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alphanumeric journal

The Journal of Operations Research, Statistics, Econometrics and Management Information Systems

Volume 10, Issue 2, 2022

Received: May 23, 2021
Accepted: October 26, 2022
Published Online: December 31, 2022

AJ ID: 2022.10.01.ECON.01
DOI: 10.17093/alphanumeric.941529
Research Article

The Characteristics of Cryptocurrency Market Volatility: Empirical Study For Five Cryptocurrency

Tuğba Güz, Ph.D. *

Assist. Prof., Faculty Of Health Sciences, İstanbul Yeniyüzyıl University, Istanbul, Turkiye, tugbaguz@gmail.com

İlayda İsabetli Fidan, Ph.D.

Assist. Prof., Faculty of Economics, Administrative and Social Sciences, İstanbul İstinye University, Istanbul, Turkiye, ilaydaisabetli@hotmail.com

* İstanbul Yeni Yüzyıl Üniversitesi Topkapı Dr. Azmi Ofluoğlu Yerleşkesi Cevizlibağ, İstanbul, Türkiye

ABSTRACT

In recent years, digital innovations especially emerged depend on the Blockchain technology have caused a substantial transformation in the finance sector as in other sectors. Different financial assets have been revealed and began to be used as an investment tool along with this transformation in the markets. Cryptocurrencies that have a digital structure hold an important place among these assets. Dramatically increases in the daily transaction volume of currencies in the market have brought along different types of risks. These risks raised uncertainty on these currencies. Moreover, because cryptocurrencies are mostly used for the purpose of investment and speculation, it is important to understand the volatility movements and co-movements of cryptocurrencies and it is substantially important, particularly because volatility can influence investment decisions. This study aims to determine the volatility transmission between cryptocurrencies to find useful answers about the volatility and the efficiency of markets. Daily logarithmic return series between 18 January 2018 – 14 February 2021 were used to analyze the volatility of five of the most common cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), IOTA by applying the RALS-ADF test, EGARCH, and DCC-GARCH models. We determined whether the market is efficient or not, and tested the existence of the asymmetric effect and volatility transmission in the market. According to our results, volatility shocks are not obtained persistent for only BTC. Furthermore, the presence of asymmetric effects and leverage effect valid for four cryptocurrencies. While asymmetric effects observed for BTC, no leverage effect has been observed during the period. We also analyzed nine pair-wise cryptocurrencies applying the DCC-GARCH model and we found that dynamic conditional correlation coefficients are statistically significant and positive for each pair.

Keywords: Cryptocurrency, Volatility, EGARCH, DCCGARCH

1. Introduction

Technological developments and digital innovations reshaped many areas including finance. Especially, over the last few years, the impact of digital innovations on financial markets has increased even more. One of the most important steps of digitalization in the financial area has been developments in Blockchain technology. Blockchain technology is leading to the emerging of different financial assets in the markets and increased the demand for these assets at a short notice. Arising the cryptocurrencies that find a place in this technology has been an important indicator of the transformation in financial markets and the emergence of alternative assets.

Bitcoin (BTC), one of the cryptocurrencies, was first produced by Satoshi Nakamoto in 2008. Along with the Bitcoin, other cryptocurrencies that emerged afterward also began to be among the most demanded investment tools in the international financial markets.

Although there are debates about whether cryptocurrencies are investment tools or a currency, the cryptocurrency market has expanded considerably since 2008. The Bitcoin has a substantial size with the highest market share among cryptocurrencies in the market. However, the other cryptocurrencies have also gained an important place in the market by increasing their market share and value such as ETH and LTH.

Cryptocurrencies, such as Bitcoin, gain greater acceptance and attract intensive attention by investors in order to diversify portfolio risks and protect against global uncertainty. In addition, as well as Bitcoin, the cryptocurrency market has diversified with new emergence cryptocurrencies in the market. Thus, newly introduced cryptocurrencies increased the competition in the market. The market value of other cryptocurrencies has also increased while Bitcoin's weight of market value runs on.

In the last decades, the number of cryptocurrencies has increased rapidly and has reached a significant transaction volume in the cryptocurrency market, which has been constantly growing. Moreover, cryptocurrencies have started to be traded on many exchanges. As of April 2021, there are almost 5000 cryptocurrencies in the market. The total market capitalization has exceeded $2 trillion and the daily trading volume in the market has reached approximately 140 billion dollars (https://tr.investing.com/crypto/currencies).

The most important characteristics of cryptocurrencies are having a decentralized distributed network structure that cannot be controlled by central authorities such as the governments or banks. They also have different properties from the other currencies although preserve some of the features of fiat money such as medium of exchange, value storage, and unit of value (Kumar and Anandarao, 2019). However, they resemble more financial assets rather than currencies by the reason of their volatility, vulnerability to speculative bubbles, heavy tail behavior, persistence, and leverage effects (Katsiampa, 2019). Therefore, they also carry different risks despite having a potentially high return on investments. For instance, the risks such as the risk of the counterparty, the problem of shallow market, risk of market, privacy-related risk, risk of the transaction, operational risk, legal and regulatory risk are among the main risks regarding cryptocurrencies in general (Böhme et al., 2015). These risks affect the volatility of cryptocurrency prices and cause increases and decreases constantly. When the risks increase, the uncertainties on these currencies also increase. Analyzing these uncertainties and volatility with various methods and finding the most appropriate estimation methods will reveal important results for cryptocurrency investors.

Volatility can basically be defined as the fluctuation property of a security price and the market in general within a short period of time. Essentially, it is a function of uncertainty. It can be measured by applying the standard deviation or variance between returns from that obtain same market index or security (Bhowmik, 2013). Especially in financial markets, estimating and accurate modeling of volatility are based on two main reasons. First, the risk of an asset is a significant factor in determining the price of the asset, and volatility is used as an indicator of risk. The second is the requirement for the correct definition of conditional variance in order to make efficient econometric inferences of the conditional mean (Ertugrul, 2019).

Volatility can directly related the efficiency of financial markets. As Fama discussed in 1970, prices in financial markets would be secure under the hypothesis of fully reflect all available information. The fact that the information in the financial markets is continuously changing makes it difficult to use information in the decision-making process and hinders the efficiency of the markets. This situation makes it possible for better-informed investors to get high profits (Fama, 1970). The theory implies that, under the normal conditions the market is efficient, means that investors are informed properly and they make decision rationally. But, the lack of a determined framework or a model for cryptocurrencies makes it difficult to predict the value of the market and damages the weak form efficiency characteristic (Naeem et al, 2021). From this viewpoint, in order to understand the fundamentals of financial markets, as well as cryptocurrencies, the efficient market hypothesis should be tested.

Volatility is an important issue in finance because it is considered to be the main input for the decision-making process in various areas such as securities pricing, trading, risk management, and monetary policy. So, estimation of volatility is an essential research area that has several theoretical and practical inferences (Naimy and Hayek, 2018). Modeling volatility is also important for risk management. Furthermore, cryptocurrencies are mainly used as an asset instead of a currency, the market is assumed quite speculative. It is also more volatile than other currencies and more susceptible to speculative bubbles. Hence, cryptocurrencies have an important place in financial markets and portfolio management. Therefore, analyzing its volatility is notably substantial.

In consequence, the topics related to the high interest, demand, volatility, and investment levels to the cryptocurrencies and the intra-day dynamics of cryptocurrencies have become an important topic of research and discussion by both academic and leading institutions. For example, the report prepared by the European Central Bank (2019) on crypto-assets, has stated that the crypto money market attracts a large number of investors. However, it has also indicated that when compared to other investment instruments, its volatility can be considered as a much higher and speculative asset. The report also emphasizes that the risks of these assets. Katsiampa (2017) has also stated that cryptocurrencies show high and relatively long-term fluctuations, however, they take a place as an important investment tool in the financial markets.

It is accepted that the financial markets should be effective and less volatile to attract investors. Otherwise, investors neither use the market as a saving tool nor a value-changing tool. Cryptocurrencies are relatively new and have rapidly growing market capitalization. Despite the high returns, volatility dynamics in crypto markets as a major concern for investors that because it damages efficiency of markets and makes the future unpredictable. Investors still need more insight about what is the volatility structure of cryptocurrencies and are the markets efficient. Starting from this point, it is aimed in this study determining the volatility transmission between cryptocurrencies to find useful answers about the efficiency and volatility of cryptocurrency markets. Daily logarithmic return series between 18 January 2018 – 14 February 2021 were used to analyze the volatility of five of the most common cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), IOTA. Applying the RALS-ADF test, EGARCH, and DCC-GARCH models we answered, how markets effect from positive and negative shocks and how market volatility reacts to shocks. This study will make an essential contribution to the literature, as the analysis of the volatility transmission and dynamic conditional correlation of cryptocurrencies will help cryptocurrency investors to predict market behavior.

The layout of the study is as follows; section two provides a brief review of the empirical literature about cryptocurrencies. Section three presents the dataset, methodology, and employed model. Emprical findings are discussed in the fourth section. Lastly, the conclusion part followed these sections.

2. Literature

As cryptocurrencies dramatically increased their value by expanding their transaction volumes recently, they have become an essential popular topic in not only leading institutions and public consideration but also academic research. The studies on cryptocurrencies in recent years have primarily focused on Bitcoin and as it is known Bitcoin dominates the market. However, as the other cryptocurrencies that emerged after Bitcoin have begun to be the most demanded investment tools in international financial markets in a short time, these currencies have also started to take place in studies. The studies that discussed the topics such as the risks, price movements, returns, and volatility of these cryptocurrencies which emerged as a new investment tool, generates an important part of the literature.

Chu et al. (2017) attempted twelve GARCH models for seven cryptocurrencies. They used the maximum likelihood model for fitting. They indicated that all the models of GARCH-type are fitted by the maximum likelihood model. They fitted the twelve GARCH models to the log-returns of the selected seven cryptocurrencies' exchange rates. According to their result, IGARCH (1,1), and GJRGARCH (1,1), models are the best fits in regard to modeling the volatility for the seven cryptocurrencies. In this regard, IGARCH (1,1) is the best proper model for Bitcoin, Maidsafecoin, Dash, Monero, and Litecoin; the model GJRGARCH (1,1) is the best fits for Dogecoin; and the GARCH (1, 1) model is the best proper model for Ripple. They also indicated that when they considered inter-daily prices of cryptocurrencies, their results showed the cryptocurrencies such as Litecoin, Bitcoin, and Ethereum and others exhibit excessive volatility.

Ceylan et. al. (2018) investigated speculative bubbles in Bitcoin and Etherium cryptocurrencies and estimated when they formed by using the method of Philips et al. They found that there are numerous bubbles in the Bitcoin and Etherium. Their results showed that these cryptocurrencies tend to movements of speculation.

Ertugrul (2019) modeled the volatility features of the return rates of Bitcoin and Ripple by using traditional ARCH-GARCH models and EGARCH-TGARCH models which is considering the asymmetry. He compared alternative models in regard to their performance of forecast. He found that the asymmetric TGARCH model is the most succeeding model in accordance with forecast performance criteria. He also stated that the higher periods of volatility correspond to the high price movements periods of the cryptocurrencies considered and analyzed in the study.

Katsiampa et al. (2019) considered the data of intra-day for eight cryptocurrencies and investigated the dynamics of conditional volatility of the cryptocurrencies and co-movements of volatility in cryptocurrencies by applying Diagonal BEKK-MGARCH and Asymmetric Diagonal BEKK- MGARCH methodologies. Their results showed that pairwise price returns of eight cryptocurrencies are positively and strongly correlated. They also found that the whole conditional variances are considerably affected from past conditional volatility and previous squared errors. They indicated that all the cryptocurrencies considered have high permanence of volatility in time.

Katsiampa (2019) employed an Asymmetric Diagonal BEKK model in order to investigate the dynamics of the volatility of five cryptocurrencies; Ripple, Ether, Bitcoin, Stellar Lumen, Litecoin. In the study, the co-movements of volatility among five selected cryptocurrencies were investigated and asymmetric effects of positive and negative shocks in the covariances and conditional variances were considered. The result of the study shows that both past conditional volatility and previous squared errors affect all the cryptocurrencies' conditional variances significantly. Katsiampa also stated that asymmetric past shocks have a substantial impact on current conditional variance, for the four cryptocurrencies, Ether, Litecoin, Bitcoin, and Ripple.

Kumar and Anandarao (2019) focused on four basis cryptocurrencies, Ethereum, Bitcoin, Litecoin and Ripple, and analyze the dynamics of volatility spillover of these cryptocurrencies returns. They employed the IGARCH(1,1)-DCC (1,1) multivariate GARCH model in order to estimate spillovers of volatility in the first step. Their results from the GARCH model show that spillovers of volatility from Bitcoin to Ethereum and Litecoin are statistically significant. In the second step, they implemented a wavelet time horizon in order to examine the effects of spillover across various time scales. In general, their results show that there is a turbulence possibility in the cryptocurrency market. Their results also point that the herding behavior possibility in the market of cryptocurrency.

Palamalai and Maity (2019) employed the Vector Error Correction method and the model of Diagonal BEKK Multivariate GARCH in order to investigate the effects of return and volatility spillover across eight cryptocurrencies. Their results showed that there is evidence of volatility co-movements and interdependencies between the various pairs of cryptocurrencies. According to the result of the Diagonal BEKK MGARCH model, conditional variances of the returns of all selected cryptocurrencies are dramatically affected by past conditional volatility and past squared errors. They also stated that the eight cryptocurrencies had a bidirectional volatility spillover effect.

Wang and Ngene (2020), investigated bilateral asymmetric and nonlinear causalities and spillover of volatility among six significant cryptocurrencies and Bitcoin (BTC) by using intra-day data. They focused on the behavior of intra-day time series, up and down market causality, and intra-day volatility transmission of cross-market. In order to test the dynamics of causality in the first moment, they applied the Mackay-Glass (M-G) model, and to examine bivariate causality in the second moment they used the conditional full BEKK-GARCH model. They also estimated the intra-day correlation of asymmetric dynamic conditional by using the AG-DCC model. According to their empirical results, BTC has a dominant power in the price movement both in the bear and bull markets. The other cryptocurrencies and LTC do not share the same power as BTC when it comes to the transmission of returns and volatility spillovers. Moreover, volatility and intraday lagged shocks of Bitcoin caused destabilizing and rapid influence on other currencies' conditional volatility than each of the other currencies has on conditional volatility of BTC.

Kayral (2020), investigated the returns of the three cryptocurrencies with the biggest market value: Ethereum (ETH), Bitcoin (BTC), and Ripple (XRP). He compared six GARCH models to estimate the most appropriate models for the volatility of these cryptocurrencies. He found that the best model for BTC and ETH in the volatility estimates is EGARCH (1,1). APARCH (1,1) model is the best model for XRP. Using these models, Kayral examined the leverage effect of three cryptocurrencies, stated that there is no leverage effect for BTC and ETH, but positive shocks cause more volatility than negative shocks. He also stated that there is a leverage effect for XRP.

Soylemez (2020) used daily logarithmic return series in order to analyze Bitcoin volatility and he considered the daily closing prices of Bitcoin when calculating the return series. He compared ARCH, GARCH, EGARCH, GJR / TARCH, CGARCH, and APARCH models in order to Bitcoin logarithmic return series volatility modeling. He indicated that the EGARCH model is the best model for the Bitcoin volatility analysis. He also found that negative shocks are more effective than positive shocks on the return of Bitcoin. This means that Bitcoin prices are more affected by negative news. Therefore, the market and investors are more likely to price bad news than good news.

Burggraf and Rudolf (2021) investigated the low volatility anomaly of 1000 cryptocurrencies in the cryptocurrency market. According to their result, there is no evidence of a considerable low volatility premium. They also indicated in their result that cryptocurrencies are more productive than expected and higher risk leads to higher returns.

Bouri et al. (2021) applied the DCC-GARCH model and obtained a time-varying measure of volatility connectedness by considering fifteen cryptocurrencies at first. Afterward, they investigated the investor sentiment role in clarifying the connectedness metric movement in a quantile-on-quantile framework. In the study, they stated that the data of the Twitter feed is a proxy for investor sensitivity, and lower quantiles of investor happiness based on this data are positively conjunction with the whole conditional connectedness distribution. However, they observed at higher values of investor happiness are the opposite of this result. Moreover, when they consider the impact of sensitivity on the common market volatility, they found that when investors become extremely unhappy, the overall volatility of the market is increasing. Therefore, they associated this with high market connectedness.

The dynamics of volatility in the prices of cryptocurrencies, which are getting more and more integrated and the number of users is increasing, shocks, interdependencies between cryptocurrencies, and the risks that may arise constitute the motivation of this study. For this reason, this study, it is aimed to determine the volatility transmission between cryptocurrencies and to find useful answers about the efficiency and volatility of cryptocurrency markets, and it is tried to answer how the markets were affected by positive and negative shocks and how the market volatility reacted to the shocks. The study will contribute significantly to the literature as it will help cryptocurrency investors predict market behavior with the analysis of volatility transmission and dynamic conditional correlation of cryptocurrencies applied in the empirical part and contains a more up-to-date dataset than the literature.

3. Data and Methodology

3.1. Data

The dataset consists of daily closing price returns of five cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), and IOTA from 18 January 2018 to 14 February 2021. This period is selected because all cryptocurrencies able to trade more than 3 years and the period also include positive and negative fluctuations. The data are sourced from the link www.investing.com. Each cryptocurrency comprise of 1124 observations and price returns are calculated using the following formula:

$$R_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1})$$

Where, i represents the cyrptocurrency, t represents time, and ln(pi,t) represents the price of cyrptocurrency.

3.2. Unit Root Tests

In the literature different types of unit root tests are used for testing weak efficiency hypothesis. In this paper, due to a time series dataset were used, testing stationary of variables were important. But traditional unit root tests, such as ADF, set aside the existence of non-normal errors, RALS-ADF unit root test is used which accepted as more powerful when error terms are non-normal distributed. The power of this test depends on to utilize non-normal errors as a useful information using higher moments of residuals. At this point RALS (residual augmented least squares) methodology is adopted to the testing regression. Like ADF, the null hypothesis indicates unit root process in RALS-ADF test, and the critical values were reported by authors (Im, et al. 2014).

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + u_t \qquad (1)$$

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \widehat{w}_t' \varphi + v_t \qquad (2)$$

Equation (1) represents to ADF unit root test. When this equation is expanded using $\widehat{w}_t$ as a RALS term, we obtained Equation (2). In Equation 2, the p represents the long term corelation coefficient between errors. If the correlation coefficient ρ obtained as equal to 1, there would be no difference between ADF and RALS-ADF tests (tRADF=tADF). We expect to obtain lower ρ values to show the differences between ADF and RALS-ADF.

3.3. E-GARCH Model

EGARCH model was developed by Nelson (1991) which using exponential function in order to eliminate asymmetric effects in positive and negative shocks (Nelson, 1991). Furthermore, the model can not be negative because of using natural log form of the variance. EGARCH model is estimated as follow:

$$y_t = \phi y_{t-1} + \varepsilon_t$$

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

$$lnh_t = \alpha_0 + \beta_1 lnh_{t-1} + \theta \frac{e_{t-1}}{\sqrt{h_{t-1}}} + \gamma \left| \frac{e_{t-1}}{\sqrt{h_{t-1}}} \right|$$

where, α, β and γ are constant parameters. The θ is a negative coefficient which all else being equal indicates positive shocks generate less volatility compared to negative shocks.

3.4. DCC GARCH Model

DCC model was developed by Engle (2002) for using to explore time-varying correlation among two or more series. The model comprises two steps: first step is evaluating the series of univariate GARCH parameters and the second is, evaluating their correlation estimations (Engle, 2002). In this method, the conditional covariance matrix is obtained as follows:

$$H_t = D_t P_t D_t$$

$$D_t = \begin{bmatrix} \sqrt{\sigma_{c,t}^2} & 0 \\ 0 & \sqrt{\sigma_{e,t}^2} \end{bmatrix}$$

Where, $D_t = diag\{\sqrt{h_{i,t}}\}$ is a diagonal kxk matrix of time-varying standard deviations from the univariate GARCH model. GARCH models able to capture two characteristics of financial data: time-varying variance and leptokurtic distribution. The standard deviations in D_t come by the following GARCH (P, Q) process: (Chang et al, 2019 & Kumar et al, 2019)

$$h_{it}^2 = \gamma_i + \sum_{p=1}^{p_i} \alpha_{ip}\, \varepsilon_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq}\, h_{i,t-q}^2,\ i = 1{,}2$$

where, α_i and β_i are the coefficients of the ARCH and GARCH terms. At this point, we expect α_i, $\beta_j \geq 0$ and satisfy $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$. The α and β coefficients are associate with the exponential smoothing process. Using these coefficients, we obtain dynamic condition correlations.

$$P_t = \begin{bmatrix} \varepsilon_{cc,t} & \varepsilon_{ce,t} \\ \varepsilon_{ec,t} & \varepsilon_{ee,t} \end{bmatrix} = \begin{bmatrix} 1 & \varepsilon_{ce,t} \\ \varepsilon_{ec,t} & 1 \end{bmatrix}$$

P_t is the conditional correlation matrix of the standardized disturbances ε_t. Furthermore, P_t is to be positive and all the parameters should be less than or equal to 1. The conditional correlation matrix P_t determined as follows:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1}$$

where, Q_t is the positive specific N×N matrix which includes conditional variances-covariances of ε_t and Q_t^{*-1} is obtained by inverting diagonal matrix using the square root of diagonal elements of Q_t.

The DCC model is given by:

$$Q_t = \left(1 - \sum_{i=1}^{M} a_i - \sum_{j=1}^{N} b_j\right) \bar{Q} + \sum_{i=1}^{M} a_i \left(\varepsilon_{t-i}\varepsilon'_{t-i}\right) + \sum_{j=1}^{N} b_j Q_{t-j}$$

Where $\bar{Q}$ is the unconditional covariance matrix of the standardized disturbances, ε_t. Finally, for time t the dynamic conditional correlations of a pair of markets i and j represents with ρ_{ij} and can be state in following equation. ρ_{ij} would be in -1 and 1 confirming P_t is positive definite. (Hongsakulvasu, et al., 2020)

$$\rho_{ij} = \frac{q_{ijt}}{\sqrt{q_{iit}\, q_{jjt}}} = \frac{(1-a-b)\overline{q_{ij}} + bq_{ij,t-1} + a\sigma_{i,t-1}\sigma_{j,t-1}}{\left[(1-a-b)\overline{q_{ii}} + a\sigma^2_{i,t-1} + bq_{ii,t-1}\right]^{1/2}\left[(1-a-b)\overline{q_{jj}} + a\sigma^2_{j,t-1} + bq_{ij,t-1}\right]^{1/2}}$$

However, the DCC model can not capture the asymmetric effects, Cappiello et al (2006), extended the notation with adding asymmetric effects as follow. Summary, in this equation, $\theta_1 = \sum_{i=1}^{M} a_i$, $\theta_2 = \sum_{j=1}^{N} b_j$ and z_t standardized residuals. The coefficient ϕ represents asymmetric effect. (Abioglu, 2021)

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} - \phi\bar{N} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} + \phi n_{t-1} n'_{t-1}$$

where, $n_t = I[z_{1t} < 0, z_{2t} > 0]$, $\bar{N} = T^{-1}\sum_1^T n_t n'_t$, and $I[\cdot] = 1$ if $z_{1t} = \frac{\varepsilon_{s,t}}{\sqrt{h_{s,t}}} < 0$ and $z_{2t} = \frac{\varepsilon_{o,t}}{\sqrt{h_{o,t}}} > 0$, and zero otherwise. At this point, z_{t-1} is scaled by Q_{t-1} to obtain consistent asymmetric DCC model:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} - \phi\bar{N} + \theta_1 (Q^*_{t-1} z_{t-1} z'_{t-1} Q^*_{t-1}) + \theta_2 Q_{t-1} + \phi n_{t-1} n'_{t-1}$$

Adopting student-t multivariate distribution of the return series helps to obtain more wisely estimation results.

4. Emprical Findings

We began our empirical analysis by investigating the volatility clustering in all the price returns series. Figure 1 vividly shows, volatility varied in return series during the period.

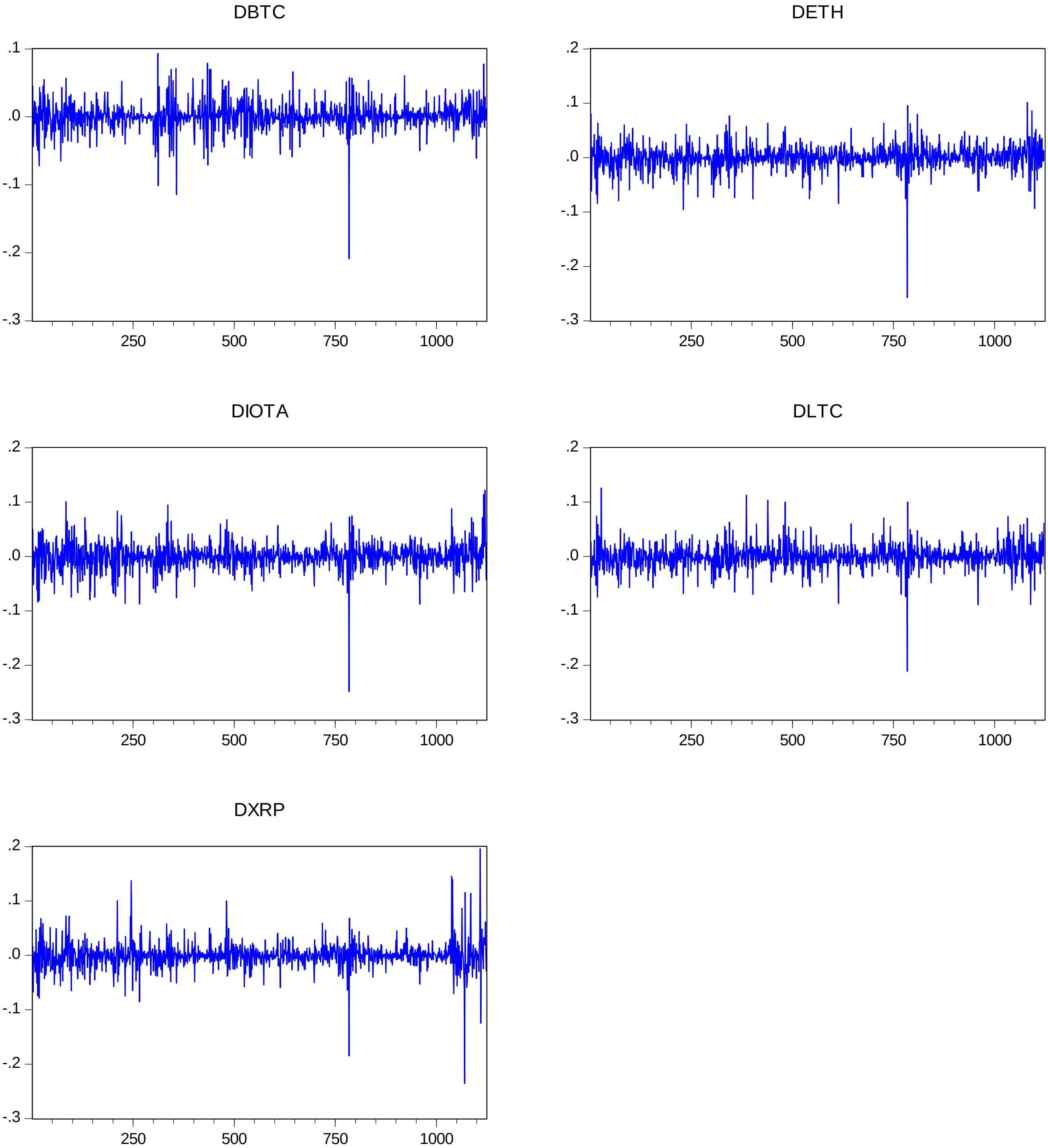

Figure 1. Closing price returns of cryptocurrencies (in US dollars).

	BTC	ETH	IOTA	LTC	XRP
Mean	0.000559	0.000231	-0.00032	2.52E-05	-0.000367
Median	0.000593	0.000301	-0.000215	-0.00056	-0.000136
Maximum	0.093247	0.101201	0.12205	0.126051	0.196057
Minimum	-0.208821	-0.2573	-0.248733	-0.211089	-0.235459
Std. Dev.	0.020971	0.023244	0.025693	0.023269	0.025387
Skewness	-0.938068	-1.34052	-0.679985	-0.322635	-0.028851
Kurtosis	14.33467	18.1271	12.38898	11.5156	18.86858
Jarque-Bera	6176.2*	11043.6*	4211.3*	3412.6*	11782.8*
Probability	0.00	0.00	0.00	0.00	0.00
ARCH LM	1109.2*	1099.3*	1102.3*	1078.6*	1084.6*
BG Test	1093.6*	1112.6*	1108.7*	1106.1*	1093.6*
ADF	-39.55	-37.88	-35.64	-36.52	-34.41
RALS-ADF	-13.08	-8.668	-15.303	-16.177	-19.305
ρ	0.746	0.793	0.763	0.712	0.618
5%	-2.732	-2.781	-2.781	-2.732	-2.662

*indicates significance at the 1% levels.

Table 1. Descriptive statistics and unit roots test

The empirical analysis begins obtaining descriptive statistics and unit root tests for the five cryptocurrencies. As shown in Table 1 during the period, except IOTA and XRP returns, remaining cryptocurrencies returns' means are obtained positive. Also, the return series distributed leptokurtic which has small negative skewness and relatively higher kurtosis values. The negative skewness indicates that major negative changes in returns emerge more often than positive changes. The excess kurtosis of each cryptocurrency's return is typical evidence of fat tails and probably as an indicator of some unknown movements which able to extremely affect the returns such as speculations, sudden rise, and the collapse of the cryptocurrencies (Wang et all, 2020).

Jarque-Bera test's results confirmed that none of the cryptocurrencies is normally distributed as all probability values lower than 0.01 level of significance, which indicate rejecting of null hypothesis of normality. Significancy of ARCH-LM and Breusch Godfrey tests results indicate the existence of heteroskedasticity and autocorrelation for all series. Also, the high level of ARCH-LM coefficients show that, shocks have an impact to increase volatility during the period (Ahmad et all, 2017). ADF unit root test results confirm the stationary of all cryptocurrencies and the weak form efficiency has been not observed. Because of the correlation coefficient, ρ, is obtained lower than 1 for each cryptocurrency, we accepted that ADF and RALS-ADF tests are not equal and RALS-ADF asymptotically stronger than ADF.

	BTC	ETH	IOTA	LTC	XRP
α_0	-12.25067*	-0.546222*	-0.361411*	-0.661878*	-1.523*
Υ	0.292583*	0.156694*	0.166824*	0.135554*	0.515923*
θ	0.086157*	-0.033884*	-0.015997**	-0.047127	0.014503
β	0.546002*	0.94242*	0.967063*	0.925215*	0.844778*
Q(20)	23.6306 (0.16)	25.7035 (0.10)	48.2505 (0.00)	23.0018 (0.23)	17.6602 (0.47)
Q(50)	38.5565 (0.83)	45.4486 (0.57)	60.9838 (0.09)	42.1054 (0.74)	41.6566 (0.72)
$Q^2(20)$	11.1593 (0.88)	7.46422 (0.98)	8.15884 (0.97)	9.35042 (0.95)	8.54056 (0.96)
$Q^2(50)$	23.2663 (0.99)	18.805 (0.99)	23.1412 (0.99)	25.6698 (0.99)	43.6912 (0.64)
ARCH (5)	0.36620 (0.87)	0.99171 (0.4215)	0.92303 (0.4651)	0.84027 (0.52)	0.44754 (0.81)
ARCH (10)	0.94896 (0.48)	0.59573 (0.8184)	0.55066 (0.8544)	0.63560 (0.78)	0.38910 (0.95)

*, **, *** indicates significance at the 1% , 5% and 10% levels. Q(20) and Q(50) are Ljung-Box Q test statistics and probabilities for standardized residuals and Q2(20) and Q2(50) are squared residuals with lags in parenthesis.

Table 2. EGARCH Estimates

Table 2 provides the results of univariate EGARCH model. According to the results, β coefficients are statistically significant and positive for all cryptocurrencies which explains volatility clustering and persistence in the long run under the market shocks. For ETH, IOTA, LTC and XRP; β coefficients are observed close to 1 and show positive market shocks have relatively strong impact on conditional volatility in the long run. But for BTC, β coefficient is 0.54 which confirming non-existence of long run effect of positive shocks. On the other hand, asymmetry measure of θ is statistically significant and positive for BTC explaining positive shocks can increase volatility while negative shocks can decrease. Overall, for BTC leveraged effect was not observed. Because of θ coefficients are significant and negative for ETH, IOTA and LTC, there was leveraged effect during the period while adverse shocks effect volatility more than positive shocks. The Box-Pierce-Ljung-Box Q-test statistics for five cryptocurrencies are also shown in Table 2. Q(20) and Q(50) are the Box-Pierce, Ljung-Box Q-test statistics for standardized and squared standardized residuals using 20 and 50 lags, respectively. There is no autocorrelation in standardized squares of error. The numbers in parenthesis below shows the p values for LB (Ljung-Box) statistics and ARCH statistics.

	BTC- ETH	BTC-IOTA	BTC-LTC	BTC-XRP	ETH-IOTA	ETH-LTC	ETH-XRP	IOTA-LTC	IOTA-XRP
$\phi 11$	0.3041*	0.3355563*	0.3487*	0.2692*	0.093728**	0.1265*	0.1034*	0.091563109**	-0.0007141
$\phi 12$	-8.86E-03	-0.064021	-0.0783***	0.0032269	0.0778296	0.0116	-0.0218	0.0262238	0.2111199*
$\phi 21$	0.0571	-0.131582	0.0419	-0.0436	0.0230361	0.1342***	-0.0237	0.1257919***	-0.0463012
$\phi 22$	0.1306**	0.2884453	0.099**	0.1877**	0.2543916**	0.036	0.1963*	-0.009529	0.5520726
$\delta 11$	0.6731*	0.6197038	0.5527*	0.7281*	0.8256017*	0.8573*	0.7399*	0.905095508*	1.05819243*
$\delta 12$	0.1322	0.2506156	0.3607***	0.0587	-0.02987	-0.009	0.105***	-0.0807932	-0.2725501*
$\delta 21$	-4.81E-03	0.2684733	0.1872	0.0687	0.0591932	-0.1221**	0.0208	-0.14740201*	0.57762217*
$\delta 22$	0.7867*	0.6444227***	0.721*	0.7261*	0.7256192*	0.9483*	0.7465*	1.001831941*	0.1014436
$\theta 1$	0.1707*	0.1837015*	0.1159**	0.1711*	0.0562202*	0.0275*	0.0323*	0.041316229*	0.08868342*
$\theta 2$	0.6389*	0.3722005***	0.4478**	0.6989*	0.9103697*	0.9677*	0.9665*	0.945570059*	0.88228506*

*, **, *** indicates significance at the 1% , 5% and 10% levels.

Table 3. DCC-GARCH Estimates

Table 3 summarizes evidence from nine pair-wise analysis of cryptocurrencies: BTC-ETH, BTC-IOTA, BTC-LTC, BTC-XRP, ETH-IOTA, ETH-LTC, ETH-XRP, IOTA-LTC, and IOTA-XRP. In Table 3, the $\phi 11$ and $\delta 11$ show volatility persistence of first cryptocurrency and $\phi 22$ and $\delta 22$ show for the second one. If sum of these parameters are close to 1, means volatility clustering occurred during the period and volatility has strong persistence effect. The $\phi 12$ and $\delta 12$ parameters show volatility transmission from the second cryptocurrency to the first and $\phi 21$ and $\delta 21$ are vice versa. $\theta 1$ and $\theta 2$ show dynamic conditional correlation coefficients between cryptocurrencies. (Akcali et al, 2020) According to the results in Table 3, $\phi 11$ and $\delta 11$ are statistically significant except last pair, and sum of them for each pair is higher than 0.90. We can accept volatility persistence of first cryptocurrency with volatility clustering. For the second cryptocurrency, $\phi 22$ and $\delta 22$ are not statistically significant for BTC-IOTA, IOTA-LTC and IOTA-XRP. But they are significant for the remaining pairs and also sum of these parameters are close to 1, which show clustering and persistence effect for the second cryptocurrency's volatility.

The volatility transmission parameters are statistically significant and it is observed unidirectional volatility transmission from LTC to BTC, from ETH to LTC, from XRP to ETH, from IOTA to LTC and bidirectional volatility transmission between IOTA and XRP. So, %1 volatility increase in LTC caused %0.28 rise in BTC, %1 volatility increase in ETH caused %0.012 rise in LTC, %1 volatility increase in XRP caused %0.08 rise in ETH and %1 volatility increase in IOTA caused %0.02 decreased in LTC. Also, two-way volatility transmission is %0.53 for IOTA and XRP. Except these pairs, volatility transmission was not observed between other cryptocurrencies. Dynamic conditional correlation coefficients, θ1 and θ2, are statistically significant and positive for each pairs. Sum of θ1 and θ2 is 0.96 for ETH-IOTA, 0.99 for ETH-LTC, 0.99 for ETH-XRP, 0.98 for IOTA-LTC and 0.97 for IOTA-XRP, 0.87 for BTC-XRP and 0.80 for BTC-ETH which confirm time varying and strong correlation between cryptocurrencies. But for BTC-IOTA and BTC-LTC time varying correlation relationship is weak, which is around 0.55.

5. Conclusion

The risk of an asset is a substantial factor in determining the asset's price, while volatility is also used as an indicator of risk. As the risk phenomenon is one of the most critical determinants of the investment process together with volatility, measuring the risk and revealing its sources and types are important in terms of risk management. In this respect, it is important to manage investments in cryptocurrencies which have emerged as a new investment tool and carry different risks due to their digital structures and understand their volatility correctly. In this study, we investigated volatility structure for the five most common cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), IOTA, by applying the RALS-ADF test, EGARCH, and DCC-GARCH models. We determined whether the market is efficient or not, as well as tested the existence of the asymmetric effect and volatility transmission in the market.

We began the empirical analyses with the RALS-ADF test and examined the market efficiency. It is known that inefficient markets are susceptible to external or internal shocks. Hence, in accordance with the literature, our results also showed that the market is not efficient for all cryptocurrencies. We continued our analysis with the EGARCH model to test the asymmetric effect and leverage effect. We found that the presence of asymmetric effect is valid for all cryptocurrencies. In other words, cryptocurrencies react differently to negative and positive shocks. But except BTC, other cryptocurrencies react more to the negative shocks than the positive shocks. For BTC, leverage effect has not been observed which means BTC reacts more to the positive shocks than the negative ones. Furthermore, according to EGARCH model results, persistence of volatility was also found to be relatively low compared to the other cryptocurrencies. We also examined the time-varying correlation between cryptocurrencies by applying the DCC-GARCH model. According to the dynamic correlation coefficient, the strongest volatility transmission has founded in the pairs namely ETH-XRP, ETH-LTC, IOTA-LTC, IOTA-XRP, and ETH-IOTA. As we can say that, these crypocurrencies have a very close relationship. When BTC included in the combination, it is seen that the dynamic correlation coefficient is relatively low compared with the pairs which do not include the BTC. Despite the pairs BTC-XRP and BTC-ETH can be considered relatively strong; for BTC-IOTA and BTC-LTC we obtained weak dynamic correlation relationship.

As cryptocurrency markets and exchanges continue to evolve, it is even more important to understand how these markets operate. Developments in the markets show a particularly speculative effect on cryptocurrencies. At this stage, investors who make decisions based on risk and expected return should have more information about the volatility effect of these currencies in the decision-making process. While the persistence of volatility, related with the magnitude and time of shocks on the cryptocurrency; the volatility transmission related strength of spillover effect of a shock that occur in a cryptocurrency. Hence, according to our results, BTC, as a dominate cryptocurrency, has been observed differentiated from others and but not totally isolated from shocks. Therefore, this study is important in providing information to investors about volatility is a kind of future predictor in the cryptocurrency market. Moreover, the study will significantly contribute to the literature, as the analysis of the volatility transmission and dynamic conditional correlation of cryptocurrencies will help cryptocurrency investors predict market behavior.

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