Cryptocurrency spectrum and 2020 pandemic: Contagion analysis

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A R T I C L E I N F O

A B S T R A C T

While several studies evaluate the impacts of the novel coronavirus pandemic on different markets, it is worth the while to also examine its contagion (fractal) effect on the top (based on their market capitalization) twenty cryptocurrency markets. These cryptocurrency markets' information (return and volatility) were sampled for both the ex-ante and ex-post coronavirus outbreak periods for this event study analysis. The detrended cross-correlation approaches are employed for both the main and robustness analyses. The results are robust and confirm a significant fractal contagion effect of the pandemic on the cryptocurrency space through their return and volatility. The contagion effect is relatively stronger for the crypto markets' volatilities compared to the returns, nonetheless. Hence, this study supports the contagious effect of the coronavirus pandemic on the cryptocurrency markets and its policy implications for investors in the crypto space.

1. Introduction

While most viruses pose little threats to life, others pose severe threats. COVID-19 is one of the coronaviruses that pose serious threats to life. The COVID-19 pandemic has been followed by momentary business closures and panics in the household in most, if not all, economies where infected patient cases are confirmed. Performances are affected due to these reactions in these economies as well as their investment dynamics. Given the rapidly increasing administration of the vaccine, most economies are gradually relaxing the strict business closures and movements of people. Besides, given the contagious nature of the pandemic, coupled with movements and migrations of people from one city or state or country to another exists, the virus can spread through to other countries, since the vaccination does not stop one from being infected. Likewise, the investment markets are simultaneously affected by business and household panics. One of the most internationalized (or popular) investment markets is the cryptocurrency market. Hence, this study investigates the contagious impact of the coronavirus pandemic on the cryptocurrency markets, based on their unconditional volatilities and returns. This study takes a step further to investigate the fractal contagion effect on the cryptocurrency spectrum. Several studies have further illustrated the impact of the pandemic on various markets (Okorie & Lin, 2021a; 2021b; Dong, Song, & Yoon, 2021; Ahmad, Kutan, & Gupta, 2021; Wang, Li, & Huang, 2021; Yousaf, 2021; Tripathi & Pandey, 2021; Umar, Gubareva, & Teplova, 2021; etc.). However, the contagion effect of the coronavirus pandemic on the cryptocurrency markets has not been explored in the literature. This is the gap this study seeks to fill.

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COVID-19 is an abbreviation for the coronavirus disease that is discovered in 2019. The coronavirus 2019 pandemic started in the Wuhan city wildlife market in China. This market was shut down given the rapid spread of this virus and its dangers to humanity. Following this, the whole city of Wuhan was shut down. Subsequently, other cities followed, the entire country, and then, other countries of the world are locked down. The lockdown is a necessary fit aimed at strategically separating and quarantining the infected persons from the uninfected. In summary, most, if not all, countries of the world are currently affected by this virus, causing the pandemic. This has resulted in several deaths and rapidly increasing infected cases in different economies concurrently. This model (involving a strategy of total lockdown) has proven to be effective in mitigating the coronavirus effects for a country, with and without the vaccines. Wherein the affected populace is subdivided over time, into infected and uninfected persons through the acid test. Thereafter, the quarantine and treatment of the infected persons begin while the uninfected persons return to their businesses as usual. This model has been very effective in salvaging economies from the consequences of the coronavirus. Overall, this results in a panic since businesses and operations would be temporarily affected until the infected people's separation is perfected. Hence, families would need sustenance resources through the periods of lockdown. Some governments offer palliatives in the form of food and money to households during these periods. On the other hand, in the absence of such provisions or in addition to such provisions, most investors liquidate part or all of their positions, this includes digital coin positions. As many cryptocurrency investors embark on this action, this affects the cryptocurrency markets through their prices & volatility and thereby, leading to a fractal contagion effect in the cryptocurrency space.

Since the outbreak of the COVID-19 pandemic, many empirical studies have investigated its impacts on different markets and areas. Some of these areas include market efficiency (Okorie & Lin, 2021a; Montasser & Benhamed, 2021; Ozkan, 2021; etc.), market dependency (Dong et al., 2021; Benlagha & Omari, 2021; Xu, 2021; etc.), market contagion (Okorie & Lin, 2021b; Rao, Goyal, Kumar, Hassan, & Shahimi, 2021; Nguyen, 2021; Maneejuk, Thongkairat, & Srichaikul, 2021; etc.), black swans (Ahmad et al., 2021), market connectedness (Li et al., 2021; Jebabli, Kouaissah, & Arouri, 2021; Wang et al., 2021; Yousaf, 2021; Tripathi & Pandey, 2021; Corbet, Hou, Hu, Oxley, & Xu, 2021; etc.), and several other studies. The phenomenon of a contagion effect, due to a global event(s) that originates in a region or country, has earned the interest of scholars or researchers both in the field of finance and economic literature. These are the Detrended Correlation approaches. For instance, Mohti, Dionísio, Vieira, and Ferreira (2019) studied the global contagion effect of the US subprime crisis and the Eurozone debt crisis using both the Detrended Cross-Correlation Analysis (DCCA) and Detrended Moving Cross-Correlation Analysis (DMCA) techniques. Their results show that the leading markets responded substantially to these crises and thereby confirm significant stock market contagious effects. Hence, they concluded a frontier stock market contagion effect. They further noted that while the contagion effect is stronger for the US subprime crisis, it is weaker for the Eurozone debt crisis. The Detrended Moving Average Partial Cross-correlation Analysis (DMPCCA) was developed by Zhang, Lin, and Yang (2020) to study the financial stock market system simultaneously. They confirm that the stock markets are cross-correlated with each other. Wang, Wei, and Wu (2010) investigated the cross-correlation, and contagion, in Chinese A-shares and B-shares markets using the DCCA modelling technique. They found that the return series from these two rated markets are significantly cross-correlated and thus confirming the presence of contagion in the Chinese stock market. They also showed that the cross-correlations fluctuations in the short run are less persistent compared with those in the long run.

To this end, the DMCA and DCCA techniques are employed in this study to analyze the fractal contagion effects of the COVID-19 pandemic on the top 20 cryptocurrency markets. The analysis and findings support a significant fractal contagious effect in the cryptocurrency spectrum while using the Bitcoin market as the reference market. This is evident through the cryptocurrency markets' returns and unconditional volatilities. The contagion effect is relatively weak for the crypto market returns relative to the volatility. Besides, the use of the DMCA and DCCA techniques to study fractal contagion is common in the finance and economic literature. To highlight a few, Mohti et al. (2019) studied the global impact of the Eurozone debt crisis and the US subprime crisis. Zhang et al. (2020) studied major stock market indexes' comovements. Bashir, Yu, Hussain, and Zebenede (2016) studied Latin America's equity market and the foreign exchange market. Comovements between the Chinese A-shares and B-shares markets (Wang et al., 2010). Financial market volume and price variations (Podobnik, Horvatic, Petersen, & Stanley, 2009). Oil prices and Asian markets comovement (Hussain, Zebende, Bashir, & Donghong, 2017). Others may include real-world issues (Podobnik, Wang, Horvatic, Grosse, & Stanley, 2010), the study of the meteor (Zebende, Brito, Filho, & Castroe, 2018), etc. Similarly, the research objective of this article is to investigate the contagious behaviour of the cryptocurrency markets spectrum, as a result of the pandemic, using both the DMCA and DCCA approach.

In the same light, other techniques apart from the detrending approaches have been adopted to establish (cross) correlations between and among various financial and non-financial markets. For example, Ang and Bekaert (2002) show that there exists a significant correlation between international equity markets. They added that during periods of high volatility, the correlation between the international equity markets is stronger relative to periods of low volatility. Ang and Chen (2002) show that there exists a significant correlation between the stock markets and the aggregate markets of the United States. They noted that this correlation is greater at the downside relative to the upside. Scheicher (2001) studied both the regional and global connectedness of the stock markets in Poland, Czechia, and Hungary. He noted that there exists a limited interconnectedness in the stock market returns at regional and global levels. For the developed economies, the United States subprime crisis resulted in a financial contagion (Paulo, Carlos, & Isabel, 2008). Their results suggest that most economies are interconnected with the United States economy and as such the intensity of the linkages or interconnectedness is stronger. Unlikely earlier findings, there exist no significant contagion effect of the 1997 Asian crisis in the global economy after adjusting for the heteroscedastic biases given that the correlation coefficient depends on the market volatility (Forbes & Rigobon, 2002). The rest of the article is structured as empirical strategy, results & discussions, and conclusion; for models development, discussion of results, and drawing conclusions based on the findings respectively.

2. Model

Fractal analyses are mainly used to model similar structures or patterns that reoccur in series. Therefore, it is capable of modelling the co-dependencies, linear and non-linear, in the sampled cryptocurrency markets due to the outbreak of COVID-19. Vandewalle and Ausloos (1998) introduced the Detrended Moving Cross-Correlation Analysis (DMCA) and it was further augmented by Kristoufek (2014). Similarly, while Peng et al. (1994) proposed the Detrended Cross-Correlation Analysis (DCCA) methods, Podobnik and Stanly (2008) modified it. In a system of markets, these tools are capable of identifying contagion effects and their dynamics within the system. These tools or techniques have been utilized in finance and economics (Wang et al., 2010; Zhang et al., 2020) and other various fields (Kristoufek, 2014; Mohti et al., 2019; Zebende, 2011). These approaches are capable of detecting fractal contagion. They are also robust to the levels of integration and applicable to stationary and asymptotically non-stationary series. Both the DMCA and the DCCA can be used jointly as complementary techniques to analyze fractal contagion as proposed by Kristoufek (2014). Subsequently, the likes of Mohti et al. (2019) have adopted these methods to jointly test contagion effects. Specifically, Mohti et al. (2019) adopted these two approaches to test the contagion effects of the US subprime crisis and the Eurozone Debt crisis in several countries on different continents. These two techniques can be adopted separately or jointly to test fractal contagion effects. For instance, Zhang et al. (2020) and Kristoufek (2014) adopted only the DMCA techniques to test the contagious effect in the stock markets. Hence, we are adopting only the DMCA technique to test the contagion effects of the coronavirus pandemic outbreak in the cryptocurrency space.

$$CC_k = \sum_{t=1}^{k}(C_t - \overline{C}) \ and \ DD_k = \sum_{t=1}^{k}(D_t - \overline{D}) \tag{1}$$

Say we have a pair of time series sets C^T and D^T of size T, the profiles are defined following equation (1) where $\overline{C}$ and $\overline{D}$ are the sample averages and $k \ \varepsilon \ \{1,...,T\}$. Following this, the profiles are subdivided as $N_n = \lfloor T/n \rfloor$ non-overlapping number of segments, s, of size λ. For each segment, s. Then, the series' moving averages are defined, $\widetilde{CC}_k$ and $\widetilde{DD}_k$.

$$Q_{CD}^2(\lambda) = \frac{1}{T - \lambda + 1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T-\theta(\lambda-1) \rfloor} \left(CC(\lambda)_k - \widetilde{CC}(\lambda)_k\right)\left(DD(\lambda)_k - \widetilde{DD}(\lambda)_k\right) \tag{2}$$

Equation (2) is the fluctuation function for DMCA. Where the choice of moving averages is θ. θ can be set to 1 or 0.5 or 0, corresponding to backwards or centred or forward respectively. Empirically, the centred moving averages outperform the rest. Therefore, $\theta = 0.5$ in this analysis. Based on equations (3) and (4), the fractal contagion is defined. It falls within zero and one, in absolute terms $|\rho_{AB}(n/\lambda)| \ \varepsilon \ [0,1]$. When it equals -1 or 1 or 0, there is a perfect anti-contagion or perfect contagion or no contagion in the system. There are more intrinsic coefficient characteristics in Zhao, Shang, and Huang (2017). The tests proposed by Podobnik, Jiang, Zhou, and Stanley (2011) and Guedes et al. (2018a, 2018b) are adopted to statistically confirm the contagious effect the pandemic has on the cryptocurrency spectrum.

$$\rho_{CD}(\lambda) = \frac{Q_{CD}^2(\lambda)}{Q_C(\lambda) \times Q_D(\lambda)} \tag{3}$$

$$\Delta\rho_{CD}(\lambda) = \rho_{CD}(\lambda|COVID - 19 \ periods) - \rho_{CD}(\lambda|Calm \ periods) \tag{4}$$

A positive $\Delta\rho_{CD}(\lambda)$ suggests an increasing level of the pandemic's contagious effect while negative values imply the dampening or fizzling contagious effect of the pandemic. The DMCA approach is used to evaluate the contagion effects of the cryptocurrency markets' unconditional volatility and returns (log-difference) as defined in equations (6) and (5).

$$r_t = 100\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \tag{5}$$

$$v_t = trace\left(\boldsymbol{I_\alpha}\mathbf{M}\mathbf{N}^T\right) \tag{6}$$

$$\mathbf{M} = \begin{bmatrix} X - Z & 0 & 0 \\ 0 & \Delta & 0 \\ 0 & 0 & Y \end{bmatrix}, \mathbf{N} = \begin{bmatrix} X - Z & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & Y \end{bmatrix}, and \Delta = X(Y - Z) + Z(Y - X)$$

r_t is defined to be the return of each market in the system. while P_t is the closing price of the asset at time t. The unconditional volatility of the market is defined as v_t at time t. Where X, Y, and Z are the differenced normalizations among the daily high, close, and low prices with the open daily prices. An alternative to the normalization is that of the logarithmic values of the market information covariates (Diebold & Yilmaz, 2016; Ji, Bouri, Lau, & Roubaud, 2019). The measure of the unconditional volatility of an asset market is rather an area of key interest in studying market volatility structure. Unlike conditional volatility measures of the autoregressive conditional heteroscedastic models (Baba, Engle, Kraft, & Kroner, 1995; Bollerslev, 1986; Engle & Shepard, 2002; Okorie, 2020a; 2020b; Okorie & Lin, 2020a; 2020b; 2020c) the unconditional measures of a market's volatility have taken different forms, for instance, the squared return, the squared conditional mean return residual, even more, sophisticated approaches, etc. This paper adopts the best analytic scale-invariant unconditional volatility estimator model proposed by Garman and Klass (1980) which has been adopted in literature by Diebold and Yilmaz (2016), Ji et al. (2019), Okorie (2021), etc. The unconditional volatility equation of each

asset market is specified in equation (6). I_α is a 3×3 $\alpha - identity$ matrix.[1] and **M** and **N** are symmetric matrices of normalized differences.

Firstly, the logged-difference technique of computing a market's return is not adopted in this study because it is only an approximation of a market's return as defined in equation (5). Notwithstanding, the logged-difference approximation also has its weaknesses since it is a conditional limiting approximation. That is to say, its approximation performs well when the limiting condition is met or satisfied. Otherwise, it performs poorly. Secondly, other methods used to compute market volatilities are conditional on the model structure, past information set, and are only dependent on the closing prices of a market. These tools include ARCH, GARCH, BEKK, CCC, DCC etc. The estimated market volatility is latent and thus, depends on the type of model adopted. It is also difficult to clearly show that a model is better at estimating a market's volatility relative to the other conditional tools. Hence, the analysis is only based on the model type, past information set, and the market's closing price. However, the volatility technique adopted, in this study, is unconditional since it does not depend on any model structure or past information set. But, each period's volatility is computed based only on the current period's closing price, opening price, high price, and low price while using the best analytical scale invariant volatility estimators developed by Garman and Klass (1980).

3. Discussions of results

3.1. Sampled data

The top 20 (based on market capitalization) cryptocurrency markets' information is sampled around the COVID-19 pandemic outbreak window,[2] from 1st October 2019 to 31st March 2020 (daily series). For this analysis, 1/10/2019 to 31/12/2020 is characterized as the cool period while 1/1/2020 to 31/3/2020 is defined as the coronavirus pandemic period. However, 2020-01-01 is pinned down as the COVID-19 pandemic point to define the ex-ante and ex-post periods following Okorie and Lin (2021a; 2020b). The choice of this date, before the WHO announcement date, is because the virus was already spreading rapidly in Wuhan, China (China constitutes a substantial cryptocurrency market) by 2020–01-01 before it was pronounced a global threat. The cryptocurrency markets studied are Bitcoin, Ethereum, XRP, Tether, Bitcoin Cash, Bitcoin SV, Litecoin, EOS, Binance Coin, Tezos, UNUS SED LEO, Monero, Stellar, Cardano, Chainlink, TRON, Huobi Token, USD Coin, Crypto.com Coin, and Dash.

A short window length around the COVID-19 outbreak is sampled to mitigate the impact of subsequent occurrences or exogenous shocks, after the pandemic outbreak, in this study. Such exogenous shocks may include the aid provided to the households by various governments and private individuals. These financial aids are capable of biasing the findings as it pertains to the contagious impact of the pandemic on the cryptocurrency space. The short window length has been supported empirically. Shortly after China banned coin ICOs, other economies followed. Okorie and Lin (2020b) and Okorie (2020a,b) adopted the short window sampling approach around the ban date to ascertain the response of the two leading cryptocurrency markets, Bitcoin and Ethereum, to this ban. In the same light, MacKinlay (1997), quoted in his article titled, "Event studies in Economics and Finance"," . thus, a measure of the event's economic impact can be constructed using security prices observed over a relatively short period …". This idea is rooted in the understanding that after a major shock, other responses are implemented to possibly stabilize the effects of the preceding shock. Keeping this in mind, a relatively longer sample would bias the true effect of the shock under study.

Table 1 reports the basic statistics for the top 20 cryptocurrency markets' return series. The average, standardized average deviations, minimum, and maximum return values are reported for each cryptocurrency market during the cool period and COVID-19 period. Generally, these distributions are higher in magnitude during the COVID-19 period relative to the cool period. In other words, negative returns became more negative and positive returns became less positive during the pandemic time against the cool seasons for most of the cryptocurrency markets. From the minimum values of the return series in the two periods, it is suggestive that the COVID-19 panics led to bigger negative returns ex-post COVID-19 period through price decreases and this is seen in most of the cryptocurrency markets, mostly the top three leading cryptocurrency markets, (Bitcoin, Ethereum, and XRP).

Similarly, Table 2, reports the unconditional volatility statistics, just like Table 1 reports that of the market's returns. The sample means, standardized deviations, least, and the highest return values are shown for each of the top 20 cryptocurrency markets during the coronavirus pandemic and cool seasons. From these results, the magnitude of the volatilities is lower in the cool periods compared to the coronavirus pandemic periods. This is equally suggestive of the ex-post COVID-19 panic of the crypto investors. Generally, the volatility distribution increased from the cool to the COVID-19 period, even for the top cryptocurrency markets. This finding is consistent with those of the returns from the sampled cryptocurrency markets. Given that these periodic changes in the cryptocurrency markets imply the existence of a contagious effect of the coronavirus pandemic on these markets. Notwithstanding, some statistical methods are applied to validate these fractal contagious effects of the pandemic in the cryptocurrency spectrum.

3.2. Analysis of cryptocurrencies' return

Considering the returns of the market, the DMCA technique is used for the periods. Afterwards, the differenced DMCA is calculated between the two periods. These results are presented in Fig. 1. These results are for the sampled top 20 cryptocurrency markets. The first row shows the returns' cross-correlations for these cryptocurrency markets for the cool period (ex-ante coronavirus outbreak).

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[1] $\alpha_1 = 0.511$, $\alpha_2 = -0.019$, and $\alpha_3 = -0.383$
[2] This information is sourced from https://www.coinmarketcap.com/.

While row-two charts report that of the coronavirus period (ex-post coronavirus outbreak). Finally, the differenced cross-correlations or contagions between these two periods are plotted in the third row. The first row graphs depict, however, weak cross-correlations among these cryptocurrency markets ex-ante the outbreak of the coronavirus pandemic. This can be seen by the level of closeness between the coefficients. During the pandemic periods, as a result of the coronavirus outbreak, the DMCA results in the second row show substantial cross-correlations in the sampled cryptocurrency markets for all these groups. In a clearer term, the dynamic of these DMCA trends converged closely, relative to the ex-ante COVID-19 era. The plots on the third row, suggest the contagious effect of the coronavirus outbreak in the cryptocurrency space. However, it is equally observed that this contagion effect tends to decrease over longer time horizons.

Following these findings, it is vital to point out and infer that the pandemic caused by the coronavirus outbreak results in a substantial contagious effect, though weak, in the cryptocurrency spectrum. This finding is very intuitive, in a practical sense, since the outbreak of the coronavirus pandemic, people panicked for the fear of death, closure of businesses or enterprises, restricting the gathering of people such as conferences, meetings, churches etc., the distance or gap between persons in public places, etc. These have been a common practice in every country. This is mostly aimed at tactically separating the populace into the affected and unaffected groups. This is done by mostly advising, asking, and enforcing that people stay at their houses. These measures have helped to adequately isolate the affected ones from the community for quarantine and treatments while the unaffected ones return to their businesses as usual. This model is developed and tried in China and after a while, the populace was purged of infected persons while the rest returned to their normal lives and treatment continued for the infected persons. However, this panic makes the investors in the cryptocurrency markets take hasty and/or non-market-based actions. Since many countries are affected, the cryptocurrency investors in these economies would respond in similar ways just to have enough liquidity to survive through the pandemic periods and finance the stay-at-home seasons. Once most of these investors start shorting their positions, others would most likely follow and this would result in the contagious effect of the pandemic on the cryptocurrency spectrum. Moreso, it is important to mention that this weak contagion effect in the crypto space suggests that some investors held onto their positions in hopes that the market prices will bounce back when this era is over and economies have recovered from the pandemic.

3.3. Analysis of cryptocurrencies' volatility

The DMCA technique is utilized on the unconditional volatilities of the top 20 cryptocurrency assets for both the cool and the coronavirus periods. The same pattern, as adopted for the markets' returns in Fig. 1, is used for the unconditional markets' volatility in Fig. 2. Similarly, Fig. 2 shows the DMCA outputs for the unconditional volatilities of the sampled cryptocurrency assets. The first-row plots show the cross-correlation for the top 20 cryptocurrency market volatilities for the cool periods (ex-ante coronavirus outbreak). Row-two graphs report the cross-correlation movements of the sampled cryptocurrency market volatilities for the coronavirus pandemic periods (ex-post coronavirus outbreak). Furthermore, row-three charts show the differences between the two periods represented in the first and second rows for the sampled cryptocurrency market volatilities, thus, the fractal contagion effect of the coronavirus pandemic in the cryptocurrency spectrum. The first row plots show that there are, more or less, increasingly strong
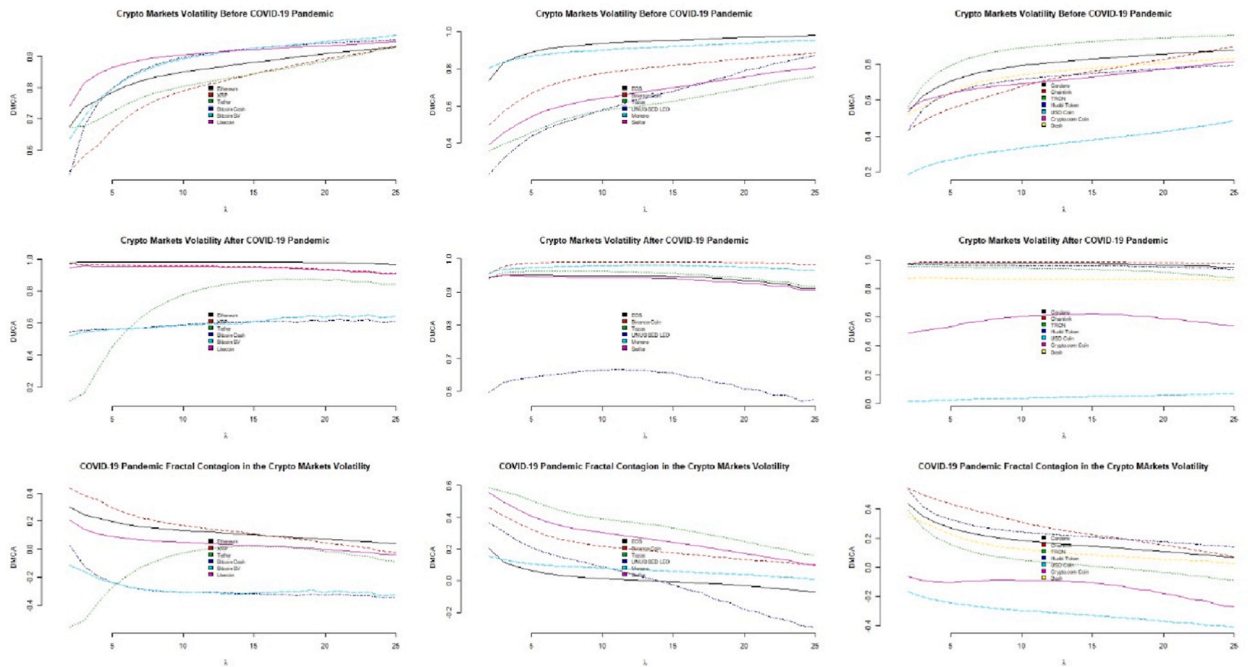

Fig. 1. DMCA on return.

Fig. 2. DMCA on volatility.

comovements among these cryptocurrency market volatilities before the COVID-19 pandemic.

Therefore, the cryptocurrency market volatilities associate greatly during the cool period. After the outbreak of COVID-19, the DMCA results in the second row confirm a significant and stronger comovement among these sampled cryptocurrency market volatilities. The last row plots confirm there exists a significant fractal contagion effect of the COVID-19 pandemic on the cryptocurrency markets. However, this contagion, in the cryptocurrency market volatilities fizzles out in longer horizons or periods just as observed for the cryptocurrency market returns. Generally, the DMCA results show that the fractal contagion effect of the coronavirus pandemic is stronger for the cryptocurrency market volatilities relative to the cryptocurrency market returns. This is very intuitive and suggests
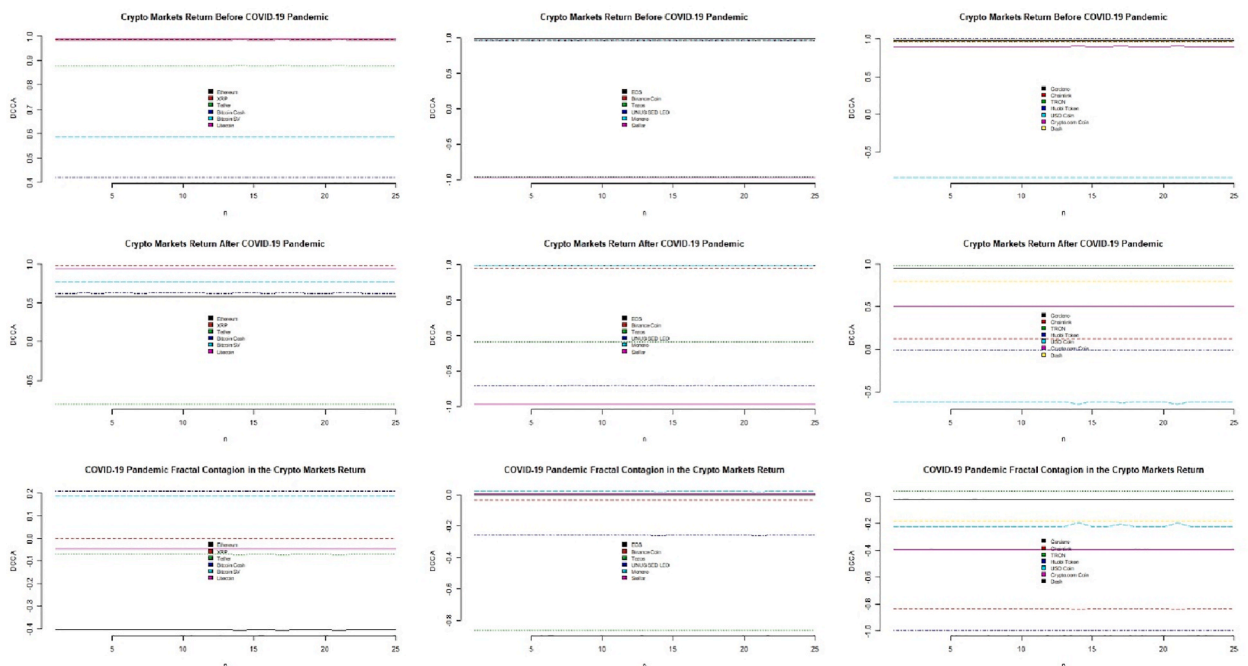
Fig. 3. DCCA on return.

that crypto space investors substantially panicked at the outbreak of COVID-19 and this led to more rapid price fluctuation in the whole cryptocurrency space. For the return and volatility analysis, the 95% confidence interval technique employed on the differences between the ex-ante and ex-post analysis confirms that the COVID-19 pandemic has a significant contagion effect on the cryptocurrency spectrum, howbeit, short-lived.

3.4. Robustness check

A robustness test or check of the existence of a fractal contagion effect in the cryptocurrency markets is carried out using the Detrended Cross-Correlation Analysis (DCCA). Among other advantages, these techniques do not require the absence of a unit root for the series and they rather directly use the moments' properties of the series to establish the cross-correlation (contagion effects). Therefore, they are counterparts. In other words, no sample observation lose as a result of differencing the series. Therefore, these contagion identification techniques and the nonlinear process are equally capable of pinning down a substantial periodic shift or switch in the time series over time. The Detrended Cross-Correlation Analysis (DCCA) method has been used to study contagion or cross-correlation dynamics among various systems (Okorie & Lin, 2021b). The DCCA is a modification (by Podobnik and Stanly (2008)) of the Detrended Fluctuation Analysis (DFA) proposed by Peng et al. (1994). In the DCCA model, equation (7), n plays the role of λ in DMCA. where $\eta = n(s-1)$ signifies the choice of sample moving averages.

$$Q^2_{CD}(n) = \frac{1}{nN_n} \sum_{s=1}^{N_n} \sum_{k=1}^{n} \left(CC(n,s)_{k+\eta} - \widetilde{CC}(n,s)_{k+\eta} \right) \left(DD(n,s)_{k+\eta} - \widetilde{DD}(n,s)_{k+\eta} \right) \tag{7}$$

Therefore, the results for the 20 sampled cryptocurrency markets returns and unconditional volatilities are analyzed and presented in Figs. 3 and 4 using the DCCA approach. Following the same formats in Figs. 1 and 2, the first (second) rows in Figs. 3 and 4 present the cross-correlation in the 20 cryptocurrency markets before (after) the COVID-19 outbreak. The vertical axes present the DCCA rhos while the segment lengths are on the horizontal axes for the first and second rows. The third and last rows in Figs. 3 and 4 represents the difference in the cross-correlations for the ex-post and ex-ante COVID-19 periods. These differences are plotted on the vertical axes of the last row. The results also confirm that there is a substantial fractal contagion effect of the COVID-19 pandemic on the cryptocurrency markets of the affected economies of the world. In other words, the findings of a fractal contagion in the cryptocurrency market, both return and volatility, are robust.

4. Conclusion and policy implications

This article sets out to investigate the contagion effects of the 2020 pandemic of coronavirus on the cryptocurrency space. Data from the top 20 cryptocurrency markets were sampled. These markets are selected based on their levels of market capitalization. Therefore, they consist or form a good representation of the cryptocurrency spectrum. The sample periods are around the outbreak of the coronavirus for ex-ante and ex-post analysis. The DMCA approach is used to establish the fractal contagion that exists in the cryptocurrency space or markets as a result of the COVID-19 outbreak. The findings provide empirical pieces of evidence to support the fractal contagion effect of the COVID-19 contagion effect on the cryptocurrency markets. This contagion effect is seen in the cryptocurrency market returns and volatilities. While there is a stronger contagion effect on the cryptocurrency market volatility, there is a fairly weak contagion effect on the cryptocurrency market return. Again, this article confirms that the cryptocurrency markets are interconnected.

Several policy implications could follow from the method and findings of this study. We only highlighted some of these policy implications below. These itemized policy implications are not exhaustive:

1. Portfolio management and adjustment strategies are not left out. Strategic investors (private or institutions) could adjust their portfolio positions adequately to improve returns and minimize risks, given the improved predictability and forecastability in these markets
2. Contagion improves the chances of profiteering from the exchange rate markets by taking well-informed scientific strategy steps. This is a result of the existence of contagion in the cryptocurrency market returns confirming comovements in the cryptocurrency returns. Therefore, predictability and forecastability are improved.
3. Given the high co-movement among these cryptocurrency markets, different financial portfolios can be formed with a lot of these cryptocurrency assets due to their increased correlations. This implies that more and more cryptocurrency assets can form parts of an investment portfolio during the COVID-19 period.
4. Similarly, the volatility contagion is relatively stronger. This evidence supports the rate of price changes or fluctuations in these cryptocurrency markets have some degree of association. However, this does not in any way mean that the cryptocurrency market risks (or volatility) are increased but that the fluctuations in price for these markets have similar movements and patterns. This also enhances forecasting and predictability for profiteering.
5. Also, the findings of this study validate the claim that market volatility is more interrelated or connected relative to market returns. As such, it is expected that the contagion effect is heavier (last longer) on the volatility relative to the returns. This appeals to the risk minimization aspect of an investment portfolio. Therefore, in minimizing an investment portfolio formed using cryptocurrencies, attention should be paid to the level of connectedness or dependence that exists among these markets.
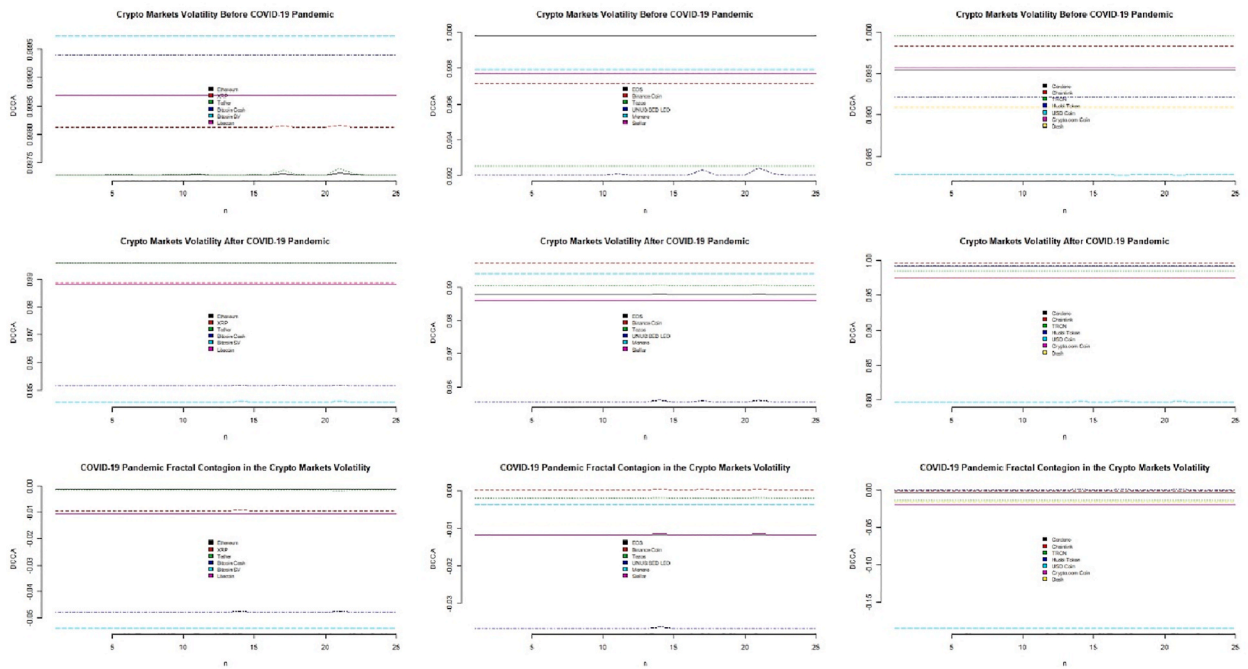
Fig. 4. DCCA on volatility.

Data availability statement

The data that support the findings of this study are openly available in Coin Market Capitalization at https://www.coinmarketcap.com/

CRediT author statement

David:Methodology, Formal analysis, interpretation, and editing, Data analysis, Writing - Original Draft, Revision.
Boqiang Lin: Conceptualization, Methodology, Data analysis, Interpretation, and editing.

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Appendices.

Table 1
Return Data Distribution

	Cool Period				COVID-19 Period			
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Bitcoin	−0.157	3.097	−7.153	15.398	−0.127	6.618	−49.728	14.594
Ethereum	−0.340	3.298	−8.226	12.121	0.031	8.226	−57.987	21.063
XRP	−0.300	3.170	−11.946	7.945	−0.094	6.570	−39.482	15.029
Tether	−0.007	0.088	−0.250	0.270	0.006	0.227	−1.473	0.520
Bitcoin Cash	0.062	2.330	−9.164	7.298	0.199	4.193	−11.719	18.247
Bitcoin SV	0.157	4.871	−9.712	22.402	0.577	14.240	−58.645	89.232
Litecoin	−0.360	3.719	−9.508	13.642	−0.035	7.655	−45.394	22.737
EOS	−0.140	3.899	−10.331	15.420	−0.173	8.168	−54.969	20.529
Binance Coin	−0.157	3.654	−8.831	10.206	−0.098	8.118	−57.906	16.572
Tezos	0.393	4.800	−10.217	17.987	0.192	9.463	−61.325	26.074
UNUS SED LEO	−0.263	1.742	−7.352	5.034	0.277	1.938	−5.129	5.638
Monero	−0.257	3.296	−9.143	9.291	0.090	7.717	−51.675	15.445

(*continued on next page*)

Table 1 (*continued*)

Cool Period					COVID-19 Period			
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Stellar	0.292	3.712	−13.856	10.354	0.108	7.145	−21.499	45.717
Cardano	−0.168	3.318	−8.011	9.769	−0.082	8.024	−53.997	20.385
Chainlink	−0.043	4.361	−11.842	10.920	0.281	9.288	−64.972	18.232
TRON	−0.052	4.620	−9.604	15.340	−0.153	8.256	−57.127	19.297
Huobi Token	−0.145	3.777	−14.953	12.822	0.202	7.179	−51.603	20.321
USD Coin	0.020	1.781	−6.473	8.506	−0.018	2.976	−8.818	20.132
Crypto.com Coin	−0.026	3.580	−8.915	14.128	0.401	8.513	−51	26
Dash	−0.585	3.482	−10.596	11.858	0.507	10.023	−48.599	40.618

Table 2
Volatility Data Distribution

Cool Period					COVID-19 Period			
Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Bitcoin	0.001	0.002	0.0001	0.011	0.005	0.013	0.0002	0.094
Ethereum	0.001	0.002	0.0001	0.010	0.004	0.010	0.0001	0.079
XRP	0.00000	0.00000	0.00000	0.00001	0.0004	0.004	0.00000	0.034
Tether	0.001	0.001	0.00002	0.006	0.002	0.003	0.0001	0.017
Bitcoin Cash	0.003	0.004	0.0001	0.017	0.010	0.021	0.0004	0.162
Bitcoin SV	0.002	0.002	0.0001	0.013	0.005	0.012	0.0002	0.099
Litecoin	0.002	0.002	0.0001	0.014	0.005	0.013	0.0001	0.103
EOS	0.001	0.002	0.0001	0.014	0.005	0.017	0.0001	0.156
Binance Coin	0.003	0.003	0.00002	0.021	0.008	0.021	0.0001	0.189
Tezos	0.0004	0.001	0.00001	0.003	0.0004	0.001	0.00000	0.003
UNUS SED LEO	0.002	0.002	0.0001	0.016	0.005	0.011	0.0003	0.092
Monero	0.001	0.002	0.00005	0.012	0.004	0.010	0.0001	0.083
Stellar	0.001	0.001	0.0001	0.007	0.005	0.013	0.0002	0.108
Cardano	0.002	0.003	0.0001	0.016	0.008	0.025	0.0002	0.213
Chainlink	0.002	0.003	0.0002	0.014	0.005	0.011	0.0002	0.087
TRON	0.001	0.002	0.0001	0.014	0.004	0.012	0.0001	0.090
Huobi Token	0.056	0.118	0.0001	0.407	4.419	18.717	0.0001	97.742
USD Coin	0.002	0.003	0.0001	0.015	0.008	0.023	0.0001	0.129
Crypto.com Coin	0.001	0.002	0.0001	0.012	0.007	0.014	0.0002	0.113
Dash	0.001	0.002	0.0001	0.011	0.507	10.023	−48.599	40.618

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