Heliyon 7 (2021) e07539

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

A short-and long-term analysis of the nexus between Bitcoin, social media and Covid-19 outbreak

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ARTICLE INFO

Keywords:
Covid-19 health crisis
Tweets
Google trends
Bitcoin
Cointegration approach

ABSTRACT

In this paper, we attempt to analyze the dynamic interplay between Bitcoin, social media, and the Covid-19 health crisis. For this end, we apply the fractional autoregressive vector model, fractional error correction model and impulse response functions on daily data over the period 31/12/2019-30/10/2020. Our results clearly show the short- and long-term evidence of the nexus between the Bitcoin price, social media metrics (Tweets and Google Trends) and the intensity of the Covid-19 pandemic. As well, the Covid-19 pandemic does not impact on social media metrics in the short- and long-term. On the other hand, the Covid-19 pandemic positively affects social media metrics. Also, the Covid-19 pandemic encourages investing in digital currencies such as Bitcoin. So, the Covid-19 health crisis significantly influences social media networks and Bitcoin prices.

1. Introduction

Undoubtedly, the Covid-19 outbreak has dramatically influenced the world economy. In this regard, corporate sales were decreased, the industrial production was declined, consumer behaviors changed, companies have experienced severe financial burden and unemployment rates have significantly risen worldwide. As well, the Covid-19 pandemic has led to panics and the temporary closure of businesses in most economies as the number of positive coronavirus cases has increased (Okorie and Lin, 2020). Goodell and Goutte (2020) report that world economies have experienced loss of employment productivity, consumer demand and adverse impact on tourism and other particular industries as well as foreign direct investment. Such reactions are bound to influence the performance of companies in such economies as well as the banking sector. Not only the banking sector, the stock markets have been significantly and negatively affected by such pandemic. For instance, the Dow Jones and S&P500 had undergone as much as a 30% decrease in values during March 2020 (Iqbal et al., 2021). Other stock markets such as markets in Europe, UK, Australia and Asia have also shown similar decrease (Zhang et al., 2020). From academic standpoint, many researchers have increasingly analyzed the effect of the Covid-19 health crisis on the behavior and dynamics of stock markets. For instance, Al-Awadhi et al. (2020) report that daily growth in total confirmed cases and cases of death due to the Covid-19 pandemic adversely and significantly influence stock returns of Chinese companies. Ashraf (2020) shows the stock markets increasingly react to the Covid-19 health crisis and such reaction changes over time according to the stage of such pandemic.

Such unprecedented shifts in stock markets and economy across the world are expected to affect cryptocurrency markets as an alternative investment. In this respect, Johnson (2020) questions if the Covid-19 outbreak leads to a rise in the Bitcoin adoption given that Bitcoin does not depend on governments' controls. Dealing with adverse effects of Covid-19 pandemic on stock markets, Bitcoin, Ethereum are used as an alternative investment and seem to outperform other assets (Iqbal et al., 2021). Goodell and Goutte (2020), among others, indicate that such pandemic positively affects Bitcoin prices. Huynh et al. (2020) display that Bitcoin can be considered as a better hedge compared to other cryptocurrencies due to its independence. Mariana et al. (2020) test if Ethereum and Bitcoin can be safe-havens for stocks during the Covid-19 pandemic. They show that cryptocurrency returns seem to be negatively correlated with S&P500 returns. They also display that Ethereum and Bitcoin can be considered as short-term safe-havens.

Not only Bitcoin, but also social media platforms have been affected significantly. The intensity of the Covid-19 pandemic as measured by the daily new cases/deaths coupled with emergency actions such as lockdowns, travel restrictions, social distancing and quarantining make them

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https://doi.org/10.1016/j.heliyon.2021.e07539
Received 24 January 2021; Received in revised form 12 May 2021; Accepted 7 July 2021

useful and effective tools to disseminate information and maintain communication with other people to decrease isolation and boredom. As mentioned by Gonzalez Padilla and Tortolero Blanco (2020), people tend to rely more on the posts and tweets shared on the social networking sites such as Twitter, Facebook and Instagram.

From the foregoing, the purpose of this paper is to explore and better understand the association between Bitcoin, social media and the Covid-19 health crisis. Analyzing such relationship is motivated by the complexity and ambiguity of Bitcoin market dynamics compared to other financial assets. Since its inception, Bitcoin can provide a valuable addition to investor's portfolio in terms of risk minimizing. In this respect, investors need more information on if they should invest uniquely within traditional assets or cryptocurrencies or combining two kinds of assets (Mokni and Ajmi, 2021), in particular during turbulent periods. At this point, social media platforms can guide investors in getting useful and valuable information on investment decision-making. Therefore, it is anticipated that social media can help investors who need to know under which conditions Bitcoin can be a good investment tool. From methodology standpoint, we develop a unified framework to jointly model the dynamic association between Bitcoin, the intensity of Covid-19 pandemic and social media metrics. More specifically, the fractional autoregressive vector model, fractional error correction model and impulse response functions are used in the short- and long-term analysis of such relationship. Our study contributes to the literature on cryptocurrency markets in many aspects. First, we offer fresh evidence concerning the relationship between Bitcoin and social media metrics coupled with the outbreak of Covid-19 pandemic. Even though recent studies have increasingly analyzed the behavior of Bitcoin market and cross-asset relationships during the Covid-19 pandemic (e.g. Sharif et al., 2020; Akhtaruzzaman et al., 2020), no analysis attempts to explore and apprehend such association in the short- and long-term. Such analysis is performed using several econometric tools. Second, it is important to consider the role social media during turbulent periods in the sense that help netizens share data and information and make investment decisions. Finally, it is well-documented that investors have panic-sold out of fears (Le et al., 2020) and such panic trading has led to many significant drops in several stock markets (Shehzad et al., 2020). Obviously, many researchers search for which asset(s) outperform(s) during turbulent periods (e.g. Ji et al., 2020) or building better risk management strategies (e.g. Broadstock et al., 2020). In this respect, our study can offer insightful implications for portfolio risk management by displaying the importance of social media in improving (or worsening) the diversification benefits during the alike Covid-19 health crisis.

The paper is organized as follows. Section 2 reports a synopsis of empirical studies and Section 3 reports, methodology, data, descriptive statistics and empirical results. Section 4 concludes.

2. What do you learn about social media, Bitcoin and Covid-19 pandemic?

Many researchers have particularly focused on the relationship between Bitcoin and social media. For example, Shen et al. (2018) analyze the linkage between the number of tweets on Twitter related to Bitcoin and Bitcoin returns, trading volume and realized volatility over the period 04/30/3014-31/08/2018. They find that the number of previous day tweets is crucial determinants of Bitcoin realized volatility and trading volume. However, the number of tweets does not affect Bitcoin returns. Feng et al. (2018) examine the dynamic interactions between social media and Bitcoin prices during the period 01/01/2012-31/12/2014. They display that more bullish forum posts are related to higher future Bitcoin prices. They also report that social media's effects on Bitcoin are mainly driven by the silent majority (95% of users which are less active and whose contributions amount to less than 40% of total messages). They afterwards indicate that messages on an Internet forum related to tweets significantly affect the future Bitcoin prices. Zhang et al. (2018) analyze the cross-correlations between Google Trends and Bitcoin market over the period 01/06/2011-01/02/2017. They indicate that the change of Google Trends and Bitcoin market is substantially cross-correlated. Dastgir et al. (2018) examine the causal relationship between Bitcoin attention (proxied by the Google Trends search queries) and Bitcoin returns over the period 01/01/2013-31/12/2017. They show that a bi-directional causal relationship between Bitcoin attention and Bitcoin returns is well-documented. Wołk (2019) analyzes the impact of social media on cryptocurrency prices. In this regard, Twitter and Google Trends are used in order to predict the short-term prices of digital currencies given that such social media platforms are employed to affect purchasing decisions. The empirical results show that cryptocurrency price fluctuations depend highly on social media sentiment and web search analytics tools such as Google Trends. Twitter sentiments about future cryptocurrency prices tend to be positive as many people tweet about digital currencies even whether cryptocurrency prices decrease. Philippas et al. (2019) examine how the increasing media attention in social networks can have an impact on jumps of Bitcoin prices during the period 01/01/2016-28/05/2018. The proxies for media attention flows in social networks are obtained from Google Trends and Twitter. The empirical results report that Bitcoin prices are partly affected by a momentum on media attention in social networks, indicating a sentimental appetite for information demand. Bouri and Gupta (2019) attempt to compare the capacity of a newspaper-based measure and an internet search-based measure of uncertainty in predicting Bitcoin returns. They show that the predictive ability of the internet-based economic uncertainty related queries index is significantly greater than the measure of uncertainty derived from newspapers in predicting Bitcoin returns. Hao et al. (2019) analyze the role of social media in predicting Bitcoin price movements using data from Twitter and Google Trends. They show correlation between each social media features and Bitcoin prices. Bleher and Dimpfl (2019) assess the usefulness of Google search volume to predict returns and volatility of many cryptocurrencies (e.g. Bitcoin, BitcoinCash). They report that the inclusion of Google's search volume indices can be used to predict cryptocurrency volatility, but does not help to predict cryptocurrency returns. More recently, Moussa et al. (2020) examine the relationship between Bitcoin prices and social media over the period 2009–2018 by using the number of Bitcoin keyword research on Google and the number of tweets on Twitter. They clearly show that social media significantly affect Bitcoin prices. Guégan and Renault (2020) explore the relationship between social media and the evolution of Bitcoin prices at various time-frequencies using StockTwits data. They show that sentiment of messages sent on Stock Twits about the Bitcoin during a period t-1 positively and significantly influences Bitcoin returns in period t. Such impact is more pronounced during the bubble period (08/2017-04/2018). Lin (2020) analyzes the causal relationship between the Google search probability from Google Trends and the returns of many cryptocurrencies (Bitcoin, Ethereum, Litecoin, XRP, and Tether) during the period 16/04/2017-23/02/2020. The empirical results clearly show that there are interaction effects between cryptocurrency returns and social media.

With the advent of Covid-19 outbreak, many researchers analyze the relationship between social media and the Covid-19 outbreak. In this regard, Chakraborty et al. (2020) attempt to explore the fact that tweets including all handles related to Covid-19 pandemic during the period 01/01/2019-23/03/2020. In this regard, they analyze two kinds of tweets collected during the Covid-19 pandemic. They clearly show that even though many people have tweeted mostly positive concerning the Covid-19 outbreak, however netizens seem to be busy engrossed in re-tweeting the negative tweets. They also find that the lack of useful words can be provided in Word Cloud or computations by employing word frequency in tweets. Obi-Ani et al. (2020) explore the social media outlets such as Facebook, Twitter, WhatsApp, blogs, online newspapers and YouTube during the Covid-19 outbreak. They particularly analyze the role of social media in spreading information about the Covid-19 pandemic in Nigeria. They report that the significance of social media outlets cannot be overemphasized with recourse to information dissemination. Gonzalez Padilla and Tortolero Blanco (2020) analyze the role of social media during the Covid-19 pandemic. They highlight the crucial role of social media in spreading new crucial information, sharing diagnostic and information processing during such pandemic. Pérez-Escoda et al. (2020) argue that the Covid-19 pandemic has increased the transformation of the communication sector, creating new challenges for the communication industry and media professionals.

Rather, many researchers have focused on the relationship between the Covid-19 outbreak and Bitcoin market. For instance, Goodell and Goutte (2020) examine the effect of the Covid-19 outbreak on Bitcoin prices during the period 31/12/2019-29/04/2020. They report that such pandemic positively influences Bitcoin prices, in particular after April 5, 2020. Chen et al. (2020) analyze the effect of fear sentiment caused by the Covid-19 pandemic on Bitcoin price dynamics. The fear sentiment proxy is calculated as the sum of Google search volume over the period 15/01/2020-24/04/2020. They display that the market volatility has been heightened by fear sentiment due to a rise in search interest in Coronavirus. They also show that negative Bitcoin returns and high trading volume can be explained by fear sentiment about Coronavirus. By taking into account the polarity and subjectivity of social media data based on the development of the Covid-19 outbreak, Corbet et al. (2020) indicate that important evolution in both returns and trading volumes on the cryptocurrency market are well-documented. This implies that digital currencies can play as a store of value during the Covid-19 pandemic. They also display that cryptocurrency returns are affected by negative sentiment related to the Covid-19 pandemic. Caferra (2020) investigates the linkages between news-driven sentiments and the cryptocurrency market behavior during the Covid-19 pandemic. The empirical results the rises and falls of optimism shape returns variability. In this regard, Caferra (2020) indicates how a rise of news positivity is related to lower returns dispersion, implying the convergence of beliefs among investors. Demir et al. (2020) analyze the relationship between some digital currencies (Bitcoin, Ethereum and Ripple) and the Covid-19 cases/deaths. They initially report that a negative relationship between Bitcoin and the number of cases and deaths. Nonetheless, such relationship becomes positive during the later period. Johnson (2020) analyzes Bitcoin's trading activity around the time of Covid-19 pandemic over the period 10/2019-03/2020. The empirical results report a high correlation between changes in the Bitcoin price and the impact on the stock market of Covid-19 outbreak. Al-Naif (2020) explores the impact of the Covid-19 outbreak on Bitcoin and gold over the period 24/06/2019-22/05/2020. The empirical results clearly show a significant and negative relationship between gold and Bitcoin before and after Covid-19 pandemic. However, the sign of such relationship becomes positive. Iqbal et al. (2021) explore the effect of the Covid-19 outbreak on cryptocurrency markets. They show the varying intensity levels of the Covid-19 influence differently the market phases. Major digital currencies tend to absorb the small shocks of the Covid-19 pandemic by realizing positive gains but fail to resist against adverse changes, except for Bitcoin and Cardano. Kristoufek (2020), among others, rather argue that the Covid-19 pandemic can be used to examine the safe-haven proprieties of Bitcoin. In this regard, Mariana et al. (2020) test if Bitcoin and Ethereum can be safe-havens for stocks during the Covid-19 pandemic. They show that cryptocurrency returns seem to be negatively correlated with S&P500 returns. They also display that Bitcoin and Ethereum can be considered as short-term safe-havens. Conlon and McGee (2020) explore the safe-haven proprieties of Bitcoin against the S&P500 market over the period 21/03/2019-20/03/2020. They report that Bitcoin cannot play as a safe haven, rather diminishing in price in lockstep with the S&P500 as the crisis develops. When held alongside the S&P500, even a small allocation to Bitcoin significantly increases portfolio downside risk. Conlon et al. (2020) analyze safe-haven capabilities of some cryptocurrencies (Bitcoin, Ethereum and Tether) against stock markets. They report that Bitcoin and Ethereum are not a safe haven for the majority of international equity markets. However, Tether can play as safe-haven asset against the international indices. Dutta et al. (2020) examine the safe-haven proprieties of Bitcoin and gold against the crude oil markets during the Covid-19 pandemic. They report that gold is a safe-haven asset for global crude oil markets. On the other hand, Bitcoin acts only as a diversifier for crude oil. Zaremba et al. (2021a) rather examine the behavior and dynamics of 67 stock markets during the Covid-19 pandemic using data from different fields. They clearly show that the effect of such pandemic differs among stock markets. Zaremba et al. (2021b) further analyze the impact of the government policy measures on global stock market liquidity for 49 countries over the period 01/2020-04/2020. They display that the effect of the policy responses seems to be small and limited in scope. Yarovaya et al. (2021) investigate the herding in cryptocurrency markets during the Covid-19 pandemic. They report that health crisis does not increase herding in cryptocurrency markets.

3. Data and descriptive statistics

In this paper, we analyze the association between, the Covid-19 health crisis, Bitcoin and social media. More precisely, we examine the dynamic relationship between the Bitcoin price, social media metrics and the intensity of the Covid-19 health crisis on a worldwide scale[1] during the period from December 31, 2019 until October 30, 2020 on daily frequencies. In our study, the choice of starting date of December 31, 2019 is to better identify and understand the investor sentiment and the evolution of response and reaction of investors to the onset and spread of the virus. Obviously, the date of December 31, 2019 is marked by the onset of cases of pneumonia in Wuhan and at this stage the virus is unknown. Nevertheless, many recent studies use the starting date to analyze the effect of the Covid-19 pandemic on financial markets, such as Goodell and Goutte (2020), Zaremba et al. (2020), Akhtaruzzaman et al. (2020), Okorie and Lin (2020), Mnif et al. (2020), Shehzad et al. (2020). In this regard, the choice of the sample starting date to study the effect of the Covid-19 pandemic on the cryptocurrency market dynamics remains challenging. Many researchers refer to the sample period starting from December 31, 2019 or January 1, 2020 to analyze the impact of the Covid–19 pandemic on behavior of cryptoccurrency market. For instance, Iqbal et al. (2021) use the sample period from January 1, 2020 to June 15, 2020. Goodell and Goutte (2020) employ daily data of Covid–19 world deaths and Bitcoin prices from December 31, 2019 to April 29, 2020. Akhtaruzzaman et al. (2020) take the starting date of Covid–19 period as December 31, 2019 as it corresponds to the date of the first case of Covid–19 according to the World Health Organization (WHO). Mnif et al. (2020) split the sample period into two periods: before and after the date of December 31, 2019 which is referred to the Covid-19 outbreak. Ji et al. (2020) use the sample period from 1/12/2019-31/03/2020. Other researchers rather prefer to divide the sample period into pre- and post-Covid periods to analyze the behavior of cryptoccurrency market. Le et al. (2020) break the sample period (January 1, 2019 to April 30, 2020) into two sub-periods: The without Covid-19 sample consists of observations before January 1, 2020 and the Covid-19 period (after January 1, 2020) given that the first case was officially reported in China in late December 2019. James et al. (2021) distinguish two different sub-periods: The pre-Covid period from 30/06/2018 to 31/12/2019 and the post-Covid period

[1] As a matter of fact, the most of studies employ the sample of the cases and deaths from Covid-19 on global scale. Obviously, whether the analysis was performed regional or even national levels, one might use the starting date which corresponds to the respective region or country's first confirmed case (or death).

from 1/1/2020 to 24/06/2020. Ali et al. (2020) divide their sample period into the so-called epidemic period (12/2019-10/03/2020) and pandemic period (after March 10, 2020). Yousaf and Ali (2020) employ two sample periods: The pre- Covid-19 period (01/01/2019-31/12/2019) and the Covid-19 period (01/01/2020-22/04/2020).

In our paper, we use dataset of Bitcoin prices which is retrieved from the website of www.coinmarketcap.com. Such dataset represent mean prices based on different platforms. The intensity of the Covid-19 health is quantified by two variables: The variable "Cases" is defined as the total (cumulative) number of people affected by the Covid-19 pandemic (i.e. the total (cumulative) confirmed cases) and the variable "Deaths" refers to the total (cumulative) number of people died by the Covid-19 pandemic. Such data (Cases and Deaths) is collected from the website https://www.worldometers.info/which is thereafter used by the UK Government, Johns Hopkins CSSE, the Government of Thailand and the New York Times, among others. Worldometer offers significant insights on global Covid-19 statistics on worldwide level.

Cognizant the fact that operationalizing the online behavior towards the topic is important for producing significant empirical results, we provide Twitter data on Bitcoin from https://bitinfocharts.com/, which highlight the number of times that the term 'Bitcoin' has been tweeted during the study period. On the other hand, search volume activity is also quantified by the search intensity on Google estimated by the number of Bitcoin keyword research (Google) during the study period. In this regard, some researchers (e.g. Arratia and Barrantes, 2019; Lyocsa et al., 2020; Massicotte and Eddelbuettel, 2020) retrieve the Google Trends on the term 'Bitcoin' obtained through the R package gtrendsR when handling Google Trends queries while others prefer to gather such data (e.g. Da et al., 2015; Moussa et al., 2020) from the web page of Google Trends over time and geography. Following Da et al. (2015) and Li and Wang (2016), we use worldwide search trends –based data from Google Trends. In this regard, Chen et al. (2020) report that Google offers search volume for search queries through Google Trends, which are scaled by the time series maximum over particular period. Such data allow us to better understand to what extent evolving patterns in search activity related to the cryptocurrency market's uncertainty. Following Mai et al. (2018), we refer to the variables 'Google Trends' and 'Tweets' as social media metrics which correspond to the media coverage indicators. Obviously, many researchers use Google Trends as a proxy for public interest (e.g. Kristoufek, 2013; Garcia et al., 2014; Bouoiyour et al., 2015) or individual investor attention, sentiment, Bitcoin attention (e.g. Da et al., 2015; Dastgir et al., 2018; Urquhart, 2018; Lin, 2020), media attention flows in social networks (e.g. Philippas et al., 2019) or information demand (e.g. Katsiampa et al., 2019). As labeled, such variable is generally used as a determinant for Bitcoin prices. Otherwise, other researchers use Google Trends as a proxy for Online Searches (e.g. Zhang et al., 2018), Google search volume (e.g. Bleher and Dimpfl, 2019). Hao et al. (2019) employ the term 'social media' when using Google Trends. In this regard, they analyze the relationship between Bitcoin prices and features from social media. So, it is interesting to analyze the evolution of the information content of social media since the outbreak of the virus. So, in our case, the social media metrics allows us to quantify the search interest associated with Bitcoin. The proxies for social media metrics are derived from Twitter and Google Trends. Both variables are quantitative data which reflect the queries of interest based on search keywords or hashtags around the world. Following many researchers, Google Trends and Twitter data are derived respectively from https://trends.google.com/trends/?geo=US and https://bitinfocharts.com/comparison/tweets-btc.html. Such procedure permits to ensure the reliability of our analysis and hinder the arbitrariness related to information about Bitcoin. Such information sources insightfully provide data retrieved from the terms 'Bitcoin' and 'btc' as search keywords and hashtag, respectively. The social media metrics are gathered over the period from December 31, 2019 until October 30, 2020. This time period covers before and during the Covid-19 pandemic.

Table 1. Descriptive statistics of variables.

	LTweets	LGoogle Trends	LCases	LDeaths	LBitcoin
Mean	3.415	3.827	14.180	11.327	10.9136
Standard deviation	0.4927	0.4775	3.7257	4.796	3.9132
Median	3.395	3.771	15.620	12.820	12.8198
Maximum	10.260	10.740	17.640	13.990	13.990
Minimum	2.603	1.960	3.296	0	8.506
Skewness	8.7545	9.8298	-1.4821	1.2875	-0.6772
Kurtosis	119.3049	141.3315	1.3831	1.6875	0.3331
Jarque-Bera (JB)	187.880	263.080	138.55	174.289	156.93
p-value	0.00000	0.00000	0.0000	0.0000	0.0000

Note: L(.) refers to the natural logarithmic operator.

All the considered variables[2] are collected on daily frequencies. From the beginning, we convert all the series into log values (Lvariable). Table 1 presents a set of descriptive statistics for returns of variables under study including mean, standard deviation, median, skewness, kurtosis and Jarque-Bera test.

From Table 1, Bitcoin has the average monthly (logarithmic) price (10.9136) whereas the lowest average (logarithmic) price is recorded for Google Trends and Tweets (resp. 3.827 and 3.415). Besides, Tweets and Google Trends are less risky whereas other variables tend to have high standard deviation. The asymmetry between different variables in terms of skewness and kurtosis are well-documented. The Jarque-Bera statistics are only significant for all the variables, implying they are not normally distributed. Afterwards, we examine the linear relationships between these variables by using the variance-covariance matrix. In this regard, it is important to analyze the potential associations between different variables based on the Variance-Covariance matrix. As a matter of matter of fact, Iqbal et al. (2021) perform a Correlation matrix between the deaths and infections and many cryptocurrencies over the period 01/01/2020-15/06/2020.

Table 2 illustrates the variance-covariance matrix. Needless to say, the diagonal elements of the matrix correspond to the variances of the variables (in bold) whereas the off-diagonal elements are the covariances between all possible pairs of variables. At first glance, certain asymmetry patterns between different variables are well-pronounced. There is a negative link between Google Trends and Bitcoin. Rather, there is positive relationship between Bitcoin and Tweets.

4. Empirical validation

We first examine the issue of stationarity for different variables using two classical unit root tests: Dickey-Fuller (1979–1981) test without trend break and Zivot and Andrews (1992) test by allowing for break in trend. The results are presented in Table 3.

From Table 3, the optimal number of lags that whitens residuals of each variable is greater than 1. Hence, we apply a unit root test without trend break such as the Augmented Dickey-Fuller (1981) test. In level, the t-statistics of these variables are greater than the critical values of Fuller (1976) and Mackinnon (1992). These variables are not stationary

[2] Using different variables, researchers (Aalborg et al., 2019; Demir et al., 2018; Urquhart, 2018) attempt to search for the potential determinants (or main drivers) of the Bitcoin price (or cryptocurrency value formation), including variables related to social media which are used as proxies for investor attention. Other researchers try to construct effective trading strategy in cryptocurrency market based on different factors (Liu et al., 2019; Li et al., 2020) or to perform portfolio-level analysis (Zhang and Li et al., 2020; 2021). Rather, our paper attempts to focus on the dynamic interplay between the Bitcoin price, social media metrics and the intensity of the Covid-19 health crisis. Without losing sight to the purpose of our paper, we prefer to use the retained variables in our model.

Table 2. Variance-covariance matrix.

	LTweets	LGoogle Trends	LCases	LDeaths	LBitcoin
LTweets	**0.2427**	0.0281	0.7559	0.7950	0.0248
LGoogle Trends	0.0281	**0.2280**	0.1337	0.1620	-0.0062
LCases	0.7559	0.1337	**13.8801**	14.5217	0.3513
LDeaths	0.7950	0.1620	14.5216	**15.3135**	0.3306
LBitcoin	0.0247	-0.0062	0.3513	0.3306	**0.0371**

Notes: - LBitcoin refers to the Bitcoin (logarithmic) price.
- LTweets refers to the logarithmic number of tweets on Bitcoin.
- LGoogle Trends" refers to the search intensity on Google estimated by the logarithmic number of Bitcoin keyword research (Google). The numbers in bold refers to variance.

Table 3. Results from unit root tests.

Dickey-Fuller test					
	LTweets	LGoogleTrend	LCases	LDeaths	LBitcoin
In Level					
Lags	4	3	4	4	3
Models	M3	M3	M3	M2	M3
T-Statistic	-3.2025	-2.7265	-2.4223	-2.2493	-2.3015
Critical value of 5%	-3.42	-3.42	-3.42	-2.87	-3.42
In first difference					
Lags	4	3	4	4	3
Models	M3	M3	M3	M2	M3
T-Statistic	-6.4579	-7.6557	-4.6326	-3.4638	-10.0887
Critical value of 5%	-3.42	-3.42	-3.42	-2.87	-3.42
Zivot and Andrews (1992) in level					
	LTweets	LGoogle Trends	LCases	LDeaths	LBitcoin
T-Statistic	-15.4536	-15.1663	-14.436	-11.2282	-4.0009
Models	M3	M2	M3	M3	M3
Critical value of 5%	-4.8	-4.58	-4.8	-4.8	-4.8
Potential break point	01/02/2020	24/10/2020	18/01/2020	20/01/2020	07/03/2020

Notes: - M3: Model with constant and trend and M2: Model with constant and without trend.
- LBitcoin refers to the Bitcoin (logarithmic) price.
- LTweets refers to the logarithmic number of tweets on Bitcoin.
- LGoogle Trends" refers to the search intensity on Google estimated by the logarithmic number of Bitcoin keyword research (Google).

in level, implying that they follow random walk with constant and trend, except for deaths which are modeled by a random walk with constant and without trend. After first-differencing, variables become stationary given that the t-Statistics are lower than the critical values of Mackinnon (1992). Hence, these variables are integrated of order one (I (1)).

The stationarity of social media metrics and the Covid-19 pandemic can be explained by break in trend given that Zivot and Andrews (1992)'s

Table 4. Univariate causality Granger test.

Explanatory variable	Explained variable	ΔLGoogle Trends	ΔLCases	ΔLDeaths	ΔLBitcoin
ΔLTweets	F-statistic	0.1055	0.0836	0.0298	0.1299
	The critical value with 5% of risk	3.087	3.087	3.087	3.087
ΔLGoogle Trends	Explained variable	ΔLTweets	ΔLCases	ΔLDeaths	ΔLBitcoin
	F-statistic	0.0026	0.0054	0.0200	0.3194
	The critical value with 5% of risk	3.087	3.087	3.087	3.087
ΔLCases	Explained variable	ΔLTweets	ΔLGoogle Trends	ΔLDeaths	ΔLBitcoin
	F-statistic	0.0272	0.0011	1.3517	0.7666
	The critical value with 5% of risk	3.087	3.087	3.087	3.087
ΔLDeaths	Explained variable	ΔLTweets	ΔLGoogle Trends	ΔLCases	ΔLBitcoin
	F-statistic	0.1555	0.0279	26.7739	0.8135
	The critical value with 5% of risk	3.087	3.087	3.087	3.087
ΔLBitcoin	Explained variable	ΔLTweets	ΔLGoogle Trends	ΔLCases	ΔLDeaths
	F-statistic	0.5158	0.4860	0.1997	0.0847
	The critical value with 5% of risk	3.087	3.087	3.087	3.087

Notes: ΔLVariable is LVariable after first-differencing in order to make it stationary.

statistics are lower than the critical values of Zivot and Andrews (1992). On the other hand, the Bitcoin (logarithmic) price is non-stationary in level in spite of break in trend given that there is a unit root for such variable. To stabilize the moments for order 1 and 2 related to the Bitcoin price, we apply the Zivot and Andrews (1992) test for the first difference of variable. We thus find that the Bitcoin price is integrated of order one. Figures related to such test are reported in Appendix. We then analyze the causal direction between variables in first difference based on the univariate Granger causality test.

From Table 4, the logarithm of Tweets (in first difference) does not Granger causes variables related to the Covid-19 pandemic and the Bitcoin price. Also, the variable ΔLCases does not Granger cause ΔLGoogle Trends and the Bitcoin return (ΔLBitcoin). The Bitcoin Bitcoin return (ΔLBitcoin) seems to be not affected by the intensity of the Covid-19 pandemic and social media metrics.

We afterwards examine the issue of long memory for different variables (in first difference) based on the exponent of Hurst (1951) by using the usual and corrected R/S tests. Table 5 reports the results of these tests for different variables.

From Table 5, the issue of long memory is well-documented for the variables ΔLDeaths and ΔLCases related to the Covid-19 pandemic and Bitcoin return (ΔLBitcoin). As well, social media metrics are characterized by long-term memory behavior given that the R/S statistics of Tweets and Google Trends are greater than 0.5 and are less than 1. We perform the procedure of Geweke-Porter-Hudak (1983) to estimate the coefficient of long-term memory "d" of each variable (in first difference).

These estimated coefficients, the asymptotic values of the standard deviations and the values of the standard deviations of the regressions are reported in Table 5. The memory coefficient or the degree of integration "d" is between 0 and 0.5. Hence, each first difference variable is characterized by an autoregressive fractionally integrated moving average (ARFIMA) process. Spectral density remains constant at low frequencies and tends to infinity as the frequency approaches zero.

From the foregoing, we analyze the effect of the Corona health crisis on the Bitcoin price and social media metrics using a Fractional Structural Autoregressive Vector (FSVAR) model and impulse response functions. To do so, we first determine the optimal order of Full Vector Autoregressive (FVAR) lags based information criteria (AIC, SC, HQ and FPE). Th results are repred in Table 6.

The optimal number of the FVAR model is equal to 7 according to the Akaike Information Criterion (AIC). On the other hand, it is equal to 4 according to the Schwartz Criterion (SC) and FPE information while it appears to be 5 from the HQ information criterion. In this case, we retain four lags according to the most dominant information criterion (i.e. SC) to gain more information for variables nested within a FVAR model. One might impose short- and long-term restrictions on the FVAR model such as nullifying the long-term effect of the Covid-19 pandemic on the Bitcoin price because such pandemic is characterized by cyclical pattern and dampens in the long-term. On the other hand, the Covid-19 pandemic influences the Bitcoin price in the short-term. Social media metrics still exert a crucial effect on the Bitcoin price in the short- and long-term. The estimation of the short (B) and long (A) matrices by the Scorings and Direct methods are presented in Appendix. Such two estimation methods seem to be convergent given that they give the same results. From the estimation results, we show that the Covid-19 pandemic does not impact on social media metrics in the short- and long-term. On the other hand, the Covid-19 pandemic positively affects social media metrics (Tweets and Google Trends). Also, the Covid-19 pandemic encourages investing in digital currencies such as Bitcoin. So, the Covid-19 pandemic significantly influences social media metrics and the Bitcoin (logarithmic) price as showed in the following impulse response functions (Figure 1).

Needless to say, the variable △LCases related to the Covid-19 pandemic generates a short- and long-term increase of the variable △L Deaths. On the other hand, such shock makes it possible to sharply reduce the logarithmic number of Tweets (in first difference), but such number increases over time. In the long-term, such shock died down. The influence of the variable △LCases due to the Covid-19 pandemic has no short- or long-term impulse response on the variable △LGoogle Trends. The variable △LCases due to the Covid-19 pandemic causes Bitcoin return (△LBitcoin) to drop sharply but it increases with such pandemic and

Table 5. Usual and corrected R/S tests.

Variables	Simple R/S Hurst estimation	Corrected R over S Hurst exponent	Empirical Hurst exponent	Corrected empirical Hurst exponent	Theoretical Hurst exponent
ΔLTweets	0.5365	0.5383	0.5792	0.5257	0.5535
ΔLGoogleTrend	0.5692	0.5719	0.5692	0.5114	0.5535
ΔLCases	0.7378	0.9234	0.9179	0.9786	0.5535
ΔLDeaths	0.7537	0.9730	0.9188	0.9734	0.5535
ΔLBitcoin	0.5432	0.6059	0.6489	0.5848	0.5535

Estimation of "d" by the Geweke-Porter-Hudak Method

Variables	$\hat{d}$	Standard Deviations Asymptotic values	Regression Standard Deviation values
ΔLTweets	0.2572	0.2018	0.2389
ΔLGoogle Trends	0.3362	0.2018	0.1191
ΔLCases	0.2497	0.2018	0.0623
ΔLDeaths	0.3816	0.2018	0.0798
ΔLBitcoin	0.1324	0.2018	0.1485

Note: △LVariable is LVariable after first-differencing in order to make it stationary.

Table 6. Optimal number of FVAR lags.

Criteria	Lags							
	1	2	3	4	5	6	7	8
AIC	-19.761	-20.115	-20.707	-21.213	-21.297	-21.319	**-21.427**	-21.427
HQ	-19.587	-19.8164	-20.284	-20.665	**-20.625**	-20.522	-20.506	-20.381
SC	-19.326	-19.369	-19.65	**-19.845**	-19.618	-19.329	-19.126	-18.815
FPE	2.616×10^{-9}	1.837×10^{-9}	1.017×10^{-9}	$\mathbf{6.136 \times 10^{-10}}$	5.646×10^{-10}	5.534×10^{-10}	4.979×10^{-10}	4.995×10^{-10}

The numbers in bold refer to the minimum values of information criteria.

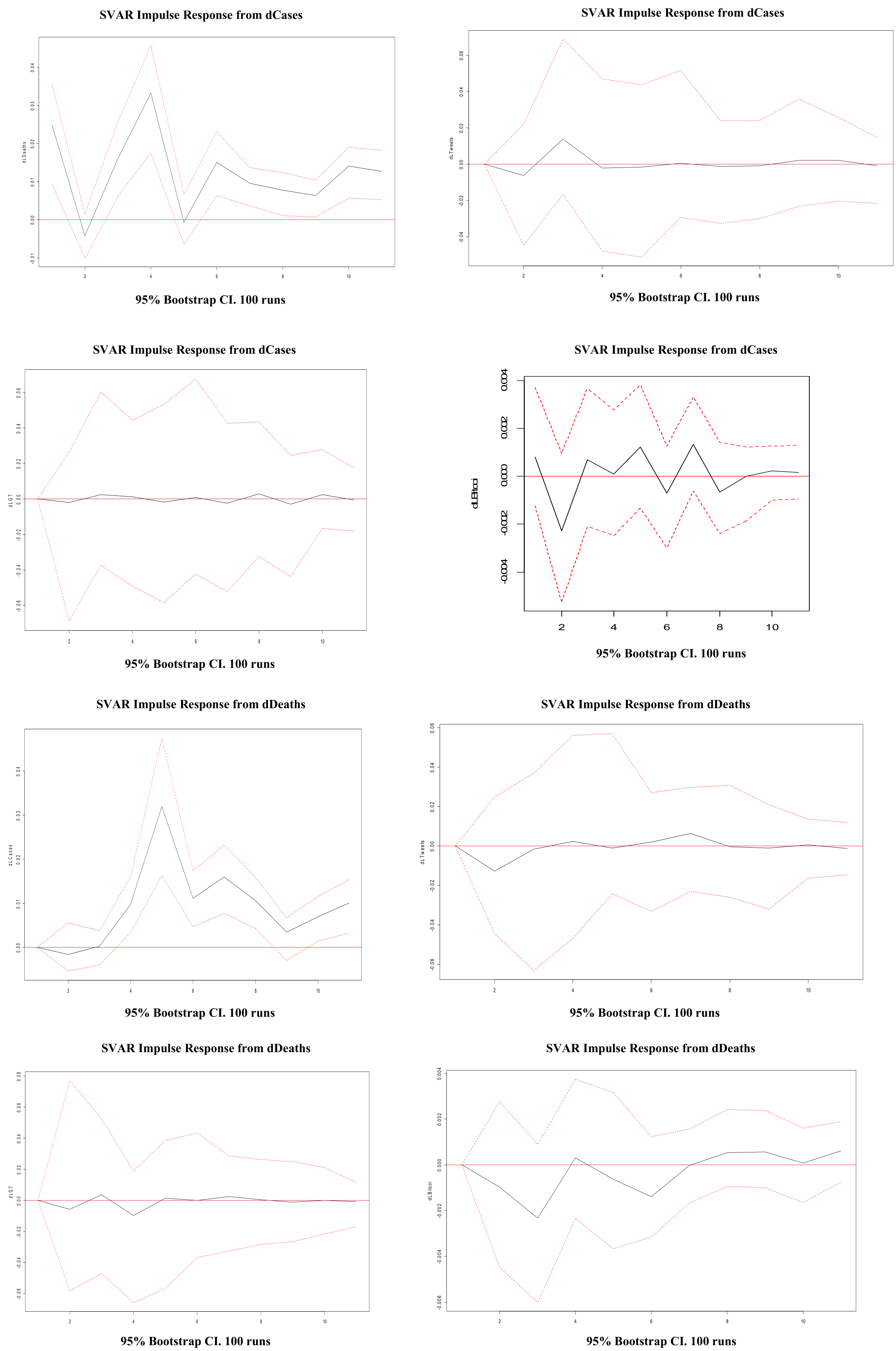

Figure 1. Impulse response functions.

Table 7. Table 7, Estimation results using different techniques.

	OLS	FM	DM	IM-OLS
Constant	7.5588***	-0.0009	-0.0006	-0.0019
LTweets	0.0358*	0.9504***	1.1938***	0.8886*
LGoogle Trends	-0.0161	1.0993***	0.9254***	0.9994***
LCases	0.3396***	1.1744***	1.1760***	1.3187***
LDeaths	-0.3021***	0.8627***	0.8325***	0.7345***
Box-Pierce test				
Khi-Deux	257.67***	0.2755	0.6048	2.6085
Box-Ljung test				
Khi-Deux	260.21***	0.2782	0.6108	2.6342
Jarque Bera Test				
Khi-Deux	177.37***	1.1182	3.1247	0.0296
Residual stationarity				
T-Statistics	-3.6024	-17.5806	-16.6338	-16.6287
Model	M1	M2	M1	M1
Critical value	-1.95	-2.87	-1.95	-1.95
Usual and corrected R/S tests				
Simple R/S Hurst estimation	0.7688	0.5117	0.5762	0.5707
Corrected R over S Hurst exponent	0.9294	0.5386	0.5160	0.6416
Empirical Hurst exponent	0.8955	0.5289	0.5750	0.5889
Corrected empirical Hurst exponent	0.8628	0.4684	0.5303	0.5471
Theoretical Hurst exponent	0.5535	0.5535	0.5535	0.5535
Estimation of "d" by the Geweke-Porter-Hudak method				
$\hat{d}$	0.2353	0.1666	0.3614	0.0516

Notes: - ***, **, * denote significant level at 1%, 5% and 10%, respectively.
- M1: Model without constant and trend and M2: Model with constant and without trend.
- LBitcoin refers to the Bitcoin (logarithmic) price.
- LTweets refers to the logarithmic number of tweets on Bitcoin.
- LGoogle Trends" refers to the logarithmic number of Bitcoin keyword research (Google).

dampens over time. The variable △LDeaths due to the Covid-19 pandemic has a negative effect on the logarithmic number of Tweets (in first difference). Nonetheless, such effect dies down in the long-run. Such impact exerts a negative influence on the search on the Google site, but disappears in the long-term. The pass-through of this shock to a weak negative response to Bitcoin return (△LBitcoin) in the short-term but this response dampens in the long-term.

All of these variables are integrated in the same order, that is, of order one (I (1)) based on the unit roots test without trend break. The theory of univarite co-integration can be thus used in order to estimate a long-term relationship between the Bitcoin price, social media metrics and the intensity of the Covid-19 pandemic. Using a nonlinear model, such relationship is formally given as follows:

$$Bitcoin_t = A\left(Tweets_t^{\alpha}\right)\left(Google\ Trend_t^{\beta}\right)\left(Cases_t^{\theta}\right)\left(Deaths_t^{\phi}\right)\exp(\varepsilon_t)\ \forall\ t : 31/12/2019 \rightarrow 30/12/2020 \tag{1}$$

We use the logarithmic operator to linearize the aforementioned model:

$$Log(Bitcoin_t) = Log(A) + \alpha Log(Tweets_t) + \beta Log(Google\ Trend_t) + \theta Log(Cases_t) + \phi log(Deaths_t) + \varepsilon_t \tag{2}$$

We use a double-step method to estimate the long-term relationship between different variables. Given some drawbacks of using such method, one might use the Fully-Modified (FM) technique, dynamic least squares (DM) method and modified integrated ordinary least squares (IM-OLS) procedure. The estimation results of the long-term relationship using different estimation techniques are reported in Table 7.

From Table 7, the estimation of this long-term relationship by the method of Engle and Granger (1987) is based on the ordinary least squares (OLS) procedure. Such relationship is accepted ex-post under the stationarity in level of the residuals of long-term relationship. We show that the number of tweets has an impact on the Bitcoin price whereas Google Trends does not influence it. The logarithmic number of people affected (LCases) by the Covid-19 pandemic positively and significantly influences the Bitcoin logarithmic price. On the other hand, the logarithmic number of people died (LDeaths) by the Covid-19 pandemic has negative and significant effect on the Bitcoin logarithmic price. The long-term relationship estimation gives a stationary target or residual in level given that the T-statistic of such target is lower in level than the critical value of Mackinnon (1992). However, the residuals from the estimation of such relationship based on the OLS method seem to be are auto-correlated based on the Box-Pierce and Box-Ljung statistics. As well, the estimated target does not follow the normal distribution given that the Jarque-Bera statistics are greater than the critical value of chi-square at two degrees of freedom. Such target can be modeled using ARFIMA-type models given that the classic and modified R/S statistics are between 0.5 and 1. We estimate the fractional degree using the Geweke-Porter-Hudak (1983) test. We re-estimate the long-term relationship between variables using the modified least squares (FM) method of Philips-Hansen (1990) and Philips (1995), the method dynamic least squares (DM) method of Saikkonen (1991) and the modified integrated least squares procedure (IM-OLS) of Stock and Watson (1993). The cointegration relationship estimated from the modified, dynamic method and integrated least squares technique shows statistically significant estimators. In this regard, we find that logarithmic number of tweets (LTweets) and Google Trends (LGoogle Trends) have positive and significant impact on the Bitcoin price. As well, the logarithmic number of people affected (LCases) and died (LDeaths) by the Covid-19 pandemic positively and significantly affects the Bitcoin logarithmic price. Besides, the re-estimated relationship makes it possible to obtain a stationary level target which is displayed using the Dickey-Fuller-Augmented test (1981), as the calculated value of the Student statistic of this target is

Table 8. Table 8, Estimation results of fractional error correction (FEC) model.

Variables	Methods			
	OLS	FM	DM	IM-OLS
Constant	0.6404***	1.0596***	1.0843***	1.1602
ΔLTweetsf	-0.2575**	-0.4129	-0.2857	-0.1625
ΔLGoogle Trendsf	0.2603*	0.2202	0.1131	0.2313
ΔLCasesf	-0.0007	0.0104	0.0512	0.0682
ΔLDeathsf	0.1082	-0.3818	-0.0780	-0.1336
Δ^dResiduals	-0.1090	-0.2740***	-0.0322***	-0.2320***

Note: - ***, **, * denote significant level at 1%, 5% and 10%, respectively.

lower than the tabulated value of Mackinnon (1992). As well, an absence of the residual autocorrelation problem is detected by the Box-Pierce and Box-Ljung statistics with the presence of a residual long memory given that the R/S statistics are between 0.5 and 1. We estimate the degree of fractional integration for the cointegration relationship residuals based on the Geweke-Porter-Hudak (1983) test. Finally, we study the adjustment of the Bitcoin price using the Fractional Error Correction (FEC) model. The estimation results of the FEC model based on different techniques are reported in Table 8.

From Table 8, the estimation results from the Fractional Error correction Model which combines the deterministic equilibrium (where the variables are stationary by the fractional difference effect) and the long-term equilibrium (where the residuals are stationary by the linear combination). The Fractional Error correction model is performed based on four estimation techniques (OLS, FM, DM and IM-OLS). Using the OLS method, there is short-term relationship between social media metrics and the Bitcoin price. But, there is no mechanism to adjust the Bitcoin price relative to its fundamental value given that the force of the recall is not significant. Using other methods (FM, DM and IM-OLS), there is no relationship between the Bitcoin price and other variables at short-term. On the other hand, a mechanism to correct the deviation of the target of the Bitcoin price from the equilibrium is well-documented given that the speeds of the adjustments are negative and significant.

5. Conclusion

In this paper, we attempt to investigate the association between Bitcoin price, social media metrics and the Covid-19 heath crisis over the period 31/12/2019-30/10/2020. In this regard, the number of Tweets and Google Trends are used as two proxies of social media metrics. The intensity of the Covid-19 pandemic is measured by the total (cumulative) number of people affected (Cases) and died (Deaths) by the Covid-19 pandemic. From methodology standpoint, we use the fractional autoregressive vector model, fractional error correction model and impulse response functions in order to perform the short- and long-term analysis of the nexus between the Bitcoin price, social media metrics and the Covid-19 pandemic. Based on such analysis, there is substantial evidence that long- and short-term associations between the Bitcoin price, social media metrics. Given that the number of new confirmed cases and mortality rates due to the Covid-19 health crisis has drastically risen, negative sentiment relating to the investment of stock markets leads investors to search for alternative investment such Bitcoin by using social media platforms. Therefore, the information content of social media in helping investment decision-making seems to be well-documented during episodes of severe turbulence.

Obviously, the financial crises, political events, contagious diseases, among others, could play a key role in market dynamics and portfolio risk management. In this respect, our findings could be of great interest to investors and portfolio managers who want to invest in cryptocurrency market and search for gathering information during turbulent periods. At this point, the increasing high market risk and the exacerbated uncertainty due to the Covid-19 health crisis have revived the interest of researchers and investors to analyze the behavior of Bitcoin market and understand the role of social media platforms as information source. Therefore, investors and traders can use social media platforms to adjust their decisions based on information regarding Bitcoin dynamics.

Declarations

Author contribution statement

Wajdi Moussa: Conceived and designed the experiments.

Azza Bejaoui: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Nidhal Mgadmi: Performed the experiments.

Tarek Sadraoui: Analyzed and interpreted the data.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability statement

No data was used for the research described in the article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2021.e07539.

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