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Bitcoin volatility, stock market and investor sentiment. Are they connected?

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A R T I C L E I N F O

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A B S T R A C T

Bitcoin is the cryptocurrency with the largest market capitalization, and many studies have examined its role in financial markets. In this manuscript, we contribute to the extant body of knowledge by analyzing the Bitcoin behavior and the effect that investor sentiment, S&P 500 returns, and VIX returns have on Bitcoin volatility using GARCH and EGARCH models. The results suggest that Bitcoin volatility is more unstable in speculative periods. In stable periods, S&P 500 returns, VIX returns, and sentiment influence Bitcoin volatility.

1. Introduction

Bitcoin is a virtual currency that uses an SHA-256 cryptographic hash algorithm and the combination of public and private keys, removing the need for a central authority to check the details of every economic transaction (Grant and Hogan, 2015). The trading in this cryptocurrency has become very common, and in December 2017, bitcoin futures were launched in the Chicago Board Options Exchange (CBOE) (Corbet et al., 2018a). Hence, Bitcoin has become a 'trending topic' in financial research, especially when considering investor sentiment. Previous research has proven that investor sentiments extracted from news or blogs (Karalevicius et al., 2018; Kjærland et al., 2018), social networks as Twitter (Georgoula et al., 2015) or investor attention from Google (Dastgir et al., 2019) influence Bitcoin. Accordingly, we aim to clarify the role of Bitcoin in the financial market and its relationship with investor sentiment.

Even though Bitcoin was created as an alternative currency, it is also used as an asset (Baur et al., 2018). In this regard, several authors analyzed the role of Bitcoin in stock markets behaving as an asset or, as a hedging instrument, and its relationship with other market variables such as Standard & Poor's 500 Index (S&P 500 Index), or the Volatility Index (VIX). While Bartos (2015) found that Bitcoin price follows the efficient market hypothesis and could be considered as an asset, Lahmiri et al. (2018) found strong evidence against the efficient market hypothesis. Regarding the hedging capabilities, Bouri et al. (2017a) concluded that Bitcoin markets are risky and cannot be considered as a hedging instrument. By contrast, Dyhrberg (2016a; 2016b) showed that Bitcoin, being similar to

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gold and US dollar, has hedging capabilities, and trades at lower spreads than stocks on prominent exchanges (Dyhrberg et al., 2018). Moreover, Al-Yahyaee et al. (2019), Bouri et al. (2017c), Urquhart and Zhang (2019), Shahzad et al. (2019) and Chan et al. (2019) also found evidence of Bitcoin as a hedging instrument. Nevertheless, Klein et al. (2018) concluded that Bitcoin has an asymmetric response to market shocks, which is similar to that of precious metals. In this manner, there is some evidence that Bitcoin is related to S&P 500 Index (Georgoula et al., 2015; Conrad et al., 2018; Kjærland et al., 2018; Erdas and Caglar, 2018; Chan et al., 2019) and to market uncertainty measured through the VIX Index (Bouri et al., 2017b; 2017c).

Hence, the objectives of this manuscript are to examine: (1) if social network sentiment and stock market (S&P 500 Index) influence Bitcoin volatility; (2) if social network sentiment and stock market volatility (VIX Index) influence Bitcoin volatility, and (3) the Bitcoin volatility behavior.

We have used EGARCH models to complement GARCH models' results and test the pattern of the Bitcoin volatility since they allow us to guarantee the positive sign of the variance without imposing restrictions on the coefficients. Since it has been proven that Bitcoin can be a speculative asset (Baek and Elbeck, 2015) or a hedging instrument (Dyhrberg, 2016a; 2016b; Bouri et al., 2017c) we have analyzed the behavior of Bitcoin volatility across different periods. To this end, daily data of the S&P 500 Index, VIX, and Bitcoin were used, while investor sentiment was extracted using the Standford CoreNLP (Manning et al., 2014) software from a social network specialized in finances, StockTwits.com. This measure of sentiment is widely used in research due to its accuracy of 80.7% since it captures the effects of negation and its scope for positive and negative phrases (Socher et al., 2013).

The results show that financial markets and social network sentiment about them influence Bitcoin volatility. Moreover, it shows different behaviors depending on market conditions. Thus, Bitcoin could act as a safe haven, implying that investors could use Bitcoin as refuge value when Bitcoin markets are stable. Otherwise, when Bitcoin markets have high volatility, and stock markets have low volatility, investors could use Bitcoin as a speculative asset. These results corroborate the results of previous studies and advance current knowledge about Bitcoin behavior.

This manuscript is structured as follows: in Section 2, we describe data and variables, while Section 3 is dedicated to the clarification of the relevant methodology. In Section 4, we present results and conclude the paper with the final remarks in Section 5.

2. Data and variables

In order to complete the analysis S&P500 Index, VIX Index, Bitcoin prices, and the sentiment about S&P500 Index were used. S&P500 Index represents the market since it contains 500 companies from several sectors, and it has been used in several Bitcoin behavioral studies (Conrad et al., 2018; Kjærland et al., 2018; Erdas and Caglar, 2018; Chan et al., 2019). VIX Index is a volatility index based on the S&P500 Index that measures the market volatility. Several authors have used this index as a measure of market volatility in their models (Piñeiro et al., 2017; Bouri et al., 2017c). Lastly, unlike other authors who have used the sentiment about bitcoin (Karalevicius et al., 2018), we refer to the sentiment of messages concerning the S&P500 Index to analyze how sentiment about the stock market influences Bitcoin volatility.

S&P500 Index data was collected from the Nasdaq website, which is the official site of the Nasdaq stock market. VIX data was sourced from the CBOE website, the official site of the CBOE options market, which has the VIX as one of its main indices. Following previous research, Bitcoin data was obtained from the website coindesk.com(Bouri et al., 2017; Chan et al., 2019; Ma and Tanizaki, 2019). And sentiment data was extracted from Stocktwits messages using the Standford CoreNLP (Manning et al., 2014). Stocktwits is a financial social network where users can post messages about stock markets by labeling them with "cashtags" (for example, $SPX). The data was collected from January 4, 2016, until September 30, 2019, resulting in 943 trading days.

The variables were calculated as follows. S&P500 Index returns, VIX returns, and Bitcoin returns were calculated as

$$Rx_t = ln(Px_t) - ln(Px_{t-1}) \tag{1}$$

Where Px_t is the closing prices of S&P500 Index, VIX, or Bitcoin at time t, respectively.

Concerning investor sentiment, the Standford Core NLP provides a measure of the sentiment of each message following a five-point Likert scale where a very negative feeling corresponds to a score of −2, the neutral sentiment corresponds to a score of 0, and a very positive sentiment corresponds to a score of 2. The daily average of sentiment was calculated as follows:

$$sent_t = \sum_{i=1}^{m} S_{it} \Big/ M_t \tag{2}$$

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Rb	942	0.0031463	0.046975	−0.2468519	0.2264123	−0.0796382	6.976553
Vsent	942	−0.0001156	0.0554832	−0.2435897	0.2	−0.0036621	4.005998
Rs	942	0.0003991	0.0082498	−0.0418429	0.0484033	−0.61592	7.538866
Rv	940	−0.0000663	0.0822613	−0.2998312	0.7682452	1.503275	13.59024

Rb: Bitcoin returns; vsent: variation of sentiment; Rs: S&P 500 returns; Rv: VIX returns. Period range: January 4, 2016 – September 30, 2019. Rv has fewer observations because, on 6/7/2018, there was no quote.

where S_{it} is the sentiment of message i posted at time t, and M_t is the number of messages posted at time t.

The variation of sentiment was calculated as:

$$vsent_t = sent_t - sent_{t-1} \tag{3}$$

where $sent_t$ is the daily sentiment in moment t.

Table 1 presents the summary statistics. The means of Bitcoin returns, and the S&P500 returns are positive, which suggests a bullish trend during the analyzed period. The mean of VIX returns suggests a decrease in the volatility since it is negative. Regarding the standard deviation, the results suggest that during the analyzed period the variation of VIX was relatively significant, indicating that market volatility has fluctuated considerably.

Fig. 1 shows different trends in Bitcoin prices and a speculative bubble (Corbet et al., 2018b). The sample was divided into different periods, and we test the volatility in each of them. To identify these periods, we have used the break-test of Zivot-Andrews (1992) unit root test. This test selects the break date where the t-statistic of the unit root is at a minimum, treating the break as the result of estimation. We have obtained three breakpoints rendering four subsamples (Table 2).

Table 3 shows the descriptive statistics of subsamples. The most striking statistical finding is the change in Bitcoin returns. The mean and the standard deviation increase while the skewness turns from negative to positive. This corroborates the change in the behavior of Bitcoin prices, as preliminary data and graph suggested.

3. Method

3.1. GARCH model

A GARCH (m, k) model (Bollerslev, 1986) was used to test the influence of investor sentiment, S&P 500 Index and VIX, respectively, on Bitcoin volatility.

Specifically, to test the individual impact of S&P 500 returns, VIX returns, and investor sentiment, respectively on Bitcoin, the model proposed was a GARCH (1,1):

Mean model:

$$Rb_t = \beta_0 + \varepsilon_t \tag{4}$$

Variance model:

$$\sigma_t^{btc} = C_{btc} + \gamma_{btc}\varepsilon_{t-1}^2 + \delta_{btc}\sigma_{t-1}^2 + \beta_1 Rx_t + \beta_2 vsent_t \tag{5}$$

where Rb_t is the daily Bitcoin returns in Eq. (4), σ_t^{btc} is the variance of the residuals derived from Eq. (4), C_{btc} is the constant, $\gamma_{btc}\varepsilon_{t-1}^2$ is the ARCH parameter, $\delta_{btc}\sigma_{t-1}^2$ is the GARCH parameter, Rx_t is one of the exogenous variables (S&P500 Index returns (Rs) in Model 1 or VIX returns (Rv) in Model 2), while $vsent_t$ is the daily variation of sentiment in Eq. (5).

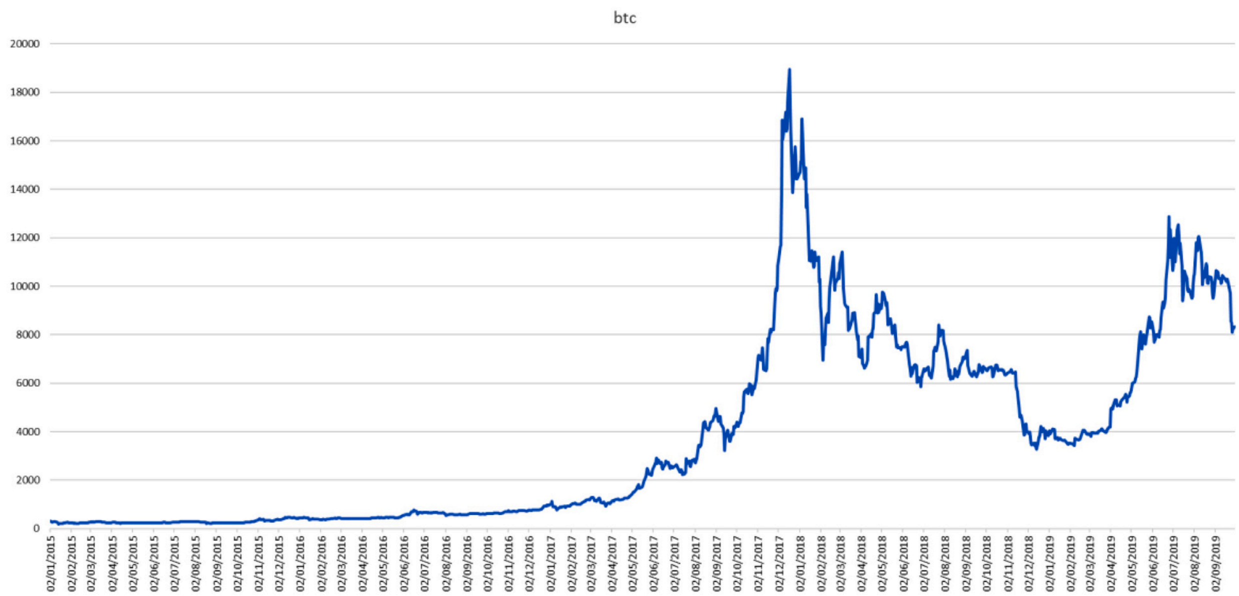

Fig. 1. Bitcoin prices (04/01/2016–30/09/2019).

Table 2
Subsamples.

Subsample	Period
Subsample 1	4/1/2016–20/3/2017
Subsample 2	21/3/2017–15/12/2017
Subsample 3	16/12/2017–11/1/2019
Subsample 4	12/1/2019–30/9/2019

Table 3
Descriptive statistics of subsamples 1, 2, 3, and 4 (4/1/2016–30/9/2019).

Subsample 1	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Rb	305	0.0028995	0.0350936	−0.1804757	0.1975498	−0.3513415	10. 7409
vsent	305	−0.0000957	0.0454808	−0.1512753	0.1517354	0.0765859	3.188219
Rs	305	0.0004901	0.0076918	−0.0365806	0.244589	−0.4565314	5.957287
Rv	305	−0.0015529	0.0726687	−0.264822	0.4010108	0.6453976	7.777406
Subsample 2							
Rb	189	0.0149603	0.0556638	−0.1829844	0.2264123	0.4974931	5.307822
vsent	189	−0.0004012	0.0554739	−0.1875	0.1818182	−0.0834162	3.732325
Rs	189	0.0006344	0.0043199	−0.0183454	0.0107818	−0.7433086	6.297472
Rv	189	−0.0009815	0.0746337	−0.2998312	0.3810699	1.076139	10.96395
Subsample 3							
Rb	268	−0.0058035	0.0513313	−0.2468519	0.1306324	−0.7086482	5.57658
vsent	268	0.0001561	0.0663199	−0.2435897	0.2	−0.0333614	4.081371
Rs	268	−0.0001126	0.0107827	−0.0418429	0.0484033	−0.4301567	6.103377
Rv	266	0.0026701	0.09915	−0.2596447	0.7682452	2.096681	16.22994
Subsample 4							
Rb	180	0.0044851	0.0453325	−0.1490488	0.1857796	0.1938332	6.167748
vsent	180	−0.000254	0.0536387	−0.134817	0.1388747	0.0799824	2.673451
Rs	180	0.0007598	0.0079802	−0.03023	0.0212059	−0.8738918	5.462865
Rv	180	−0.00063	0.0781623	−0.1981435	0.333873	0.8943371	5.293478

Rb: Bitcoin returns; vsent: variation of sentiment; Rs: S&P 500 returns; Rv: VIX returns. Subsample 1: Period range: January 4, 2016 – March 20, 2017. Subsample 2: Period range: March 21, 2017 – December 15, 2017. Subsample 3: Period range: December 16, 2017– January 11, 2019. Subsample 4: Period range: January 12, 2019 – September 30, 2019. Rv has fewer observations in Subsample 3 because, on 6/7/2018, there was no quote.

3.2. EGARCH model

An Exponential GARCH or E-GARCH model (Nelson, 1991) was proposed to confirm the influence of investor sentiment, the S&P 500 Index and VIX, respectively, on Bitcoin volatility and test the pattern of the Bitcoin volatility. This model allows for the positive sign of the variance without imposing restrictions on the coefficients. The conditional variance equation is formulated in logarithmic terms, with the variation being always positive (Alexander, 2008).

The model proposed was an E-GARCH (1,1) to test the influence of S&P 500 returns, VIX returns, and investor sentiment, respectively over Bitcoin, and also to examine the volatility behavior of Bitcoin:

Mean model:

Table 4
GARCH (1,1) and EGARCH (1,1) estimation results for the entire sample.

Mean equation	Bitcoin (M1)	Bitcoin (M2)	Bitcoin (M3)	Bitcoin (M4)
Cons	0.0033706**	0.0032201**	0.0022795*	0.002407**
Variance equation				
Rv		7.129336**		2.241731**
Rs	−83.18694**		−17.12402**	
Vsent	−17.13471**	−14.54193**	−2.330498**	−2.765909**
ARCH	0.1680649**	0.1507955**		
GARCH	0.7387548**	0.7670604**		
EARCH			0.0277301**	0.0168652
EARCH_a			0.2503213**	0.233618**
EGARCH			0.9340532**	0.9408944**
Cons	−8.987139**	−9.05345**	−0.3795676**	−0.3475816**

Vsent: variation of sentiment; Rs: S&P 500 returns; Rv: VIX returns. ARCH: ARCH parameter; GARCH: GARCH parameter; EARCH and EARCH_ a: EARCH parameters; EGARCH: EGARCH parameter; Cons: constant. Significance:

** 5%.

* 10%. N: 942 Period range: January 4, 2016 – September 30, 2019.

$$Rb_t = \beta_0 + \varepsilon_t \tag{6}$$

Variance model:

$$\ln\left(\sigma_t^{btc}\right) = C_{btc} + \theta_{btc} z_{t-1} + \gamma\left(|z_t| - \sqrt{\frac{2}{\pi}}\right) + \delta_{btc}\ln\left(\sigma_{t-1}^2\right) + \beta_1 Rx_t + \beta_2 vsent_t \tag{7}$$

where, Rb_t is the daily Bitcoin returns in Eq. (6), σ_t^{btc} is the variance of the residuals derived from Eq. (6), C_{btc} is a constant, $\theta_{btc}z_{t-1}$ is the EARCH parameter; $\gamma(|z_t|-\sqrt{2/\pi})$ is the EARCH_a parameter, $\delta_{btc}\ln(\sigma_{t-1}^2)$ is the EGARCH parameter,Rx_t represents exogenous variables (S&P500 Index returns (*Rs*) in Model 3 or VIX returns (*Rv*) in Model 4), while $vsent_t$ represents sentiment variation in Eq. (7).

4. Results

Table 4 comprises estimation results for GARCH (1,1) models (Model 1 and 2), and the estimation results for E-GARCH (1,1) models (Model 3 and 4). The LM test for ARCH effects in the residuals for all models renders a *p*-value equal to 0.000, which supports GARCH (1,1) and E-GARCH (1,1) models.

Regarding Model 1 results, S&P500 returns, and social network sentiment about the S&P500 Index are significant, which means that both influence Bitcoin volatility. The coefficient estimate for S&P500 returns is significantly higher than the coefficient estimates for sentiment, which means that S&P500 returns have a greater influence on Bitcoin volatility. These results reinforce the statement that Bitcoin could act as a safe haven, as claimed by Bouri et al. (2017b). Regarding Model 2 results, VIX returns are significant, which implies that market volatility influences Bitcoin volatility, in line with the results obtained by Bouri et al. (2017c). The coefficient for investor sentiment is higher than the coefficient for VIX returns, which means that the influence of social network sentiment is stronger than that of market risk (VIX).

ARCH coefficient estimates for Model 1 and 2 are significant, indicating that the volatility of Bitcoin returns in the previous day influences Bitcoin volatility. The GARCH coefficient estimates are also significant, indicating that the volatility of the previous day influences Bitcoin volatility (Dyhrberg, 2016a). In this way, it is possible to conclude that the GARCH(1,1) model is suitable for modeling Bitcoin volatility.

The results for EGARCH(1,1) Model 3 are similar to GARCH(1,1) estimations. In line with previous research (Bouri et al., 2017b), S&P500 returns, and sentiment influence Bitcoin volatility. In line with the study of Bouri et al. (2017c), the results for Model 4 show similarity to GARCH(1,1) estimations since the coefficient estimates of sentiment variation and VIX returns, respectively, have the same sign and significance. However, the EARCH coefficient is not significant. Regarding Model 3, the positive EARCH coefficient estimate implies that positive innovations (an unanticipated price increase), are more destabilizing than negative innovations. However, the effect is weak (0.027) and considerably smaller than the symmetric effect (0.25) represented by EARCH_a. EGARCH coefficient estimates imply that E-GARCH(1,1) is suitable for modeling Bitcoin volatility only for Model 3.

To analyze the behavior of Bitcoin in the subsamples, a GARCH (1,1) model was estimated for each subsample for Model 1 (Table 5) and Model 2 (Table 6).

For subsample 1, GARCH models provide results similar to those obtained for the entire sample. These findings are in line with Dyhrberg (2016b) and Chan et al. (2019). However, the results obtained by applying GARCH models for subsample 2 are quite different. The coefficient estimates for S&P500 returns, sentiment, and VIX returns are not significant. This suggests that in this period, investors reacted by referring to the news and the returns of the previous days, without consideration for S&P500 returns, investor sentiment about the stock market, and VIX returns. In this sense, these results are similar to Kjærland et al. (2018), who also did not find a relationship between Bitcoin and VIX. Moreover, these results suggest that during this period, Bitcoin had a speculative behavior, and investors only paid attention to Bitcoin data to make their investments and disregarded other market information, such as volatility or investor sentiment about the stock market.

For subsample 3, VIX returns and sentiment are significant, but S&P500 returns are not. This period is characterized by a significant decrease in Bitcoin prices due to the bursting of the bubble that had been created. The fact that the S&P does not influence the volatility of Bitcoin could be justified because, during this period of Bitcoin volatility, investors did not pay attention to market data (reflected in the S&P500 Index) as in the previous period. Their decisions were based more on information regarding Bitcoin technical analysis, market sentiment, and market volatility. The results for subsample 4 are similar to those obtained for subsample 1 since, in this period, Bitcoin prices and volatility calmed down once the bubble was overcome.

5. Conclusion

Bitcoin has become one of the most important and by far the largest cryptocurrency in terms of market capitalization. This study provides new evidence regarding the behavior of Bitcoin volatility across different periods, and the effect that S&P500 returns, VIX returns, and investor sentiment have on Bitcoin volatility. Specifically, the results obtained suggest that Bitcoin could act as a safe haven and that Bitcoin investors could consider sentiment about the stock market from social networks rather than market volatility when designing their investment strategies. This suggests that Bitcoin investors are more "technological", and therefore pay more attention to the information that comes from these media. Moreover, it has been shown that Bitcoin volatility behaves differently across time. Thus, in periods where stock markets have high volatility, Bitcoin can be used as a safe haven, but when stock markets are stable, Bitcoin becomes attractive to speculative investors. The further analysis of Bitcoin behavior, the analysis of the possible

Table 5
. GARCH (1,1) estimation results for Model 1 for subsamples.

Mean equation	Subsample 1	Subsample 2	Subsample 3	Subsample 4
Cons	0.0027645**	0.015878**	−0.0043782	0.0043187
Variance equation				
Rs	−127.3435**	−22.58092	−22.30379	−101.8016**
vsent	−26.66757**	−1.326113	−16.4723**	−8.812362**
ARCH	0.2537305**	0.1986995**	0.0726035**	0.3602565**
GARCH	0.613958**	−0.4436697**	0.8716512**	0.2130121**
Cons	−9.543264**	−5.539625**	−9.558196**	−7.302848**

Vsent: variation of sentiment; Rs: S&P 500 returns. ARCH: ARCH parameter; GARCH: GARCH parameter; Cons: constant. Significance: **5%; * 10%. Subsample 1: N: 305 Period range: January 4, 2016 – March 20, 2017. Subsample 2: N: 189 Period range: March 21, 2017 – December 15, 2017. Subsample 3: N:268 Period range: December 16, 2017– January 11, 2019; Subsample 4: N: 180 Period range: January 12, 2019 – September 30, 2019.

Table 6
GARCH (1,1) estimation results for Model 2 for subsamples.

Mean equation	Subsample 1	Subsample 2	Subsample 3	Subsample 4
Cons	0.0026412*	0.0159892**	−0.0046833	0.0048893
Variance equation				
Rv	13.55216**	0.0774212	5.582302**	9.472497**
vsent	−23.11289**	−1.132207	−12.05221**	−9.100739**
ARCH	0.2231954**	0.1922094**	0.0827777**	0.3451019**
GARCH	0.6581802**	−0.4684429**	0.8521449**	0.2393803**
Cons	−9.680772**	−5.527823**	−9.404897**	−7.360785**

Vsent: variation of sentiment; Rv: VIX returns. ARCH: ARCH parameter; GARCH: GARCH parameter; Cons: constant. Significance:
** 5%.
* 10%. Subsample 1: N: 305 Period range: January 4, 2016 – March 20, 2017. Subsample 2: N: 189 Period range: March 21, 2017 – December 15, 2017. Subsample 3: N:268 Period range: December 16, 2017– January 11, 2019; Subsample 4: N: 180 Period range: January 12, 2019 – September 30, 2019.

existence of a bidirectional relationship between Bitcoin and investor sentiment, and the analysis of the relationships between Bitcoin and other financial variables (currencies, indexes…), could be the starting points for future research ideas.

CRediT authorship contribution statement

M. Ángeles López-Cabarcos: Supervision, Conceptualization, Writing - original draft. **Ada M. Pérez-Pico:** Software, Writing - original draft. **Juan Piñeiro-Chousa:** Conceptualization, Methodology, Formal analysis, Writing - original draft. **Aleksandar Šević:** Project administration, Formal analysis, Writing - original draft.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2019.101399.

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