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Do collective emotions drive bitcoin volatility? A triple regime-switching vector approach

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ABSTRACT

In this paper, we build an empirical specification that helps to explain bitcoin volatility and to characterize phases of the bitcoin bubble using information derived from investors' emotions and sentiment that captures investment intentions and investors' aversion to risk. To this end, we investigated the bilateral relations between bitcoin volatility and investor emotions between 2018 and 2021, a period characterized by significant changes in bitcoin prices as well as wide disparities in investor emotions, especially in the context of the ongoing COVID-19 pandemic. The study was based on a linear and nonlinear Vector Autoregressive (VAR) model that we applied to data related to bitcoin prices and market sentiment as expressed by the Fear and Greed index. Overall, our results evince the key role played by collective emotions in the formation and collapse of the bitcoin bubble. Two findings in particular stand out. First, our model shows significant time-varying lead-lag effects between bitcoin volatility and investor sentiment that come into play bilaterally and help to characterize the dynamics of bitcoin volatility. Second, these interactions exhibit asymmetry and nonlinearity as the sign and size of collective emotions (resp. bitcoin volatility) vary with the regime and market state under consideration (calm state versus period of bubble formation, etc.). In other words, the power of sentiment has a time-varying effect on the market. Indeed, in the first regime ("calm state"), where bitcoin volatility is relatively low and the market shows evidence of stability, collective emotions have a negative impact on bitcoin volatility, prompting a stabilizing strength. However, in the second regime ("bubble formation"), the effect of emotions turns significantly positive as investors gradually become less fearful and more reassured, which can simultaneously increase volatility and destabilize the market. Finally, in the third regime ("bubble collapse"), when bitcoin reaches a high level of value and experiences impressive volatility excess, the effect of emotions again turns negative, resulting in further switching behavior that pushes investor action to provoke a bitcoin price correction, moving it toward a new state of stability. Our conclusion helps improve predictions of bitcoin price dynamics informed by the information provided by investor emotions.

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1. Introduction

Rationality, a key dimension of Fama (1965)'s informational efficiency theory, implies the presence of a representative agent who behaves rationally and makes basically rational decisions. Rationality and efficiency are a cornerstone of mainstream modern financial theory and have been considered benchmark rules since the 1970s.

However, with the regular occurrence of crises, crashes and market dysfunction (1987 stock market crash, dot.com Internet bubble, 2008 global financial crisis, etc.), these assumptions have become less credible and even questionable, and have gradually given way to a behavioral finance theory (Thaler, 1993; Shiller, 2000; Shiller and Akerlof, 2009; Aggarwal, 2014) that relies more on irrational behavior, investor heterogeneity, irrational exuberance, animal spirits, narrative economics and collective emotions to document asset price dynamics. Indeed, it appears that investors' feelings can determine psychic reality and affect investment judgement which, accordingly, can be one of the factors that explain how markets periodically crash (Baker, Nosfinger, 2010).

Robert Shiller, who shared the Nobel Prize in Economics with Eugene Fama and Lars Hansen in 2013, wrote various seminal papers showing that fundamentals are not enough to justify stock price variations and that the above behavioral variables instead help us to better understand stock price changes. Regarding cryptocurrencies, for instance, we do not always identify specific fundamentals for these assets. Rather, decisions by corporate managers such as Elon Musk have a hyperbolic effect on the value of bitcoin (Ante, 2021). According to explanations by psychologists and economists such as Richard Thaler (who also won the Nobel Prize in Economics in 2017 for his work on behavioral economics), the financial market fluctuates in line with human behavior. Indeed, markets have mood swings like humans, which can turn on a dime from irritable to euphoric, resulting in diverse episodes of under- and overreaction.

When a financial market has its formal/own fundamentals, these fundamentals not unexpectedly drive its price. Behavioral finance theory thus focuses on the contribution of behavioral factors, considered as non-fundamental variables. However, when the market does not rely on, or have, specific fundamentals such as cryptocurrencies as mentioned earlier, the question becomes more pertinent. This is one of the main motivations for the current study's investigation of the role played by investors' emotions to better understand changes in cryptocurrency prices. In particular, the analysis of investor sentiment helps us to capture the degree of investors' aversion to risk and thus their investment intentions. Both investment intention and investors' aversion to risk are reliable drivers of risk-taking and therefore of bitcoin volatility.

Accordingly, in line with the behavioral finance literature, this paper asks the following question: Can collective emotions really drive (resp. be driven by) bitcoin volatility? Its originality thus relates to testing the contribution of behavioral factors on the bitcoin market.

The study motivation is twofold. First, bitcoin is a decentralized currency that is not directly linked to any policy instruments or fundamentals and does not therefore obey a formal regulation system or have legal tender status in almost any jurisdiction. This raises a key question about its valuation. What is its fundamental value? The question becomes even more relevant when we look at the extreme excess volatility of bitcoin in recent years.¹ Indeed, after reaching US\$20,000 in 2017, bitcoin experienced a strong correction in 2018, then abruptly jumped to US\$65,000 in April 2021, before losing 30% in more recent months, partly due to a Chinese policy decision when the People's Bank of China made an announcement that appeared to effectively ban Chinese financial institutions or payment companies from offering services involving cryptocurrencies. Further, the direct and indirect transmission of the COVID-19 pandemic into the real economy impacted liquidity and consequently cryptocurrency investment and pricing.

Second, at least since March 2020, investors have experienced diverse episodes of uncertainty and anxiety (induced by the coronavirus outbreak, lockdown decisions and new post-COVID-19 measures, among other things), and collective emotions have been time-varying.

It is thus highly interesting to investigate whether bitcoin volatility and collective emotions interact in a significant way or not. It is a crucial issue, especially since the value of bitcoin has been the subject of much controversy and raises several questions: Is bitcoin a purely speculative asset that is relatively disconnected from market liquidity and, more generally, from the real economy? Are there points of contact between bitcoin volatility and investor sentiment on the financial markets (Aalborg et al., 2019; Baig et al., 2019; Eom et al., 2019)? Further, given that emotions and bitcoin volatility may interact with some asymmetry, complexity, and irregularity, it is interesting to investigate this relationship in a nonlinear framework to capture all forms of interaction and lead-lag effects.

In the related literature, bitcoin volatility has been the focus of several recent and ongoing research papers, although no unanimous conclusions have as yet been reached. Several studies² have pointed to the various drivers of bitcoin, including investor sentiment. However, both sentiment and volatility are unobserved variables, making it challenging to address this issue.

Our paper thus makes a dual contribution to the literature. First, we use a multi-dimensional measure for investor sentiment, applying three different proxies for volatility to minimize any potential measurement error for these variables. Second, we propose a flexible vector nonlinear econometric framework that offers significant modeling flexibility to examine different forms of interaction between investor emotions and bitcoin volatility.

¹ For more details on bitcoin volatility, see Cheah and Fry (2015), Corbet et al. (2018).

² See section 2 for more details.

Accordingly, we reveal two interesting factors. First, we demonstrate significant bilateral time-varying lead-lag effects between bitcoin volatility and investor sentiment. Second, these interactions exhibit asymmetry and nonlinearity. Indeed, in line with Taffler et al. (2018, 2019), the sign and size of collective emotions (resp. bitcoin volatility) vary with the regime and the state of the market under consideration (calm state versus period of bubble formation, bubble collapse, etc.). Our conclusion can thus help improve our understanding of changes in bitcoin pricing and future bitcoin price dynamics predictions.

The remainder of the paper is organized into four sections. Section 2 briefly discusses the related literature and shows its limitations and controversies. Section 3 presents the data and discusses the main empirical results. Section 4 concludes.

2. Literature

In the related literature, many studies have addressed the question of bitcoin's volatility, giving rise to diverse and inconclusive results. For example, using an Empirical Mode Decomposition (EMD), Selmi and Tiwari (2016) showed that bitcoin is driven by long-term fundamentals (over one year). Conrad et al. (2018) studied the relationship between the volatility of the S&P500 and that of bitcoin. They also showed that volatility of the S&P500 risk premium has a significant effect on the long-term volatility of bitcoin, suggesting a long-term convergence of the two, and indicating that bitcoin volatility is not distinct from the fundamental determinants of traditional stock indexes. On the other hand, Molnár and Širaňová (2020) argued that the macroeconomic news has a strong impact on bitcoin volatility. Indeed, using high frequency data, the authors found that bitcoin volatility and its discontinuous part (jumps) reacts strongly to macroeconomic news announcements. They also showed that bitcoin volatility reacts most strongly to news about bitcoin regulations, and that positive investor sentiment regarding bitcoin regulations plays a decisive role. Katsiampa (2019) and Katsiampa et al. (2019) pointed to a significant asymmetric reaction of bitcoin volatility to positive and negative shocks, while Bouoiyour et al. (2016) showed how bitcoin's prices are driven by long-term fundamentals. In similar vein, Kaizogi et al. (2019) noted the usefulness of past volatility in predicting changes in bitcoin volatility, but also pointed to the dependency of bitcoin volatility on investor sentiment rather than on monetary assets. Gurdgiev and O'Loughlin (2020) also focused on the relationship between cryptocurrency price movements and behavioral factors and showed that investor sentiment can predict the price trends of cryptocurrencies. Meanwhile, Chen and Hafner (2019) used a sentiment index to devise a model that tests for speculative bubbles in cryptocurrencies. They showed that four cryptocurrencies are often associated with speculative bubbles that appear to be driven by exuberant sentiment. However, F. Pervaiz et al. (2020) tested the implied volatility of bitcoin over a time horizon of 5 min by incorporating lagged price and volatility movements of the bitcoin index together with Google trends. They concluded that bitcoin volatility is inadequately predictable using price, volatility momentum and sentiment information. Anastasiou et al. (2021) examined the effect of crisis sentiment on the risk of a cryptocurrency price collapse and showed that such a risk is positively related to the FEARS index. This result indicates that a higher sense of crisis among investors increases the risk of cryptocurrency price collapse.

In a nonlinear context, Thu and Walter (2018) and Ardia et al. (2019) showed further evidence of switching regimes in the dynamics of bitcoin volatility, each regime being impacted by different drivers as in López-Cabarcos et al. (2019). In the same context, Bukovina and Martiček (2016) examined investor sentiment as a driver of bitcoin volatility. By breaking down bitcoin prices into rational and less rational components with sentiment intraday data over the period of 12/12/2013–12/31/2015, the authors showed that the explanatory power of sentiment significantly increases during periods of excessive volatility. Rajput et al. (2020) later used a comprehensive volume-based Bitcoin Sentiment Index (BSI) Google search. They investigated its symmetric and asymmetric association with bitcoin returns, volume and volatility and found a positive association of BSI with bitcoin returns and volume, but a negative relationship with its return volatility. Moreover, they noted that bitcoin's optimistic sentiments have an asymmetrical relationship with the USD exchange rate in the short run, while bitcoin price has an asymmetrical and negative association with the USD in the short and long run.

In the context of COVID-19, Chen et al. (2020) examined the impact of fear caused by the pandemic on bitcoin price dynamics, arguing that bitcoin volatility is exacerbated by the fear sentiment fueled by increased interest in coronavirus via the internet. In a more recent paper focusing on the bitcoin bubble period, Guégan and Renault (2021) explored the relationship between investor sentiment on social media and intraday bitcoin returns. They found a significant link between investor sentiment and bitcoin returns for frequencies of up to 15 min, while for lower frequencies, the relationship disappears. Naem et al. (2021) analyzed the predictive ability of online investor sentiment for six major cryptocurrency returns and found that the Happiness Sentiment Index significantly predicts bitcoin returns as well as those of other major cryptocurrencies in both extreme market states and at extreme sentiment levels.

Overall, unlike traditional assets, bitcoin trading appears to be highly sensitive to official news about regulation rules, official announcements (especially from countries that have adopted cryptocurrencies), as well as non-fundamental variables including the behavior of hedgers and speculators, investor emotions, etc. (Hung et al., 2021). However, measurement of some of these variables is not always error-free.

Accordingly, bitcoin volatility remains difficult to forecast, especially during a pandemic. Indeed, the related ongoing studies above are either inconclusive or yield different findings. The current study aims to fill this gap while investigating the contribution of investors' emotion-related behavioral variables to bitcoin volatility. However, given that both bitcoin volatility and investor sentiment are unobserved variables, we relied on a large and composite class of investor sentiment proxies and three different measures of volatility to reduce the bias associated with any potential measurement error of

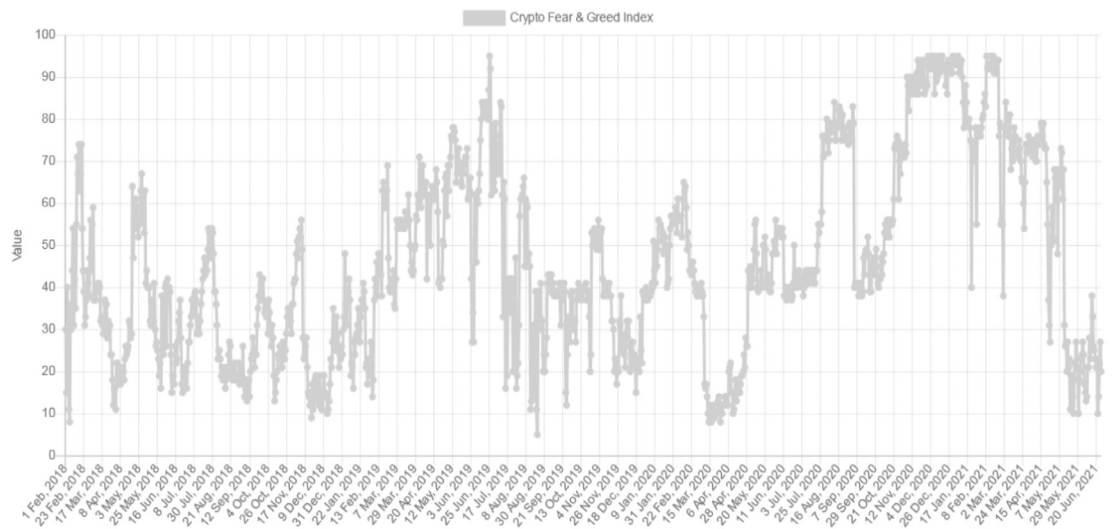


Fig. 1. Crypto Fear & Greed Index dynamics
Source: <https://alternative.me/crypto/fear-and-greed-index/>.

these proxies. Further, we built a highly flexible nonlinear vector model to assess both linear and nonlinear lead-lag effects between these variables which alter with the state of the market. The combination of a flexible econometric framework and robust measurement of our variables should provide stronger, more reliable results.

3. Empirical analysis

3.1. The data

Our data is daily and includes three types of information. First, we used closed, high and low bitcoin prices to compute bitcoin volatility. To ensure robustness, we used three proxies for volatility, which is especially useful to assess for different forms of changes in bitcoin price. Information on trading volume was also used as a control variable, as is commonplace in the financial literature when considering volatility modeling with reference to the Mixture Distribution Hypothesis (MDH). Second, we relied on the Fear & Greed sentiment index to capture investor behavior and emotions. By using this sentiment index, we were able to capture different levels of investors' feelings and to develop a continuous measure of their emotions. Third, we took information and news related to COVID-19 in the US into account since the pandemic has had the greatest impact on this country, with over 800,000 COVID-19-related deaths by December 2021. Data was daily, giving us access to a large amount of information. It covers the period 1st February 2018–25th May 2021, thereby including both the May 2021 bitcoin bubble, the big crash in the bitcoin market, as well as the impact of the ongoing coronavirus outbreak. For COVID news, we used data covering the period 21st January 2020–25th May 2021, since the first COVID-19 case was announced in the US on 21st January 2020.

The two variables of interest are bitcoin volatility and the sentiment index, which we investigated for their interactions and further lead-lag effects. In line with the Mixture Distribution Hypothesis (MDH) literature, volume was used as a control variable, while COVID-19 news was also used as a control variable to assess the direct impact of the coronavirus pandemic on bitcoin volatility and investor emotions.

In Fig. 1, we plot the Fear & Greed Index for bitcoin and other large cryptocurrencies that we obtained from the following source: <https://alternative.me/crypto/fear-and-greed-index/>. Basically, the Fear & Greed daily index is computed from various sources and has different dimensions that cover distinct and rich forms of emotions and sentiments. The numbers were analyzed and crunched into one simple indicator, with each data point valued the same as the previous day in order to visualize meaningful progress in change of sentiment in the crypto market. In particular, current bitcoin market sentiment was analyzed and crunched into a simple variable from 0 to 100. The zero value implies "Extreme Fear" and indicates that investors are very worried, while the 100 value denotes "Extreme Greed" and indicates that investors are getting too greedy, suggesting that the market is due for correction.

3.2. Preliminary analysis

First, the closing bitcoin price data (in logarithm) and the sentiment index were plotted in Figs. 2 and 3 respectively to better characterize their respective dynamics. From Fig. 2, we can note that the COVID-19 outbreak does not appear to have had a serious impact on bitcoin, unlike most stock markets. In fact, the bitcoin price showed an abrupt increase that



Fig. 2. Bitcoin Price Dynamics
Note: Cbitcoin denotes the closing daily bitcoin price.

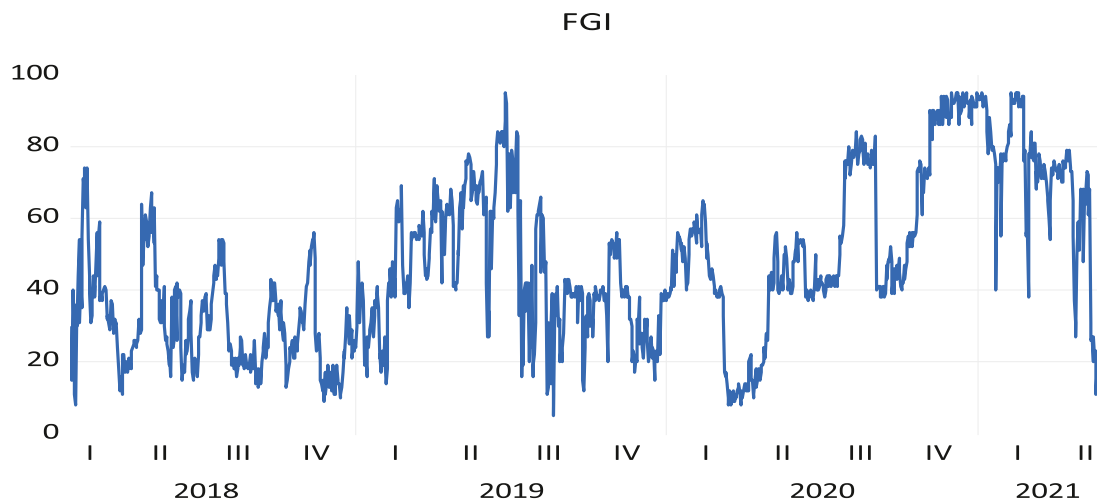


Fig. 3. Sentiment Dynamics Index
Note: FGI denotes the daily Fear & Greed Sentiment Index.

began in October 2020, pushing it to exceed US\$60,000 in March 2021, although it collapsed thereafter. In Fig. 3, we can observe extreme volatility of the sentiment index, which was significantly time-varying between the levels of “Extreme Fear” and “Extreme Greed”. In particular, the fact that it was close to zero suggests further evidence of investor anxiety and uncertainty.

To obtain an overview of the interactions between the sentiment index and bitcoin, we report the two series in the logarithm in Fig. 4. Accordingly, while bitcoin does not appear to be affected by variations in investor sentiment in early 2018, emotions seem to share a common trend, showing signs that drive bitcoin prices and vice versa from March 2020.

To double check this observation, we investigate hereafter the linkages between the sentiment index and bitcoin volatility. We proxy bitcoin volatility differently, using three distinct proxies. First, we proxy volatility by absolute bitcoin returns that we compute as the absolute value of the logarithmic difference of bitcoin closing prices, as in Zheng et al. (2014). This measure of volatility is common to related studies in the financial literature, providing a simple measure for volatility. Second, we use M. Parkinson (1980)’s volatility proxy that relies on High and Low bitcoin prices. Unlike the first one, this measure can be seen as realized volatility proxy since, while using information provided by high and low prices, it can assess for major bitcoin price changes that occur over the course of a day, including minute to minute price changes. Third, we use Garman-Klass (1980)’s volatility proxy, noted G-K hereafter, which takes Opening, High, Low and Closing prices into

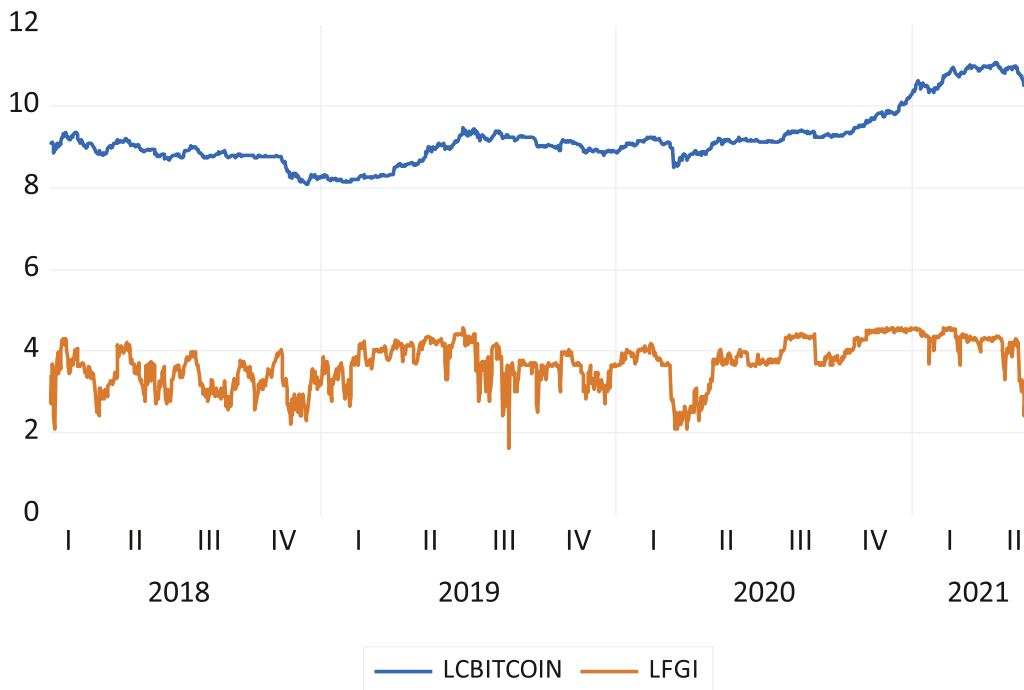


Fig. 4. Time-varying interactions between bitcoin and sentiment indexes in logarithm
 Note: LFGI denotes the logarithm of the daily Fear & Greed Sentiment Index and LCBitcoin is the logarithm of the daily bitcoin closing price.

account. This third proxy is able to capture not only minute to minute price changes but also the opening-closing price range, which is useful to capture different forms of price change and sources of volatility. These three different proxies for bitcoin volatility are relevant and useful as closing prices are not always sufficient to adequately apprehend the volatility of an underlying asset over the course of a day. Accordingly, it is important to use the asset’s ‘real’ volatility during the day rather than just relying on closing prices, which is what Parkinson’s volatility proxy does. In fact, the High Low Range Volatility developed by M. Parkinson (1980) captures additional information from the highs and lows of any given day. Parkinson’s volatility proxy captures the difference between the maximum and minimum position over the same time interval and tracks book orders as a continuous-time process. In practice, this proxy estimates the volatility of returns for a random walk using the high and low prices in any particular period. Prices can be considered over a fixed time interval: $N = 10, 20, 30, 60, 90, 120$ or 180 days.

Formally, M. Parkinson (1980)’s proxy corresponds to³:

$$\sigma_{\text{PARK},n} = \sqrt{\frac{1}{4 \ln(2)} \sum_{i=1}^n \ln\left(\frac{H_i}{L_i}\right)^2} \tag{1}$$

where: H_i is a high bitcoin price on day i and L_i is a low bitcoin price on day i . N denotes the fixed time interval. The high/low return is calculated as the natural logarithm of the ratio of a high bitcoin price to a low stock price.

The third volatility proxy corresponds to the Garman–Klass (1980) volatility measure, which takes the high and low price into account as well as opening and closing prices. Formally, the G-K proxy corresponds to:

$$\sigma_{\text{GK},n} = \sqrt{\sum_{i=1}^n \left[\frac{1}{2} \ln\left(\frac{H_t}{L_t}\right)^2 - (2 \ln(2) - 1) \ln\left(\frac{C_t}{O_t}\right)^2 \right]} \tag{2}$$

where: H_t is a high bitcoin price on day t and L_t is a low bitcoin price on day t . O_t is bitcoin’s opening price on day t and C_t is bitcoin’s closing price on day t .

Considering this measure of intraday volatility is particularly useful as the average difference between any given day’s high and low price during the study period represents nearly 5% of the opening price of bitcoin.

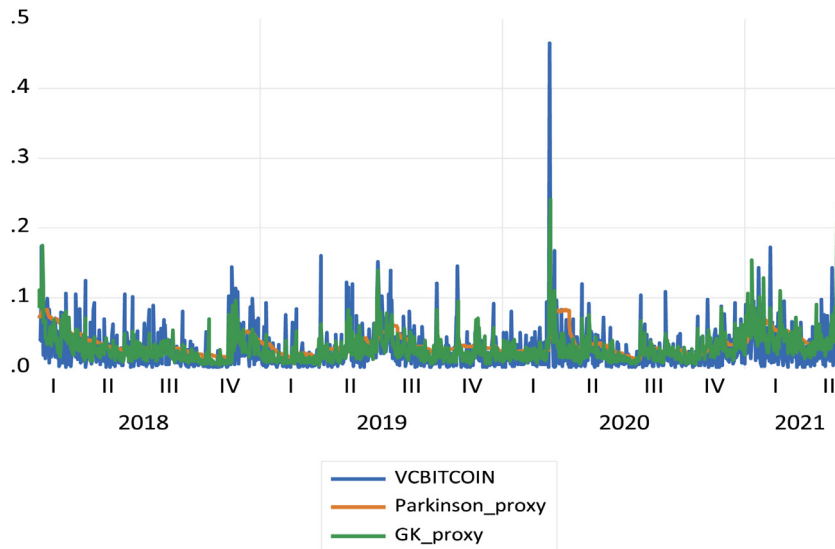


Fig. 5. Bitcoin Volatility Dynamics
 Note: VCBITCOIN measures volatility as the absolute value of bitcoin returns; Parkinson proxy measures the volatility of F. Parkinson (1980); G-K proxy refers to the volatility of Garman–Klass (1980).

Table 1
 Unconditional Correlation Matrix.

-whole sample-				
	VCBITCOIN	PARKINSON_PROXY	GK_PROXY	LFGI
VCBITCOIN	1	0.3466	0.6466	- 0.0441
PARKINSON_PROXY		1	0.5348	- 0.1407
GK_PROXY			1	-0.0363
LFGI				1
-COVID-19 outbreak-				
	VCBITCOIN	PARKINSON_PROXY	GK_PROXY	LFGI
VCBITCOIN	1	0.2981	0.6294	- 0.1214
PARKINSON_PROXY		1	0.4873	- 0.3557
GK_PROXY			1	-0.1125
LFGI				1

From Fig. 5, we can see that whatever the proxy of volatility under consideration, bitcoin shows a significant level of price change, reaching the highest level during the first wave of the coronavirus pandemic.

Before looking at the interactions between bitcoin volatility and the sentiment index (FGI index), we checked the stationarity of the FGI and volatility series. The results of the unit root tests show that both the sentiment index and the volatility proxies are stationary.⁴ We thus compute the unconditional correlation matrix that we report in Table 1. Accordingly, we can note that whatever the volatility proxy for bitcoin, the sentiment index shows a weak but negative correlation. The bilateral correlation (still negative) increased during the pandemic, suggesting that when the sentiment index increases (toward extreme greed), it leads to a decrease in bitcoin volatility. This also suggests that when investors become more confident, their emotions have a greater impact on bitcoin volatility and vice versa.

3.3. Linear lead-lag effects between bitcoin volatility and sentiment

In order to better analyze the above bilateral and unconditional correlations, we next assess for further causality between these two variables. To this end, we apply the Granger causality and report the main results in Table 2. Accordingly, we can note significant evidence of causality effects between the sentiment index and bitcoin volatility, suggesting lead-lag effects.

³ From Taleb (1987), “An important use of the Parkinson number is the assessment of the distribution prices during the day as well as a better understanding of the market dynamics. Comparing the Parkinson number and periodically sampled volatility helps traders understand the tendency towards mean reversion in the market as well as the distribution of stop-losses.”

⁴ We do not report the results in order to save space, but they are available upon request.

Table 2
Results of Granger Causality Tests.

Null hypothesis:	Obs	F-Statistic	Prob.
PARKINSON_PROXY does not Granger Cause VCBITCOIN	1205	9.166	3.E-07
VCBITCOIN does not Granger Cause PARKINSON_PROXY		6.167	7.E-05
GK_PROXY does not Granger Cause VCBITCOIN	1205	10.29	3.E-08
VCBITCOIN does not Granger Cause GK_PROXY		18.72	6.E-15
LFGI does not Granger Cause VCBITCOIN	1205	1.513	0.1960
VCBITCOIN does not Granger Cause LFGI		6.941	2.E-05
GK_PROXY does not Granger Cause PARKINSON_PROXY	1206	10.62	2.E-08
PARKINSON_PROXY does not Granger Cause GK_PROXY		9.098	3.E-07
LFGI does not Granger Cause PARKINSON_PROXY	1206	3.320	0.0102
PARKINSON_PROXY does not Granger Cause LFGI		2.317	0.0553
LFGI does not Granger Cause GK_PROXY	1206	3.892	0.0038
GK_PROXY does not Granger Cause LFGI		7.780	3.E-06

Note: **Obs** denotes the number of observations. **F-Statistic** is the statistic of the Fisher test and **Prob.** denotes the p-value of the test.

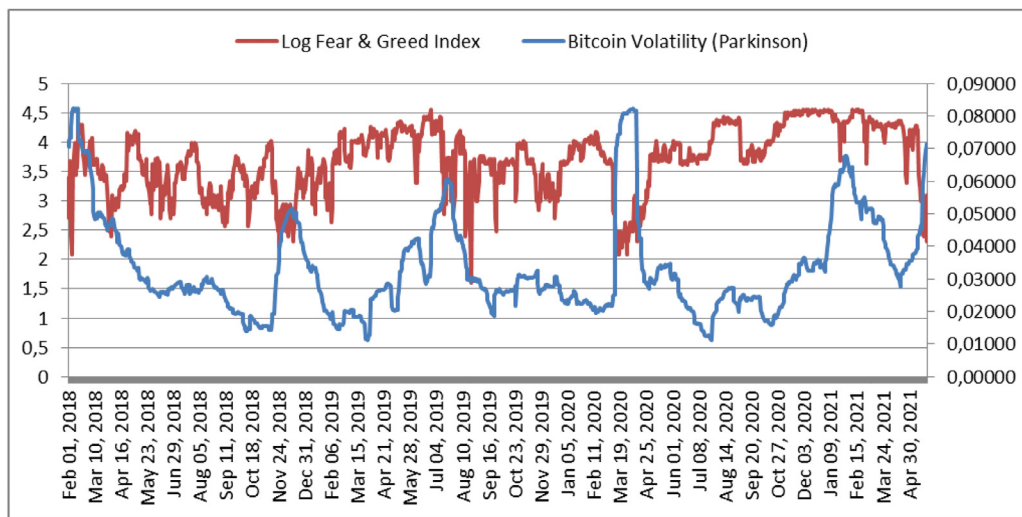


Fig. 6. Dynamic interactions between the sentiment index and bitcoin volatility.

Further and interestingly, this causality relationship always occurs bilaterally between the volatility and the sentiment index, confirming a bilateral Granger causality effect and thus significant interaction between investors’ emotions and changes in bitcoin prices. This helps us to better understand and forecast changes in bitcoin prices.

To better clarify these lead-lag effects, we ran a linear two equation-VAR model and report the main empirical results in [Table 3](#). The advantage of the VAR specification is that it can model the behavior or dynamics of bitcoin volatility and investors’ emotions within a system, allowing for lead-lag effects between these two variables. We thus performed a VAR(1,1) with two equations and one lag that was specified using information criteria. From [Table 3](#), we can confirm a negative relationship between the sentiment index and bitcoin volatility, whatever the volatility proxy under consideration. Further, this lead-lag effect is bilateral as bitcoin volatility has a negative and significant effect on sentiment and vice versa, indicating that emotions (resp. bitcoin volatility) drive bitcoin volatility (resp. emotions). This finding confirms the above result of the Granger causality test. In fact, when emotions reach an extreme fear level, investors display a high level of anxiety and panic, and may consequently wish to intervene and sell their bitcoin massively, and at times irrationally, leading to excess volatility. Otherwise, trading volume positively and significantly impacts bitcoin volatility in line with the MDH. Trading volume also shows a positive impact on investors’ emotions.

Overall, while the above model points to further evidence of a linear lead-lag effect between investor sentiment and bitcoin volatility, the VAR model under consideration only captures a linear relationship between sentiment and volatility. However, excess bitcoin volatility and a significant change in collective investor emotions could generate asymmetrical and nonlinear interactions. Indeed, from [Fig. 6](#), we can see that collective emotions may be subject to switching regimes and it is possible that this regime switching could yield time-varying effects on bitcoin volatility and vice versa. In the next step, we investigate these two options while reconsidering further linkages between bitcoin volatility and investor emotions in a nonlinear framework. To this end, we first apply a threshold and linearity test to test for the presence of nonlinearity in the volatility-sentiment relationship. Next, when the null hypothesis of linearity is rejected, we perform a nonlinear multivariate model.

Table 3
Results of a linear VAR model.

-Proxy VCBITCOIN-		
	LFGI	VCBITCOIN
LFGI(−1)	0.8942*** [70.80]	−0.0058*** [−3.39]
VCBITCOIN(−1)	−1.0632*** [−5.10]	0.1226*** [4.28]
C	−0.2748* [−1.69]	−0.1125*** [−5.06]
LVOLUME	0.0295*** [3.86]	0.0066*** [6.37]
Adj. R-squared	0.851	0.054
F-statistic	2301.53	24.403
Log likelihood	146.39	2544.22
Akaike AIC	−0.235	−4.205
Schwarz SC	−0.218	−4.188

Note: (***), (**) and (*) denote significance at 1%, 5% and 10% statistical level respectively. Values in [.] denote the robust t-ratios. C denotes the constant.

- G-K_Proxy-		
	LFGI	GK_PROXY
LFGI(−1)	0.8937*** [69.64]	−0.0040*** [−3.85]
GK_PROXY(−1)	−1.184*** [−4.12]	0.5302*** [22.44]
C	−0.3272** [−1.96]	−0.1048*** [−7.64]
LVOLUME	0.0320*** [4.03]	0.0056*** [8.65]
Adj. R-squared	0.8490	0.390
F-statistic	2266.40	259.02
Log likelihood	137.08	3155.30
Akaike AIC	−0.2201	−5.213
Schwarz SC	−0.2032	−5.196

Note: (***), (**) and (*) denote significance at 1%, 5% and 10% statistical level respectively. Values in [.] denote the robust t-ratios. C denotes the constant.

- Parkinson Proxy -		
	LFGI	PARKINSON_PROXY
LFGI(−1)	0.8951*** [67.65]	−0.0003*** [−3.25]
PARKINSON_PROXY(−1)	−0.9531*** [−2.17]	0.9856*** [275.4]
C	−0.2313 [−1.39]	−0.0077*** [−5.74]
LVOLUME	0.0276*** [3.43]	0.0004*** [6.18]
Adj. R-squared	0.847	0.986
F-statistic	2239.52	29,573.75
Log likelihood	130.96	5943.77
Akaike AIC	−0.2100	−9.8259
Schwarz SC	−0.1931	−9.8090

Note: (***), (**) and (*) denote significance at 1%, 5% and 10% statistical level respectively. Values in [.] denote the robust t-ratios. C denotes the constant.

3.4. Linearity tests

Here, when linearity is rejected, the alternative model is a nonlinear model among the large class of nonlinear models. However, given that this nonlinear model cannot be concisely specified, we proceed using different classes of linearity tests so as to identify the most suitable nonlinear model taking the characteristics of the data under consideration into account. Accordingly, we proceed by applying general nonlinearity tests as well as more specific nonlinear tests. As an example, we first apply the structural break test of Bai and Perron (2003). We also apply two tests of linearity and threshold tests to the series of volatility proxies and the investor sentiment index to check whether these variables exhibit nonlinearity.⁵

⁵ For more details on nonlinear models in general and threshold models in particular, see Tong and Lim (1980), Teräsvirta and Anderson (1992), and Granger and Teräsvirta (1993).

Table 4
Results of the linearity tests.

	LFGI	VCBITCOIN	PARKINSON_PROXY	G-K Proxy
Bai and Perron (2003) test	0.00***	0.00***	0.00***	0.00***
Tsay (1998) test	0.00***	0.00***	0.00***	0.00***
Hansen (1999) test	0.00***	0.00***	0.00***	0.00***

Note: The values reported in Table 4 denote the probabilities of the structural break and nonlinearity tests. (***) denotes the rejection of the null hypothesis at the 1% statistical level.

In particular, we run two threshold tests developed by Tsay (1998) and Hansen (1999) which check the null hypothesis of linearity against the alternative hypothesis of nonlinearity. When linearity is rejected, nonlinearity is reproduced by a threshold model.

The nonlinear modeling is performed in two steps. First, we check for structural breaks and nonlinearity in the data through the application of a structural break test (Bai and Perron, 2003) and threshold tests (Tsay, 1998; Hansen, 1999). In a second step, after rejecting linearity, we estimate the nonlinear model by the Nonlinear Least Squares method and, as the baseline model is a VAR, we estimate the nonlinear model in a nonlinear system too. This is particularly useful to provide unbiased estimators as the model is more robust than the estimation of the system equation by equation. Further, the VAR framework helps to assess the dynamics of our series in the short term under the assumption of nonlinearity, giving our model greater flexibility.

We report the main results of these nonlinear tests in Table 4. Accordingly, we find evidence of structural breaks and nonlinearity in the data for both the volatility and the investor sentiment series. This finding is in line with the time-varying dynamics of these variables shown in Fig. 4. In particular, we identify two interesting facts. First, the Bai and Perron (2003) test points to the presence of a structural break in the dynamics of all our series. Second, both the Tsay and Hansen threshold tests reject the null hypothesis of linearity. This suggests further evidence of nonlinear and switching regime dynamics in our variables, which is in line with our preliminary analysis. We assess for this nonlinearity hereafter while estimating a nonlinear VAR model. It is important to recall that the further asymmetry and nonlinearity in the data as well as the bitcoin volatility-investor sentiment relationship can be captured through different nonlinear models: threshold and switching models (Threshold Autoregressive (TAR) model, Smooth TAR, Markov model, etc.), asymmetrical Moving Average model, Exponential AR model, bilinear model, etc. We preferred a Threshold Vector AR model for several reasons. First, this multivariate framework (taking the series of volatility and investor sentiment within a system) is able to model bilateral relations between bitcoin volatility and investors' emotions and to assess for further lead-lag effects. Second, a nonlinear/threshold VAR specification enables both variables to display dynamics that switch from one regime to another when an endogenous threshold variable exceeds a given threshold. Third, our nonlinear specification is flexible enough to allow for more than two regimes with an abrupt rather than smooth transition, which is more suitable when considering rapid changes in bitcoin prices. Fourth, the nonlinear VAR specification enables us to estimate nonlinear impulse-response functions that track the reaction of bitcoin volatility (resp. investors' sentiment) following a shock impacting investor sentiment (resp. bitcoin volatility).

3.5. A threshold vector analysis⁶

As mentioned earlier, nonlinear vector models encompass a large class of nonlinear specifications. Among these models, the threshold vector market model, which is based on the univariate threshold models of Tong and Lim (1980), Teräsvirta and Anderson (1992), and Granger and Teräsvirta (1993), is a useful framework for estimating a time-varying relationship between the sentiment index and bitcoin volatility within a system. Indeed, this model enables us to capture the joint dynamics of both variables, while allowing the variables to interact asymmetrically and nonlinearly. Interestingly, a threshold vector model allows us to assess for a time-varying interaction that varies with regimes. This is particularly useful as changes in collective emotions may affect bitcoin volatility differently from the level of market volatility prevailing at the time of the emotional changes and vice versa. Further, depending on the market state and the sign or size of a shock, investors may react differently, resulting in asymmetry that can be appropriately captured by our nonlinear VAR model.

In practice, we perform a three-regime VAR(1,1) model with two equations: one equation to capture the sentiment dynamics and one to capture bitcoin volatility. For greater flexibility, coefficients for some exogenous variables and lagged endogenous variables were allowed to vary per regime. The number of regimes is required to assess for volatility-sentiment regimes, not only for low and high levels of bitcoin volatility, but also when bitcoin price changes are quite moderate and the market is almost stable. The threshold VAR model is estimated using the BFGS algorithm and following the Marquardt approach. This model requires initial values that are started randomly through iterations. Further, Huber-White robust standard errors and covariance are provided to produce robust estimators. We report the main empirical results in Table 5.

⁶ We briefly present hereafter the threshold vector model. For more details on the methodology of the threshold VAR model and its statistical properties, the reader can refer to Tsay (1998).

Table 5
Results of the Switching VAR model.

	VCBITCOIN	LFGI		
	Regime 1			
VCBITCOIN(−1)	0.2099*** [2.46]	−6.4735*** [−11.16]		
LFGI(−1)	−0.0043*** [−2.04]	0.8934*** [42.70]		
	Regime 2			
VCBITCOIN(−1)	−0.7092** [−1.91]	7.0464*** [3.71]		
LFGI(−1)	0.0260*** [4.34]	0.8523*** [27.43]		
	Regime 3			
VCBITCOIN(−1)	0.1242*** [3.44]	−0.1735 [−0.38]		
LFGI(−1)	−0.0046*** [−2.39]	0.8899*** [38.96]		
C	Common −0.0987*** [−4.23]	−0.1786 [−1.21]		
LVOLUME	0.0057*** [4.64]	0.0262*** [2.96]		
Transition Matrix Parameters				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
P1-C	−1.2612	0.2918	−4.3211	0.000
P2-C	−2.8129	0.3636	−7.7347	0.000
Log likelihood		2911.60		
Akaike info criterion		−4.7857		
Schwarz criterion		−4.6971		
Number of iterations to ensure algorithm convergence		67		

Note: [.] are robust t-ratios. (***), (**) and (*) denote significance at 1%, 5% and 10% statistical level respectively. Values in [.] denote the robust t-ratios. C denotes the constant. P1-C and P2-C refer to the transition matrix parameters.

Our estimation presents various interesting results. First, we found that sentiment and bitcoin volatility interact significantly and, in line with our previous analysis, these interactions across collective emotions and bitcoin volatility enter nonlinearly and vary per regime.⁷ This suggests that the response of bitcoin volatility (resp. emotions) to collective emotions (resp. to volatility) effectively depends on the market state.

In particular, we identify three different regimes. In the first regime (“calm state”), where bitcoin volatility is relatively low and the market shows evidence of stability, collective emotions (further evidence of extreme fear or panic) may have a negative impact on volatility, ensuring the stability of volatility over a certain time. In this regime, emotions play a stabilizing role and are a source of market calmness and stability. At the same time, the low degree of bitcoin volatility may reassure investors and reduce their level of extreme fear.

In the second regime (“bubble formation”), we noted a stimulating switch and an acceleration of interaction between these two variables. Indeed, the market shows further evidence of price increases in this regime. This may be because investors gradually become less fearful and more reassured, and the switch in their behavior and emotions can increase volatility due to their recent confidence in the market and may even be a source of bitcoin volatility or instability. Further and interestingly, bitcoin volatility in this regime can also switch, displaying a positive effect that stimulates, encourages and drives investors to take more and more risks, as well as inciting them to follow this volatility excess and to be more enthusiastic and optimistic, increasing their appetite for trading and risk-taking. Thus, in this regime, bilateral and positive interactions between sentiment and volatility are supported and intensified by a runaway. This result is in line with Kalyvas et al. (2020). In fact, we observe that the formation of a bitcoin bubble begins in this regime.

In the third regime (“bubble collapse”), bitcoin reaches a high level and shows impressive volatility excess. This leads to more questioning and uncertainty about the real or true price, with a negative impact on collective emotions. Indeed, again in this third regime, investors’ emotions experience further switching behavior, pushing investors to increasingly worry about the high bitcoin levels, to act negatively with regard to volatility, and ultimately prompting a bitcoin price correction. The intensity of this correction and of the feedback or signal sent by collective emotions may drive investors to begin a massive and purely imitative selling trend, along with further mimetic behavior, pushing bitcoin prices to collapse abruptly,

⁷ The results remain similar when considering the three different proxies for volatility. We only report the results of volatility that is proxied using the absolute bitcoin return to save space. The others results are available upon request.

which in turn triggers a burst in the bubble. Accordingly, our main finding is that investor emotions are a key variable in the formation of the bitcoin bubble and its collapse.

Otherwise, with regard to our control variables, estimated under the assumption of no-switching coefficients, we found that trading volume has a positive effect on bitcoin volatility (which is in line with the MDH) as well as on collective emotions. Finally, both the volatility and the emotions series show evidence of memory effects, suggesting further evidence of persistence in their dynamics. However, the COVID-19 news variable is not statistically significant, which could be explained by the fact that coronavirus news was potentially already captured by the sentiment index.

Overall, we confirm the presence of significant asymmetrical lead-lag effects between bitcoin volatility and sentiment. Interestingly, these lead-lag effects enter nonlinearly and by regime, implying that the interaction between investor emotions and bitcoin varies with the regime under consideration. Indeed, while investor emotions attenuate bitcoin volatility when volatility is low, emotions become stimulating in the intermediate regime during the formation of a bubble as, in this regime, both volatility excess and emotions (excess optimism) commove, following a positive trend. However, in the third regime, when bitcoin reaches a high level and shows an impressive degree of volatility, the feedback from volatility to emotions is cut short, while emotions begin to send a negative signal that pushes bitcoin prices to correct, causing a further collapse in the above-mentioned bitcoin bubble.

4. Conclusion

Bitcoin recently experienced a massive crash, making this asset's instability more debatable than ever. The present study investigates whether investor emotions could be useful to explain bitcoin volatility. To this end, we investigated the relationship between investor emotions and bitcoin volatility during calm and pandemic periods using different proxies in linear and nonlinear frameworks. Accordingly, we developed an empirical specification that helps to explain bitcoin volatility, as well as phases of the bitcoin bubble, using information provided by investor emotions and sentiment. Overall, our main finding is that investor emotions are a key variable behind the formation of the bitcoin bubble and its collapse, leading us to two interesting findings. First, we reviewed and confirmed a significant relationship between bitcoin price volatility and market sentiment, represented by the Crypto Fear & Greed Index. In particular, our model identifies significant and time-varying lead-lag effects between bitcoin volatility and investor sentiment that occur bilaterally and can usefully characterize the dynamics of bitcoin volatility. Second, these interactions exhibit asymmetry and nonlinearity as collective emotions are subject to switching regimes that yield time-varying effects on bitcoin volatility and vice versa.

Indeed, the sign and size of collective emotions (resp. bitcoin volatility) vary with the market state (calm state versus period of bubble formation/collapse), suggesting that the state of the market has a significant impact on the relationship between collective emotions and volatility. Further, the power of sentiment on the market has a time-varying effect, yielding a runaway between sentiment and bitcoin volatility that is revised by regime. Indeed, in the first regime ("calm state"), where bitcoin volatility is relatively low and the market shows evidence of stability, collective emotions have a negative impact on volatility to make it increasingly stable. However, in the second regime ("bubble formation"), the effect of emotions turns significantly positive as investors gradually become less fearful and more reassured, which could in turn increase volatility and even be a source of bitcoin volatility or instability. Finally, in the third regime ("bubble collapse"), when bitcoin reaches a high level and shows impressive excess volatility, the effect of emotions turns negative, leading to another form of switching behavior that drives investors to act negatively with regard to volatility and ultimately prompts a bitcoin price correction. These findings clearly show the usefulness of market sentiment in predicting bitcoin volatility. A future extension of the present study would be to test the forecasting performance of our model.

Declaration of Competing Interest

None

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