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What matters for The Bitcoin Price and Volatility during the Covid-19 Pandemic: Social Media based- Evidence

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Abstract

In this paper, we try to examine the relationship between the Bitcoin price, social media metrics and the intensity of Covid-19 pandemic. We also attempt to investigate the behavior of Bitcoin volatility during such pandemic. For this end, we use the error correction model, Co-integration processing tool and vector error correction model to detect potential transmission mechanisms among different variables and the dynamic coupling between them. We also apply the GARCH-type models to better apprehend the behavior of Bitcoin volatility. Our results clearly display the short- and long term evidences of the relationship between the Bitcoin price, severity of the Covid-19 health crisis and social media metrics. Moreover, there is strong evidence related to the information content of social media during turbulent phases. We also report some distinctive and salient features of Bitcoin volatility. The information spillover from pandemic-related news to the Bitcoin prices is well-documented. Using the Covid-19 deaths and confirmed cases can be considered as measure of pandemic severity. As well, the information transmission mechanism is well-documented through social media which seems to have an added value during the stressful periods. Such analysis could have insightful implications for investors in crypto-currency market.

Keywords: *Covid-19 pandemic, Cryptocurrency volatility, Leverage effect, Cryptocurrency dynamics, Social media, Econometric modeling, Portfolio management, Bitcoin.*

1. Introduction

Overwhelmingly, the advent of Covid-19 health crisis has drastically affected the world and national economy. In this respect, companies have undergone important losses and unemployment rate has dramatically increased around the world. As a matter of fact, Goodell and Goutte (2020) indicate that salient dramatic facts emerge during the post-Covid-19 period including loss of consumer demand and low revenues of tourism and industry sectors. Not only has the real economy been adversely influenced by the Covid-19 outbreak but also the financial system worldwide. For instance, the financial markets in different countries such as UK, Australia, Europe and United States had experienced a strong bearish trend with no signals of slowing. In this context, Iqbal et al. (2021) indicate that S&P500 and Dow Jones had suffered from a 30% decrease in values during March 2020 (Iqbal et al. (2021)). That why many researchers have increasingly analyzed the impact of the Covid-19 outbreak on the behavior and dynamics of financial markets. For example, Al-Awadhi et al. (2020) display the severity of the Covid-19 pandemic in terms

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of confirmed cases and deaths negatively and substantially affect Chinese companies' stock returns. Ashraf (2020) clearly show that the financial markets significantly and negatively respond to the Covid-19 pandemic and such response evolves depending on the phase of such pandemic.

Such surprising alteration in financial markets around the world also seems to influence crypto-currency markets. In this regard, many researchers have rather focused to revisit the safe-haven, hedging and diversifying proprieties of Bitcoin after the advent of the Covid-19 pandemic. For instance, Huynh et al. (2020) show that Bitcoin can be considered as an effective hedge asset. Mariana et al. (2020) examine Bitcoin and Ethereum can play as safe-havens for stocks during the Covid-19 pandemic.

Not only Bitcoin, but also social media platforms seem to be crucially impacted by the severity of Covid-19 health crisis. Recall that the intensity of the Covid-19 pandemic has nudged policymakers to adopt emergency measures such as lockdowns, travel restrictions, social distancing and quarantining. This obviously makes the social media platforms useful and effective tools to disseminate information and maintain communication with other people to attenuate isolation and boredom. In this respect, Gonzalez-Padilla and Tortolero-Blanco (2020) argue that people tend to peruse much more to the posts and tweets shared on the social networking sites such as Twitter, Facebook and Instagram.

Overall, the existing literature examines the potential effect of Covid-19 pandemic in cryptocurrency market given that such unprecedented event has negatively influenced the global markets and financial markets and the lack of relationship between cryptocurrency and economic fundamentals. All of these facts lead investors to search for investment alternatives and in particular digital currencies during the stressful periods. In this respect, we contribute to the current research in different ways. We focus on the effect of the Covid-19 pandemic by using both the total number of deaths and confirmed cases as proxys of the severity of the health crisis. This can allow us to better understand how the cryptocurrency market responded in the aftermath of different news announcements. It can also understand the cryptocurrency market dynamics in the times of stressful events. In particular, we pay attention to information flow shared through social media. As such, our study provides new insights on the information sharing of Bicoin and their reaction to shocks such as the health crisis and highlights a sentimental appetite for the information demand.

This paper is related to the aforementioned literature and has two-fold goals. First, we attempt to investigate the dynamic coupling between the Bitcoin price, intensity of Covid-19 pandemic and social media metrics over the period 12/31/2019-10/30/2020. Then, we try to explore and better understand the behavior of Bitcoin volatility after the Covid-19 outbreak. That is why we adopt error correction model and Co-integration processing tool for identifying potential transmission mechanisms between different variables. The vector error correction model is also applied to analyze the dynamics of such relationships. As well, we use GARCH-type models to better apprehend the behavior of Bitcoin volatility.

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. Related Literature Review

Many researchers have particularly focused on the behavior of Bitcoin volatility. For instance, Katsiampa (2018) uses a bivariate Diagonal BEKK model to analyze the dynamic behavior of Bitcoin and Ether volatilities. The empirical results clearly show the interdependencies in the crypto-currency market over the period 8/07//2015-1/15/2018.

Meanwhile, both crypto-currencies' conditional volatility and correlation are responsive to major news. As well, Ether can be considered as an effective hedge against Bitcoin. Nevertheless, the optimal portfolio weights indicate that Bitcoin should outweigh Ether. Aalborg et al. (2018) analyze which variables (return, volatility, trading volume, transaction volume and change in the number of unique Bitcoin addresses) could explain and forecast the volatility, trading volume and return of Bitcoin over the period 3/01/2012-3/19/2017. They show that the heterogeneous autoregressive model seems to be adequate model for Bitcoin volatility and the trading volume can enhance such model. The trading volume of Bitcoin can be forecasted from Google queries for "Bitcoin". Fang et al. (2018) examine whether the impact of global economic policy uncertainty on long-term volatilities of Bitcoin, commodities, bonds and global equities. They strongly support such impact, except for bonds during the period 9/21/2010-1/26/2018. Such empirical results involve the capability of using information related to the state of global economic uncertainty to better forecast the Bitcoin volatility. Aysan et al. (2018) analyze the predictive power of global geopolitical risks index on daily returns and volatility of Bitcoin during the period 7/18/2010-5/31/2018. Based on the Bayesian Graphical Structural Vector Autoregressive technique, they show that such index seems to have a predictive power on both returns and volatility of Bitcoin. Lopez-Cabarcos et al. (2019) investigate the behavior of Bitcoin and the possible effects of S&P500 returns, VIX returns and investor sentiment on the Bitcoin volatility over the period 1/04/2016-9/30/2019. Based on GARCH-type models, they show that Bitcoin volatility seems to be more unstable during turbulent phases. Nonetheless, VIX returns, S&P500 returns and investor sentiment significantly affect Bitcoin volatility during stable phases. Kinateder and Papavassiliou (2019) analyze the calendar effects on Bitcoin volatility and returns over the period 2013-2019. Based on GARCH dummy model, they do not support evidence of a Halloween calendar anomaly. However, a reverse January effect seems to be well-documented. Yu (2019) studies the potential impacts of economic policy uncertainty (EPU) and leverage effect on one-step-ahead Bitcoin volatility over the period 3/01/2003-9/30/2018. The empirical results clearly display that the leverage effect seems to significantly affect future volatility. Nonetheless, the EPU and jumps do not influence future volatility during in-sample period. Takaishi (2020) tries to analyze the anti-persistence of Bitcoin volatility over the period 1/28/2015-1/06/2019. Based on multi-fractal detrended fluctuation analysis, the empirical results clearly display the presence of rough log-volatility increments. Thus, the log-volatility is characterized by a multi-fractal property.

More recently, several researchers have rather analyzed behavior and dynamics of crypto-currency markets during the Covid-19 period by analyzing the information content of such new information. For example, Naeem et al. (2021) analyze the asymmetric efficiency of Bitcoin, Ethereum, Litecoin, and Ripple during the Covid-19 period. The empirical results indicate significant asymmetric multi-fatality in the crypto-currency prices. They also display that the Covid-19 outbreak negatively affects the efficiency of crypto-currency markets. By taking into consideration the polarity and subjectivity of social media data based on the development of the Covid-19 outbreak, Corbet et al. (2020a) indicate that important evolution in both returns and trading volumes are well-documented. This implies that digital currencies can play as a store of value during the Covid-19 pandemic. They also display that crypto-currency returns are affected by negative sentiment related to the Covid-19 pandemic. Iqbal et al. (2021) explore the effect of the Covid-19 outbreak on crypto-currency 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 Covid-19 by realizing positive gains but fail to resist against adverse changes, expect for Bitcoin and Cardano. James et al. (2021) analyze the effect of the Covid-19 outbreak on crypto-currency market dynamics. They report some asymmetries in crypto-currency markets behavior. In this regard, Tether and True USD are consistent outliers with respect to their returns whereas Holo, NEXO, Maker and

NEM are frequently observed as anomalous with respect to both behaviours and time. Goodell and Goutte (2020) examine that the effect of the Covid-19 outbreak on Bitcoin prices during the period 12/31/2019-4/29/2020. They report that such pandemic positively influences Bitcoin prices, in particular for the period post April 5. Caferra (2020) investigates the linkages between news-driven sentiments and the crypto-currency market behavior. 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.

Mnif et al. (2020) analyze the behavior of crypto-currency markets during the Covid-19 pandemic. They show that such pandemic positively affect the crypto-currency market efficiency. Lahmiri and Bekiros (2020b) examine the informational efficiency in 45 crypto-currency markets and 16 international stock markets before and during Covid-19 pandemic. They prove that the level of stability in crypto-currency markets has significantly diminished while the irregularity level significantly increases during the Covid-19 pandemic period. They also indicate that the level of stability in international equity markets has not changed but gained more irregularity. The crypto-currencies tend to be more volatile. As well, crypto-currency and stock markets show a similar degree of stability in price dynamics. They afterwards report that digital markets experience a low level of regularity compared to international equity markets. They finally indicate that crypto-currencies are characterized by more instability and irregularity during the Covid-19 pandemic compared to international stock markets. Yousaf and Ali (2020) explore return and volatility transmission among Bitcoin, Ethereum, and Litecoin during the pre-Covid-19 and Covid-19 periods. They indicate that the return spillovers change through both periods for the Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin pairs. The volatility transmission seems to be insignificant between crypto-currencies during the pre-Covid-19 period. They afterwards show that the volatility spillover is unidirectional from Bitcoin to Ethereum and bidirectional between Ethereum and Litecoin during the Covid-19 period. As well, volatility transmission is not significant between Bitcoin and Litecoin during the Covid-19 period. The dynamic conditional correlations between all pairs of crypto-currencies are higher during the Covid-19 period than during the pre-Covid-19 period.

Other researchers rather prefer to study the safe-haven proprieties of crypto-currency (in particular Bitcoin) market during the outbreak of Covid-19 health crisis. For instance, Umar and Gubareva (2020) analyze the effect of the Covid-19 fueled panic on the volatility of major fiat and crypto-currency markets over the period 1/2020-5/2020. They show the cross-currency hedge strategies could not implement during the Covid-19 pandemic. They also report some key differences in currency markets behavior. Mariana et al. (2020) test if Ethereum and Bitcoin can be safe-havens for stocks during the Covid-19 pandemic. They show that crypto-currency 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. Conlon et al. (2020) analyze safe-haven capabilities of some crypto-currencies (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. Mokni and Ajmi (2021) report the causal analysis between crypto-currencies (Bitcoin, Ethereum, Litecoin, Ripple and Bitcoin Cash) and the US dollar during the Covid-19 health crisis. They report a significant causal relationship between the two markets during such pandemic. They also indicate that the US dollar loses its predictive power in favor of crypto-currencies, which can play a hedging role against the US dollar variations. Conlon and McGee (2020) explore the safe-haven proprieties of Bitcoin against the S&P500 market over the period 3/21/2019-3/20/2020. 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. Ji et al. (2020) examine the safe-haven role of some assets (gold, crypto-currency, foreign exchange and commodities) during the Covid-19 pandemic. They display that the role of safe haven becomes less effective for major assets while gold and soybean commodity futures remain robust as safe-haven assets during this pandemic. Corbet et al. (2020c) analyze the relationship between the Chinese financial markets and crypto-currency market during the Covid-19 health crisis. The volatility relationship between the main Chinese stock markets and Bitcoin tend to change significantly during such period.

3. Data Presentation and Descriptive Statistics

In this paper, we use the Bitcoin price, social media metrics and the intensity (or severity) of the Covid-19 pandemic on daily frequencies over the period 12/31/2019 -10/30/2020. The choice of the ending date for our paper is not arbitrary. Our study is tailored to allow for analyzing the relationship between the Bitcoin price, social media metrics and Covid-19 severity and examine the behavior of Bitcoin volatility. Such period is characterized by the first waves of pandemic with its wide scale devastation in terms of lockdowns, deaths, panic, fear, psychological distress and uncertainty in the absence of any vaccine or a sound cure. In this respect, we collect Bitcoin prices from the website www.coinmarketcap.com. The severity of the Covid-19 pandemic is approximated by two measures: The variable “Cases” refers to the total (cumulative) number of people affected by the Covid-19 health crisis and the variable “Deaths” corresponds to the total (cumulative) number of people died by the Covid-19 health crisis. Such data is collected from the website www.worldometers.info/ which provides insightful information on global Covid-19 statistics on worldwide level. With regard to social metrics, we use Twitter data on Bitcoin from https://bitinfocharts.com/ which indicate the number of times “Bitcoin” has tweeted over the period 12/31/2019-10/30/2020. Afterwards, the number of Bitcoin keyword research on Google is used as an indicator of the search intensity on Google during the study period. Following several researchers (e.g. Da et al. (2015); Li and Wang, (2016); Moussa et al. (2020)), we use worldwide search trends-based data from Google Trends.

Table 1 reports a snapshot of descriptive statistics of variables including Mean, Standard Deviation, Median, Skewness, Kurtosis and Jarque-Bera test. Needless to say, we converted all the series into log values (Lvariable).

Table 1. Descriptive Statistics of Variables

Variables	LTweets	LGoogle Trends	LCases	LDeaths	LBTC
Mean	3.41	3.83	14.18	10.91	9.14
Standard Deviation	0.49	0.48	3.73	3.91	0.19
Median	3.39	3.77	15.62	12.82	9.15
Minimum	2.6	1.96	3.3	0	8.51
Maximum	10.26	10.74	17.64	13.99	9.53
Skewness	8.75	9.83	-1.48	-1.58	-0.68
Kurtosis	119.31	141.33	1.38	1.48	0.33
Jarque-Berra	187.881	263.081	138.55	156.93	25.227
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
N	306	306	306	306	306

Notes: - L(.) refers to the natural logarithmic operator;

- BTC refers to Bitcoin;

- N is number of observations.

As reported in Table 1, the total (cumulative) confirmed cases (LCases) have recorded the highest average (10.91) whereas the lowest average is recorded for Google Trends and Tweets (resp. 3.827 and 3.415). As well, Tweets and Google Trends seem to be less risky while other variables have recorded high value of standard deviation. The asymmetry features in terms of skewness and kurtosis among different variables seem to be well-pronounced. The Jarque-Bera statistics are only significant for all the variables. This clearly indicates that such variables are not normally distributed. We thereafter analyze the possible linear linkages between the variables under study. Table 2 reports the variance-covariance matrix.

Table 2. Variance-Covariance Matrix

Variables	LTweets	LGoogle Trend	LCases	LDeaths	LBTC
LTweets	**0.2427**	0.0281	0.7559	0.7950	0.0247
LGoogle Trend	0.0280	**0.2280**	0.1337	0.1620	-0.0062
LCases	0.7559	0.1337	**13.8810**	14.5217	0.3513
LDeaths	0.7950	0.1620	14.5217	**15.3135**	0.3306
LBTC	0.0247	-0.0062	0.3513	0.3306	**0.0371**

Notes: - L(.) refers to the natural logarithmic operator;

- BTC refers to Bitcoin.

Recall that it is worth-noting to examine the eventual relationships between different variables using the Variance-Covariance matrix. Needless to say, the off-diagonal elements are the covariance's between all possible pairs of variables while the diagonal elements of the matrix correspond to the variances of the variables (in bold). From Table 2, some asymmetry features between variables under study seem to be well-documented. For instance, the relationship between the severity of the Covid-19 pandemic (LCases and LDeaths) and the Bitcoin (logarithmic) price tends to be positive. However, there is a negative linkage between the Bitcoin (logarithmic) price and Google Trends.

Table 3. Results from Unit Root Tests

Phillips-Perron (1988) Test (in level)					
Variables	LTweets	LGoogle Trend	LCases	LDeaths	LBTC
Dickey-Fuller Z (alpha)	-2.1436	-2.18312	-4.5648	-3.1134	-10.738
Truncation Lag parameter	5	5	5	5	5
p-value	0.9743	0.9712	0.8544	0.9288	0.5083
Phillips-Perron (1988) Test (in first difference)					
Variables	LTweets	LGoogle Trend	LCases	LDeaths	LBTC
Dickey-Fuller Z (alpha)	-312.54	-243.97	-233.48	-245.62	-342.02
Truncation Lag parameter	5	5	5	5	5
p-value	0.01	0.01	0.01	0.01	0.01

Notes: - L(.) refers to the natural logarithmic operator;

- BTC refers to Bitcoin.

We afterwards examine the issue of stationarity (in level and first difference) of all the variables over the period 12/31/2019-10/30/2020. Table 3 reports the results obtained from Phillips-Perron (1988) test. Overall, the Z(alpha) or Z(t-alpha) statistic for all variables are not statistically significant. Therefore, all the variables are not stationary in level. After first-differencing, variables become stationary given that Z(t-alpha) statistics are statistically significant. Hence, these variables are integrated of order one (I(1)).

4. Empirical Validation

We first examine the intertwining between the Bitcoin price, social media metrics and the severity of Covid-19 pandemic. To this end, we employ the univariate and multivariate Co-integration theory in order to avoid the estimation of fallacious relationships using traditional econometric techniques given that all the variables are not stationary in level. More precisely, we apply the error correction model (ECM), Co-integration technique and error correction vector model (VECM) to analyze the linkages between Bitcoin price, social metrics and the intensity of the Covid-19 health crisis over the period 12/31/2019-10/30/2020. Afterwards, we attempt to analyze the behavior of Bitcoin volatility during the Covid-19 outbreak using different models (ARCH, GARCH, EGARCH and TGARCH models).

4.1. Estimation Results of Long-Term Relationship between the Bitcoin Price, Covid-19 Pandemic and Social Media Metrics

We first investigate the relationship between the Bitcoin price, social metrics and the intensity of the Covid-19 pandemic using the Engle-Granger (1987)'s univariate Co-integration. Such method is based on two steps. In a first step, the following model is estimated based on the ordinary least squares (OLS) technique:

$$BTC = A(Tweets)_t^{\alpha}(GoogleTrend)_t^{\beta}(Cases)_t^{\gamma}(Deaths)_t^{\theta}\exp(\varepsilon_t) \qquad (1)$$

with:

BTC: The Bitcoin price;

exp (.) corresponds to the exponential operator;

ε_t the error term, $\varepsilon_t \sim (0,)$.

One might employ the logarithmic operator in order to linearize the aforementioned model:

$$Log(BTC) = Log(A) + \alpha Log(Tweets)_t + \beta Log(GoogleTrend)_t + \gamma Log(Cases)_t + \theta Log(Deaths)_t + \varepsilon_t \qquad (2)$$

The estimation results of the aforementioned model using the OLS technique are reported in Table 4.

Table 4. Estimation Results of the Long-Term Relationship

Variables	Estimated Coefficient	T-Statistic	Significance
Intercept	7.5588 [0.1194]	63.305	0.0000
LTweets	0.0358 [0.0167]	2.149	0.0325
LGoogle Trend	-0.0161 [0.0158]	-1.018	0.3094
LCases	0.3396 [0.0226]	15.016	0.0000
LDeaths	0.3021 [0.0215]	-14.022	0.0000

Notes: - L(.) refers to the natural logarithmic operator;

- [.] refers to standard deviation.

From Table 4, the Google Trend (LGoogle Trend) does not affect the Bitcoin (logarithmic) price. Nonetheless, the number of tweets (LTweets) seems to significantly and positively influence the Bitcoin (logarithmic) price. As well, the total number of people affected (LCases) by the Covid-19 pandemic positively and significantly influences the Bitcoin price. Nevertheless, the cumulative number of people died by the Covid-19 pandemic tends to significantly and negatively affect the Bitcoin (logarithmic) price.

We afterwards test for the residuals stationarity based on Phillips-Perron (1988)) test. If the variable is stationary in level, one might accept the estimation results of such relationship using the OLS technique. In this case, one might analyze the long-term relationship between the Bitcoin price and other independent variables using the CM model. Otherwise (if the residuals are not stationary in level), one might reject the existence of long-term relationship between variables. Table reports the results of unit root test which is applied on residuals.

Table N° 5. Residual stationnarity (in level) using Phillips-Perron (1988) Test

Dickey-Fuller Z (alpha)	Optimal delay Parameter	p-value
-22.102	5	0.04398

From Table 5, the relationship residuals are stationary in level given that Z(t-alpha) statistic under the Phillips-Perron (1988) test is statistically significant at level of 0.05. In a second step, one might use the ECM error correction model which gets together the deterministic equilibrium (where the variables are stationary by the first difference) and the long-term equilibrium (where the variables are stationary by the residuals are stationary by the linear combination). The estimation results are reported in Table 6.

Table N°6. Estimation Results of the ECM Model

Variables	Estimated Coefficient	T-Statistic	Significance
Intercept	1.240×10^{-3} [2.337×10^{-3}]	0.530	0.59620
Δ LTweets	-2.691×10^{-5}[3.473×10^{-3}]	-0.008	0.99382
Δ LGoogle Trend	-2.628×10^{-5}[3.459×10^{-3}]	-0.008	0.99394
Δ LCases	-1.265×10^{-2}[3.024×10^{-2}]	-0.418	0.67607
Δ LDeaths	3.130×10^{-2}[2.747×10^{-2}]	1.139	0.25544
Residuals	4.254×10^{-2}[1.616×10^{-2}]	2.632	0.00864

Notes: - $\triangle$LVariable is LVariable after first-differencing in order to make it stationary;

- [.] refers to standard deviation.

From Table 6, the empirical results clearly show that all the variables seem not to significantly affect the Bitcoin return (ΔLBTC). Also, there is no mechanism to adjust the Bitcoin return relative to its fundamental value given that the force of the recall is not significant.

We thereafter use the multiple Co-integrations in order to better apprehend the relationship between the Bitcoin (logarithmic) price and other variables related to the severity of the Covid-19 pandemic and social media metrics. In this regard, Smith and Harrison (1994) extend the concept of Co-integration by examining the multiple Co-integrations with 3 or more Co-integrated variables. Recall that multiple Co-integrations arise when more than one Co-integration relation amongst than two non-stationary exists (Kang, 2002). For example, the rank of Co-integration can be either 0 (no-Co-integration), 1 (one Co-integration), 2 (two Co-integrations) or 3 (three Co-integrations). Indeed, one might assess the Co-integration process among variables using the Johansen (1990-1995) test. If a Co-integration is detected, the VECM model will be used through the maximum likelihood technique. The Johansen (1990-1995) test is found on the Max-Eigen and Trace criteria.

Table N°7. Johansen Cointegration Test

λ_{trace} Test					
LBTC, LTweets, LGoogle Trend, LCases, LDeaths					
Null hypothesis	r = 0	r ≤ 1	r ≤ 2	r ≤ 3	r ≤ 4
Alternative hypothesis	r > 1	r > 2	r > 3	r > 4	r > 4
Statistical values	**261.93**	**148.05**	**73.52**	16.51	1.56
Critical values of 5%	**76.07**	**53.12**	**34.91**	19.96	9.24
λ_{max} Test					
LBTC, LTweets, LGoogle Trend, LCases, LDeaths					
Null hypothesis	r = 0	r = 1	r = 2	r = 3	r = 4
Alternative hypothesis	r = 1	r = 2	r = 3	r = 4	r = 5
Statistical values	**113.88**	**74.53**	**57.01**	14.95	1.56
Critical values of 5%	**34.40**	**28.14**	**22.00**	15.67	9.24

Variables	Cointegrating vectors	Loading matrix
LBTC	1.0000	-0.0025
LTweets	-1.8846	0.4025
LGoogle Trend	0.8783	-0.1742
LCases	-0.1923	0.0092
LDeaths	0.2321	0.0041
Intercept	-5.8107	

Notes: - L(.) refers to the natural logarithmic operator;

- [.] refers to standard deviation.

Table 7 displays the results of the Johansen (1990-1995) Co-integration test for different variables. The Max-Eigen and Trace criteria illustrate the presence of three Co-integration relations. Therefore, one might check the Co-integration of all the variables. In this context, we retain only one interpretable Co-integration relation. Indeed, the number of Tweets (LTweets) has a negative and significant impact on the Bitcoin (logarithmic) price while Google Trend (LGoogle Trend) positively and significantly influences it. The total number of people affected (resp. died) by the Covid-19 pandemic negatively (resp. positively) affect the Bitcoin (logarithmic) price. Such empirical result is explained by the fact that the effects of news announcements related to pandemic severity on the Bitcoin prices are not the same in terms of direction and scale. As well, we use the total number of confirmed cases and deaths, unlike the daily numbers which are employed in other studies.

4.2. Estimation Results of the Bitcoin Volatility

We attempt to model each variable (in first difference) using the ARMA model. Meanwhile, we determine an optimal number of lags. Also, we test for the presence (or absence) of the heteroscedasticity issue using the Breusch-Pagan (1979) test. If heterogeneity of residual variance is well-documented, one might model any variable (in first difference) using the linear and nonlinear ARCH models. Table 8 reports the empirical results related the model specification.

Table N°8. Specification Model for Each Variable & Detection of ARCH Effect

Specification Model for Each Variable					
	dLBTC	dLTweets	dLGoogle Trend	dLCases	dLDeaths
Intercept	0.0022	0.0064	0.0020	0.0025	0.0020
AR(1)	-0.0519**	-0.6215***	0.0448***	0.9444***	0.9565***
AR(2)	0.1136	-0.2953			
MA(1)			-0.8729**	-0.6432	-0.7242
Model	AR (2)	AR (2)	ARMA (1,1)	ARMA (1,1)	ARMA (1,1)
BP test	53.527***	23.7372***	18.153***	136.89***	26.367***
Detection of ARCH Effect					
	dLBTC	dLTweets	dLGoogle Trend	dLCases	dLDeaths
Intercept	1.0421**	9.651×10^{-1}***	6.511×10^{-3}***	1.924×10^{-3}***	6.357×10^{-3}***
ARCH (1)	0.0228	9.426×10^{-15}	1.500×10^{-1}***	1.169***	1.038*
Jarque-Bera	2.145	0.5992	87.338***	104.912***	21.087***
Box-Ljung	0.0036	0.9290	0.0263	0.0212	76.567***
GARCH Model					
	dLBTC	dLTweets	dLGoogle Trend	dLCases	dLDeaths
Intercept	0.9661	0.9141	0.1861	1.345×10^{-9}	6.023×10^{-6}
a_1	0.0235	1.341×10^{-14}	0.1389***	0.3202***	0.9581
b_1	0.0706	6.125×10^{-2}	9.350×10^{-16}	0.6839***	6.761×10^{-8}
Jarque-Bera	2.1299	0.5992	46.1962***	71.207***	21.187***
Box-Ljung	0.0055	0.9290	0.1885	30.739***	77.037***

Notes: - dLVariable is LVariable after first-differencing in order to make it stationary;

- BTC refers to Bitcoin;
- BP test refers to Breusch-Pagan (1979) test;
- * Significant at 10% level;
- ** Significant at 5% level;
- *** Significant at 1% level.

From Table 8, the empirical results show that the Bitcoin return (dLBTC) and the number of Tweets (dLTweets) can be modelled by the AR(2) model. On the other hand, one might specify the other variables (in first difference) using ARMA(1,1) model. The empirical results also display the heteroscedaticity issue given that the Breusch-Pagon statistics are statistically significant.

We thereafter analyze the ARCH effect for each variable. From Table 8, no ARCH effect can be detected in the time series of Bitcoin return and the number of Tweets (dLTweets). On the other hand, the other variable time series are modelled by an ARCH(1) model given that the estimated residuals of each variable are not statistically significant. Such variable time series seem not to be normally distributed given that the Jarque-Bera statistics are significant. Otherwise, the lack of the residual autocorrelation issue for these variables is well-documented given that the Box-Ljung statistics are not statistically significant. Therefore, one might model different variables using the GARCH model. The empirical results are also reported in Table 8.

From Table 8, the asymmetric volatility pattern of time series with respect to the (good and bad) news seems not to be detected in the Bitcoin return and social media metrics. But, the volatility pattern of the variables is detected for variables (in first difference) related to the severity of the Covid-19 pandemic (dLCases and dLDeaths). That is why we choose the EGARCH model to better the volatility's behavior for each variable. Such model does not require any restrictions on the EGARCH model parameters given that it is based on log variance and the variance's positivity is thus satisfied. The estimation results are also reported in Table 9. Needless to say, the EGARCH model is estimated using the maximum likelihood technique.

Table N°9. Estimation Results of EGARCH and TGARCH Models

EGARCH Model					
	dLBTC	dLTweets	dLGoogleTrend	dLCases	dLDeaths
Mu	0.002075	0.014525***	0.000791	0.016968***	0.007082
Omega	-0.157586***	-1.938514***	-0.400530***	-0.079447	-0.236091
alpha1	-0.109831*	-0.913660***	-1.278219***	0.008431	0.011770
beta1	0.976372***	0.086746	0.786556***	0.996232***	0.981158
gamma1	0.039038	1.847731***	1.042057***	0.705443***	0.227588
TGARCH model					
	dLBTC	dLTweets	dLGoogleTrend	dLCases	dLDeaths
Omega	0.0017464*	0.1933***	5.973×10^{-7}	9.320×10^{-8}	4.611×10^{-5}
alpha1	0.0579425	1.00000***	1.00000***	1.00000***	1.00000***
gamma1	1.00000***	0.7682***	0.3872***	0.5678	1.00000***
beta1	0.9147456***	1.000×10^{-8}	0.6486***	0.6672	0.9835***

Notes: - dLVariable is LVariable after first-differencing in order to make it stationary;

- BTC refers to Bitcoin;

-* Significant at 1% level;

- *** Significant at 1% level.

From Table 9, the empirical results clearly show that all the estimated coefficients are statistically significant, except for the variable "dLDeaths". The amplitude of volatility for social media metrics seems to be noticeable given that the estimated alpha is negative and statistically significant. Therefore, a leverage effect for the social media metrics seems to be well-documented. Nevertheless, such amplitude is low for the Bitcoin return and variables related to the severity of Covid-19 pandemic. The estimated coefficients of the lagged asymmetric volatility are important and statistically significant for different variables, except for the variable dLTweets. One might model the volatility's behavior based on the TGARCH model. From Table 9, the estimation results from modeling the asymmetric volatility based on the TGARCH specification clearly show that the estimated coefficients are positive and statistically significant. The estimated asymmetry coefficient of each variable is equal to 1. But, it seems to be low for the Bitcoin return. Also, the volatility parameter for each variable is positive and it is low for the number of Tweets (dLTweets). The transition speed is less than 1 for the variables related to the social media and the cumulative number of confirmed cases. On the other hand, it is equal to 1 for the variable dLDeaths and the Bitcoin return.

5. Conclusion

In this paper, the purpose is two-fold. First, we try to analyze the linkages between the Bitcoin price, social media metrics and the severity of the Covid-19 pandemic over the period 12/31/2019-10/31/2020. In this respect, the total (cumulative) number of cases and deaths are two variables which serve to quantify the severity of the Covid-19 pandemic. As well, we use the number of Tweets and that of Bitcoin keyword research on Google are considered as indicators of social media metrics. From a methodological standpoint, we apply the Engle-Granger (1987)'s univariate Co-integration, the error correction model (ECM) and error correction vector model (VECM) to analyze the relationship between the Bitcoin price, social metrics and the intensity of the Covid-19 health crisis. Then, we attempt to study the behavior of the Bitcoin volatility during the outbreak of Covid-19 pandemic. That is why we use a battery of GARCH-type models. The empirical results clearly show that long- and short-term between the Bitcoin price, the intensity of the Covid-19 pandemic and social media metrics. We also display some distinctive features in the behavior of Bitcoin volatility such as the leverage effect. Not surprisingly, the severity of contagious disease along with sharing different information on social media platforms seems to increasingly affect the volatility's dynamics.

The empirical results clearly show that the number of tweets affects significantly and positively the Bitcoin prices whereas Google trend does not influence it. The total number of people contaminated (resp. died) by the pandemic influences significantly and positively (resp. negatively) the Bitcoin prices. Therefore, there are differences between the effects of news announcements related to pandemic severity on the Bitcoin prices. The information spillover from pandemic-related news to the Bitcoin prices is well-documented. Using the Covid-19 deaths and confirmed cases can be considered as measure of pandemic severity. As well, the information transmission mechanism is well-documented through social media which seems to have an added value during the stressful periods.

Overall, the outbreak of pandemics seems to play a crucial role in the dynamic behavior of financial markets and portfolio risk management. In this regard, our findings could be of great interest to portfolio managers and investors who search for to invest in digital markets and collect information during turbulent phases. Thus, participants to crypto-currency market could use social media platforms to better make decisions by using information regarding Bitcoin dynamics.

Compliance with Ethical Standards:

Conflict of Interest: We declare no conflict interest between all authors in this paper.

Ethical Approval: This article does not contain any studies with human participants performed by any of the authors.

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