ASIAN ACADEMY *of*
MANAGEMENT JOURNAL
of ACCOUNTING
and FINANCE

AAMJAF Vol. 17, No. 1, 125–152, 2021

IS THERE ANY INFLUENCE OF OTHER CRYPTOCURRENCIES ON BITCOIN?

Md. Jamal Hossain[1,2]* and Mohd Tahir Ismail[1]

[1]*School of Mathematical Sciences, Universiti Sains Malaysia, 11800 USM Pulau Pinang, Malaysia*
[2]*Department of Applied Mathematics, Noakhali Science and Technology University, Noakhali-3814, Bangladesh*

*Corresponding author: z_math_du@yahoo.com

ABSTRACT

In recent years, cryptocurrency or virtual currency is becoming an essential medium of exchange in consumer and domestic trading. Nevertheless, the trading values of cryptocurrency compared to real money are very uncertain and can change dramatically. This article is aimed to assess the uncertainty or volatility of cryptocurrencies, mostly on Bitcoin. In the digital currencies market, Bitcoin is a widely accepted currency. Other digital currencies of the market may influence Bitcoin. For example, Ethereum, Litecoin, Zcash, Monero, Dash and Ripple have a positive impact on Bitcoin. Previous research only focuses on Bitcoin and other markets such as stock markets, energy markets, and exchange rates. However, here we focus on interlinkages and volatility dynamics within cryptocurrency markets by applying some econometrics models. In this article, we have shown that the relationship between Bitcoin and other currencies can be modelled in the ARCH, GARCH, VAR and MGARCH framework. Forecast values of the GARCH (3,3) model are given very close to the original data. VAR stability result shows that the model is stable. Using the CCC, VCC, and DCC of the MGARCH model on daily returns from 1st January 2017 to 15th March 2019, we found significant volatility and strong correlations between the variables.

Keywords: Bitcoin, GARCH, VAR, MGARCH, cryptocurrency, volatility

Publication date: 30 June 2021

To cite this article: Hossain, M. J., & Ismail, M. T. (2021). Is there any influence of other cryptocurrencies on bitcoin? *Asian Academy of Management Journal of Accounting and Finance, 17*(1), 125–152. https://doi.org/10.21315/aamjaf2021.17.1.5

To link to this article: https://doi.org/10.21315/aamjaf2021.17.1.5

INTRODUCTION

After the inauguration of Bitcoin in 2009, cryptocurrency markets have been spreading rapidly throughout the world. These digital currencies are spreading globally because of frequently mentioned by printed media, electronic media, financial and governmental institutions (Glaser et al., 2014). The popularity of these digital currencies is increasing day by day due to security failure in the banking sector and ongoing financial crises throughout the world. For example, a Bangladesh bank robbery, also known as a cyber heist, happened in February 2016. About USD1 billion has been transferred from Federal Reserve Bank of New York, and this account belongs to Bangladesh bank (Matt Middleton-Leal, http://www.financedigest.com). Such a security breach can be avoided in cryptocurrency. Cryptocurrency is using blockchain technology, in which less sensitive data will be provided in a transaction as compared to those involving standard currencies (Corbet et al., 2019). Another example of financial instability throughout the world is the recent China-U.S. trading war. So, Bitcoin (cryptocurrencies) can be an alternative investment, because it increases within this period and become peaks USD19,497 on 17 December 2017. There is also another reason many financial institutions (the number of institution is gradually increase) are accepted cryptocurrency as a transaction media. Governmental restrictions, hacking problems, lack of computer knowledge, etc., could not create a barrier to the growth of cryptocurrencies' popularity. The investors, those who invested their money for buying precious metals, now investing their money in the cryptocurrency. Unlike conventional currencies, the foundation of cryptocurrencies is cryptographic proof, which has lots of advantages over usual payment systems (like debit and credit cards) and lowers operational costs, high liquidity and secrecy. Among the cryptocurrency's Bitcoin is the largest cryptocurrency, both in volume and capital. As of May 2019, there are more than 1,800 cryptocurrencies existed (Li et al., 2020). Bitcoin (BTC), Ripple (XRP), Ethereum (ETH), Zcash (ZEC), Monero (XMR), Dash (DASH) and Litecoin (LTC) are dominant cryptocurrencies in the market.

Cryptocurrencies return are much more volatile as well as riskier than traditional currencies and stock. As asset returns, cryptocurrencies have a place in financial markets, also in portfolio management (Dyhrberg, 2016a; Wu & Pandey, 2014). These assets are nonstationary and violate the normality assumption. Volatilities in the financial markets are intercorrelated and cross-correlated across assets returns, and markets are widely accepted (Jondeau et al., 2007; Ismail et al., 2013). Cryptocurrency returns are much more than other asset returns and have hedging capabilities when incorporated in stakeholders' portfolios. However, in recent days, fluctuations in the exchange rate have become vital concerns amongst researchers, stakeholders, economists, financial institutions who are involved in these markets. One of the essential concerns for the investors to better understand cryptocurrencies markets and generate more knowledge to make an appropriate decision in improbability and risks is the study of cryptocurrencies' interconnectedness well as volatility co-movements (see Gkillas & Katsiampa, 2018). When the potential investors have sufficient information about correlation factors, covariances, and operational mechanisms of cryptocurrencies, they will get privileged opt-to-alter or diversify their investment to reach the desired goal. From the existing studies related to cryptocurrencies, it has been seen that literature of interlinkages and correlation among cryptocurrencies are minimal and remain unexplored. In recent years, research on cryptocurrencies has started analysing connectedness between them as mainstream assets.

According to our best of knowledge, only a few researchers (Corbet et al., 2018; Katsiampa et al., 2019; Ciaian et al., 2018) have taken into account connectedness between cryptocurrencies. Corbet et al. (2018) have applied the Dynamic Conditional Correlation (DCC) model to observe interlinkages and correlation among cryptocurrencies, and they have found interconnection between cryptocurrencies. But their number of cryptocurrencies is limited, with only three cryptocurrencies, namely Bitcoin, Litecoin and Ripple. On the other side, Ciaian et al. (2018) have examined connectedness between cryptocurrencies using Autoregressive Distributed Lag (ARDL) model and observed that Bitcoin returns and returns of other cryptocurrencies are interdependent, but they did not consider spill over effect and hedging abilities. Katsiampa et al. (2019) have used the BEKK model with only three cryptocurrencies (Bitcoin, Ether and Litecoin) as pairwise to examine volatility dynamics, connectedness and correlations between the pairs. They have found volatility of these currencies depends on their own lagged shocks and lagged volatility. They have also found shock transmitted bi-directionally between Bitcoin and other two cryptocurrencies and shock spill overs among Ether and Litecoin unidirectionally.

Many kinds of research have been done on Bitcoin, but no one focuses on other cryptocurrencies' influence on Bitcoin. Our focus is visualising the other cryptocurrencies' influences on Bitcoin. It is very challenging for modelling and forecasting due to the volatility, unpredictability, as well as stochastic behaviour of Bitcoin (Urquhart, 2016; Alotaibi & Mishra, 2015). The major problem of modelling with the volatility is unpredictably changing, suddenly low volatility and then suddenly high volatility, which means volatility clustering. One of the popular ways to model volatility is allowing conditional variance, which changes over time as the functions of past errors and this process parameterised. The Nobel laureate R. Engle in 1982, presumed that volatility is inconstant in the ARCH (Autoregressive Conditional Heteroskedasticity) model. ARCH term captures heteroskedasticity to which today's volatility shock feeds the next period of volatility (Campbell et al., 1996). For these reasons, we used ARCH and GARCH models in this paper to capture heteroskedasticity and volatility.

We used a Vector Autoregressive (VAR) model to find the types of interrelationships of the currencies and stability analysis purposes. We also tested causality using Wald tests to identify interlinkages between currencies. We took raw data from 1 January 2017 to 15 March 2019. The digital currency market is stochastic, and MGARCH (Multivariate GARCH) models can capture time-varying correlations. The MGARCH models allowed us to capture the dynamics of variance, volatility persistence, and covariance overtime (Sun et al., 2017; Ardia et al., 2018). We are interested in identifying innovations, volatility persistence, and types of intercorrelations between the currencies.

Other parts of this paper are organised as data description and reason behind the selection of raw data, and the methodology section describes the methods used in this paper. Empirical results are discussed in the results section, physical significances are elaborately discussed in the discussion section, and finally, there is a concluding remark in the conclusion section.

LITERATURE REVIEW

Yermack (2013) has studied basic characteristics (the function of exchange facility, storage value and transaction unit) of Bitcoin from an economic perspective. He found that it mostly fails to fulfill all basic characteristics compared to conventional currencies and cannot be a traditional currency. The daily transaction has zero correlation along with worldwide accepted currencies and compared to gold, it is inept for risk managing and hedging capabilities. He also added that Bitcoin prices are influence by geopolitical, government, digital crime, global socioeconomic events and many other reasons. Most researchers have compared Bitcoin with gold in their analysis (Grinberg, 2012; Dyhrberg, 2016a, 2016b; Zhu et al., 2017). The researchers mainly focus on the correlation between Bitcoin and precious metals, compare behaviour with traditional currencies, economic value, hedging properties, volatility co-movement, spillover effect, risk management, relation with energy, etc. Barber et al. (2012) have investigated Bitcoin in-depth to understand better its long-term stability, weakness, strengths and security issues. They have found that there is a lack of simplicity, lack of flexibility, and difficulty making decentralisation, and it is easily grabbled but challenging to subvert. They have concluded that if Bitcoin operates in the right way, then it can be treated as a decentralised currency.

Yelowitz and Wilson (2015) have analysed Bitcoin based on its users' characteristics from Google search and categorised the clients into four types. Computer programming and illegal activity have positive influence on Bitcoin price, whereas political and speculation terms do not have any influence on Bitcoin price. Bergstra and Weijland (2014) have tried to classify Bitcoin from traditional currency, informational currency, or money-like commodity and concluded it as a money-like commodity. Cusumano (2014) has intuitively analysed the Bitcoin ecosystem and found that it is less-alike like a currency but more as a computer-generated commodity. Cheah and Fry (2015) have studied Bitcoin in a speculative-bubble aspect and also investigated whether there are trends of Google search or not for additional perception, and they come to the conclusion that it is much prone to speculative-bubbles and has no fundamental value. Zhu et al. (2017) have considered stock price, custom price, currency (US dollar), Federal funds, and gold price to see the influence on Bitcoin and made a decision; it has an influence of microeconomics index and also assets price and cannot be a real currency. Another finding is all variables exhibit long-term impact. US dollar has the highest impact on Bitcoin value, whereas the least influence is the gold price. Klein et al. (2018) have studied Bitcoin and gold and with other assets to observe their structure, correlation and portfolio components. They have argued that it has asymmetric returns during market shocks and similar movements like other precious metals. They also argued that it is unable to hedging; therefore, it is not safe heaven.

Based on the Whittle function, Adebola et al. (2019) have used parametric and semi-parametric techniques for fractional integration. Using bivariate relationships among cryptocurrencies and gold for fractional cointegration, they have inspected the level of persistence and probability of short-run and long-run stability between them. They have found an indication of mean-reversion in gold values and few cryptocurrencies, and in the long-run, a small amount of cointegration only in few cases. They concluded that there is significantly less connection between cryptocurrencies and precious metals, and one market cannot influence others. Katsiampa (2019) has used bivariate Diagonal-BEKK to analyse volatility dynamics and co-movement of two cryptocurrencies, Bitcoin and Ether, and concluded that cryptocurrency markets are interdependent. These currencies are prone to essential news, and Ether has hedging capabilities against Bitcoin. The literature of cryptocurrencies is very limited and in a concise area, therefore, the necessity of much attention from academic viewpoints. Corbet et al. (2019) have review published researches from 2009 to 2018 and found that this area is immature and needs more attention to explore these newly attractive e-cashes. They have also found 10 research gaps and concluded that Bitcoin is nothing but an asset, and there is no value like traditional currency. Guesmi et al. (2019) have investigated in pair bases such as Bitcoin and exchange rates, Bitcoin and the stock market, and Bitcoin and commodity to observe spillover effect, portfolio diversifications, and hedge properties. They have found spillovers effect among Bitcoin and other assets (gold and stock), and Bitcoin, oil, gold and equities have hedging capabilities against portfolio risk while Bitcoin decrease significantly portfolio's risk compare to the risk of other assets' portfolio. Okorie and Lin (2020) have studied connectedness and hedge properties between two markets, namely cryptocurrencies and energy (crude oil), by applying *VAR–MGARCH–GJR–BEKK* model. They have found presence of bidirectional spillover effect between energy market and Bit-Capital Vendor and unidirectional spillover effect from energy market to Bitcoin-Cash market. They have also found other cryptocurrencies markets have significant unidirectional spillover effect to energy market. They have added that they found evidence of hedging capabilities between these two markets.

Based on the Smooth-Transition-GARCH model, the asymmetric effects of cryptocurrencies were studied by Cheikh et al. (2019). They have observed robust evidence of reversed asymmetric impact for almost all major digital currencies, i.e., positive news are having more effect on cryptocurrencies volatility than negative news. They have also added that the asymmetric effect of digital currencies is similar to gold so that it can be treated as a safe heaven. Caporale and Zekokh (2019) have examined four major cryptocurrencies, namely Bitcoin, Litecoin, Ethereum and Ripple from a different angle. They have fitted these four digital currencies on the 1000 GARCH family model, from which find the best-fitted one so that investors and policymakers can get the right information. Their findings suggested that the Markov-switching GARCH technique is suitable for digital currencies modelling and the possibility of getting more relevant results. Charles and Darné (2019) have replicated Katsiampa's (2019) work in the same sample (2010–2016), they fitted six GARCH family models and reproduced the same work for an extended period (2010–2018). Their results were similar to Katsiampa's (2019) only with a minor difference and found the existence of jump features on Bitcoin returns. They have found that these GARCH family models were not suitable for modelling extended periods of Bitcoin returns; therefore, they need to switch the model into Markov-switching models.

Chan et al. (2019) have inspected whether the presence of Bitcoin hedging abilities and risk diversification against five well-known stock indices using different frequency data (daily, weekly, monthly). They found that Bitcoin has powerful hedging abilities against all these indices when considering monthly data, whereas medium and high-frequency returns did not show any strong hedging capabilities. Canh et al. (2019) have considered structural breaks and, at the same time, spillover effects in seven major cryptocurrencies and modelled them with DCC MGARCH. They have found in their empirical results, the presence of structural breaks in all cryptocurrencies and correlations between cryptocurrencies are positive and very strong with the existence of spillover effects. Their main finding was the limitation of diversifying advantages within cryptocurrency markets. Al-Yahyaee et al. (2019) have considered the Bitcoin price and gold price on oil investors and S&P GSCI-investors for diversifying properties and hedge abilities purposes and used five DCC-GARCH type models. They have observed that Bitcoin and gold exhibit diversification advantages against oil and S&P GSCI and robustness of hedge with capabilities of risk reduction. Beneki et al. (2019) have only considered two cryptocurrencies (namely Bitcoin, Ethereum) to investigate volatility spillovers and hedge properties under the BEKK-GARCH model framework. Their findings revealed that Bitcoin volatility shows positive shocks on Ethereum and unidirectional volatility-transmission from Ethereum returns to Bitcoin returns, which sustain not more than 10 days, then weakens over two weeks. Tu and Xue (2019) have examined bifurcation properties among two cryptocurrencies (such as Bitcoin and Litecoin) in the BEKK-MGARCH model framework from 2013–2018. They have found a unidirectional effect from Bitcoin returns to Litecoin returns and the shock's transmission direction before bifurcation being inverted after bifurcation. Bouri et al. (2018) have considered Bitcoin and five assets, namely commodities, equities, bonds, stocks and currencies, to examine volatility spillovers from July 2010 to October 2017. They found that Bitcoin returns and other asset returns were closely related to each other, and substantial evidence of volatility spillovers between these two markets.

Based on previous literature, almost all researchers consider Bitcoin with other assets. Only very few of them consider Bitcoin with other cryptocurrencies (but only take two or three cryptocurrencies). They have studied spillover effect and hedge or influence on other assets or bifurcation properties, but no one focuses interlinkages within cryptocurrencies and other cryptocurrencies' influences on Bitcoin. We focuses on other cryptocurrencies (major six cryptocurrencies) impact on Bitcoin, interlinkages between them, and also take into account volatility persistence.

MATERIALS AND METHODS

Data sources

The historical data collected from Yahoo Finance are the daily closing price of Bitcoin, Ethereum, Ripple, Zcash, Monero, Dash and Litecoin from 1 January 2017 to 15 March 2019 (804 observations). We have chosen this period because, in this time interval, these currencies are extremely volatile, that is, maximum fluctuations are present within this time.

In the first step, we have taken a natural log on daily price and then have taken the first difference in natural logarithm values. The reason behind this is to make our data stationary. The ADF (Augmented Dickey-Fuller) test (result shown in Table 1) on transformed data of Bitcoin, Ethereum, Ripple, Zcash, Monero, Dash and Litecoin suggest a p-value of 0.0000, meaning that we can reject the null hypothesis of non-stationarity at 1% level of significance. That is, our data is now stationary.

In Figure 1, the top left shows the original data graphs clustered between November 2017 and February 2018, and the top right shows transformed data graphs are stationary. The bottom left shows the histogram of cryptocurrencies' original data that are not normally distributed. The distributions are highly skewed, and the distributions' right tail is longer than the left tail. However, in the bottom right, the histogram of cryptocurrencies transformed data is normally distributed, although there are some peakedness in the distributions.

Descriptive statistics for returns of the daily closing price of seven cryptocurrencies are presented in Table 2. Average returns of seven cryptocurrencies are ranging from 0.011% to 0.487%, where Zcash possesses the lowest value, and Ripple possesses the highest value. The standard deviation of Bitcoin returns is 4.53% implying less volatile while Ripple returns possess high volatility. Returns of Bitcoin, Ethereum, Dash and Monero are nearly symmetric distribution, Zcash is moderately skewed, and Ripple is highly skewed. When the distribution is positively skewed, it implies that there is a long tail in the right. Kurtosis of all returns is higher than three, which means leptokurtic distribution, i.e., heavy-tailed presence.

Table 1
ADF test for unit root

Variables	Test statistic	1% critical value	5% critical value	10% critical value	*p*-value	Remarks
Bitcoin	–1.681	–3.430	–2.860	–2.570	0.4410	Non-stationary
d.lnBitcoin	–28.710	–3.430	–2.860	–2.570	0.0000	Stationary
Ethereum	–1.588	–3.430	–2.860	–2.570	0.4897	Non-stationary
d.lnEthereum	–28.046	–3.430	–2.860	–2.570	0.0000	Stationary
Litecoin	–1.917	–3.430	–2.860	–2.570	0.3239	Non-stationary
d.lnLitecoin	–28.515	–3.430	–2.860	–2.570	0.0000	Stationary
Zcash	–1.953	–3.430	–2.860	–2.570	0.3075	Non-stationary
d.lnZcash	–28.979	–3.430	–2.860	–2.570	0.0000	Stationary
Dash	–1.662	–3.430	–2.860	–2.570	0.4508	Non-stationary
d.lnDash	–29.552	–3.430	–2.860	–2.570	0.0000	Stationary
Monero	–1.858	–3.430	–2.860	–2.570	0.3521	Non-stationary
d.lnMonero	–31.762	–3.430	–2.860	–2.570	0.0000	Stationary
Ripple	–2.191	–3.430	–2.860	–2.570	0.2096	Non-stationary
d.lnRipple	–30.075	–3.430	–2.860	–2.570	0.0000	Stationary

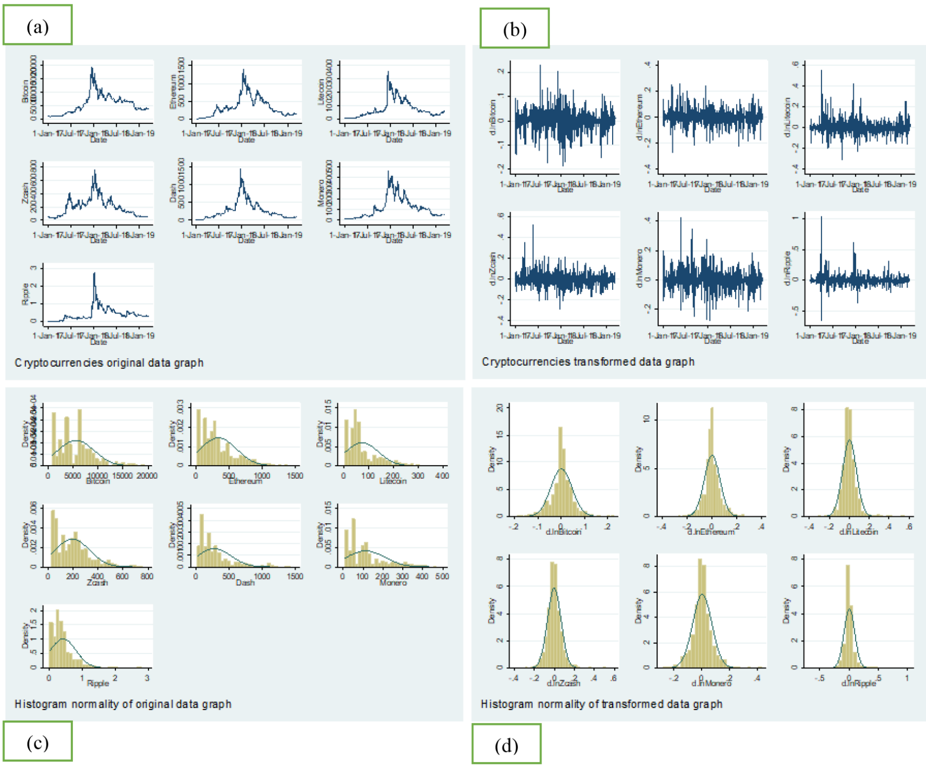

Figure 1. Graphical representation of descriptive statistics: (a) original data graph, (b) returns data graph, (c) normality of original data graph, and (d) normality of returns data graph

Table 2
Descriptive statistics of seven cryptocurrencies

Variables	Mean	Variance	SD	Skewness	Kurtosis
d.lnBitcoin	0.00171	0.00205	0.04533	–0.13055	5.76744
d.lnEthereum	0.00352	0.00396	0.06293	0.26093	5.45144
d.lnLitecoin	0.00323	0.00481	0.06939	1.45037	12.41621
d.lnZcash	0.00011	0.00461	0.06787	0.78764	8.83419
d.lnDash	0.00262	0.00440	0.06637	0.58994	6.97623
d.lnMonero	0.00169	0.00472	0.06870	0.35610	6.80145
d.lnRipple	0.00487	0.00832	0.09120	2.49786	31.04189

A simple AR (*p*) or MA (*q*) or even ARMA (*p, q*) model cannot capture volatility when there is a presence of heteroskedasticity or arch effect. For that reason, Engle (1982) proposed the ARCH (*p, q*) model, and then a generalised version of the ARCH model was introduced by Bollerslev (1986). Like Dyhrberg (2016a), in our analysis, we only use the GARCH (*p, q*) model, because according to Hansen and Lunde (2005) and Köksal (2009), this model is enough to capture volatility dynamics. Similar to Zhu et al. (2017), VAR is used here to test the stability of the model and interrelationship among the variables. Following Corbet et al. (2018), we used DCC along with CCC and VCC model to compare model performance and find the correlation between the cryptocurrencies. Below a short description of the models used in this research.

ARCH Model

The ARCH model is applied for capturing the volatility of asset return. Robert F. Engle first introduces this model in 1982 to capture the volatility of the U.K. inflation rate. Due to the characteristics of volatility on any financial time-series, this model consists of two assumptions. The first one is that there is clustering in high volatility, and therefore the return of the assets depends on previous values, but it is uncorrelated in whole time-series. The second one is the distribution of returns of the assets (at) depend on previous values can be explained by a quadratic function of previous lagged values. At time $t-1$ the model is established on this information set. Conditional variance is depending on the former q lagged innovations term.

$$\sigma_t^2 = \omega + \alpha_1 \alpha_{t-1}^2 + \ldots + \alpha_q \alpha_{t-q}^2$$

From the above equation, we can see that because of squared innovation term of return of the assets has a more significant impact on conditional variance. It indicates a large shock tends to other large shocks, and a small shock tends to other short shocks, which is the same characteristic of clustering of volatility (Engle, 1982).

The ARCH (q) model becomes:

$$\alpha_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha_1 \alpha_{t-1}^2 + \ldots + \alpha_q \alpha_{t-q}^2$$

where $\varepsilon_t \sim N(0, 1)\ iid$, $\omega > 0$ and $\alpha_i \geq 0$ for $i > 0$. An assumption of the model is, ε_t presumed to follow standard normal, student *t* or generalised error distribution (Tsay, 2010).

GARCH (*p, q*) model

Let ε_t denote a real-valued discrete-time stochastic process, h_t variance returns, and Y_t at time t denote information set (σ-field). The GARCH (*p, q*) model can be written as:

$$\varepsilon_t \mid Y_{t-1} \sim N(0, h_t),$$

$$d.\ln Bitcoin_t = \alpha_0 + \alpha_i d.\ln cryptocurrency + \varepsilon_t$$

$$h_t = \alpha_0 + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t$$

where $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$ ($i = 1, 2, \ldots \ldots, q$), $\beta_j \geq 0$ ($j = 1, 2, \ldots, p$).

When $p = 0$ the model reduces to ARCH (q) and when $p = q = 0$, ε_t is white noise. In the ARCH (q) model, the conditional variance is represented as a linear function of only past sample variances, whereas the GARCH (*p, q*) model allows lagged conditional variances (Bollerslev, 1986). When the study aims to analyse and forecast volatility, in these cases, the GARCH (*p, q*) model is beneficial. GARCH process implies that very smooth and very high volatility forecasting.

VAR Model

In multivariate analysis, the vector autoregression (VAR) model is useful, reliable and easily adjustable. It is an annex of the univariate model to dynamic multivariate time series. It is corroborated that the VAR is very pragmatic in describing econometric, finance and forecasting's dynamical behaviour. The basic VAR is introduced by Sims (1980), consists of a set of N endogenous variables $y_t = y_1, y_2, \ldots, y_k, \ldots, y_N$. Then VAR($p$) is defined as:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

where A_i for $i = 1, 2, \ldots, p$ are $(N \times N)$ coefficient matrices and u_t is N-dimensional process with $E(u_t) = 0$ and time-invariant positive definite covariance matrix, $E(u_t u_t^T) = \sum_u$.

CCC (Constant Conditional Correlations)

The $N \times N$ conditional covariance matrix with $N \times 1$ vector process ε_t, let Ω_t, can be decomposed by

$$\Omega_t = R_t D_t R_t \,,$$

where R_t indicates $N \times N$ matrix of conditional correlations together

$$\rho_{ijt} = \frac{Cov_{t-1}(\varepsilon_{it}, \varepsilon_{jt})}{Var_{t-1}(\varepsilon_{it})^{1/2} Var_{t-1}(\varepsilon_{jt})^{1/2}}$$

and D_t indicates $N \times N$ diagonal matrix together $Var_{t-1}(\varepsilon_{it})$. Bollerslev (1990) established the CCC-MGARCH model and assumed constant conditional correlations $\rho_{ijt} = \rho_{ij}$, so that, in Ω_t the time-varying conditional variances only determine temporal variation for every element in ε_t. If each of the conditional variances is positive, then the CCC model guarantee the positive definiteness of the resultant conditional covariance matrices (Bollerslev, 1990).

DCC (Dynamic Conditional Correlations)

DCC-MGARCH model is an extension of CCC of Engle (2002) works by allowing time-varying conditional correlations. To simplify the analysis of wide dimensional systems, the elementary DCC model assumes that exponential smoothing can describe temporal variation within conditional correlations (Engle, 2002), so that:

$$\rho_{ijt} = \frac{q_{ijt}}{q_{iit}^{1/2} q_{jjt}^{1/2}}$$

where $q_{ijt} = (1-\lambda)\varepsilon_{it-1}\varepsilon_{it-1} + \lambda q_{ijt-1}$ and ε_t indicates $N \times 1$ vector process. Tse and Tsui (2002) independently proposed a very closed formulation related to this model, which is referred to as their approach a Varying Conditional Correlation (or VCC-MGARCH) model.

RESULTS

Results from ARCH and GARCH Models

For the heteroskedasticity test, the p-value is 0.0000 suggests that there is evidence of heteroskedasticity. For the ARCH test, a p-value is 0.0000 means, there are ARCH effects in our model, which is analogous with existing literature. The presence of long return and persistence volatility suggests applying the GARCH model (Bariviera et al., 2017).

The AIC value is meaningless if we take it as an absolute value, i.e., it is treated as an arbitrary constant. When this constant depends on data, then AIC is used to find a fitted model from identical samples. The best model can be considered from a set of models when the AIC value is the smallest (the lowest information loss compares to the actual model). Negative AIC implies the lowest information loss compare to positive AIC and, therefore, the best model (Baguley, 2012). From below Table 3, we can see that the GARCH (3, 3) model is the best according to AIC and BIC.

Table 3
AIC and BIC for transformed cryptocurrencies

Models	AIC	BIC
GARCH (1, 1)	–3721.805	–3674.921
GARCH (1, 2)	–3727.012	–3675.44
GARCH (1, 3)	–3725.053	–3668.793
GARCH (2, 1)	–3719.875	–3668.303
GARCH (2, 2)	–3725.099	–3668.839
GARCH (3, 1)	–3722.343	–3666.083
GARCH (3, 2)	–3725.338	–3664.389
GARCH (3, 3)	**–3743.405**	**–3677.768**
GARCH (4, 1)	–3723.977	–3663.029
GARCH (1, 4)	–3723.486	–3662.537
GARCH (4, 2)	–3723.789	–3658.152
GARCH (3, 4)	–3728.605	–3658.28
GARCH (4, 4)	–3729.829	–3654.815

Note: Number of observations = 803

Table 4 shows that all variables and ARCH terms are statistically significant for ARCH (1,1). Moreover, all the currencies have positive shocks on returns of Bitcoin. Similarly, for GARCH (3,3), all variables, ARCH term, and GARCH term are statistically significant except Ripple. All currencies have positive shocks on returns of Bitcoin.

Figure 2 presents the residual plot and conditional variance plot of the GARCH (3,3) model. There is a lot more volatility between January 2017 and November 2017. That means there is high volatility during this prolonged period. The returns jump between December 2017 and February 2018. Then low volatility towards the end. The autocorrelations plot shows that there are two spikes outside of a 10% significant level, and others are within 5% or 10% significant level, which is statistically accepted. According to the Durbin-Watson d-statistic, the test result is 1.815813 (close to 2), which means no serial correlation. Also, from a correlogram, in ACF and PACF for predicted value, serial correlation is not present. Finally, the d.lnBitcoin graph and linear predicted graph are well fitted in the forecast plot.

Table 4
Summary results of ARCH (1,1) and GARCH (3,3) models

Variables	d.lnBitcoin	ARCH	d.lnBitcoin	GARCH
d.lnEthereum	0.113*** (0.0161)		0.112*** (0.0154)	
d.lnLitecoin	0.159*** (0.0115)		0.152*** (0.0158)	
d.lnZcash	0.0887*** (0.0132)		0.0803*** (0.0151)	
d.lnDash	0.0571*** (0.0154)		0.0712*** (0.0166)	
d.lnMonero	0.231*** (0.00838)		0.185*** (0.0147)	
d.lnRipple	0.0142** (0.00618)		0.0108 (0.0135)	
L.arch$_{\alpha}$		0.596*** (0.0673)		0.173*** (0.0189)
L2.arch$_{\alpha}$				0.188*** (0.0261)
L3.arch$_{\alpha}$				0.0547** (0.0216)
L.garch$_{\beta}$				-0.966*** (0.0195)
L2.garch$_{\beta}$				0.718*** (0.0245)
L3.garch$_{\beta}$				0.821*** (0.0169)
Constant	0.00184** (0.000854)	0.000520*** (2.29e-05)	0.000428 (0.000575)	1.92e-05*** (5.02e-06)

Note: Number of observations = 803. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

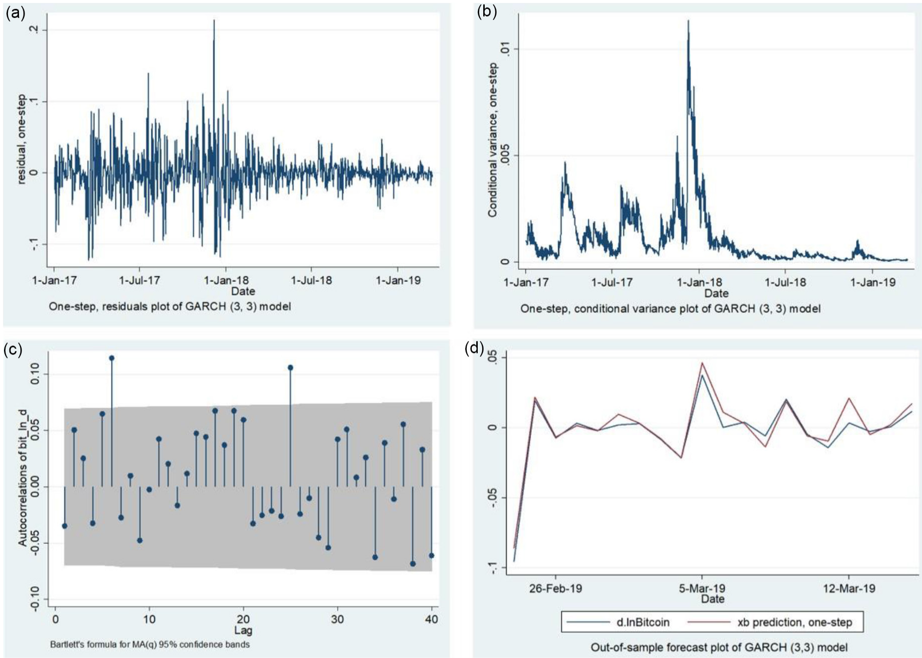

Figure 2. Different types of a graph of GARCH (3,3) model: (a) residuals plot of GARCH (3,3), (b) conditional variance plot of GARCH (3,3), (c) ACF plot of GARCH (3,3), and (d) fitted plot of d.lnBitcoin and forecast plot of GARCH (3,3)

Results from the VAR Model

According to Hannan–Quinn information criterion (HQIC) (–21.6935*) and Schwarz's Bayesian information criterion (SBIC) (–21.4908*), VAR (1,1) is the best model. From VAR (1,1) results (in Table 5), all seven variables are significant at 1% level in the mean equation. In the variance equation, sixteen variables are significant at 1% level, six variables are significant at 5% level, and one variable is significant at 10% level out of forty-nine variables. Lagrange-multiplier test confirms the existence of autocorrelation.

Table 5
Results of VAR (1,1) model

Variables	lnBitcoin	lnEthereum	lnLitecoin	lnZcash	lnDash	lnMonero	lnRipple
L.lnBitcoin	1.006*** (0.00988)	0.0138 (0.0136)	0.0149 (0.0151)	0.00894 (0.0148)	0.0429*** (0.0143)	0.0535*** (0.0148)	–0.0108 (0.0197)
L.lnEthereum	–0.00579 (0.00815)	0.963*** (0.0112)	0.00887 (0.0125)	0.00439 (0.0122)	–0.00237 (0.0118)	–0.00917 (0.0122)	–0.0158 (0.0162)
L.lnLitecoin	0.00915 (0.00816)	0.000288 (0.0112)	0.983*** (0.0125)	0.00188 (0.0122)	0.0169 (0.0118)	0.0141 (0.0122)	0.0438*** (0.0163)
L.lnZcash	–0.000459 (0.00598)	0.00113 (0.00820)	–0.0117 (0.00913)	0.980*** (0.00894)	0.00271 (0.00867)	–0.000872 (0.00895)	–0.0289** (0.0119)
L.lnDash	0.0146** (0.00690)	0.0428*** (0.00946)	0.0261** (0.0105)	0.0301*** (0.0103)	1.008*** (0.0100)	0.0324*** (0.0103)	0.0455*** (0.0137)
L.lnMonero	–0.0259*** (0.00963)	–0.0315** (0.0132)	–0.0244* (0.0147)	–0.0312** (0.0144)	–0.0518*** (0.0140)	0.923*** (0.0144)	–0.0289 (0.0192)
L.lnRipple	–0.000532 (0.00417)	0.00882 (0.00572)	–0.00141 (0.00637)	–0.00269 (0.00624)	–0.0130** (0.00605)	–0.00542 (0.00624)	0.981*** (0.00831)
Constant	–0.0180 (0.0614)	0.00576 (0.0842)	–0.0770 (0.0938)	–0.0295 (0.0918)	–0.258*** (0.0890)	–0.288*** (0.0919)	0.0186 (0.122)

Notes: Number of observation = 803. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Results from MGARCH Models

From Table 7, all variables are statistically significant in three models CCC (1,1), VCC (1,1) and DCC (1,1). Adjusted lambda also significant in 1% level both in DCC (1,1) and VCC (1,1) models. DCC (1,1) and VCC (1,1) models reduce to CCC (1,1) model when lambda1 = lambda2 = 0.

Figure 3 shows the residuals and variance plot portray low volatility from January 2017 to June 2017, high volatility from July 2017 to February 2018, low volatility from March 2018 to October 2018, and finally, high volatility from November 2018 to February 2019. At the same time, the conditional correlation is inconstant over time. Based on significant conditional correlations, there is evidence that the spillover effects of volatility indicate an increase of returns on volatility co-movements over time (Katsiampa, 2019).

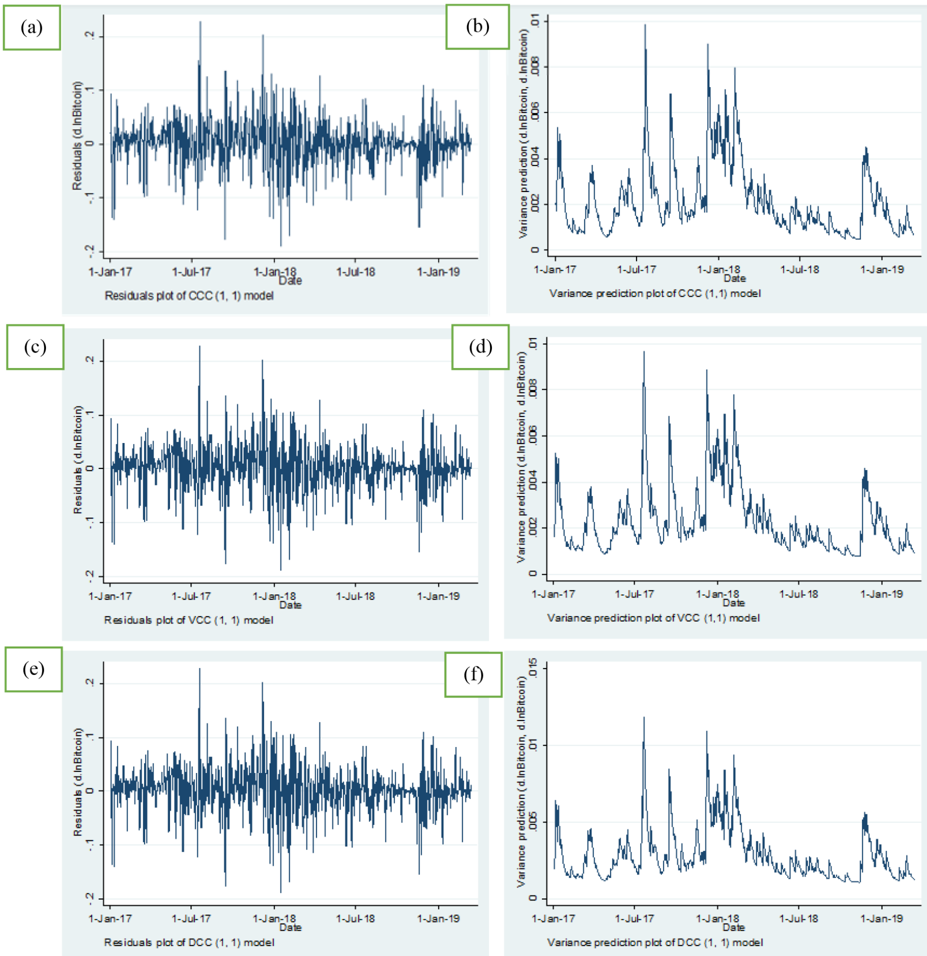

Figure 3. Different type graph of MGARCH models: (a) residuals plot of CCC (1,1); (b) variance plot of CCC (1,1); (c) residuals plot of VCC (1,1); (d) variance plot of VCC (1,1); (e) residuals plot of DCC (1,1); and (f) variance plot of DCC (1,1)

DISCUSSION

From ARCH (1,1) and GARCH (3,3) models (results shown in Table 4), all variables are statistically significant. All six variables have an impact on Bitcoin. All lags of ARCH and GARCH terms have positive shocks on Bitcoin returns except lag one of the GARCH term. This lag has negative shocks on Bitcoin returns, which means that negative shocks have a more massive effect on volatility than the very magnitude of positive shocks (Tse & Tsui, 2002). The importance of negative shocks' persistence signifies that investors are tending to negative influence compared to positive influence. Alpha captures the ARCH effect and Beta captures the GARCH effect, and the sum of them is very close to 1, which implies volatility is sustainable. The GARCH term is larger than the ARCH term indicates that future volatilizes will influence due to more tremendous volatility changes for a prolonged period since slower decay. This result is analogous with Dyhrberg (2016a) where Bitcoin shows high volatility persistence and volatility clustering. The GARCH reaction parameter (ARCH term) is above 0.1 means that the market is jumpy or nervous, and the GARCH persistence parameter (GARCH term) is within 0.85, and 0.98 means that GARCH volatility is low [similar results found by Carol (2008)]. The predicted plot is very similar to the original plot. It is statistically significant in 5% criterion level. That is why we can say that our model is well fitted.

According to Granger causality Wald tests (in Table 6), returns of Dash and Monero causes returns of Bitcoin, and returns of all six variables causes returns of Bitcoin (significant in 10% level), returns of Dash and Monero causes returns of Ethereum, and returns of all six variables causes returns of Ethereum (significant in 1% level), returns of Dash and Monero causes returns of Litecoin, and returns of all six variables causes returns of Litecoin (significant in 5% level), returns of Dash and Monero causes returns of Zcash, and returns of all six variables causes returns of Zcash (significant in 5% level), returns of Bitcoin, Monero and Ripple causes returns of Dash and returns of all six variables causes returns of Dash (significant in 1% level), returns of Bitcoin and Dash causes returns of Monero, and returns of all six variables causes returns of Monero (significant in 1% level), returns of Litecoin, Zcash and Dash causes returns of Ripple, and returns of all six variables causes returns of Ripple (significant in 1% level).

Table 6
Granger Causality Wald tests results

Variables	lnBitcoin	lnEthereum	lnLitecoin	lnZcash	lnDash	lnMonero	lnRipple	All
lnBitcoin		0.478	0.262	0.939	0.034	0.007	0.899	0.084
lnEthereum	0.307		0.979	0.890	0.000	0.017	0.123	0.000
lnLitecoin	0.323	0.476		0.202	0.013	0.098	0.825	0.036
lnZcash	0.545	0.719	0.877		0.004	0.030	0.666	0.016
lnDash	0.003	0.841	0.154	0.754		0.000	0.031	0.001
lnMonero	0.000	0.453	0.250	0.922	0.002		0.385	0.000
lnRipple	0.583	0.331	0.007	0.015	0.001	0.132		0.000

Note: Values in the table are the *p*-value

The stability test shows all eigenvalues lie inside the unit circle. The VAR satisfies stability conditions; therefore, we can conclude that our model is stable and well fitted. Zhu et al. (2017) also obtained similar findings, FFR, DJIA and CPI are not Granger-causes of Bitcoin and long-run dynamic relationship amid Bitcoin and other variables. Nevertheless, the autocorrelation is very significant, which indicates the necessity of the MGARCH model for further analysis (Chevallier, 2012). Table 7 illustrates the CCC (1,1) shows that arch coefficients suggest that new information reaction is little. The sum of coefficient, α and β is very close to one for every time-series, which means that variance process is not integrated (Bollerslev & Engle, 1986; Ismail et al., 2017; Chaim & Laurini, 2018). The correlation between variables is low; all above 0.5, i.e., Bitcoin returns are dependent on a large scale, it also depends on other parameters. If this return has low correlations, then their relationship is not stable, suggesting that time-series be time-varying and coherent with Chevallier (2012).

Table 7

Summary results of CCC (1,1), DCC (1,1), and VCC (1,1) models and their corresponding correlation between variables and adjusted lambda

Variables	CCC (1, 1)			DCC (1, 1)			VCC (1, 1)		
	L.arch$_\alpha$	L.garch$_\beta$	Constant	L.arch$_\alpha$	L.garch$_\beta$	Constant	L.arch$_\alpha$	L.garch$_\beta$	Constant
ARCH_d.lnBTC	0.119*** (–0.0179)	0.858*** (–0.0187)	0.0000571*** (–0.00001)	0.141*** (–0.0206)	0.842*** (–0.0217)	0.000160*** (–0.0000343)	0.114*** (–0.0175)	0.855*** (–0.0206)	0.000105*** (–0.00002)
ARCH_d.lnETH	0.194*** (–0.032)	0.705*** (–0.0441)	0.000444*** (–0.00010)	0.190*** (–0.0298)	0.721*** (–0.0418)	0.000803*** (–0.000163)	0.143*** (–0.0229)	0.753*** (–0.038)	0.000539*** (–0.000111)
ARCH_d.lnLTC	0.0634*** (–0.0136)	0.859*** (–0.0303)	0.000363*** (–0.00010)	0.0921*** (–0.0241)	0.823*** (–0.0493)	0.000628*** (–0.000203)	0.0774*** (–0.0187)	0.815*** (–0.046)	0.000561*** (–0.000163)
ARCH_d.lnZEC	0.213*** (–0.034)	0.730*** (–0.0397)	0.000419*** (–0.00012)	0.260*** (–0.0431)	0.696*** (–0.0464)	0.000855*** (–0.000211)	0.181*** (–0.0332)	0.717*** (–0.0506)	0.000681*** (–0.000187)
ARCH_d.lnDASH	0.130*** (–0.0233)	0.804*** (–0.0285)	0.000326*** (–0.00008)	0.127*** (–0.0243)	0.805*** (–0.0322)	0.000586*** (–0.00014)	0.112*** (–0.0226)	0.786*** (–0.0373)	0.000525*** (–0.000126)
ARCH_d.lnXMR	0.156*** (–0.0257)	0.766*** (–0.0327)	0.000401*** (–0.00009)	0.175*** (–0.0318)	0.728*** (–0.0433)	0.000938*** (–0.00021)	0.139*** (–0.0265)	0.744*** (–0.0447)	0.000693*** (–0.000171)
ARCH_d.lnXRP	0.298*** (–0.0502)	0.728*** (–0.0369)	0.000263*** (–0.00007)	0.353*** (–0.0499)	0.682*** (–0.0343)	0.000697*** (–0.000118)	0.307*** (–0.045)	0.697*** (–0.0339)	0.000494*** (–0.00009)

(*continued on next page*)

Table 7: (*continued*)

Correlation	corr (d.lnBTC, d.lnETH)	corr (d.lnBTC, d.lnLTC)	corr (d.lnBTC, d.lnZEC)	corr (d.lnBTC, d.lnDASH)	corr (d.lnBTC, d.lnXMR)	corr (d.lnBTC, d.lnXRP)	corr (d.lnETH, d.lnLTC)	corr (d.lnETH, d.lnZEC)	corr (d.lnETH, d.lnDASH)	corr (d.lnETH, d.lnXMR)	corr (d.lnETH, d.lnXRP)	corr (d.lnLTC, d.lnZEC)
CCC (1,1)	0.652*** (–0.0202)	0.624*** (–0.0214)	0.558*** (–0.0242)	0.571*** (–0.0236)	0.634*** (–0.0209)	0.501*** (–0.0263)	0.614*** (–0.0218)	0.679*** (–0.019)	0.660*** (–0.0197)	0.665*** (–0.0194)	0.580*** (–0.0233)	0.511*** (–0.026)
DCC (1,1)	0.953*** (–0.0182)	0.966*** (–0.0176)	0.921*** (–0.0299)	0.906*** (–0.0284)	0.954*** (–0.0237)	0.925*** (–0.0312)	0.947*** (–0.0185)	0.862*** (–0.035)	0.870*** (–0.0311)	0.910*** (–0.0285)	0.936*** (–0.0231)	0.865*** (–0.037)
VCC (1,1)	0.942*** (–0.051)	0.885*** (–0.0661)	0.913*** (–0.0937)	0.859*** (–0.0783)	1.000*** (–0.0877)	0.812*** (–0.0916)	0.822*** (–0.0673)	0.746*** (–0.0859)	0.706*** (–0.0859)	0.903*** (–0.0817)	0.841*** (–0.0703)	0.608*** (–0.119)
Correlation	corr (d.lnLTC, d.lnDASH)	corr (d.lnLTC, d.lnXMR)	corr (d.lnLTC, d.lnXRP)	corr (d.lnZEC, d.lnDASH)	corr (d.lnZEC, d.lnXMR)	corr (d.lnZEC, d.lnXRP)	corr (d.lnDASH, d.lnXMR)	corr (d.lnDASH, d.lnXRP)	corr (d.lnXMR, d.lnXRP)	lambda1	lambda2	
CCC (1,1)	0.514*** (–0.0257)	0.577*** (–0.0234)	0.560*** (–0.0242)	0.678*** (–0.0189)	0.617*** (–0.0217)	0.538*** (–0.0251)	0.668*** (–0.0193)	0.443*** (–0.0281)	0.551*** (–0.0244)			
DCC (1,1)	0.879*** (–0.0337)	0.927*** (–0.0296)	0.907*** (–0.0316)	0.910*** (–0.0292)	0.874*** (–0.0394)	0.811*** (–0.0482)	0.892*** (–0.0319)	0.828*** (–0.0459)	0.902*** (–0.0348)	0.0348*** (–0.00369)	0.954*** (–0.0039)	
VCC (1,1)	0.703*** (–0.0995)	0.869*** (–0.0998)	0.624*** (–0.11)	0.824*** (–0.0846)	0.807*** (–0.101)	0.518*** (–0.128)	0.891*** (–0.0903)	0.497*** (–0.134)	0.776*** (–0.0971)	0.0266*** (–0.00277)	0.969*** (–0.0034)	

Table 7 also displays that for VCC (1,1), arch coefficients suggest that reaction of new information is not very high. The sum of the values of α and β is very close to one for each time-series, which means the variance process is not integrated. The correlation between variables is very high, all above 0.9. That is, there is a strong correlation between the variables. Therefore, relationships are stable over-time. Furthermore, for DCC (1,1), arch coefficients are a little high than VCC (1,1), which means that there is more new information. The sum of the coefficients, α and β is very close to one for each time-series, implies that the variance process is not integrated. The correlation between variables is very high than VCC (1,1), all above 0.9. Adjusted lambdas are statistically significant and higher than VCC (1,1). Thus, there is a significant correlation between the variables which is similar to Corbet et al. (2018) findings where there is a strong correlation between the variables. Therefore, relationships are stable over-time. DCC (1,1) model also explains interlinkage between the currencies very well than the other two correlation models.

From CCC (1,1), VCC (1,1), and DCC (1,1) models, estimated parameters α and β are significant and different from zero, suggest that there exist individualised ARCH and GARCH effects. In all three models, the sum of parameters is very close to one suggesting volatility persistence. All estimated models show that the conditional correlation between markets is relatively very high, which is evidence of strong volatility spillover effects. The estimated lambdas show strong evidence of time- varying conditional correlation both in DCC (1,1) and VCC (1,1) models. The sum of lambdas is very close to one, exhibits very high persistent volatility. Despite that, the sum of coefficients is less than one, which implies mean-reverting dynamic conditional correlations. The significance of lambdas in DCC (1,1) and VCC (1,1) models suggest that conditional correlations are a greater degree of dynamic as well as time-varying, which indicates presumptions of CCC (1,1) model does not conserve, is coherent with literature (McAleer et al., 2008; Katusiime, 2018).

CONCLUSION

The digital currencies (Bitcoin and other cryptocurrencies) are strongly related to stock markets, energy markets, precious metals and exchange rate markets. Therefore, researchers relate Bitcoin with stock markets, energy markets, precious metals, exchange rates and study their dynamic behaviour. However, these digital currencies also relate to each other, where one currency can strongly influence other currencies. For this reason, we focus on within the cryptocurrency markets, modelled under GARCH (p, q) and MGARCH models to study volatility persistence and dynamical behaviour. Our findings suggest that there is evidence of persistence volatility and volatility clustering, which is captured and explained by GARCH (3,3) very well. The result has detailed that due to slower decay, volatility remains long, and we have also seen that the markets are jumpy or nervous. VAR model estimations confirm the model's stability and well fitted, and Granger causes of Bitcoin and other cryptocurrencies. Based on the MGARCH model (CCC, VCC, DCC), we are able to highlight the rates of volatility among the digital currencies and positive correlations. The presence of steady volatility persistence indicates strong ARCH and GARCH effects. There is strong evidence that correlation is positive and very high among the cryptocurrencies indicates co-movement of Bitcoin and other currencies, which is coherent with earlier studies. From the MGARCH model, DCC(1,1) estimates the best output to examine interrelationships in volatility and correlations, which is analogue with Guesmi et al. (2019). We found that the time-varying correlation between seven cryptocurrencies is above 0.9 in all markets from this model. That is, interlinkages between the cryptocurrencies are very high and stable over-time. These results will emphasise existing research and further progress of cryptocurrency market analyses. Additionally, the results we obtained will be significant for investors and financial institutions that lack depth knowledge on correlations between cryptocurrencies for risk management purposes. In this paper, we did not consider a structural break, and the volume of observation is small, so in the future, we will discuss a break in the observation and increase observation volume. Here we have studied the inter-linkage and volatility of cryptocurrency, but not try to make decisions on an alternative investment. This feature is known as hedge, diversification, and safe-haven properties, which is a different aspect, and we left it as our future work. Nevertheless, based on the popularity, value, and volume of Bitcoin, we would suggest that investors focus more on Bitcoin than other types of cryptocurrencies, as they are interdependent.

REFERENCES

Adebola, S. S., Gil-Alana, L. A., & Madigu, G. (2019). Gold prices and the cryptocurrencies: Evidence of convergence and cointegration. *Physica A: Statistical Mechanics and Its Applications, 523*, 1227–1236. https://doi.org/10.1016/j.physa.2019.04.123

Al-Yahyaee, K. H., Mensi, W., Al-Jarrah, I. M. W., Hamdi, A., & Kang, S. H. (2019). Volatility forecasting, downside risk, and diversification benefits of Bitcoin and oil and international commodity markets: A comparative analysis with yellow metal. *North American Journal of Economics and Finance, 49*, 104–120. https://doi.org/10.1016/j.najef.2019.04.001

Alotaibi, A. R., & Mishra, A. V. (2015). Global and regional volatility spillovers to GCC stock markets. *Economic Modelling, 45*, 38–49. https://doi.org/10.1016/j.econmod.2014.10.052

Ardia, D., Bluteau, K., & Rüede, M. (2018*). Regime changes in Bitcoin GARCH volatility dynamics*. SSRN. https://doi.org/10.2139/ssrn.3180830

Baguley, T. (2012). *Serious stats: A guide to advanced statistics for the behavioral sciences*. Palgrave Macmillan.

Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012). Bitter to better: How to make bitcoin a better currency. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7397 LNCS*, 399–414. https://doi.org/10.1007/978-3-642-32946-3_29

Bariviera, A. F., Basgall, M. J., Waldo, H., & Naiouf, M. (2017). Some stylized facts of the Bitcoin market. *Physica A: Statistical Mechanics and Its Applications, 484*, 82–90. https://doi.org/10.1016/j.physa.2017.04.159

Beneki, C., Koulis, A., Kyriazis, N. A., & Papadamou, S. (2019). Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance, 48*, 219–227. https://doi.org/10.1016/j.ribaf.2019.01.001

Bergstra, J. A., & Weijland, P. (2014). Bitcoin: A money-like informational commodity. *MLIC*, 1–26. http://arxiv.org/abs/1402.4778

Bollerslev, T. (1986). Generalized auroregressive conditional hetroskedasticity. *Journal of Econometrics, 31*, 307–327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized arch model. *The Review of Economics and Statistics*, *72*(3), 498–505. https://doi.org/10.2307/2109358

Bollerslev, T., & Engle, R. F. (1986). Modelling the persistence of conditional variances. *Econometric Reviews, 5*(1), 1–50. https://doi.org/10.1080/07474938608800095

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics, 50*(55), 5935–5949. https://doi.org/10.1080/00036846.2018.1488075

Campbell, J. D., Trapnell, P. D., Heine, S. J., Katz, I. M., Lavallee, L. F., & Lehman, D. R. (1996). Self-concept clarity: Measurement, personality correlates, and cultural boundaries. *Journal of Personality and Social Psychology, 70*(1), 141–156. https://doi.org/10.1037/0022-3514.70.1.141

Canh, N. P., Wongchoti, U., Thanh, S. D., & Thong, N. T. (2019). Systematic risk in cryptocurrency market: Evidence from DCC-MGARCH model. *Finance Research Letters, 29*(January), 90–100. https://doi.org/10.1016/j.frl.2019.03.011

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov- Switching GARCH models. *Research in International Business and Finance, 48*(October 2018), 143–155. https://doi.org/10.1016/j.ribaf.2018.12.009

Carol, A. (2008). *Market risk analysis volume III: Pricing, hedging and trading financial instruments.* John Wiley & Sons Ltd.

Chaim, P., & Laurini, M. P. (2018). Volatility and return jumps in bitcoin. *Economics Letters, 173*, 158–163. https://doi.org/10.1016/j.econlet.2018.10.011

Chan, W. H., Le, M., & Wu, Y. W. (2019). Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *Quarterly Review of Economics and Finance, 71,* 107–113. https://doi.org/10.1016/j.qref.2018.07.004

Charles, A., & Darné, O. (2019). Volatility estimation for Bitcoin: Replication and robustness. *International Economics, 157*, 23–32. https://doi.org/10.1016/j.inteco.2018.06.004

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters, 130*, 32–36. https://doi.org/10.1016/j.econlet.2015.02.029

Cheikh, N. Ben, Zaied, Y. Ben, & Chevallier, J. (2019). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters, 35*, 1–9. https://doi.org/10.1016/j.frl.2019.09.008

Chevallier, J. (2012). Time-varying correlations in oil, gas and CO2 prices: An application using BEKK, CCC and DCC-MGARCH models. *Applied Economics, 44*(32), 4257–4274. https://doi.org/10.1080/00036846.2011.589809

Ciaian, P., Rajcaniova, M., & Kancs, d. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money, 52*, 173–195. https://doi.org/10.1016/j.intfin.2017.11.001

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62*, 182–199. https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004

Cusumano, M. A. (2014). Technology strategy and management. *Communications of the ACM, 57*(10), 22–24. https://doi.org/10.1145/2661047

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar: A GARCH volatility analysis. *Finance Research Letters, 16*, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters, 16*, 139–144. https://doi.org/10.1016/j.frl.2015.10.025

Engle, R. F. (1982). Autoregressive conditional heteroscedacity with estimates of variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007. https://doi.org/10.2307/1912773

Engle, R. F. (2002). New frontiers for ARCH models. *Journal of Applied Econometrics, 17*(5), 425–446. https://doi.org/10.1002/jae.683

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters, 164*, 109–111. https://doi.org/10.1016/j.econlet.2018.01.020

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin: Asset or currency? revealing users' hidden intentions. 22nd *European Conference on Information Systems (ECIS)*, January, 1–14.

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. *Hastings Science and Technology Law Journal, 4*(1), 159.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis, 63*(2017), 431–437. https://doi.org/10.1016/j.irfa.2018.03.004

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics, 20*(7), 873–889. https://doi.org/10.1002/jae.800

Ismail, M. T., Abdullah, N. A., & Abdul Karim, S. A. (2013). Impact of global financial crisis on precious metals returns: An application of ARCH and GARCH methods. *AIP Conference Proceedings, 1522*(1), 1116–1122. https://doi.org/10.1063/1.4801256

Ismail, M. T., Audu, B., & Tumala, M. M. (2017). Comparison of forecasting performance between MODWT-GARCH (1,1) and MODWT-EGARCH (1,1) models: Evidence from African stock markets. *The Journal of Finance and Data Science, 2*(4), 254–264. https://doi.org/10.1016/j.jfds.2017.03.001

Jondeau, E., Poon, S.-H., & Rockinger, M. (2007). *Financial modeling under non-gaussian distributions.* Springer Finance. https://doi.org/10.1007/978-1-84628-696-4

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30,* 221–227. https://doi.org/10.1016/j.frl.2018.10.005

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*(March), 68–74. https://doi.org/10.1016/j.frl.2019.03.009

Katusiime, L. (2018). Investigating spillover effects between foreign exchange rate volatility and commodity price volatility in Uganda. *Economies, 7*(1), 1–17. https://doi.org/10.3390/economies7010001

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the New Gold: A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis, 59*, 105–116. https://doi.org/10.1016/j.irfa.2018.07.010

Köksal, B. (2009). A comparison of conditional volatility estimators for the ISE national 100 index returns. *Journal of Economic and Social Research, 2*(11), 1–29.

Li, Y., Zhang, W., Xiong, X., & Wang, P. (2020). Does size matter in the cryptocurrency market? Applied *Economics Letters, 27*(14), 1141–1149. https://doi.org/10.1080/13504851.2019.1673298

McAleer, M., Chan, F., Hoti, S., & Lieberman, O. (2008). Generalized autoregressive conditional correlation. *Econometric Theory, 24*, 1554–1583. https://doi.org/10+10170S0266466608080614

Okorie, D. I., & Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. *Energy Economics, 87*, 104703. https://doi.org/10.1016/j.eneco.2020.104703

Sun, Y., An, N., Wang, B., Pan, P., & Guo, K. (2017). Study on the influence mechanism of air quality on stock market yield and volatility: Empirical test from China based on GARCH model. *Finance Research Letters, 26*, 119–125. https://doi.org/10.1016/j.frl.2017.12.002

Tsay, R. S. (2010). *Analysis of financial time series* (3rd ed.). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470644560

Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business & Economic Statistics, 20*(3), 351–362. https://doi.org/10.1198/073500102288618496

Tu, Z., & Xue, C. (2019). Effect of bifurcation on the interaction between Bitcoin and Litecoin. *Finance Research Letters, 31*, 382–385. https://doi.org/10.1016/j.frl.2018.12.010

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters, 148*, 80–82. https://doi.org/10.1016/j.econlet.2016.09.019

Wu, C. Y., & Pandey, V. K. (2014). The value of bitcoin in enhancing the efficiency of an investor's portfolio. *Journal of Financial Planning, 27*(9), 44–52. http://eds.a.ebscohost.com.ezproxy.unal.edu.co/eds/pdfviewer/pdfviewer?sid=153c24ab-355a-4b53-bc87-d77a37864377@sessionmgr4002&vid=9&hid=4110

Yelowitz, A., & Wilson, M. (2015). Characteristics of Bitcoin users: An analysis of Google search data. *Applied Economics Letters, 22*(13), 1030–1036. https://doi.org/10.1080/13504851.2014.995359

Yermack, D. (2013). Is Bitcoin a real currency? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2361599

Zhu, Y., Dickinson, D., & Li, J. (2017). Analysis on the influence factors of Bitcoin's price based on VEC model. *Financial Innovation*, *3*(1), 1–13. https://doi.org/10.1186/s40854-017-0054-0