crisis-related keywords on the previous week foreshadows a higher price crash risk in the cryptocurrencies' market. Regarding the control variables in the multivariate regressions, our results are compatible with those of Kalyvas et al. (2020).

Then we proceed to the results from models in which we employ DUVOL as our second measure of cryptocurrencies' price crash risk (see Table 2). When we change our independent variable, our findings are consistent with those of Table 1 since we find once again a positive and significant association between the cryptocurrencies' price crash risk and FEARS index. In other words, when investors become more (less) aware of the crisis-related keywords incorporated into the FEARS index, cryptocurrencies' price crash risk increases (declines). This finding is consistent with this of López-Cabarcos et al. (2019) since we find that cryptocurrencies' investors pay much attention to the information steaming from the Google Searches of the crisis-related keywords. Finally, our results indicate that when investors have a relatively high crisis sentiment, then they should not rely on cryptocurrencies as an alternative investment.

Conclusions

Cryptocurrencies are assets that face very often periods of extreme bubbles and have significant volatility. These two elements make them risky assets, therefore having an increased probability of price crash risk.

Having as a working environment the determinants of price crash risk, we extend the literature in a threefold manner: (i) we augment the assets under scrutiny, not limited to Bitcoin (as in Kalyvas et al., 2020), by considering the top 23 cryptocurrencies in terms of capitalization which account for over 90% of the total market capitalization, and thus offer a near holistic treatment of the

Table 1
Fixed Effects Estimation Results for NCSKEW

	Dependent variable: NCSKEW(t)				
VARIABLES	Univariate regressions		Multivariate regressions		
FEARS(t)	0.372 [0.395]	-	0.442[0.396]	-	-
EPUI(t)	-	-	-0.077*** [0.023]	-0.078***[0.023]	-
VIX(t)	-	-	-2.546***[0.889]	-2.569***[0.881]	-
MSCI(t)	-	-	-4.986***[0.791]	-4.936***[0.804]	-
FEARS(t-1)	-	0.612**[0.263]	-	0.497*[0.262]	0.643**[0.262]
EPUI(t-1)	-	-	-	-	0.138***[0.025]
VIX(t-1)	-	-	-	-	-7.326[5.202]
MSCI(t-1)	-	-	-	-	-16.693***[4.767]
Constant	-0.135***[0.001]	-0.934***[0.297]	-0.107***[0.006]	-0.106***[0.006]	-0.157***[0.005]
Observations	4,981	4,974	4,981	4,974	4,974
R^2	0.000	0.001	0.010	0.010	0.004

Notes: (a) *, **, *** denote statistical significance at the 10, 5 and 1 percent level respectively, (b) numbers in brackets denote cluster robust standard errors.

Table 2
Fixed Effects Estimation Results for DUVOL

	Dependent variable: DUVOL(t)				
VARIABLES	Univariate regressions	Multivariate regressions			
FEARS(t)	0.551 [0.374]	-	0.588 [0.376]	-	-
EPUI(t)	-	-	0.063**[0.023]	0.062** [0.023]	-
VIX(t)	-	-	-1.380*[0.779]	-1.402*[0.777]	-
MSCI(t)	-	-	-2.751***[0.815]	-2.666***[0.827]	-
FEARS(t-1)	-	0.740** [0.274]	-	0.678** [0.265]	0.770** [0.275]
EPUI(t-1)	-	-	-	-	0.112*** [0.031]
VIX(t-1)	-	-	-	-	0.374 [0.696]
MSCI(t-1)	-	-	-	-	-9.047 [6.514]
Constant	-0.501***[0.001]	-0.501***[0.001]	-0.504***[0.006]	-0.504***[0.005]	-0.519***[0.007]
Observations	4,258	4,252	4,258	4,252	4,252
R^2	0.001	0.001	0.005	0.005	0.005

Notes: (a) *, **, *** denote statistical significance at the 10, 5 and 1 percent level respectively, (b) numbers in brackets denote cluster robust standard errors.

Table A1
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
NCSKEW	4,981	-0.13	1.52	-2.50	2.38
DUVOL	4,258	-0.49	1.38	-3.18	1.88
FEARS	6,923	-0.002	0.05	-0.33	0.25
EPUI	6,923	109.53	91.77	35.08	600.36
MSCI	6,923	464.63	52.43	359.09	579.63
VIX	6,923	16.69	7.74	9.44	69.16

cryptocurrency market, (ii) as a consequence of these, given the resulting panel structure of the dataset we conduct an econometric analysis utilizing the appropriate panel estimation techniques, and (iii) we offer a further, and perhaps a more innovative in nature, extension by considering another potential determinant of price crash risk, namely crisis sentiment proxied by the FEARS index.

We find that investors' crisis sentiment, as captured by the FEARS index, has a noticeable positive impact on cryptocurrencies' market price crash risk. Our results are in line with those of Subramaniam and Chakraborty (2020) since we also find that investors' attention influence cryptocurrencies' prices and thus their price crash risk behavior. In addition, cryptocurrencies are not fundamental-driven. Thus, in the absence of fundamentals, the evidence that investors' attention to crisis-related keywords is able to affect the cryptocurrency market can have tremendous value in shaping the trading strategies for both the newer and established cryptocurrencies.

Declaration of Competing Interest

No conflict of interest exists in the submission of this manuscript, and this manuscript is approved by all authors for publication.

Disclaimer

The views and opinions expressed in this paper are those of the authors and do not reflect those of their respective institutions.

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