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Cryptomarket Volatility in Times of COVID-19 Pandemic: Application of GARCH Models

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Abstract

COVID-19 pandemic has caused significant losses and an increase in the level of risk in the financial markets and global economy. Thus in this study, we model the crypto market volatility behavior during the COVID-19 crisis. GARCH (1, 1) and GJR-GARCH (1, 1) were applied to model the volatility clustering and leverage effects in the intraday day (15-minute interval) returns of Bitcoin, Ethereum, and Litcoin ranging from 11th April 2019 to 8th February 2021. The empirical findings from GARCH (1, 1) model indicates the presence of volatility clustering in the crypto market. Moreover, the results of the GJR-GARCH (1, 1) indicate the presence of leverage effects in the financial returns series of all three crypto currencies. Furthermore, the excess kurtosis confirms the existence of fat-tail phenomena in the crypto market. Overall, the findings from this study showed that in times of COVID-19 pandemic the crypto market returns series showed volatility persistence, fat-tail phenomena, and leverage effects. These outcomes provide a better understanding for financial investors to invest rationally and cautiously during pandemic times.

Keywords: COVID-19, GARCH, GJR-GARCH, Volatility, Cryptocurrency

JEL Classification: C22, C55, G15

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1. Introduction

COVD-19 pandemic has spread across the world and affected millions of human lives. The pandemic also has a severe impact on the global economy (Elgin et al., 2020; Hossain, 2021; Ozili et al., 2020; Pak et al., 2020; Şenol et al., 2020; Sharif et al., 2020; Sułkowski, 2020). Economy shut down due to the COVID-19 lockdown has generated fears among investors (Lahmiri et al., 2020b; Ortmann et al., 2020; Smales, 2020). The pandemic has a strong influence on global financial markets resulting in significant losses (Ashraf, 2020; Aslam, Aziz, et al., 2020; Aslam, Mohmand, et al., 2020; Fernandez-Perez et al., 2021; Khan et al., 2021; Okorie et al., 2021; Sharif et al., 2020; Sharma, 2020; So et al., 2021; Zhang et al., 2020).

Crypto currencies are an extremely complex system and highly volatile (Antonakakis et al., 2019; Bakar et al., 2017; Chaim et al., 2018; Katsiampa et al., 2019; Kumar et al., 2019; Mensi et al., 2019). The crypto market has experienced potential growth in the past five years due to the increase of digitization across the world. The crypto currencies show an irregular and unstable response during the COVID-19 pandemic (Lahmiri et al., 2020a) but few suggest that pandemic have a positive impact on the crypto currencies market (Mnif et al., 2020). Recently, the crypto currencies market gained a high level of attention, and price fluctuations are highly unexpected and uncertain which can be defined by extreme volatility. For example, In March 2020 the Bitcoin price dropped more than 50% from $10,000 to $4,000[1] Ethereum also experienced a 20 declined on 12 March 2020[2]. But recently, In Feb 2021, Bitcoin price is rise to $44,000 therefore the purpose of this study to capture the volatility behavior, of cryptocurrencies during COVID-19 pandemic.

Volatility modeling is the most important move in the examination of financial time series in times of crisis. The evidence shows that financial returns exhibit a high degree of volatility clustering and asymmetric behavior. The occurrence of volatility clustering in the financial markets is highly associated with a substantial change in asset prices. During the Financial crisis, Various volatility models have been adopted to analyze the volatility behavior of financial market returns such as ARCH (McKenzie et al., 2002; Savva et al., 2017), asymmetric power ARCH (Degiannakis, 2004; McKenzie et al., 2002), exponential GARCH (Hansen et al., 2016; Oseni et al., 2011). GARCH models are considered the most essential model to identify leptokurtosis and volatility (Brooks et al., 2002).

During this paper, we investigated the performance of the cryptocurrency market in terms of return volatility during the times of the COVID-19 pandemic by adopting both symmetric and asymmetric GARCH models. This research study contributes to the existing literature by identifying the different behavior of crypto currencies in COVID-19 pandemic. Secondly, this study by nature is the first to include the crypto currencies intraday returns during the COVID-19. Thirdly, the study models the volatility clustering, leptokurtic phenomena, and leverage effects in crypto market returns during the COVID-19.

2. Methodology

2.1. Data

To model the volatile behavior of crypto market returns during pandemic, this study has used intraday data of 15-min frequency of three major crypto currencies based on market capitalization namely; Bitcoin (BTC), Ethereum (ETH), and Litcoin (LTC). On March 11th 2020, WHO declared COVID-19 pandemic globally, therefore in this study we divided the entire data set ranging from April 10th 2019 to February 8th 2021 into two periods; Before COVID-19 period (April 10th 2019 to March 10th 2020) and During COVID-19 period (March 11th 2020 to February 8th 2021).

Initially, the study has calculated the summary statistics which includes measures of central tendency and measures of variability. Additionally, In order to check the distribution of returns, we adopted the Jarque-Bera test along with the volatility clustering graphs. Besides, the

[1] Bitcoin Plunged 50% In March; 5 Reasons That Isn't Likely To Happen Again by Joseph Young https://www.forbes.com/sites/youngjoseph/2020/09/05/bitcoin-price-march/?sh=76b97ca13657
[2] Ethereum suffers biggest one-day percentage drop since March 12, 2020 by Olumide Adesina.

correlation matrix was calculated to show the association between the selected crypto currencies. The financial returns of cryptocurrencies are represent by:

$$\boldsymbol{R_t = ln\left(\frac{P_t}{P_{t-1}}\right)} \tag{1}$$

Where R_t shows the cryptocurrency returns at time t, ln indicates the log natural function, P_t is the current price and P_{t-1} is the previous period price.

2.2. GARCH Model

The generalized autoregressive conditional heteroscedasticity (GARCH) model is an extension of the ARCH model. GARCH (p, q) family initially presented by Bollerslev (1986), gives the conditional variance. GARCH family models are the mostly used in financial time series data because of their robustness in terms of modeling the volatility of the returns. The GARCH (p, q) model can be mathematically summarized as follows (Brooks et al., 2002):

$$\boldsymbol{\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\, u_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2} \tag{2}$$

Where conditional variance and returns square at time $t-j$ and $t-i$ are denoted by σ_{t-j}^2 and u_{t-i}^2 also known as GARCH and ARCH terms, p and q is the order whereas α_i , β_i are the weights assigned to them, ω can be defined as the product of weight and long-term variance. Moreover, the selection of appropriate order for the model will be according to the Akaike information criteria i.e. Order with the least AIC value is regarded as the best fitted one. The reason for using the GARCH (p, q) family to model the returns volatility is its ability to account for volatility clustering and dynamic volatility phenomena (Chris, 2014). The parameters of the GARCH (p, q) family are measured using the maximum likelihood function, which includes selecting values of the parameters that maximize the probability or likelihood of data occurring.

Moreover, among GARCH family GARCH (1, 1) model is also called the 'plain vanilla' GARCH model. Karmakar (2005) has suggested to incorporate GARCH (1, 1) for capturing the financial returns conditional volatility. Furthermore, conditional volatility using GARCH (1, 1) can be computed as follows:

$$\boldsymbol{\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2} \tag{3}$$

2.3. GJR-GARCH Model

For modeling the leverage effects in the returns series of the selected crypto currencies, GJR-GARCH (1, 1) model was applied. It assumes investors tend to react more to negative returns as compared to positive returns resulting in the leverage effect. Therefore, the GJR-GARCH (1, 1) model includes an additional indicator for the leverage effect, which becomes zero when the conditional variance is positive whereas, it takes the value of 1 when the conditional variance is negative.

Furthermore, the standard GARCH (1, 1) model is symmetric. However, studies suggest that time-varying asymmetry is a major part of volatility dynamics (Hsieh, 1991). Therefore, in order to incorporate asymmetry in the volatility science, the GJR leverage term is included. The mathematical representation of the GJR-GARCH (1, 1) proposed by Glosten et al. (1993), is given in equation 4. Note that γ shows the leverage effects.

$$\boldsymbol{\sigma_t^2 = \alpha_o + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}} \quad (4)$$

where, $\boldsymbol{I_{t-1}} = \begin{cases} \mathbf{1}\ \boldsymbol{if}\ \boldsymbol{u_{t-1}} < 0,\ positive\ shock \\ \mathbf{0}\ \boldsymbol{if}\ \boldsymbol{u_{t-1}} \geq \mathbf{0}, \boldsymbol{negative\ shock} \end{cases}$.

3. Empirical Result and Discussion

Table 1 exhibits the summary statistics of intraday returns for BTC, ETH, and LTC ranging from April 11th 2019 to February 8th 2021 with 64,322 observations. The intraday returns of the cryptocurrencies has been divided into two periods of COVID-19 pandemic (Before and During). Before COVID-19 pandemic the cryptocurrencies exhibit positive mean returns except LTC showing the negative mean returns. Additionally, before the global pandemic, the minimum value for BTC is -0.13686, ETH is -0.12869 and LTC is -0.09113 whereas, 0.08258, 0.06728, and 0.08666 refer to the maximum values that belong to BTC, ETH, and LTC. However, the basic tool for measuring risk, i.e., the standard deviation is high in magnitude for these digital currencies with BTC (0.00417) being the riskiest. Besides, the returns of BTC, ETH and LTC are negatively skewed before the COVID-19. In contrast, the intraday returns of the cryptocurrencies during the COVID-19 pandemic exhibit positive mean returns with LTC showing the least positive mean returns. Additionally, during this global pandemic, the minimum value for BTC is -0.15670, ETH is -0.15968 and LTC is -0.15026 whereas, 0.15388, 0.20979, and 0.15232 refer to the maximum values that belong to BTC, ETH, and LTC. Moreover, the standard deviation is high in magnitude for these digital currencies with LTC (0.00642) being the riskiest. Besides, the returns of BTC and ETH are positively skewed during the COVID-19 on the other side, LTC intraday returns are negatively skewed. Furthermore, in both the periods the kurtosis measure for all the selected crypto currencies is greater than 3, which confirms the presence of leptokurtic phenomena and the Jarque-Bera test results show significant results with a p-value less than 0.05 which proves that the returns distributions are non-normal.

Table 1 - Summary Statistics

Currency	BTC	ETH	LTC
Before COVID-19			
Mean	0.00001	0.00003	-0.00002
Maximum	0.08258	0.06728	0.08666
Minimum	-0.1369	-0.1287	-0.0911
Std. Deviation	0.00417	0.00002	0.00003
Skewness	-1.7494	-2.5354	-0.7762
Kurtosis	92.4374	68.1365	22.637
Jarque-Bera Test	11000000	6253545	689667
Probability	0	0	0
Observations	32161	32161	32161
During COVID-19			
Mean	0.00006	0.00007	0.00004
Maximum	0.15388	0.20979	0.15232
Minimum	-0.1567	-0.15968	-0.15026
Std. Deviation	0.00494	0.00608	0.00642
Skewness	0.15636	0.58438	-0.31091
Kurtosis	119.023	111.7056	47.43136
Jarque-Bera Test	19000000	16717274	3014294
Probability	0	0	0
Observations	32161	32161	32161

Figure 1 illustrates the intraday price and returns fluctuations of the cryptocurrencies before and during the COVID-19 pandemic. A consistent increased has been observed in the price during the COVID-19 pandemic. The massive increased in BTC has generated high level of attention in the market. Some analysts believe that the BTC price will cross $100,000 at the end of 2021. Whereas, return graphs indicate high volatility especially at the beginning COVID-19 pandemic. In March, 2020, high level of returns fluctuations has been noted in the cryptocurrencies market. Additionally, all the returns graphs exhibit volatility clustering and all the returns series tend to follow mean-reverting process which also signifies the presence of stationary.

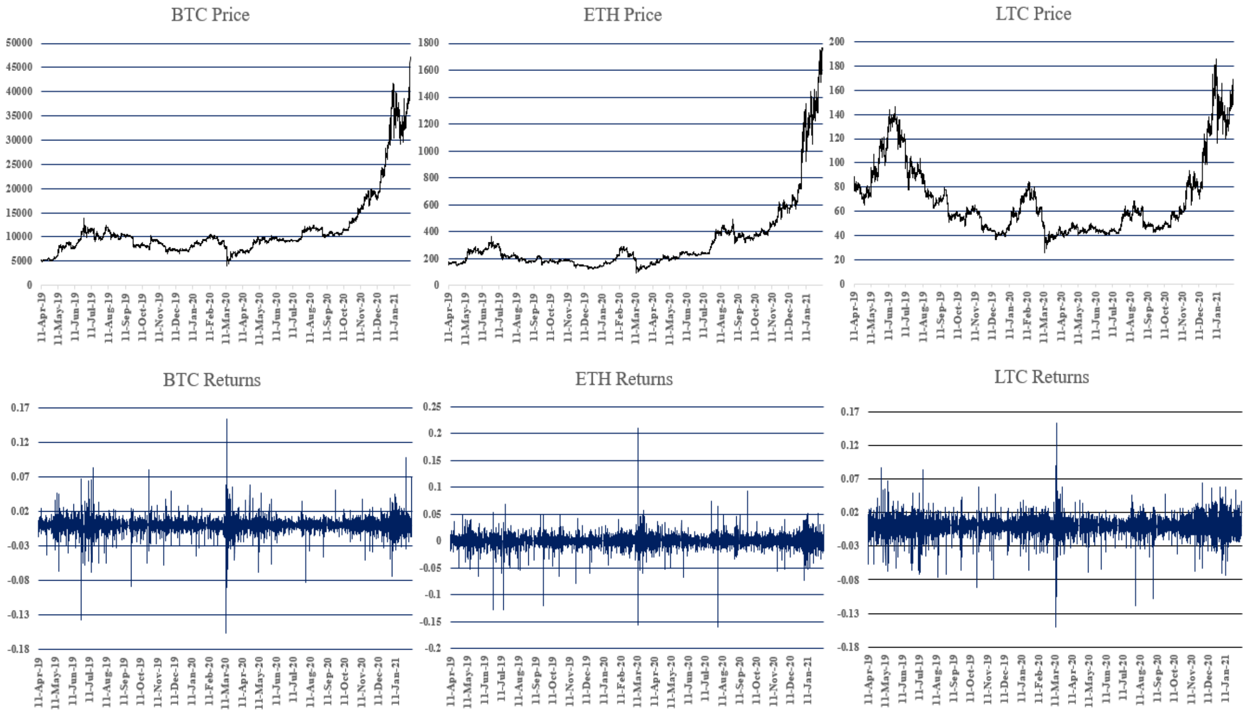

Figure 1 - Prices and returns fluctuations of cryptocurrencies

Furthermore, the correlation of cryptocurrencies for both periods are shown in Figure 2. The upper triangle of correlation plot represents before COVID-19 and the lower triangle of plot represents during COVID-19 period. As shown in Figure 2, all of the correlation pairs exhibit positive correlations before COVID-19 pandemic. In the whole set of correlation pair BTC and ETH shows strong positive correlation of 0.70. However during COVID-19 pandemic the direction of correlation between BTC and ETH changed to negative with value of -0.007. It is also observed that LTC shows a strong positive correlation with all cryptocurrencies before COVID-19 pandemic, however the direction of LTC correlation with other currencies didn't changed but the strength of correlation between ETH has become weaker from 0.51 to 0.006 during COVID-19 pandemic. The overall correlation analysis shows a significant relationship between cryptocurrencies in the market. The world has becomes highly integrated and connected in term of globalization and economic integration economic activities across the globe heavily depends upon each other. Generally, financial markets across the globe become much more connected because of any economic turbulence known as the 'contagion effect' (Roll, 1989). The cryptocurrency market received an effective attention from investors across the world during pandemic since businesses has been operated remotely and we are moving towards digital economy.

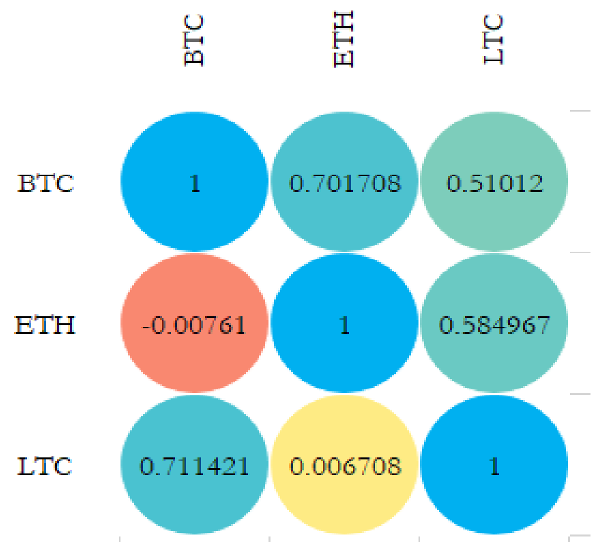

Figure 2 - Correlation of Cryptocurrencies before and during COVID-19. The upper triangle of plot indicates the correlation coefficient of cryptocurrencies before COVID-19, whereas the lower triangle indicates the correlation coefficients of cryptocurrencies during COVID-19

In this study, we have applied both GARCH (1, 1) and asymmetric GJR-GARCH (1, 1) model for the empirical analysis of financial returns data of the cryptocurrencies. Moreover, the initial requirements of stationary and the ARCH effect test were also applied. Note that Augmented Dickey-Fuller (ADF) test was used for unit root testing and the returns graphs were used to confirm the heteroscedasticity and for residuals. Table 2 represents ADF test results for the crypto currencies, which shows that all the three cryptocurrencies form have higher test statistics than the critical value with p-value less than 0.05 thus, rejecting the null hypothesis and accepting the alternate one which means there exists stationary in the returns series of the BTC, ETH, and LTC.

Table 2 - Augmented Dickey-Fuller Test results

Currency	BTC	ETH	LTC
Augmented Dickey-Fuller Test Value	-190.23	192.94	-195.23
P-value	0.01	0.01	0.01

An empirical finding of GARCH (1, 1) and GJR-GARCH (1, 1) based on skew student-t distribution for BTC, ETH, and LTC are presented in Table 3 and Table 4. As illustrated in Table 3, before the COVID-19 period the conditional mean parameter shows that both BTC and ETH are significantly positive and LTC is significantly negative whereas, during the COVID-19 period the conditional mean equation parameter shows that ETH and LTC are significantly positive whereas the coefficient for BTC is negative and significant. Additionally, In GARCH equation, the parameters of the constant variance term, ARCH, and GARCH for all the cryptocurrencies are significantly positive for both the selected periods (Before COVID-19 period, and During COVID-19 period). The parameters, i.e., α (ARCH effect) and β (GARCH effect) refer to the news. Particularly, α shows the recent news and the value here is statistically significant for both the periods, which means that recent news has affected cryptomarket volatility. On the other hand, β refers to the old news, and the value here is also statistically significant which provides evidence that old news has also affected cryptomarket volatility. In addition to this, high GARCH coefficients in both the periods show that shocks to conditional variance tend to die after a long time thus, volatility exhibits "persistent behavior". Furthermore, Table 3 also reveals that the sum of ARCH and GARCH parameters is approximately equal to one in both the periods. Note that if $\alpha + \beta$ is near to one, then a shock at time t will remain for a longer period. In simple words, the higher value of $\alpha + \beta$ indicates conditional variance as persistent. However, the results also show the presence of a mean-reverting process in both the periods because the sum of both the ARCH and GARCH effect is below one. Additionally, $\alpha + \beta$ also monitors the speed of mean reversion. Moreover, before the COVID-19 period, ETH has the slowest mean reversion and LTC has the fastest. Furthermore, during the COVID-19 period, ETH has the slowest mean reversion whereas BTC has the fastest with LTC being in between. Hence based on the results extracted from the GARCH (1, 1) model, the study rejects the null hypothesis that is "the presence of no volatility" and accepts the alternation hypothesis that is "the presence of a change in volatility" in both the periods.

Table 3 - GARCH (1, 1) model estimation results

Currency	BTC	ETH	LTC
Before COVID-19			
μ	0.000100	0.000009	-0.000531
ω	0.000000	0.000000	0.000000
α	0.070194	0.071277	0.070240
β	0.917015	0.914119	0.924428
$\alpha + \beta$	0.987209	0.985396	0.994668
Log likelihood	136524.1	130372.2	122613.9
AIC	-8.4901	-8.1075	-7.6250
During COVID-19			
μ	-0.000226	0.000440	0.000540
ω	0.000000	0.000000	0.000000
α	0.072356	0.068632	0.064066
β	0.920244	0.908752	0.918561
$\alpha + \beta$	0.9926	0.977384	0.982627
Log likelihood	137495.2	125524.3	123125.6
AIC	-8.5502	-7.8060	-7.6566

Furthermore, Table 4 represents the results extracted from GJR-GARCH (1, 1) model for the two selected periods. As shown in Table 4, for both the periods, the parameter of the ARCH effect (α_1) is significant at 1% significance level, which indicates news regarding previous period volatility has its explanatory power on current volatility. Meanwhile, the lagged conditional variance parameter (β_1), is also significant at 1%, thus proving the presence of volatility clusters in returns series of BTC, ETH, and LTC in both before and during the COVID-19 periods.

Additionally, it can also be seen from Table 4, the asymmetry gamma parameter (γ) is positive. The sign of gamma shows that investors' response to negative shocks is greater than positive shocks. It also reflects the variance distribution of the selected crypto currencies (BTC, ETH and LTC) are skewed towards the left in both the periods, thus higher chances of negative returns than positive ones. Furthermore, the positive sign of the gamma parameter also indicates the presence of leverage effects in BTC, ETH and LTC returns before and during the COVID-19 phases. However, the results from GARCH (1, 1) and GJR-GARCH (1, 1) shows the presence of volatility clustering, leverage effects, and fat-tail phenomena in the crypto currencies market before and during the COVID-19 pandemic.

Table 4 - GJR-GARCH (1, 1) model estimation results.

Currency	BTC	ETH	LTC
Before COVID-19			
μ	0.000000	0.000000	0.000000
α_o	0.000000	0.000000	0.000000
α_1	0.095884	0.093035	0.106753
β_1	0.849058	0.806980	0.847566
γ	0.081690	0.180003	0.069822
Log likelihood	151390.4	144779	135910.3
AIC	-9.4144	-9.0032	-8.4517
During COVID-19			
μ	0.000000	0.000000	0.00000
α_o	0.000000	0.000000	0.00000
α_1	0.104944	0.103834	0.15302
β_1	0.845506	0.856805	0.83703
γ	0.082393	0.059186	0.062173
Log likelihood	136768.8	146951.5	135511.2
AIC	-8.5051	-9.1381	-8.4267

4. Conclusion

Since the COVID-19 pandemic had its footprints on almost every walk of life including the global financial markets such as crypto market. As a result, financial markets tend to show increased volatility during pandemic times. Therefore, this study model the volatility behavior of the selected crypto currencies namely; BTC, ETH, and LTC in times of COVID-19 pandemic. The empirical findings showed that all the crypto currencies exhibit volatility clustering, fat tail phenomena, and leverage effects in both the before and during periods of COVID-19 pandemic. Furthermore, the conditional volatility of the BTC, ETH, and LTC are affected by the recent news (ARCH effect) and also by the old news (GARCH effect). These shocks tend to vanish after a long time thus volatility of the crypto market shows the "persistent behavior".

COVID-19 pandemic is an ongoing crisis that has jolted the global economy and the policies to nullify the COVID-19 effects have not been effective so far. The increased level of volatilities in the financial markets has resulted in a panic situation among the investors during the COVID-19 pandemic. This study will provide a deep understanding of the crypto currencies risk which will eventually help investors and portfolio managers to reassess their investment strategies and decisions in order to reduce the potential risk in the crypto market.

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