



Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models



Nikolaos A. Kyriazis^{*}, Kalliopi Daskalou, Marios Arampatzis, Paraskevi Prassa, Evangelia Papaioannou

Department of Economics, University of Thessaly, 28th October 78 Street, 38333, Volos, Greece

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ABSTRACT

This study examines the volatility of certain cryptocurrencies and how they are influenced by the three highest capitalization digital currencies, namely the Bitcoin, the Ethereum and the Ripple. We use daily data for the period 1 January 2018–16 September 2018, which represents the bearish market of cryptocurrencies. The impact of the decline of these three cryptocurrencies on the returns of the other virtual currencies is examined with models of the ARCH and GARCH family, as well as the DCC-GARCH. The main conclusion of the study is that the majority of cryptocurrencies are complementary with Bitcoin, Ethereum and Ripple and that no hedging abilities exist among principal digital currencies in distressed times.

1. Introduction

In recent years, and especially after 2008, the interest of investors and analysts for cryptocurrencies has been extensive and growing. Cryptocurrencies constitute an alternative form of coin with a digital character [Dwyer \(2015\)](#). Through these, it is possible to make direct payments from one party to the other without the assistance of a financial institution, and because of this and other similarities, many economists compare the cryptocurrencies with gold [\(Dyhrberg, 2016a\)](#). In contrast to traditional financial assets, cryptocurrencies are based on the security of an algorithm that detects all transactions and has low transaction costs [\(Corbet et al., 2018\)](#), they are not issued by a central bank or government resulting in detachment from the real economy [Dwyer \(2015\)](#). Moreover, due to their digital form, they become extremely sensitive to cyber attacks [\(Bouoiyour et al., 2015\)](#). The market in which the cryptocurrencies are traded is dominated by short-term investors as well as speculators [\(Kyriazis, 2019\)](#).

Bitcoin (BTC) is the most popular digital coin among the general public, with which several SMEs have been involved, yet there are also other important ones like Ethereum (ETH), Ripple (XRP) and other high-capitalization ones. It seems that in 2017 Bitcoin's course was dramatically upward, which drove the interest of many investors. More specifically, during the period from October 2016 to October 2017, its capitalization increased from \$10.1 million to \$79.7 billion, with its price rising from \$616 to \$4800. However, since the end of December 2017, its

downward trend influenced the dropping down of the price of most other cryptocurrencies, and that is why it is extremely attractive to analyze them. Bitcoin is primarily used as an asset and not as a currency in a speculative and volatile market, and in combination with its recent fluctuations in prices, a climate of high volatility has been created [\(Katsiampa, 2017\)](#).

The purpose of this research is to determine the impact that the three highest capitalization cryptocurrencies -that is, Bitcoin, Ethereum and Ripple- has exerted on other high capitalization digital currencies. The currencies to be investigated are Dogecoin (DOGE), Zcash (ZEC), OmiseGO (OMG), Bitcoin Gold (BTG), Bytecoin (BCN), Lisk (LSK), Tezos (XTZ), Monero (XEM), Decred (DCR), Nano (NANO), and BitShares (BTS). Despite a significant number of studies having examined volatility characteristics of digital currencies, no academic paper up to the present has looked into the complementarity or substitutability of large-capitalization cryptocurrencies with the three principal digital coins that are considered to be responsible for the herding behavior in the markets of digital coins. Our study casts light on diversifying or hedging capabilities among high-capitalization digital currencies during the most distressed period as concerns cryptocurrencies, that is when hedging is most necessary than ever. Examination of famous and attractive currencies among investors grasps the core of investment decisions and enlightens as regards motivation for and mentality of transactions regarding the greatest bulk of cryptocurrency trading.

In order to accomplish this, the ARCH (Autoregressive Conditional

^{*} Corresponding author.

E-mail address: knikolaos@uth.gr (A. Kyriazis).

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Heteroskedasticity), GARCH (Generalized Autoregressive Conditional Heteroskedasticity), ARCH-type and GARCH-type models as well as Dynamic Conditional Correlation (DCC) are employed. These models are adopted by economists so as to calculate and predict the volatility of economic returns. Such specifications are adopted to study many economic phenomena such as controlling exchange rate volatility and pricing of exchange rate options used for risk management (Klaassen, 2002). Proceeding with a similar research mentality as Katsiampa (2017), we analyze twelve cryptocurrencies in order to compare their price instability with the Bitcoin, Ethereum and Ripple major currencies.

The structure of the present paper is as follows: Chapter 2 presents fundamental previous investigations that have been carried out with regard to cryptocurrencies and GARCH models. Chapter 3 presents the data and Chapter 4 lays out the methodologies employed. Subsequently, Chapter 5 analyzes the empirical results derived by econometric estimations and explains the economic significance of these findings. Finally, Chapter 6 provides the overall implications of the study and expresses some thoughts about future research.

2. Background

Engle (1982) developed the ARCH model in order to generalize the traditional econometric models that accept a constant one-period forecast variance. He estimated the median and the variance of inflation in the United Kingdom in the 1970s and presented for the first time the ARCH model, on which many surveys were based in the future. Then Bollerslev (1986), based on Engle (1982), attempted to generalize the ARCH model by presenting his own GARCH model. He examined the rate of change of the deflator in the United States, taking into account the method of maximum likelihood and presenting his empirical example.

Since 2017 the increasing interest in cryptocurrencies has brought about a highly proliferating bulk of relevant academic research, such as Chu et al. (2017) and Kyriazis (2019). One of the first studies investigating volatility in digital currencies was conducted by Katsiampa (2017) and it estimates Bitcoin's volatility by comparing various GARCH models and concludes that AR-GARCH is the model best describing Bitcoin's volatility.

Since Bitcoin has emerged as the most important digital currency so far, many have tried to investigate the benefits of such new e-currency technology. Bonneau et al. (2015) identified Bitcoin's key features and proposed modifications to achieve its future stability. Additionally, they examined the issue of anonymity in such transactions and suggested measures to eliminate the intermediaries. Another study that highlights the positive elements of cryptocurrencies is that by Corbet et al. (2018). They provide arguments in favor of cryptocurrencies being a safe and reliable investment asset.

On the contrary, there are academic papers that highlight the negative characteristics of cryptocurrencies. Such a study has been carried out by Eyal and Sirer (2018) that supports Bitcoin's conservative negotiators having earned more than their share. An additional study is that of Bucko et al. (2015) that examines the high volatility of cryptocurrencies' prices, possible thefts and possible funding of anonymous criminal activities, as well as security, transport and trust issues.

As Bitcoin's popularity increased, it was vital to adopt econometric models in order to profoundly investigate cryptocurrencies' volatility. Thus, many researchers support that the appropriate models for studying cryptocurrencies are the conventional ARCH and GARCH because they are designed to evaluate heteroscedasticity in periods of large alterations in cryptocurrency markets.

Previous academic work about cryptocurrencies' volatility have implemented a variety of GARCH models, such as Linear GARCH, Threshold GARCH, Exponential GARCH and Multiple Threshold-GARCH. Bouoiyour and Selmi (2015) studied the price of Bitcoin, using a sample of daily data from December 2010 until June 2015. Among the models they adopted, the one with the best fit was the GARCH and showed that the volatility was significantly decreased despite the market not being

mature yet.

Gronwald (2014) compared the gold and bitcoin market and analyzed bitcoin's prices using GARCH models. He found that there were extremely large changes in its price and that the market in which it was trading was not mature. Dyhrberg (2016b) employs an asymmetric GARCH methodology to investigate whether Bitcoin indicates hedging capabilities and functions as a medium of exchange similar to gold and the US dollar from July 2010 to May 2015. Results indicate that Bitcoin can be regarded as being between gold and the US dollar as regards these functions. Furthermore, there is evidence that Bitcoin can lead to profit as it serves as an investment but also as a risk management tool. In the same vein, Dyhrberg (2016a) using GARCH models, examined Bitcoin's potentials as a financial product. Evidence supported that it had similarities with gold and the US dollar. The asymmetric GARCH model provided evidence that this product could be used in portfolio management, as it was ideal for risk-averse investors. Moreover, Klein et al. (2018) compared Bitcoin with gold by applying a BEKK-GARCH model. According to their findings, gold had an important role in financial markets when they were characterized by a bearish trend, while Bitcoin behaved exactly the opposite and it was positively related with bearish markets. Furthermore, no hedging capabilities in a portfolio have been revealed.

Use asymmetric GARCH models in order to investigate the correlation between prices and volatility changes in the Bitcoin market around the bearish market in 2013. The results for the whole period do not provide any indication of an asymmetric relationship between yields and volatility in the Bitcoin market. In addition, positive shocks had increased conditional volatility more than negative shocks. Chu et al. (2017) investigate which GARCH models are suitably adapted to Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple. They demonstrate that the IGARCH and GJRGARCH models provide the optimal specification for modeling the volatility of the most popular cryptocurrencies during their flourishing eras. Finally, Beneki et al. (2019) relied on Bitcoin and Ethereum which they examined with the BEKK-GARCH model, to identify any differences in volatility and hedging abilities. Their results reveal significant swaps in the time-varying correlation, as well as certain diversification skills especially in the early years of the period that they studied.

Guesmi et al. (2018) studied the period from January 2012 to January 2018 period and employed different multivariate GARCH methodologies to examine the conditional cross-impacts and volatility spillovers between Bitcoin and financial indicators. Results reveal that the VARMA (1, 1)-DCC-GJR-GARCH specification is the most suitable for estimations. It is documented that hedging strategies with gold, oil, emerging equity markets and Bitcoin lead to lower risk than if Bitcoin was not included. Charle and Lema (2018) employed the same sample and period as Katsiampa (2017) when replicating the latter's study but they also conducted estimations by extending the time period until March 2018. They also employed QML estimators for reanalyzing and considered jumps in Bitcoin returns when extension of the study took place. Outcomes show that none of the six GARCH models employed with short-memory, asymmetric impacts and short-run or long-run characteristics is suitable for modelling Bitcoin returns. Employing another view, Symitsi and Chalvatzis (2018) employ VAR(1)-BEKK-AGARCH specifications and examine spillovers of Bitcoin with energy and technology companies during the period from August 2011 to February 2018. There is evidence that return spillovers from such companies to Bitcoin emerge. Furthermore, short-run volatility spillovers from technology companies to Bitcoin and long-run spillovers from the latter to energy companies are detected. Bidirectional asymmetric shock spillovers are also revealed between Bitcoin and equity indices. Overall, the weak linkage of Bitcoin with stock indices permits profitable trading.

Chan et al. (2019) investigate Bitcoin's hedging capabilities by employing a frequency dependence approach and DCC-GARCH and CCC-GARCH processes for the period of October 2010–October 2017. They provide evidence that Bitcoin is a strong hedge against the Euro-Index, Shanghai A-Share, S&P500, Nikkei and the TSX index.

Table 1
Cryptocurrencies under scrutiny.

Symbol	Name
BTC	Bitcoin
ETH	Ethereum
XRP	Ripple
XTZ	Tezos
BNB	Binance Coin
XEM	Nem
DCR	Decred
NANO	Nano
BTS	BitShares
DOGE	Dogecoin
ZEC	Zcash
OMG	OmiseGo
LSK	Lisk
BTG	Bitcoin Gold
BCN	Bytecoin

Moreover, [Baur et al. \(2018\)](#) argue that Bitcoin is not a safe haven because it exhibits a weak correlation with stocks, bonds and commodities in normal but also in distressed times. [Takaishi \(2018\)](#) examines the statistical properties of Bitcoin by employing 1-min data from January 2014 to December 2016, by adopting the multifractal detrended fluctuation analysis (MF-DFA) and GARCH, GJR-GARCH and RGARCH models. Results indicate that Bitcoin prices exhibit multifractality, which comes from temporal correlation as well as the fat-tailed distribution so, inefficiency in the Bitcoin market is detected. Moreover, the Brexit decision is found not to have influenced the Bitcoin. [Troster et al. \(2018\)](#) adopt heavy-tailed GARCH specifications and GAS models based on the score function of the predictive conditional density of Bitcoin's returns. Moreover, they compare out-of-sample 1% Value-at-Risk forecasts under 45 alternative specifications. Results indicate that heavy-tailed GAS models present the best goodness-of-fit as well as the best coverage for risk derived from Bitcoin. Through their own perspective, [Chan et al. \(2019\)](#) look into Bitcoin's hedging capabilities concerning the period October 2010 to October 2017 by a frequency dependence approach and DCC-GARCH and CCC-GARCH methodologies. They document that Bitcoin can provide a strong hedge against the Euro-Index, Shanghai A-Share, S&P500, Nikkei and the TSX index.

3. Design

The data on which this study is based refer to daily -including weekends- closing prices of 15 cryptocurrencies. The period under scrutiny covers 1 January 2018 to 16 September 2018, i.e. the data consists of 258 observations. During this time period, there has been the most rapid fall in the prices of digital currencies. Therefore, it is of great interest to evaluate and analyze the determinants of volatility of these currencies returns during this extra bearish period. In the present study,

Table 2
Descriptive statistics of digital currencies.

Variable	Obs	Mean	Std. Deviation	Min	Max	Skewness	Kurtosis
BTC	258	-0.00287	0.04512	-0.18458	0.12413	-0.45688	4.7167
ETH	258	-0.00486	0.05692	-0.20685	0.14223	-0.31891	4.14359
XRP	258	-0.0083	0.06873	-0.35328	0.22636	-0.43796	7.41314
XTZ	258	-0.00389	0.08697	-0.37501	0.24669	-0.43148	5.46101
BNB	258	0.00065	0.07715	-0.34232	0.48241	1.27563	13.11009
XEM	258	-0.00945	0.07661	-0.29975	0.4338	0.61304	8.21947
DCR	258	-0.00409	0.0668	-0.2306	0.21499	-0.09411	4.24096
NANO	258	-0.00962	0.10334	-0.36548	0.33632	0.07739	4.18038
BTS	258	-0.00727	0.07949	-0.39026	0.2339	-0.5995	5.56408
DOGE	258	-0.00120	0.08055	-0.08055	0.40234	0.33090	7.22183
ZEC	258	-0.00615	0.06655	0.23616	0.26073	0.26514	4.72936
OMG	258	-0.00671	0.07145	0.26311	0.23436	-0.09041	4.49032
LSK	258	-0.00688	0.07636	-0.27955	0.26049	0.17701	4.77183
BTG	258	-0.00987	0.08008	-0.34218	0.46727	0.74658	10.8482
BCN	258	-0.00433	0.14732	-0.91030	1.49344	3.62245	5.00961

we examine how the volatility in returns of twelve high-capitalization cryptocurrencies vary as a function of the changes of the three most common and liquid digital coins, that is Bitcoin, Ethereum and Ripple.

In addition, autocorrelation and heteroskedasticity tests have taken place in order to be certain of the suitability of data for estimations. In order to derive more reliable results, the returns in the form of logarithmic differences of variables have been employed for estimations. All raw data on closing prices are extracted from the reliable source of [coinmarketcap.com](#). Table 1 lists the names of the twelve cryptocurrencies under consideration that are analyzed along with the three main cryptocurrencies, which are also listed.

Table 2 below provides descriptive statistics of the digital currencies investigated. More specifically, we observe that all cryptocurrencies exhibit a negative performance. NANO presents the lowest mean whereas the BNB is characterized by the highest. Also, we can observe that five of the cryptocurrencies have a higher than average performance while the remaining 10 are less than the average. In addition, it can be seen that the smallest standard deviation, hence the smallest risk, is found with the BTC, while the largest is detected in NANO. It should be emphasized that 10 out of 15 cryptocurrencies are revealed to have a lower risk than the average. Considering that the prices of these cryptocurrencies had many steep downward movements in 2018 and by taking into consideration their performance, it can be argued that buying such cryptocurrencies would not be a reliable profit-making opportunity for investors (see Tables 3, 4, 5, 6 and 7).

Finally, as far as asymmetry is concerned, 7 out of the 15 cryptocurrencies have left (i.e. negative) asymmetry, something that is not positive for investors. Conversely, the eight digital coins show a positive asymmetry, which is an advantage for investors. Regarding the curvature coefficient, it is observed that all cryptocurrencies have fine-grained distributions which means that there is a high concentration of values around the medium. According to the above, the use of ARCH-GARCH models is imperative because it will help to correct the problem of the variability of the cryptocurrencies.

4. Model

Based on Katsiampa's study (2017), we proceeded to analyze twelve cryptocurrencies in order to evaluate their price volatility in relation to the three most powerful cryptocurrencies concerning market-capitalization: Bitcoin, Ethereum and Ripple. Initially, we perform the Dickey-Fuller and Phillips-Perron tests to detect whether autocorrelation exists. Then, we select the ARCH and GARCH models to observe the alterations in volatility over time in the specific time series we control and to find which model best suits each currency.

In more detail, the ARCH-GARCH models were first presented by [Engle \(1982\)](#) and consider the variance of the current error as a function of the fluctuations of the error conditions of the previous time periods. In

Table 3

The optimal model for DOGE, BTG, XEM, ZEC, BNB, OMG and LSK according to AIC criterion.

Power GARCH					GJR of THRESHOLD GARCH					Simple Asymmetric GARCH			NELSON'S EGARCH	
		DOGE	BTG	XEM			ZEC	BNB			OMG			LSK
mean equation	BTC	0.7846 (0.000)***	0.5972 (0.000)***	0.2514 (0.000)***	mean equation	BTC	0.50665 (0.000)***	0.5973159 (0.000)***	mean equation	BTC	0.36229 (0.000)***	mean equation	BTC	0.62449 (0.000)***
	ETH	0.1343 (0.256)	0.3486 (0.000)***	0.2854 (0.000)***		ETH	0.41850 (0.000)***	0.2887 (0.011)		ETH	0.55859 (0.000)***		ETH	0.36232 (0.000)***
	XRP	0.2011 (0.007)***	0.2852 (0.000)***	0.5716 (0.000)***		XRP	0.1701 (0.004)***	0.1599 (0.125)		XRP	0.28884 (0.000)***		XRP	0.24679 (0.000)***
	constant	0.0012 (0.682)	−0.0001 (0.881)	−0.0046 (0.000)***		constant	−0.0024 (0.369)	0.0010 (0.803)		constant	−0.00056 (0.796)		constant	−0.00202 (0.278)
variance equation	parch	0.5723 (0.513)	0.1262 (0.000)***	0.1394 (0.002)***	variance equation	arch	0.2926 (0.009)***	−0.6856 (0.000)***	variance equation	arch	0.11268 (0.007)***	variance equation	earch	0.13741 (0.049)**
	pgarch	0.5025 (0.000)***	0.7893 (0.000)***	0.7689 (0.000)***		tarch	−0.1913 (0.056)*	0.8426 (0.002)		saarch	0.00144 (0.425)		earch_a	0.90806 (0.000)***
	constant	0.0000 (0.926)	0.1087 (0.188)	0.1241 (0.366)		garch	0.6349 (0.000)***	0.4573 (0.000)***		garch	0.83514 (0.000)***		egarch	−0.33442 (0.000)***
						constant	0.0003 (0.011)**	0.0007 (0.000)***		constant	0.00006 (0.107)		constant	−0.86171 (0.000)***
Power	power	5.7561 (0.081)*	−0.2311 (0.140)	−0.2098 (0.435)										
criteria	AIC	−842.4755	−894.7629	−953.2822	criteria	AIC	−969.6184	−800.5806	Criteria	AIC	−987.1275	criteria	AIC	−927.3718

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

Table 4

The optimal model for BCN, DCR, NANO, BTS and XTZ according to AIC criterion

NELSON'S EARCH			Non-linear Power GARCH			THRESHOLD SDGARCH			Asymmetric Power GARCH		
BCN			DCR			NANO			BTS		
mean equation	BTC	−1.24935 (0.000)***	mean equation	BTC	0.6369 (0.000)***	mean equation	BTC	0.7627 (0.000)***	mean equation	BTC	0.347758 (0.000)***
	ETH	1.14253 (0.000)***		ETH	0.4372 (0.000)***		ETH	0.8144 (0.000)***		ETH	0.489263 (0.000)***
	XRP	0.11741 (0.006)***		XRP	0.0207 (0.513)		XRP	−0.0709 (0.212)		XRP	0.059508 (0.000)***
	constant	0.00485 (0.240)		constant	−0.00123 (0.586)		constant	−0.0064 (0.031)**		constant	0.002853 (0.000)***
variance equation	earch	−0.74239 (0.000)***	variance equation	nparch	0.0541 (0.171)	variance equation	Abarch	0.2614 (0.000)***	variance equation	aparch	0.132505 0,001
	earch_a	1.61271 (0.000)***		nparch_k	0.0115 (0.000)***		atarch	−0.081 (0.143)**		aparch_e	0.641406 (0.000)***
				pgarch	0.7407 (0.000)***		Sdgarch	0.830 (0.000)***		pgarch	0.741402 (0.000)***
	constant	−0.432409 (0.000)***		constant	0.12526 (0.468)		constant	0.0006 (0.381)		constant	0.150615 0,01
			Power	power	−0.6382 (0.129)				Power	power	−0.199561 0,164
criteria	AIC	−402.0311	criteria	AIC	−920.8614	criteria	AIC	−710.6234	criteria	AIC	−682.3905

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

Table 5

The optimal model for BNB, XTZ, BTS and DCR according to BIC criterion.

GJR of THRESHOLD GARCH			Asymmetric Power GARCH			THRESHOLD SDGARCH			Non-linear Power GARCH		
BNB			XTZ			BTS			DCR		
mean equation	BTC	0.59732 (0.000)***	mean equation	BTC	0.34776 (0.000)***	mean equation	BTC	0.5295 (0.000)***	mean equation	BTC	0.6369 (0.000)***
	ETH	0.28865 (0.011)		ETH	0.48926 (0.000)***		ETH	0.3913 (0.000)***		ETH	0.4372 (0.000)***
	XRP	0.15989 (0.125)		XRP	0.05951 (0.000)***		XRP	0.3671 (0.000)***		XRP	0.0207 (0.513)
	constant	0.00101 (0.803)		constant	0.00285 (0.000)***		constant	0.0018 (0.450)		constant	−0.00123 (0.586)
variance equation	arch	−0.68558 (0.000)***	variance equation	aparch	0.13251 (0.001)***	variance equation	abarch	0.0221 (0.024)**	variance equation	nparch	0.0541 (0.171)
	tarch	0.84260 (0.002)***		aparch_e	0.64141 (0.000)***		atarch	0.0592 (0.027)**		nparch_k	0.0115 (0.000)***
	garch	0.45734 (0.000)***		pgarch	0.7414 (0.000)***		sdgarch	0.9551 (0.000)***		pgarch	0.7407 (0.000)***
	constant	0.00069 (0.000)***		constant	0.15062 (0.01)**		constant	0.00027 (0.511)		constant	0.12526 (0.468)
			Power	power	−0.199561 0.164				Power	power	−0.6382 (0.129)
Criteria	BIC	−772,1569	criteria	BIC	−650,4139	Criteria	BIC	−852.894	criteria	BIC	−888.8848

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

these models, the error condition is the residual effect left unexplained by other models.

The calculation formula for the ARCH model is as follows:

$$h_t^2 = \omega + \alpha u_{t-1}^2$$

while the model of the GARCH model is:

$$h_t^2 = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}^2$$

where:

- h_t^2 : variance
- ω : the fixed term
- u : residual h_{t-1}^2 : lagged variance
- β : coefficient of variance

The remaining ARCH-type and GARCH-type models used in our research are: Nelson's EARCH, Nelson's EGARCH, Threshold ARCH, Threshold SDGARCH, GJR Form of Threshold ARCH, GJR Form of Threshold GARCH, Simple asymmetric ARCH, Simple asymmetric GARCH, Power ARCH, Power GARCH, Nonlinear ARCH, Nonlinear GARCH, Nonlinear ARCH with one shift, Nonlinear GARCH with one shift, Asymmetric Power ARCH, Asymmetric Power GARCH, Nonlinear Power ARCH and Nonlinear Power GARCH.

In addition, another model we use below is GARCH with Dynamic Conditional Correlations GARCH (DCC). The particular model presented by Engle (2002), has the versatility of GARCH models in combination

with sparse parametric models for correlations. They are not linear, but they can be estimated very simply with univariate functions. In particular, it offers an easy way to simultaneously model the dynamic processes of volatility conditions and dependent conditions. The current values of dependent sets in this model are related to their values and square innovations that have been delayed. To illustrate this model let $y_t = y_{2t}, y_{2t}$ be a 2×1 vector containing the output lines and the series values in a mean condition. A common representation for the conditional mean equation is a VAR of reduced form such as the following:

$$A(L)y_t = e_t$$

where $A(L)$ is a polynomial matrix at the termination effector L , and $y_t = [e_{1t} e_{2t}]'$ V is a vector of variability function innovations.

The GARCH element of the frame can be easily understood by the first rewriting of the function of covariance-covariance function as:

$$H_t = D_t R_t D_t$$

where $D_t = \text{diag}\{\sqrt{h_{it}}\}$ is a 2×2 diagonal matrix of time-varying standard deviations from univariate models GARCH and $R_t = \{\rho_{ij}\}_t$ for $i, j = 1, 2$ which is a correlation matrix that contains conditional association factors. The elements of D_t follow the GARCH single-generation processes (P, Q) in the following way:

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} a_{ip} \varepsilon_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q}$$

Table 6

The optimal model for BCN, LSK and NANO according to BIC criterion.

NELSON'S EARCH				NELSON'S EGARCH		
BCN				NANO		
mean equation	BTC	−1.24935 (0.000)***	0.63352 (0.000)***	mean equation	BTC	0.7677 (0.000)***
	ETH	1.14253 (0.000)***	0.36385 (0.000)***		ETH	0.8237 (0.000)***
	XRP	0.11741 (0.006)	0.21796 (0.000)***		XRP	−0.0845 (0.160)
	constant	0.00485 (0.240)	−0.00345 (0.104)		constant	−0.0068 (0.026)**
variance equation	earch	−0.74239 (0.000)***	0.14174 (0.120)	variance equation	earch	−0.0699 (0.107)
	earch_a	1.61271 (0.000)***	0.97655 (0.000)***		earch_a	0.3998 (0.000)***
	constant	−432.409 (0.000)***	−641.166 (0.000)***		egarch	0.9777 (0.000)***
					constant	−0.1071 (0.200)
criteria	BIC	−377.1604	−900.3661	criteria	BIC	−682.4514

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

Table 7

The optimal model for BTG, XEM, ZEC, DOGE and OMG according to BIC criterion.

Power GARCH				GARCH				
		BTG	XEM			ZEC	DOGE	OMG
mean equation	BTC	0.59717 (0.000) ***	0.25143 (0.000)***	mean equation	BTC	0.55273 (0.000) ***	0.75080 (0.000) ***	0.38300 (0.000) ***
	ETH	0.34860 (0.000) ***	0.28544 (0.000)***		ETH	0.41511 (0.000) ***	0.15101 (0.210)	0.55145 (0.000) ***
	XRP	0.28522 (0.000) ***	0,57162 (0.000)***		XRP	0.13671 (0.000) ***	0.19644 (0.057)	0.28498 (0.000) ***
	constant	−0.00008 (0.881)	−0.00456 (0.000) ***		constant	−0.00171 (0.519)	−0.00036 (0.904)	−0.00094 (0.668)
variance equation	Parch	0.12620 (0.000) ***	0.13943 (0.002)	variance equation	Arch	0.20493 (0.018)	0.33271 (0.000) ***	0.12476 (0.004)
	pgarch	0.78932 (0.000) ***	0.7689 (0.000)***		Garch	0.54596 (0.002) ***	0.45542 (0.000) ***	0.82459 (0.000) ***
	constant	0.10872 (0.188)	0.12411 (0.366)		constant	0.00036 (0.016)	0.0006 (0.000)***	0.00006 (0.088)
Power criteria	power	−0.23110 (0.140)	−0.20981 (0.435)	criteria	BIC	−942.3949	−816.7406	−963.7147
	BIC	−894.7629	−924.8586					

Note: (*), (**) and (***) stand for 90%, 95% and 99% significance levels, respectively.

The second component of the frame consists of a specific structure DCC (M, N), which can be expressed as:

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

where,

$$Q_t = \left(1 - \sum_{m=1}^M a_m - \sum_{n=1}^N b_n\right) \bar{Q} + \sum_{m=1}^M a_m (\varepsilon_{t-m} \varepsilon_{t-m}) + \sum_{n=1}^N b_n Q_{t-n}$$

The implementation of the above models was carried out in an attempt to select the most appropriate model, which will interpret as accurately as possible the variability of each of the six cryptocurrencies analyzed in this survey. All GARCH models were applied using the maximum probability method. Selecting the most appropriate model is done by applying several criteria, such as the [Akaike Information Criterion \(1974\)](#), which is defined as:

$$AIC = 2k - 2nL(\hat{\theta})$$

where k denotes the number of unknown parameters, and L denotes estimates of maximum probability and $\hat{\theta}$ are the maximum likelihood estimates of unknown parameters. Another equally important criterion is the Information Bayesian Criterion ([Schwarz, 1978](#)):

$$BIC = k \ln n - 2nL(\hat{\theta}).$$

where n denotes the number of observations. The lower the values of these criteria, the better the adaptation of the model.

5. Results

In order to investigate the volatility and the relationship between the cryptocurrencies, 20 different models of the ARCH and GARCH family were evaluated using STATA 15 for each of the 12 cryptocurrencies. However, it is worth mentioning that some models could not be applied in all cryptocurrencies. The most appropriate model for each currency was selected using the AIC and BIC criteria.

The following Tables 3, 4, 5, 6 and 7 present the results of the most appropriate model for each cryptocurrency investigated.

From the tables, we conclude that with regard to the DCR digital coin, the optimal model is in the form of Non-linear Power GARCH, both based on the AIC and the BIC criterion. Bitcoin and Ethereum are statistically significant at every level of significance, while Ripple is statistically insignificant. All three key cryptocurrencies are positively related to DCR and this suggests that they are complementary to each other. This means

that when the three key cryptocurrencies have a higher performance, so will DCR and will become more appealing to investors. In this case, we observe the phenomenon commonly referred to as the “leverage effect”, suggesting that negative returns increase future volatility to a higher percentage than positive returns of the same size.

Regarding the NANO and BTS cryptocurrencies, according to the AIC criterion for both but according to the BIC criterion for BTS, the best model is THRESHOLD SDGARCH. This means that we have indications that from a threshold/critical point the volatility of these cryptocurrencies changes. After that threshold, their volatility follows a different (nonlinear) path compared to before the threshold, so it is difficult to predict their exact volatility. In this model, Bitcoin and Ethereum are statistically significant while Ripple is statistically insignificant. Bitcoin, Ethereum and NANO are positively related, while Ripple and Nano are negatively related. This means that the first three are complementary products, while the last two are substitutes.

With regard to XTZ cryptocurrency, the best model describing it is Asymmetric Power GARCH, in accordance with AIC and BIC criteria. This means that the currency exhibits asymmetric exponential volatility and is therefore quite dangerous as its values can change course at any time. Bitcoin, Ethereum and Ripple, and the constant term are statistically significant at each level of statistical significance. All three cryptocurrencies are positively related to XTZ and this suggests they are complementary, so XTZ is more appealing to investors. In the variance equation, the terms aparch, aparch_e and pgarch are statistically significant whereas its constant term is statistically insignificant, but all the terms of the equation have a positive sign. Also, the power term is statistically insignificant and negative.

For BNB cryptocurrency, the best model is GJR of THRESHOLD GARCH, both on the basis of the AIC and BIC criteria, and the same applies to the ZEC coin based on the AIC criterion. These cryptocurrencies are considered too risky, as their volatility can take proliferating dimensions from one point (threshold) and thereafter. They are, therefore, considered highly volatile and totally unpredictable. For the BNB, Bitcoin is statistically significant at each level of statistical significance, while Bitcoin, Ethereum and Ripple are significant in estimations about ZEC. In addition, BNB and ZEC have a positive relationship with the three cryptocurrencies, so they are complementary to the three key cryptocurrencies.

Concerning BTG and NEM cryptocurrencies, the optimal model is in the form of Power GARCH, both on the AIC and BIC criteria, meaning that any change in the value will be characterized by an exponentially ascending or descending path. Similarly, it is the appropriate model for the DOGE currency, according to the AIC criterion. Bitcoin, Ethereum, and Ripple are statistically significant and positively related to BTG, NEM and DOGE, and this suggests that they are complementary to each other

and so are more attractive to investors. Notably, the power terms have a negative sign and are statistically insignificant.

Nelson's EARCH appears to be the appropriate model for the BCN coin, based on both the AIC and BIC criteria, but also for the LSK digital coin according to the BIC criterion. This suggests that there is a negative correlation between inventory returns and changes in volatility return, so volatility tends to increase in response to excess output, less than expected. Bitcoin, Ethereum and Ripple are found to be statistically significant at almost all levels of statistical significance, and the terms of the earch, earch_a, and the constant term are equally statistically significant.

For LSK and NANO cryptocurrencies, the optimal model is Nelson's EGARCH according to the AIC criterion for the first and according to the BIC for the second. This means that if you invest in those currencies, it is more likely that the profits or losses from them will be exponential (e.g. increasing fast for a period of time). There is high reliability of their volatility results as they are statistically significant at a 99% confidence interval (***) according to both criteria. Therefore, there is stronger evidence that this form of expression of variance is indeed important in explaining the performance behavior of the particular cryptocurrencies.

With regard to ZEC, DOGE, and OMG, these cryptocurrencies are better described by the GARCH model according to the BIC criterion which aims to minimize forecast errors by recording errors in previous predictions and thus enhancing the accuracy of ongoing forecasts. These digital coins are complementary to the three basic currencies, meaning that, if for example the BTC value is increased by one unit, then the ZEC value will be reduced by 0.55273.

Last but not least, concerning the OMG currency, the optimal model is in the form of Simple Asymmetric GARCH according to the AIC criterion. This provides indications that the currency exhibits asymmetric form volatility. Bitcoin, Ripple and Ethereum are statistically significant at each level of statistical significance and are positively related to OMG. This suggests that they are complementary to each other, so OMG renders more attractive to investors.

6. Conclusions

Cryptocurrencies have received much attention nowadays from both investors and analysts, as they are a new form of investment that offers very large profits but can also cause huge losses. The main feature of cryptocurrencies is their decentralized character and their resilience to any form of effort for control and intervention and is therefore preferred instead of other established forms of investment. However, it is of great interest that most cryptocurrencies exhibited great price decreases, due to the negative climate in this market in the extremely bearish period from 1 January 2018 to 16 September 2018. For this reason, daily data and volatility-centered specifications are adopted in this paper to better examine the major digital currencies' effect on volatility of other high-capitalized digital coins in these stressed eras.

The evaluation process of these highly fluctuating currencies is complex and depends on many parameters. The purpose of this academic study is to evaluate the volatility determinants and forms of the 12 most traded digital coins, following Bitcoin, Ethereum and Ripple. Using ARCH-GARCH models and their specializations, as well as DCC-GARCH, we determine the most suitable relationship of each of them with each of these three highly dominant digital coins. Then, in order to select the most appropriate model among the many models that were implemented, the Akaike Information and Bayesian Schwartz criteria are adopted.

According to the AIC criterion, the most appropriate model describing the volatility of DOGE and BTG is Power ARCH, whereas regarding ZEC and BNB it is GJR of THRESHOLD GARCH, for BTS it is THRESHOLD SDGARCH and for OMG it is Simple Asymmetric GARCH. Also, XTZ is explained better with Asymmetric Power GARCH, XEM with Power GARCH, DCR with Nonlinear Power GARCH, LSK with Nelson's EGARCH, and BCN and NANO with Nelson's EARCH. The results point to the direction that most digital currencies are complementary to the three basic coins and almost all are statistically significant. This shows us that our

results are reliable and that investors could rely on them for future purchases.

According to the BIC criterion, we have great evidence that the most accurate model for DOGE, ZEC and OMG is GARCH, for LSK and BCN it is NELSON'S EARCH, and for BTG and XEM it is Power GARCH. XTZ is more appropriately described with Asymmetric Power GARCH, BNB with GJR of THRESHOLD GARCH and DCR with Nonlinear Power GARCH. Finally, NANO and BTS are explained more accurately with the THRESHOLD SDGARCH model. Likewise, almost all cryptocurrencies are complementary to the three key coins and almost all are statistically significant.

This paper investigates how some of the highest capitalization cryptocurrencies are related to the three principal ones and the direction and size by which their performance is affected. We investigate the complementarity or substitutability of large-capitalization cryptocurrencies with the three principal digital coins that are mainly responsible for the herding behavior in the markets of digital currencies. The innovative character of our findings enables portfolio managers as well as investors to be more agile in evaluating their investments, in taking optimal decisions and making future forecasts as we fill a significant gap in decision-making concerning trading of digital currencies in distressed times. Finally, this study could provide avenues for further research in complementarity or substitutability among cryptocurrencies and how this could impact the risk-return tradeoff in digital currency portfolios.

Declarations

Author contribution statement

N. Kyriazis, K. Daskalou, M. Arampatzis, P. Prassa, E. Papaioannou: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

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References

- Akaike, H., 1974. A new look at the statistical model identification. *IEEE Trans. Autom. Control* 19 (6), 716–723.
- Baur, D.G., Hong, K., Lee, A.D., 2018. Bitcoin: medium of exchange or speculative assets? *J. Int. Financ. Mark. Inst. Money* 54, 177–189.
- Beneki, C., Koulis, A., Kyriazis, N.A., Papadamou, S., 2019. Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Res. Int. Bus. Financ.* 48, 219–227.
- Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *J. Econom.* 31 (3), 307–327.
- Bonneau, J., Miller, A., Clark, J., Narayanan, A., Kroll, J.A., Felten, E.W., 2015. May). Sok: research perspectives and challenges for bitcoin and cryptocurrencies. *Security and Privacy (SP)*, 2015 IEEE Symposium on. IEEE, pp. 104–121.
- Bouoiyour, J., Selmi, R., 2015. Bitcoin Price: Is it Really that New Round of Volatility Can Be on Way? University Library of Munich, Germany.
- Bouoiyour, J., Selmi, R., Tiwari, A.K., 2015. Is Bitcoin business income or speculative foolery? New ideas through an improved frequency domain analysis. *Ann. Stat.Econ.* 10 (01), 1550002.
- Bucko, J.O.Z.E.F., Pal'ová, D., Vejacka, M., 2015. Security and trust in cryptocurrencies. *Central European Conference in Finance and Economics*, pp. 14–24.
- Chan, W.H., Le, M., Wu, Y.W., 2019. Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *Q. Rev. Econ. Financ.* 71, 107–113.
- Charles, A., Darné, O., 2019. Volatility estimation for Bitcoin: Replication and robustness. *Int. Econ.* 157, 23–32.

- Chu, J., Chan, S., Nadarajah, S., Osterrieder, J., 2017. GARCH modelling of cryptocurrencies. *J. Risk Financ. Manag.* 10 (4), 17.
- Corbet, S., Lucey, B.M., Urquhart, A., Yarovaya, L., 2018. Cryptocurrencies as a Financial Asset: A Systematic Analysis.
- Dyhrberg, A.H., 2016a. Bitcoin, gold and the dollar—A GARCH volatility analysis. *Financ. Res. Lett.* 16, 85–92.
- Dyhrberg, A.H., 2016b. Hedging capabilities of bitcoin. Is it the virtual gold? *Financ. Res. Lett.* 16, 139–144.
- Dwyer, G.P., 2015. The economics of Bitcoin and similar private digital currencies. *J. Financ. Stab.* 17, 81–91.
- Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* 20 (3), 339–350.
- Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: J. Econ. Soc.* 987–1007.
- Eyal, I., Sirer, E.G., 2018. Majority is not enough: bitcoin mining is vulnerable. *Commun. ACM* 61 (7), 95–102.
- Gronwald, M., 2014. *The Economics of Bitcoins-Market Characteristics and Price Jumps* (No. 5121). CESifo Group Munich.
- Guesmi, K., Saadi, S., Abid, I., Ftiti, Z., 2018. Portfolio diversification with virtual currency: evidence from bitcoin. *Int. Rev. Financ. Anal.*
- Katsiampa, P., 2017. Volatility estimation for Bitcoin: a comparison of GARCH models. *Econ. Lett.* 158, 3–6.
- Klein, T., Thu, H.P., Walther, T., 2018. Bitcoin is not the New Gold—A comparison of volatility, correlation, and portfolio performance. *Int. Rev. Financ. Anal.* 59, 105–116.
- Klaassen, F., 2002. Improving GARCH volatility forecasts with regime-switching GARCH. In: *Advances in Markov-Switching Models*. Physica, Heidelberg, pp. 223–254.
- Kyriazis, N.A., 2019. A survey on efficiency and profitable trading opportunities in cryptocurrency markets. *J. Risk Financ. Manag.* 12 (2), 67.
- Schwarz, G., 1978. Estimating the dimension of a model. *Ann. Stat.* 6 (2), 461–464.
- Symitsi, E., Chalvatzis, K.J., 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Econ. Lett.* 170, 127–130.
- Takaishi, T., 2018. Statistical properties and multifractality of Bitcoin. *Phys. A Stat. Mech. Appl.* 506, 507–519.
- Troster, V., Tiwari, A.K., Shahbaz, M., Macedo, D.N., 2018. Bitcoin returns and risk: a general GARCH and GAS analysis. *Financ. Res. Lett.*