Explosivity in the Cryptocurrency Market: A Panel GSADF Approach

Anoop S Kumar*, Hafsal K** and S Anandarao***

The paper studies the synchronized explosive behavior in six major cryptocurrency prices by employing a recursive panel Generalized Supremum Augmented Dickey-Fuller (GSADF) unit root test method. Towards this purpose, daily log prices of six cryptocurrencies—Bitcoin, Ethereum, Ripple, Nem, Dash and Litecoin—are employed for the period August 7, 2015 to May 31, 2020. Using the GSADF unit root test, the study finds strong evidence in favor of explosivity in the individual currencies and the panel. Employing the recursive Backwards Supremum ADF (BSADF) date-stamping procedure, significant periods of explosive behavior in the individual cryptocurrencies are identified. In the next stage, the possible exogenous and endogenous reasons behind the explosive price movements are identified. Finally, the panel GSADF analysis is employed and a common turbulent period during 2017-18 is identified, coinciding with the cryptocurrency boom and the subsequent crash of 2018 January. The study presents evidence suggesting synchronization in the cryptocurrency market during the periods of turbulence. Based on the results, the study does not recommend investing in a cryptocurrency portfolio.

Introduction

Cryptocurrencies have been a matter of hot discussion both in academia and the investor community since their inception. Cryptocurrencies are digital financial assets for which records and transfers of ownership are guaranteed by cryptographic technology rather than a bank or other trustworthy third party. However, cryptocurrencies can be described as a set of asset classes as they have fundamental economic connections to other assets but with distinct characteristics (Greer, 1997). Apart from not being considered legal tender money, cryptocurrencies have neither intrinsic value nor promise to pay any sum (Geuder *et al.*, 2019). The lack of an intrinsic value and the substantial changes in their price gave rise to a discussion in the financial literature.

* Assistant Professor, Gulati Institute of Finance and Taxation, Sreekaryam, Thiruvananthapuram 695017, Kerala, India; and is the corresponding author. E-mail: askumar@gift.res.in

** Research Associate, IIM Bangalore, Bengaluru 560076, Karnataka, India. E-mail: hafsal.k2020@gmail.com

*** Assistant Professor, Department of Economics, SRM University, Amaravathi 522502, Andhra Pradesh, India. E-mail: suvvari.anand@gmail.com

The growth in the prices of Bitcoin and other cryptocurrencies in recent years has attracted remarkable attention. According to coincapmarket.com, the price of Bitcoin was $134.21 in April 2013, and it was $50,000 in April 2021. The compound annual growth rate is around 109%, which is enormous. There are 9,671 (according to coinmarketcap.com) cryptos with 376 exchanges with a market cap of $2.3 tn. Bitcoin is dominant with a massive 50% of the market share among all cryptocurrencies, followed by Ethereum with nearly 15% and Binance coin and Dogecoin with 4.23% and 1.76%, respectively. Bitcoin's supremacy in the cryptocurrency market has gradually reduced due to other cryptocurrencies (Bouri *et al*., 2019).

The amount of transparency and decentralization inherent in the cryptocurrency market is significantly more than any traditional financial market. Further, the level of regulation existent in any of these marketplaces is almost nil. The Bitcoin market should be informationally efficient and free of extreme explosive occurrences in such a circumstance. However, the research shows a different picture. Unlike other financial assets, cryptocurrencies have been prone to severe price movements. In the literature, we can find studies discussing the volatile nature of the cryptocurrency market and the volatility spillover across different cryptocurrencies (e.g., Baur and Dimpfl, 2018; Katsiampa, 2018; Yi *et al*., 2018; Katsiampa, 2019; and Kumar and Anandarao, 2019, to name a few). The excessive volatility and rapid price appreciation in cryptocurrencies indicate possible price explosiveness and bubble-like behavior in cryptocurrency prices. We examine select studies in the forthcoming paragraphs.

MacDonell (2014) studied bubbles in Bitcoin using the Log-Periodic Power Law (LPPL) model. He found bubbles at the end of 2013. He established a relationship between variables such as news index, Chicago Board of Exchange Market Volatility Index (VIX), exchange rate and gold rush on Bitcoin, and explosive price behavior. Cheah and Fry (2015) studied the speculative bubbles in Bitcoin returns and found that Bitcoin prices are prone to substantial bubbles and identified that Bitcoin's fundamental value is zero.

A commonly used method to capture explosive behavior in cryptocurrency markets is the recursive unit root testing procedure. Cheung *et al*. (2015), Su *et al*. (2018), and Bouri *et al*. (2018) employed the recursive unit root test of Phillips *et al*. (2015) and found the presence of bubbles in the Bitcoin market. Geuder *et al*. (2019) employed both LPPL and Generalized Supremum Augmented Dickey-Fuller (GSADF) methods to identify the bubble behavior in the Bitcoin market.

Fry and Cheah (2016) identified negative bubbles in two cryptocurrencies, namely, Bitcoin and Ripple. Further, they found a spillover from Ripple to Bitcoin, affecting the price drops in Bitcoin. Corbet *et al*. (2018) analyzed Bitcoin and Ethereum prices and found multiple explosive behavior instances in both the markets.

Bouri *et al*. (2018) attempted to study the co-explosivity among the seven cryptocurrencies to check whether explosivity in one market can lead to explosivity in other markets. They employed the GSADF method of Phillips *et al*. (2015). They used a logistic regression model to see if the explosive behavior in a market leads to volatile behavior in other markets. The results indicated evidence of a multidirectional co-explosivity irrespective of the market size and age.

After going through the studies mentioned above, it is clear that there is no research discussing possible synchronization among explosive price behavior across different cryptocurrencies. While Bouri *et al*. (2018) identified the possibility of co-explosivity in the market, they could not identify periods of synchronized explosive behavior in the cryptocurrency market. Considering the already existing evidence related to volatility spillover and co-movement across cryptocurrencies, synchronized explosive behavior in cryptocurrency prices looks like a definite possibility.

The present study intends to analyze and provide answers to this question. In this study, we first investigate the episodes of exuberance in individual cryptocurrency markets. Next, we test for any possible synchronization across cryptocurrencies, leading to common exuberance among the markets. By addressing these issues, the study helps to improve the proper understanding of the cryptocurrency markets to facilitate and manage investment opportunities. We employ recursive univariate unit root tests Supremum Augmented Dickey-Fuller (SADF) and GSADF, recently developed by Phillips *et al*. (2011) and Phillips *et al*. (2015), to analyze the individual market price explosiveness. To get an overall picture of price exuberance in the cryptocurrency market, we employ the panel GSADF test of Pavlidis *et al*. (2016). To the best of our knowledge, this is the first study analyzing the explosiveness in the cryptocurrency market using a panel framework to identify possible synchronization in explosive behavior. The method delivers a consistent date stamping strategy for the origination and termination of explosive price behavior in the markets.

The rest of the paper is structured as follows: the next section describes the data and methodology employed, followed by a discussion on the empirical findings. Finally, the last section provides conclusion.

Data and Methodology

We employed daily close prices of six major cryptocurrencies, namely, Bitcoin, Ethereum, Litecoin, Nem, Dash and Ripple for the period August 7, 2015 to May 31, 2020. The cryptocurrencies were selected based on their market share. We selected this particular period for analysis as the cryptocurrencies started gaining the attention of the investors during this period. The starting date was selected based on the data availability. We have downloaded the data from coinmarketcap.com, a cryptocurrency data aggregation website. In order to avoid the scale difference, we have calculated the log values of the cryptocurrency prices and used them in the estimation.

To identify the explosive behavior in the cryptocurrencies, we have employed univariate SADF of Phillips *et al*. (2011), the GSADF of Phillips *et al*. (2015) as well as the panel GSADF of Pavlidis *et al*. (2016) test for multivariate analysis.

The Univariate SADF and GSADF Tests

We test for the explosiveness for cryptocurrencies implementing forward recursive application of Augmented Dickey-Fuller (ADF) unit root test and its variants, i.e., the SADF and GSADF tests. Both SADF and the GSADF are based on the following ADF structure,

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \Sigma_{i-1}^{k} \varphi_{r_1,r_2}^{i} \Delta P_{t-i} + \varepsilon_t, \varepsilon_t \sim^{iid} N(0, \sigma_{r_1,r_2}^2) \quad ...(1)$$

where P_t is the price series, r_1 and r_2 indicate window fractions of the total sample size, specifying the starting and ending points of each window and k is the lag length. The emergence of the explosive behavior is indicated by the shift from random walk against the null of unit root, i.e., the series is $I(1)$. Therefore, we test the null hypothesis of $H_0 : \beta_{r1,r2} = 0$, against the alternative of $H_1 : \beta_{r_1,r_2} > 0$. Then the test statistics is:

$$ADF_{r_1}^{r_2} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})} \quad ...(2)$$

If we set $r_1 = 0$, $r_2 = 1$, then the test statistic is reduced to the standard ADF statistic ADF_0^1. The limiting distribution of ADF_0^1 is given by:

$$\frac{\int_0^1 W dW}{\left(\int_0^1 W^2\right)^{\frac{1}{2}}}$$

where W is a Wiener process. The ADF test compares the ADF_0^1 statistic with the right-tailed critical value and the null of unit root is rejected when the test statistic exceeds the corresponding critical value. The standard ADF test has low power while dealing with extreme price movements. In order to address this issue, Phillips and Yu (2011) proposed a recursive unit root procedure for the estimation of $ADF_{r_1}^{r_2}$ using different subsamples to identify explosive price movements.

We estimate the ADF regression after normalizing the end of the original sample to $T = 1$ and using a forward expanding sample with the end of the sample period r_2 increasing from $r0$ (the minimum window size) to 1 (the last observation). Initially, the sample is held constant at $r1 = 0$, and the expanding window size of the regression is denoted by $r_w = r_2 - r_1$. We keep the starting point fixed at $r_1 = 0$ and recursively estimate the ADF regression while increasing the window size r_2 by adding an additional observation till we reach the last data point. Each estimation provides us with an ADF statistic, $ADF_0^{r_2}$. The test statistic is the supremum value of the $ADF_0^{r_2}$ (SADF), defined as:

$$SADF(r_0) = \sup_{r_2 \in [r_0,1]} ADF_0^{r_2} \qquad ...(3)$$

As *SADF* may not consistently identify multiple periods of explosiveness, Phillips *et al.* (2015) proposed the GSADF to identify multiple episodes of explosiveness. The GSADF methodology uses a rolling and recursive sample as like SADF statistics, covering large number of subsamples by allowing changes in both the initial point (r_1) and the end point (r_2). The GSADF statistic is defined as:

$$GSADF(r_0) = \sup_{r_2 \in [r_0,1], r_1 \in [0, r_2 - r_0]} ADF_0^{r_2} \qquad ...(4)$$

Both the SADF and GSADF tests help us to date-stamp periods with explosive behavior. We employ a Backwards Supremum ADF (BSADF) procedure to identify periods with explosive behavior (Phillips *et al.*, 2015). The origination date of the period of exuberance is defined as the first observation for which the BSADF statistic exceeds its critical value,

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} \{r_2 : BSADF_{r_2}(r_0) > CV(BSADF_{r_2 T})\} \qquad ...(5)$$

and the termination date as the first observation after $\hat{r}_e$ for which the BSADF falls below its critical value:

$$\hat{r}_f = \inf_{s \geq \hat{r}_e} \{r_2 : BSADF_{r_2}(r_0) < CV(BSADF_{r_2 T})\} \qquad ...(6)$$

The Panel GSADF Procedure

Pavlidis *et al.* (2016) extended GSADF method into a panel analysis. The proposed panel GSADF is:

$$\Delta P_{it} = \alpha_{i,r_1,r_2} + \beta_{i,r_1,r_2} P_{i,t-1} + \sum_{i-1}^{k} \varphi_{i,r_1,r_2}^{j} \Delta P_{i,t-i} + \varepsilon_{i,t}, \varepsilon_{it} \sim^{iid} N(0, \sigma_{i,r_1,r_2}^2) \qquad ...(7)$$

where *i* denotes the individual series and the other variables are explained as in the previous sub-section. We test the null hypothesis of a unit root, $H_0 = \beta_{i,r_1,r_2} = 0$ for all N coins, against the alternative of explosive behavior in a subset of coins, $H_1 = \beta_{i,r_1,r_2} > 0$ for some *i*, allowing for β_{i,r_1,r_2} to differ across coins. We rewrite the univariate test statistics as:

$$ADF_{i,r_1}^{r_2} = \frac{\hat{\beta}_{i,r_1,r_2}}{s.e.(\hat{\beta}_{i,r_1,r_2})} \qquad ...(8)$$

$$SADF_{i,r_1}^{r_2} = \sup_{r_2 \in [r_1, r_2]} ADF_{i,r_1}^{r_2} \qquad ...(9)$$

$$BSADF_{i,r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} SADF_{i,r_1}^{r_2} \qquad ...(10)$$

where i denotes the i^{th} coin under analysis. Using this, we define the panel BSADF statistics is:

$$Panel\,BSADF_{r_2}(r_0) = \frac{1}{N}\Sigma_{i=1}^{N} BSADF_{i,r_2}(r_0). \qquad ...(11)$$

The panel GSADF stat is supremum of panel BSADF statistic:

$$Panel\,GSADF(r_0) = \sup_{r_2 \in [r_0, r_1]} Panel\,BSADF_{r_2}(r_0) \qquad ...(12)$$

A sieve bootstrap approach, designed to resolve the problem of using cross-correlated errors in the panel framework, is employed to estimate critical values. Dating the episodes of exuberance in the panel is performed by comparing the Panel BSADF values with the essential sequence of bootstrap values. Panel GSADF procedure has been successfully implemented to capture synchronized explosive behavior in house prices (Pavlidis *et al.*, 2019), equity markets (Liaqat *et al.*, 2019) and energy markets (Li *et al.*, 2020).

Results and Discussion

Table 1 summarizes the univariate SADF and GSADF results, whereas panel GSADF test results are shown in Table 2. We present the test statistic and 90%, 95% and 99% critical

Table 1: Individual SADF and GSADF Test Results

Currency	Bitcoin		Ethereum		Ripple	
	SADF	GSADF	SADF	GSADF	SADF	GSADF
Test Statistic	2.92***	3.28***	1.21	3.82***	6.28***	8.51***
90% Critical Value	1.36	2.21	1.36	2.21	1.36	2.21
95% Critical Value	1.58	2.45	1.58	2.45	1.58	2.45
99% Critical Value	2.08	3.02	2.08	3.02	2.08	3.02
Currency	Nem		Dash		Litecoin	
	SADF	GSADF	SADF	GSADF	SADF	GSADF
Test Statistic	1.54*	4.86***	3.38***	4.95***	4.39***	4.78***
90% Critical Value	1.36	2.21	1.36	2.21	1.36	2.21
95% Critical Value	1.58	2.45	1.58	2.45	1.58	2.45
99% Critical Value	2.08	3.02	2.08	3.02	2.08	3.02

Note: The null hypothesis is that there is a unit root and the alternative that there is explosive behavior. *** and * indicate the rejection of null at 1% and 10% significance levels.

Table 2: Panel GSADF Statistics	
	GSADF
Test Statistic	3.16***
90% Critical Value	0.42
95% Critical Value	0.47
99% Critical Value	0.54

Note: The null hypothesis is that there is a unit root and the alternative that there is explosive behavior. *** indicates the rejection of null at 1% significance.

values for each cryptocurrency. If the test statistic exceeds its critical value, we reject the null hypothesis of a unit root. The univariate SADF and GSADF tests provide evidence of explosive price behavior for all cryptocurrency markets. The SADF test rejects the null of unit root for Bitcoin, Dash and Litecoin at 1% significance, whereas in the case of Nem, the null is rejected at 10% significance. Looking at the GSADF test results, we can see that the null of unit root is rejected in favor of explosive behavior for all the cryptocurrencies. Notably, both tests reject the null of unit roots, and we find evidence of volatile behavior for all cryptocurrency markets. The GSADF tests for the cryptocurrency prices point towards the possibility of multiple episodes of explosive price behavior.

From Table 2, we can see that the null of unit root behavior for the whole panel is rejected at 1% significance, pointing towards synchronized explosive behavior in the cryptocurrency market. Since the test results indicate strong evidence of exuberance in all cryptocurrency markets, we employ the BSADF testing procedure to date stamp the origin and collapse date of the explosive periods for each market. We consider a duration of a minimum of 10 days to count as explosive behavior for analytical purposes. We show the periods of explosive behavior in Table 3.

Table 3: Periods of Explosive Behavior

Currency	Start	End	Duration	Currency	Start	End	Duration
Ripple	3/31/2017	4/11/2017	11	Litecoin	04/22/2017	05/26/2017	34
	4/29/2017	7/10/2017	72		06/16/2017	07/14/2017	28
	12/21/2017	1/16/2018	26		12/09/2017	01/11/2018	33
Bitcoin	06/01/2016	06/21/2016	10	Panel	05/30/2016	06/09/2016	10
	12/27/2016	01/06/2017	10		06/10/2016	06/21/2016	11
	05/31/2017	06/14/2017	14		03/11/2017	03/17/2018	371
	08/22/2017	09/04/2017	13		11/19/2018	12/19/2018	30
	10/31/2017	11/10/2017	10				
	11/15/2017	1/11/2018	57				

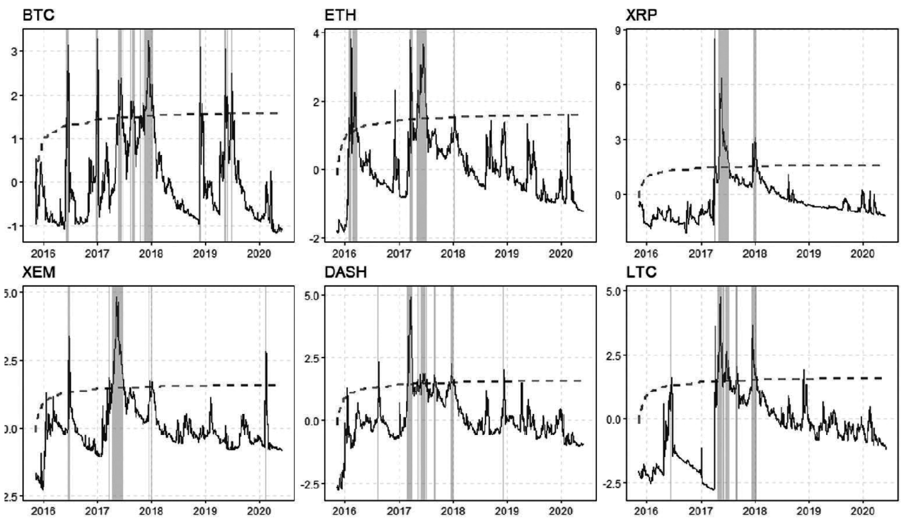
Table 3 (Cont.)

Currency	Start	End	Duration	Currency	Start	End	Duration
Ethereum	02/07/2016	2/17/2016	10				
	2/22/2016	03/18/2016	25				
	3/19/2017	04/03/2017	15				
	4/28/2017	07/17/2017	70				
NEM	04/14/2017	06/27/2017	74				
DASH	02/28/2017	04/02/2017	33				
	06/08/2017	06/26/2017	18				
	08/24/2017	09/04/2017	11				
	12/12/2017	12/30/2018	18				

Note: The dates against each cryptocurrency indicates the beginning and end of explosive behavior observed in the particular cryptocurrency price series. "Start" indicates the starting of a particular episode of explosive behavior, "End" indicates the ending of the explosive behavior, and "Duration" gives the total duration of explosive behavior in days. The standard periods of explosive behavior of the cryptocurrency market are identified under the "Panel" section.

Figure 1 exhibits the periods during which the individual currencies demonstrated explosive dynamics, identified by the periods during which the estimated BSADF statistics exceed the

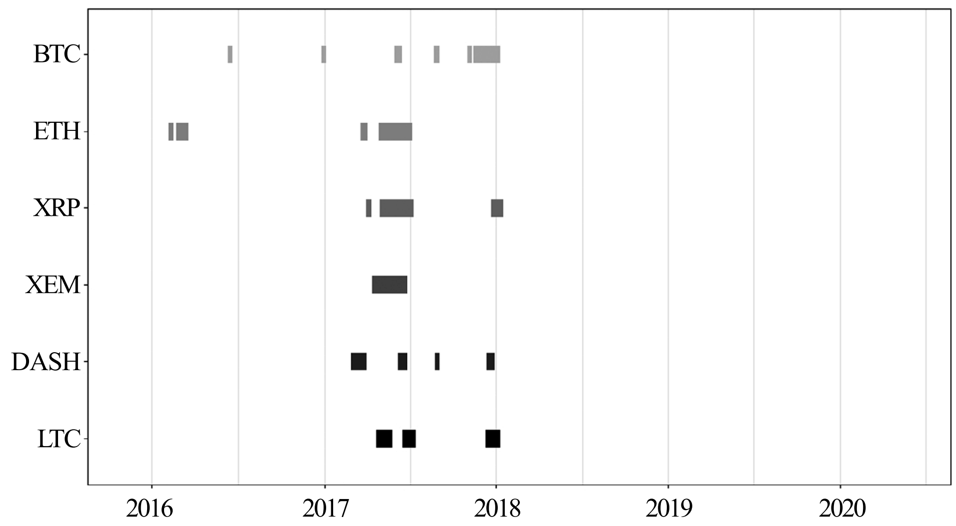
Figure 1: Explosive Behavior of Individual Cryptocurrencies



Note: BTC indicates Bitcoin, ETH indicates Ethereum, XRP indicates Ripple, XEM indicates NEM, DASH indicates Dashcoin and LTC indicates Litecoin.

corresponding critical values, explosive periods (shaded area) for all individual currencies. Figure 2 provides a comparison of significant explosive periods.

Figure 2: Explosive Behavior Period Comparison for Individual Cryptocurrencies



Note: BTC indicates Bitcoin, ETH indicates Ethereum, XRP indicates Ripple, XEM indicates NEM, DASH indicates Dashcoin and LTC indicates Litecoin.

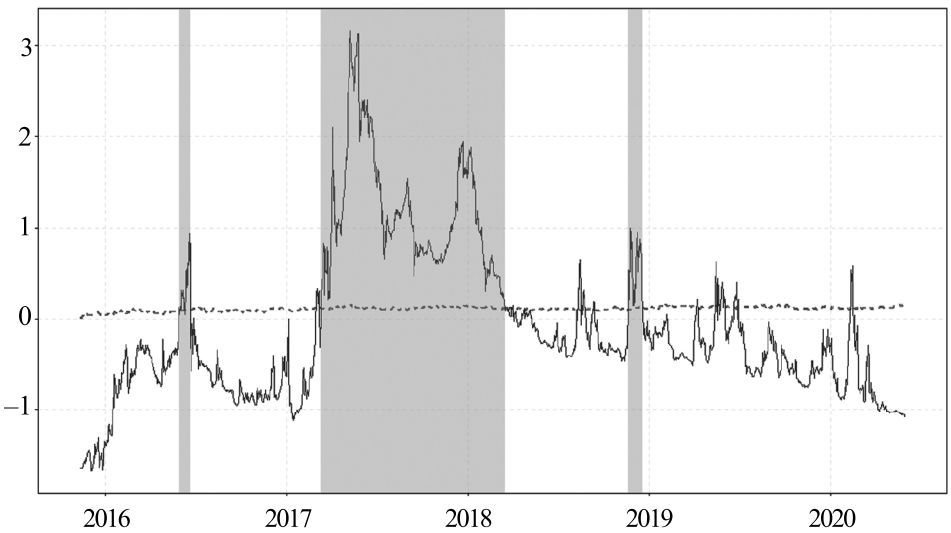
The initial instance of explosiveness in Bitcoin and Ethereum took place during 2015-16. During this period, Bitcoin was affected by various exogenous and endogenous shocks. In August 2015, a new fork was created in Bitcoin, resulting in creating a new cryptocurrency named Bitcoin Cash. In January 2016, Mike Hearn, one of Bitcoin's major developers, withdrew his investments from cryptocurrencies and called it a failure. Investors raised security concerns about Bitcoin trading after Hackers stole 120,000 Bitcoin from BitFinex, a cryptocurrency exchange.

Among the cryptocurrencies, Bitcoin, Ethereum, and Dash show the highest number of explosive periods (6, 4 and 4, respectively) compared to the other three. The most prolonged explosive period is visible in the NEM prices lasted around 74 days from April 14, 2017 to June 27, 2017, followed by Ethereum and Ripple (70 and 72 days, respectively). NEM seems to be the least affected among the individual cryptocurrencies, with a single instance of explosive behavior. Further, there is no explosive behavior visible in cryptocurrencies before 2017 other than Bitcoin and Ethereum. As for the panel, four common explosive periods are identified during 2016-2018, capturing the cryptocurrency bubble and the resulting collapse.

There is high synchronization in the episodes of explosive behavior across most of the cryptocurrencies in the market during 2017-2018. During this period, the cryptocurrency market faced multiple shocks, both exogenous and endogenous. In January 2017, the Chinese government cracked down on cryptocurrency activities, creating instability in the cryptocurrency market. It was the first step towards a systematic crackdown on cryptocurrency-related activities in China. Further, in August 2017, a hard fork[1] was introduced in Bitcoin, resulting in creating a new cryptocurrency named Bitcoin cash. In November 2017, there was another episode of a crackdown on cryptocurrency activities by the Chinese government. Chicago Board Options Exchange (CBOE) had listed Bitcoin futures in December 2017 and thus providing fuel to the cryptocurrency bull-run. However, Bitcoin prices started collapsing shortly after that. We can attribute this collapse to (i) Rumors about South Korea banning cryptocurrency operations; (ii) Cryptocurrency exchange Bitconnet's announcement of winding up their operations; and (iii) Hacking of the Japanese OTC market Coincheck, where hackers stole NEM coins worth $540 mn. By February 2018, Bitcoin prices reached around $6,000, registering a 65% drop in value after touching the all-time high of $19,891 in December 2017. Another significant explosive period recorded in the panel GSADF was from November 19, 2018 to December 19, 2018. After the 2018 January crash, cryptocurrency prices had stabilized for a short period between August-November 2018, with Bitcoin reaching a value of $6,377.78 on November 1, 2018. However, prices started collapsing around the second week of November. By the second week of December, Bitcoin's value reached $3,424.588. A similar trend was visible in other cryptocurrency markets as well. During this period, all individual markets, except Ripple, exhibited explosive price behavior, reflecting the sudden crash.

The cryptocurrency market's overall behavior is analyzed using the panel GSADF procedure (Figure 3). The panel GSADF test results are statistically significant, indicating

Figure 3: Common Periods of Explosive Behavior Across the Panel of Cryptocurrencies



[1] A fork occurs where there is a change in the software. In the case of hard fork, there is no backward compatibility, whereas in the soft fork, the new version is compatible with the old version.

strong evidence in favor of global exuberance in the market. Figure 3 shows synchronized explosive periods in the overall cryptocurrency market. The initial exuberance captured in the panel GSADF is during May-June 2016, only coinciding with two individual currencies, namely Nem and Bitcoin. The explosive period with the most significant duration for the panel is from March 11, 2017 to March 17, 2018, lasting 371 days. Univariate GSADF plots clearly identify the same periods of explosive behavior in the individual cryptocurrencies during this period. Even though no individual currency is exhibiting continuous explosive price movements, turbulence is visible across all the currencies during this period. This period is characterized by overall upward momentum in the cryptocurrency prices until the crash of 2018. Later, we see another instance of explosive behavior during November-December 2018. The panel GSADF test results provide further support to the view that exuberance in cryptocurrency markets during the 2017 and 2018 period is indeed a global phenomenon.

Conclusion

We studied possible individual and common explosive behavior in six major cryptocurrencies using a recursive unit root framework. In the first stage, we employed the SADF and GSADF tests to confirm explosive price behavior in individual cryptocurrencies. The unit root test results suggested that individual cryptocurrency prices exhibit explosive behavior. We employed the BSADF date-stamping procedure to identify significant periods of explosive behavior in the individual cryptocurrencies. We identified significant exogenous as well as endogenous events coinciding with periods of explosive behavior. By this, we were able to confirm the impact of these events leading to cryptocurrency market crashes. In the second stage, we implemented a panel version of the recursive GSADF to test for synchronized explosive behavior.

The panel GSADF analysis identified a common period of turbulence during 2017-18 in the cryptocurrency market that included the cryptocurrency boom and the subsequent crash of 2018 January. Evidence points towards synchronization in the cryptocurrency market during periods of turbulence. From the investor perspective, synchronized explosive behavior prevalent in the cryptocurrency market rules out the possibility of creating an investment portfolio consisting of only cryptocurrencies, as it points towards the possibility of strong comovement between the cryptocurrencies (Ajaz and Kumar, 2018).

The price movements of cryptocurrencies raise serious concerns. The explosive behavior can be attributed mainly to its market structure. Unlike other financial market segments, cryptocurrencies are virtually unregulated. However, that does not change the nature of market stakeholders. Like in every other financial market, there is speculative trading in the cryptocurrency market. However, due to the lack of regulatory control, the speculative segment may gain the upper hand and result in scenarios like herding. There are already studies showing evidence of herding in cryptocurrency markets (Bouri *et al.*, 2019). Herding could lead to building bubble-like behavior in cryptocurrency prices, which could collapse due to exogenous or endogenous factors. Our analysis has identified many such potential factors (such as regulatory actions by China and South Korea) leading towards a price crash.

Due to the extreme price movements, usage of cryptocurrencies as a stable medium of exchange is limited and it becomes difficult to carry out any cryptocurrency denominated transactions. It is largely employed as a speculative asset, which is not desirable in the long run. One way to tackle this issue is to formalize cryptocurrency transactions. That is, bringing them into the ambit of formal financial market. Chicago Mercantile Exchange (CME) and CBOE had launched Bitcoin futures in 2017, aiming at increased participation of institutional investors in cryptocurrency markets. Currently, CME offers Bitcoin futures and options as well as Ethereum futures. However, the trade volume is not sufficient to affect cryptocurrency prices. Another way to control extreme price movement is stable coins, i.e., cryptocurrencies whose value is backed by any external assets such as gold or US$. Even though there are stable coins such as Tether with a significant market presence, this asset sub-class is yet to gain traction.

Considering the price movements of cryptocurrencies, the next logical step would be to check the possibility of employing cryptocurrencies as potential instruments of hedge, diversification and safe-haven. It would be interesting to see if this asset class is used for anything other than mere speculation. With the Covid-19 induced uncertainty, it is worthwhile to explore this possibility. The literature has already discussed the hedging, diversification, and safe-haven property of cryptocurrencies (Stensås *et al.*, 2019, for example). Therefore, using the same methodology, one could see how cryptocurrencies behave while tested for synchronized explosive behavior along with other financial segments such as commodity and equity markets. We intend to extend future research in this direction. ❖

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