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GARCH Modelling of High-Capitalization Cryptocurrencies' Impacts During Bearish Markets

Abstract: This study investigates how twelve cryptocurrencies with large capitalization get influenced by the three cryptocurrencies with the largest market capitalization (Bitcoin, Ethereum, and Ripple). Twenty alternative specifications of ARCH, GARCH as well as DCC-GARCH are employed. Daily data covers the period from 1 January 1 2018 to 16 September 2018, representing the intense bearish cryptocurrency market. Empirical outcomes reveal that volatility among digital currencies is not best described by the same specification but varies according to the currency. It is evident that most cryptocurrencies have a positive relationship with Bitcoin, Ethereum and Ripple, therefore, there is no great possibility of hedging for cryptocurrency portfolio managers and investors in distressed times.

Keywords: Bitcoin; Ethereum; Ripple; Garch; Volatility; Bear market

JEL Classification: G11, G15

1. Introduction

A new phenomenon that constitutes a pole of attraction for modern academic literature is cryptocurrencies. Cryptocurrencies are an alternative form of currency with a digital character (Kristoufek, 2013) while they have been considered as the next milestone in the history of money paving the way to a future cashless society (Fabris, 2019). Through them it is possible to make direct payments from one contracting party to another without the assistance of a financial institution. Unlike the majority of other available financial assets, they have no relation to any higher authority or physical representation. The value of cryptocurrencies is not based on any physical asset, country or enterprise economies but on the security of an algorithm that is able to trace all transactions. Increased use of cryptocurrencies may be associated with their low transaction costs, the peer-to-peer system, and the fact that they are free from any government interference. This led to an increase in the volume of transactions, volatility and price of cryptocurrencies (Corbet et al., 2019). In fact, the price volatility of cryptocurrencies has led to opinions that emphasize the speculative extensions of their market, triggering academic research that shows bubble phenomena in a variety of cryptocurrencies (Kyriazis et al., 2020). A school of thought holds that monetary policy leaders may not have the know-how, the will and the political independence to do what is necessary to achieve economic stability (Fabris, 2018). Therefore, despite their volatility, the decentralized and independent nature of cryptocurrencies has been considered a solution to phenomena such as those mentioned above, especially in emerging economies (Clegg, 2014).Interesting surveys on characteristics of cryptocurrencies have also been conducted by Kyriazis (2019a,b, 2020) and Fang et al. (2020).

Cryptocurrencies attracted the interest of investors, researchers and regulators when a hacker named Satoshi Nakamoto created the world's first virtual and decentralized currency, Bitcoin (Nakamoto, 2008). It is the first decentralized digital currency and remains the leader of the cryptocurrency market. Between October 2016 and October 2017 Bitcoin's stock market value rose from $10.1 billion to $79.7 billion, while the price rose from $616 to $4,800. This significant increase has presented the opportunity to acquire 680% of return on investment annually, something that canot be provided by other assets. In December 2017, the price of Bitcoin reached $19,500. Today, there are more than 1,600 cryptocurrencies, including new products such as Ethereum, Ripple, Litecoin, and Dash which have created a market that has a total stock market value of approximately $190 billion (Ammous, 2018). Because of the popularity of cryptocurrencies among common users, they have attracted the attention of the media and have become a popular subject in the academic world.

Cryptocurrencies is a term used to describe all digital means of exchange that implement a cryptographic framework and security features. Cryptocurrencies are protected by technology that makes it impossible to expand money supply with more than one predetermined algorithm already known to the public. Similarly to precious metals, each cryptocurrency's algorithm has a limit beyond of which it cannot be produced. Transport between cryptocurrencies is almost instantaneous and the source code on which it is built is secure (Ammous, 2018). Their decentralized instance comes to life through a decentralized digital ledger storing details required for conducting transactions and validating ownership (Vučinić, 2020), essentially enforcing their security model.

Prior to ARCH's invention researchers knew about fluctuations in variance well but used unofficial methods to take this into account. Engle solved this issue in 1982 by introducing a new class of stochastic processes under the name ARCH (Autoregressive Conditionally Heteroscedasticity). ARCH was the first official model to capture the variance of the current error term as a function of the actual magnitude of the error terms of the previous time periods (Engle, 1982). It is still used today in numerous areas such as: developing tests for assessing market volatility and risk, developing optimal risk hedging strategies, studying the implications of central bank interventions and building debt portfolios. Based on Engle's research, in 1986 Bollerslev introduced a new category of stochastic processes called GARCH (Generalized Autoregressive Conditional Heteroskedastic). This model has only three parameters that allow an infinite number of square roots to influence conditional variance. A feature that makes it more versatile than ARCH models (Bollerslev, 1986).

Katsiampa (2017) investigated Bitcoin's variability by comparing GARCH models and discovered that the AR-CGARCH model described it better. Dyhrberg (2016a) adopts GARCH models to examine Bitcoin's potential as a financial product. Results reveal that Bitcoin has similarities with gold and the US dollar. The asymmetric GARCH model provides evidence that this specific product can be used in portfolio management as it is ideal for risk averse investors. Furthermore, by employing data from July 2010 to May 2015 and an asymmetric GARCH methodology Dyhrberg (2016b) revealed that Bitcoin can serve as an effective hedger against the FTSE index. Moreover, hedging capacities against the USD are found in the short-run. In the same context, Gronwald (2014) compared the gold and bitcoin market and analysed Bitcoin's prices using GARCH models. His main conclusion is that there are significant changes in its price and that the market it`s trading in is not mature.

Bouri et al. (2016) use asymmetric GARCH models to investigate the relationship between price and volatility variations in the Bitcoin market in 2013 (the period of sharp decline in prices for all cryptocurrencies. Blau (2018) adopts a GARCH methodology and probit regressions and looks into whether the price and volume of Bitcoin are connected to speculation. He documents that speculative trading is not to be blamed for high levels of volatility. Furthermore, Corelli (2018) investigates the nexus between the most popular cryptocurrencies and a range of selected fiat currencies for detecting causality linkages. Evidence indicates that cryptocurrencies are connected to Asian markets and a type of Asian effect is revealed. Beneki et al. (2019) employ a multivariate BEKK-GARCH methodology and impulse response analysis applied within a VAR model and provide evidence of a delayed positive response of Bitcoin volatility detected on a volatility shock of a positive sign on Ethereum returns. Furthermore, they document that profitable trading strategies could be developed. Troster et al. (2018) adopt heavy-tailed GARCH specifications and GAS models to investigate Bitcoin's returns. They argue that heavy-tailed GAS models are the most appropriate to estimate risk from Bitcoin.

This paper adds to existing relevant literature since, to the best of our knowledge, no academic work to date has studied the connection between the risk-benefit relationship of the three principal cryptocurrencies and its influence on other cryptocurrencies of primary importance by so many alternative GARCH specifications.

The remainder of this study is structured as follows: Section 2 describes the data and Section 3 analyses the methodology. Section 4 provides and comments on the empirical outcomes and analyses the financial implications. Finally, section 5 concludes.

2. Data

Our study is based on daily data of 15 cryptocurrencies, expressed in US dollars, during the period 01/01/2018 - 16/09/2018 which represents the downward market for cryptocurrencies. Specifically, we study Litecoin, Tether, Monero, Cardano, Dash, IOTA, BitcoinCash, EOS, Stellar Lumens, TRON, Neo, Ethereum Classic and their relation to Bitcoin, Ethereum, Ripple which are the digital coins with the biggest capitalization. The data have been gathered from coinmarket.cap platform and the study observations are 258, corresponding to the first 258 days of 2018.

This period has been selected as it follows the explosive boom in the market of cryptocurrencies (a period which was characterized by an unprecedented rise in popularity and prices over the previous year). The period under review is characterized by high volatility, price variance and a steep drop in the value of cryptocurrencies. In Table 1 we lay out the currencies, their symbolism, and their total capitalization.

Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP) are the currencies with the biggest market capitalization. Table 2 presents the descriptive statistics of the digital coins based on their daily yield through logarithmic differences.

Table 2 – Descriptive statistics[1]

	Average	Std.Dev.	Min	Max	Var	Asymm.	Kyrt.
BTC	-0.00287	0.04512	-0.18458	0.12413	0.00204	-0.45688	4.71669
ETH	-0.00486	0.05692	-0.20685	0.14223	0.00324	-0.31891	4.14360
XRP	-0.00830	0.06873	-0.35328	0.22636	0.00472	-0.43796	7.41313
LTC	-0.00539	0.05797	-0.21186	0.29062	0.00336	0.39358	6.20638
USDT	-0.00004	0.00591	-0.01980	0.01980	0.00004	0.08619	5.40226
XMR	-0.00434	0.06633	-0.25880	0.17626	0.00440	-0.30133	4.09068
ADA	-0.00908	0.07343	-0.21734	0.32211	0.00539	0.67802	5.66007
DASH	-0.00659	0.06237	-0.21633	0.25593	0.00389	-0.00387	4.79526
MIOTA	-0.00746	0.07440	-0.29152	0.22501	0.00554	-0.23640	3.70571
BCH	-0.00655	0.06958	-0.30396	0.29336	0.00484	-0.04926	5.87637
EOS	-0.00190	0.08481	-0.25623	0.34713	0.00719	0.55518	5.9223
XLM	-0.00327	0.07453	-0.30622	0.46178	0.00555	0.65335	9.20044
TRX	-0.00369	0.10315	-0.32872	0.78667	0.01064	1.99197	17.08308
NEO	-0.00570	0.07449	-0.26590	0.25175	0.00555	0.14809	4.33646
ETC	-0.00432	0.07093	-0.35282	0.21373	0.00503	-0.53385	5.70641

Based on the descriptive statistics, eight of the fifteen cryptocurrencies depict a negative asymmetry with lower average yields over the majority of weeks. The most negative ones are Ethereum Classic (ETC) and Tron (TRX).

All cryptocurrencies exhibit fine-grained performance distributions with Tron (TRX) depicting the most fine-grained one. An analyst might consider overwhelmingly higher than the other cryptocurrencies of our study the likelihood of yielding near expected to bear, given the stability of all other factors (ceteris paribus) that may affect this particular currency. In the same way, an analyst could consider the possibility of achieving near-expected returns for the IOTA (MIOTA) coinage much lower.

[1] The descriptive statistics in Table 2 are estimated on 258 logarithmic differences of the corresponding time series.

3. Methodology

This paper focuses on the behaviour and correlation of Litecoin, Tether, Monero, Cardano, Dash, IOTA, Bitcoin Cash, EOS, Stellar, Tron, NEO, Ethereum Classic cryptocurrencies in relation to Bitcoin, Ethereum and Ripple which are the top three cryptocurrencies from a market capitalization perspective. For the calculation of daily yields, we used the first logarithmic differences of the quotes of the variables.

We rely on a series of 12 regressions, one for each tested cryptocurrency, using Bitcoin, Ethereum and Ripple yields as independent variables, and the variable representing the yields of each cryptocurrency studied as the dependent one in each case. We then applied a series of 21 ARCH specifications for each cryptocurrency under consideration in order to conclude with the most appropriate model for each case.

Our study is based on the following ARCH specifications: ARCH, GARCH, Nelson's EARCH, Nelson's EGARCH, Threshold ARCH, Threshold GARCH, GJR of Threshold ARCH, GJR of Threshold GARCH, Simple Asymmetric ARCH, Simple Asymmetric GARCH, Power ARCH, Power GARCH, Non-linear ARCH, Non-linear GARCH, Non-linear ARCH with one shift, Non-linear GARCH with one shift, Asymmetric Power ARCH, Asymmetric Power GARCH, Non-linear Power ARCH, Non-linear Power GARCH, DCC-GARCH.

In order to decide on the most appropriate ARCH specification for each cryptocurrency, we relied on the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC), comparing the results of each specification and preferring in each case the specification with the lowest indices for the specific criteria.

Finally, we conduct an analysis of the estimated models to draw conclusions about the behaviour of each cryptocurrency based on the specifications selected through the AIC and BIC criteria.

ARCH / GARCH models

According to Bollerslev et al. (1992), Engle (1982) introduced the concept of the ARCH effect (Autoregressive Conditionally Heteroscedasticity) as the statistical phenomenon where the variance in the values of a time series does not remain constant over time, depending on past values, causing a non-constant variance in the residuals of an econometric process and hence in less accurate estimates.

As a result, Engle (1982) introduced the ARCH model as a way of modelling and taking into account the volatility of variance over time.

Let X_t be the values of a time series with no constant variance over time:

$$X_t = \mu_t + \sigma_t Z_t$$

With:

- X_t be the values of the time series
- μ_t be the expected value of the variable
- Z_t be the values of the time series expressed in terms of the standard normal distribution

If the variance depends on the immediately preceding period of the time series, then it will follow the following procedure:

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2$$

$$with\, \omega \geq 0, \alpha_1 \geq 0$$

In this case we have an ARCH (1) model, that is, with one lag. If the variance depends on q previous periods of the time series, then we say we have an ARCH (q) model where the variance is derived from the following procedure:

$$\sigma_t^2 = \omega + \sum_{1}^{q} \alpha_q Z_{t-q}^2$$

According to Chan et al. (2017), based on the ARCH (q) model, Bollerslev (1986) introduced the GARCH (p, q) model where the variance depends on its own values of p previous periods in addition to the values of the variable's time series of previous q periods. Specifically, for a GARCH model (1, 1) the variance follows the following procedure:

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$\text{with}\, \omega \geq 0, \alpha_1 \geq 0, \beta_1 \geq 0$$

For a GARCH model (p, q) the variance follows the following procedure:

$$\sigma_t^2 = \omega + \sum_{1}^{q} \alpha_q Z_{t-q}^2 + \sum_{1}^{p} \beta_p Z_{t-p}^2$$

$$\pi o \upsilon\; \omega \geq 0, \alpha_q \geq 0, \beta_q \geq 0$$

4. Empirical results

For the purposes of our study, we rely on the AIC and BIC criteria to select the best fit model for each cryptocurrency. The specifications that carry the smallest AIC and BIC for each cryptocurrency are considered to be more accurate in explaining its behaviour. In the case of the LTC, USDT, ADA, DASH, MIOTA, BCH, EOS, XLM, TRX, NEO, and ETC, the AIC and BIC criteria indicate the most appropriate model. In the case of XMR cryptocurrency, the AIC and BIC criteria[2] indicate different models as more appropriate.

GARCH – LTC, DASH

Table 3a below shows the estimated coefficients of the GARCH model for LTC and DASH cryptocurrency.

Table 3a – LTC and DASH best expressed by GARCH specification

	COEFFICIENT	LTC	DASH
Mean Equation	BTC	0.52929 (0.000) ***	0.53896 (0.000) ***
	ETH	0.31639 (0.000) ***	0.33918 (0.000) ***
	XRP	0.22344 (0.000) ***	0.19272 (0.000) ***
	constant	-0.00141 (0.264)	-0.00196 (0.369)
Variance Equation	arch	0.04789 (0.000) ***	0.0423 (0.054) *
	garch	0.94249 (0.000) ***	0.89969 (0.000) ***
	constant	0.00000 (0.128)	0.00006 (0.206)

In the case of LTC cryptocurrency, the estimated GARCH model presents statistically significant arch and garch coefficients at a statistical significance level of 1%. The coefficients of the BTC, ETH, XRP variables also appear statistically significant at the same level, indicating a valid positive relationship between the latter and the LTC currency.

Outcomes indicate that an increase (decrease) in the performance of BTC, ETH, XRP by one unit will result in an increase (decrease) in LTC returns of about 0.53, 0.32 and 0.22, respectively. Thereby, findings provide evidence towards the LTC being a complementary coin for BTC, ETH, XRP, following a similar market trend and being affected by the BTC market more than by the XRP market.

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[2] Analytical AIC and BIC results are available upon request.

In the case of DASH, the coefficient of the garch term appears statistically significant at a statistical significance level of 1%, whereas the coefficient of the arch term at a statistical significance level of 10%. The BTC, ETH, and XRP variables are statistically significant for a 1% statistical significance level, while they are positive showing that the DASH is complementary to BTC, ETH, XRP, and moves towards the same direction as those.

In particular, an increase (decrease) in the performance of BTC, ETH, XRP by a unit with constant yields of the remaining key cryptocurrencies of the model (ceteris paribus) will result in an increase in DASH returns by approximately 0.54, 0.34 and 0.19 respectively. Finally, DASH is more affected by the BTC in comparison to its impact by XRP.

Asymmetric Power GARCH - USDT

Table 3b lays out the estimated coefficients of the Asymmetric Power GARCH model for the USDT coin.

Table 3b – USDT best expressed by Asymmetric Power GARCH specification

	COEFFICIENT	USDT
Mean Equation	BTC	-0.01092 (0.000) ***
	ETH	0.00587 (0.000) ***
	XRP	-0.009 (0.000) ***
	constant	-0.00002 (0.000) ***
Variance Equation	aparch	0.09929 (0.000) ***
	aparch_e	0.90796 (0.000) ***
	pgarch	0.78485 (0.000) ***
	constant	0.16317 (0.004) ***
	power	-0.1438 (0.000) *

The estimated model presents all coefficients of statistical significance at a statistical significance level of 1%. USDT cryptocurrencies are negatively correlated with BTC and XRP and positively with ETH. There is evidence towards being a substitute for BTC and XRP while being complementary to ETH so both following a market path of the same direction.

In particular, one should expect that an increase (decrease) in BTC or XRP performance by one unit, with the performance of the remaining key currencies of the fixed model (ceteris paribus), will reduce the USDT's performance by approximately 0.01 and 0.009, respectively. Conversely, an increase in (decrease) in ETH yield by 1 unit will increase (decrease) the USDT's return by about 0.006.

ARCH – XMR

Table 3c presents the estimated coefficients of the ARCH model regarding the XMR cryptocurrency.

Table 3c – XMR best expressed by ARCH specification

	COEFFICIENT	XMR
Mean Equation	BTC	0.86728 (0.000) ***
	ETH	0.20504 (0.000) ***
	XRP	0.1461 (0.000) ***
	constant	0.0001 (0.000) ***
Variance Equation	arch	0.32509 (0.000) ***
	constant	0.00089 (0.000) ***

Considering the AIC criterion for choosing the appropriate model for XMR cryptocurrency, the variability of XMR yields is best expressed by an ARCH model. Based on the ARCH model, XMR correlates positively with all of the key currencies investigated. Thereby, there is evidence towards following their own market trend and being complementary to these currencies.

XMR is most affected by the BTC as a 1-unit increase in BTC yield will reduce XMR by approximately 0.86 units, as the yields of the remaining key digital currencies (ETH, XRP) of our study remain stable (ceteris paribus). Correspondingly, for ETH and XRP, the change in one unit (ceteris paribus) will change in the same direction the XMR return by approximately 0.21 and 0.15 units, respectively.

Nelson's EARCH – XMR

Table 3d shows the estimated coefficients of the Nelson's EARCH for the XMR cryptocurrency.

Outcomes exhibit a statistically insignificant coefficient of earch in the volatility equation. However, the coefficients of the three key cryptocurrencies are statistically significant in a 99% confidence interval, meaning that the Nelson's EARCH model also shows that the key cryptocurrencies and XMR are complementary and follow a similar market trend. In particular, an increase (decrease) in the performance of BTC, ETH, XRP by 1 unit, with stable yields of the remaining key digital coins will lead to an increase in XMR performance by about 0.89, 0.21 and 0.14 units, respectively.

Table 3d – XMR best expressed by Nelson's EARCH specification

	COEFFICIENT	XMR
Mean Equation	BTC	0.88664 (0.000) ***
	ETH	0.20572 (0.000) ***
	XRP	0.13638 (0.000) ***
	constant	-0.00097 (0.648)
Variance Equation	earch	-0.08145 (0.311)
	earch_a	0.61706 (0.000) ***
	constant	-6.73873 (0.000) ***

Finally, considering the lack of statistical significance of the variable earch coefficient, the investigator should admit with great caution any conclusion derived from the use of the particular model, while alternatively he would prefer the ARCH model indicated to be appropriate based on the AIC criterion statistically significant coefficients of the volatility equation.

Non-linear GARCH with one shift – ADA

Table 3e below shows the estimated coefficients of the Non-linear GARCH model with one shift for the ADA curve.

Table 3e – ADA best expressed by Non-linear GARCH with one shift specification

	COEFFICIENT	ADA
Mean Equation	BTC	0.22261 (0.003) ***
	ETH	0.40226 (0.000) ***
	XRP	0.53975 (0.000) ***
	constant	-0.00157 (0.500) **
Variance Equation	narch	0.11768 (0.001) ***
	narch_k	-0.01493 (0.011) **
	garch	0.84136 (0.000) ***
	constant	0.00005 (0.047) **

Regarding the volatility equation, the coefficients of the narch and garch variables are statistically significant at a statistical significance level of 1%, while the coefficient of the variable narch_k is statistically significant at 5%. Therefore, the variability in the ADA cryptocurrency returns is explained by the model at a statistical significance level of 5%.

The coefficients of the BTC, ETH, XRP variables are statistically significant at a level of 1%, while the constant term of the equation at a statistical significance level of 5%. There is a positive correlation between ADA and BTC, ETH, XRP where evidence shows towards the former being complementary to the latter. Thereby, alterations in XRP returns exert a higher influence on ADA performance, followed by the impact of ETH and the BTC.

It should be noted that an increase (decrease) in the performance of BTC, ETH, XRP by one unit, will lead to an increase (decrease) in yield of ADA of about 0.22, 0.40 and 0.54 units respectively. In contrast to findings about other digital currencies, Ripple is found to be more influential in comparison to Bitcoin and Ethereum. Thereby, a tighter connection of ADA with Ripple is detected that enables us to understand that Bitcoin is not always the most influential coin in cryptocurrency markets. This could prove very useful for investors.

Non-linear GARCH – MIOTA

Table 3f presents the estimated coefficients of the Non-linear GARCH model for the MIOTA coin.

Table 3f – MIOTA best expressed by Non-linear GARCH specification

	COEFFICIENT	MIOTA
Mean Equation	BTC	0.27408 (0.000) ***
	ETH	0.57528 (0.000) ***
	XRP	0.33369 (0.000) ***
	constant	0.00049 (0.838)
Variance Equation	narch	0.33115 (0.001) ***
	narch_k	-0.02902 (0.001) ***
	garch	0.38629 (0.003) ***
	constant	0.0003 (0.129)

All coefficients of the equation of mean and of the volatility equation with the exception of the constant term of the equation of mean and of the coefficient of variation are statistically significant for a statistical significance level of 1%.

Taking into consideration the estimated coefficients of the variables of the key cryptocurrencies of the study, the reader should expect the MIOTA currency coin to be complementary to BTC, ETH, XRP, presenting a common course with those on the market while being affected to a greater extent by changes in ETH , after XRP and finally by the BTC.

It can be seen that a one-unit change in the yield of BTC, ETH or XRP, with stable yields of the remaining cryptocurrencies of the model (ceteris paribus), will result in a similar MIOTA directional shift of approximately 0.27, 0.58, and 0.33, respectively. It should be noted that Ethereum is found to be more influential than Bitcoin, providing further evidence that other important currencies than Bitcoin can have a serious impact on interrelation dynamics in the cryptocurrency market.

Non-linear Power GARCH – BCH, EOS

Table 3g reveals the estimated coefficients of the Non-linear Power GARCH model for BCH, EOS currencies.

Table 3g – BCH and EOS best expressed by Non-linear Power GARCH specification

	COEFFICIENT	BCH	EOS
Mean Equation	BTC	0.66033 (0.000) ***	0.44185 (0.000) ***
	ETH	0.5292 (0.000) ***	0.31419 (0.000) ***
	XRP	0.09694 (0.000) ***	0.57923 (0.000) ***
	constant	-0.00328 (0.036) **	0.00072 (0.766)
Variance Equation	nparch	0.06936 (0.000) ***	0.00013 (0.712)
	nparch_k	-0.00017 (0.915)	0.01191 (0.000) ***
	pgarch	0.83496 (0.000) ***	0.97775 (0.000) ***
	constant	0.156 (0.016) **	-13.2585 (0.668)
	power	-0.19903 (0.033) **	-2.3021 (0.0004) ***

All coefficients of the equation of mean for the basic cryptocurrencies of the BCH model are statistically significant at least at a statistical significance level of 5%. Respectively, most coefficients of the volatility equation are also statistically significant at least at a statistical significance level of 5% with the exception of the nparch_k coefficient that is not statistically significant.

With regard to the EOS cryptocurrency coin, most of the equation coefficients are statistically significant at 1%, with the exception of the stable term that is not statistically significant at any level. Most coefficients of the EOS model's volatility equation are statistically significant at 1%, with the exception of the nparch coefficient and the stable term.

In conclusion, BCH and EOS have a positive correlation with the key cryptocurrencies and are therefore complementary to these. BCH is most affected by BTC, then ETH, and finally by XRP. In particular, a decrease in the yield of BTC, ETH, XRP by one unit, with the yields of the remaining cryptocurrencies of the model remain constant (ceteris paribus), will lead to an increase in BCH of about 0.66, 0.53, and 0.10 respectively. EOS is most affected by XRP, after BTC, and ultimately by ETH where a BTC, ETH, XRP, (ceteris paribus) increase (decrease) in EOS currency return about 0.44, 0.31, and 0.58 units, respectively. Once more, there is evidence that Ripple is very influential regarding alternative important digital currencies.

Threshold ARCH – XLM

Table 3h shows the estimated coefficients of the Threshold ARCH model for the XLM cryptocurrency.

Table 3h – XLM best expressed by Threshold ARCH specification

	COEFFICIENT	XLM
Mean Equation	BTC	0.15061 (0.023) **
	ETH	0.27112 (0.000) ***
	XRP	0.51877 (0.000) ***
	constant	-0.00146 (0.526)
Variance Equation	abarch	0.26759 (0.009) ***
	atarch	0.46863 (0.000) ***
	constant	0.02749 (0.000) ***

In the Threshold ARCH specification estimated for the XLM cryptocurrency, statistically significant coefficients of the mean equation of BTC, ETH, and XRP are found in 5%, 1%, and 1% levels, respectively. Moreover, all volatility equation coefficients are statistically significant at 1%.

The XLM cryptocurrency is positively correlated with the three key cryptocurrencies investigated, and is mainly influenced by XRP, then ETH, and ultimately by the BTC. To be more precise, an increase in the performance of BTC, ETH, XRP by one unit will lead to an increase in the performance of XLM about 0.15, 0.27 and 0.52, respectively. Once again, it can be seen that no hedging is feasible during the distressed period under scrutiny.

Threshold SDGARCH – TRX

Table 3i presents the estimated coefficients of the Threshold SDGARCH for the TRX currency.

Table 3i – TRX best expressed by Threshold SDGARCH specification

	COEFFICIENT	TRX
Mean Equation	BTC	0.3477 (0.000) ***
	ETH	0.4471 (0.000) ***
	XRP	0.4338 (0.000) ***
	constant	0.0017 (0.496)
Variance Equation	abarch	-0.0235 (0.498)
	atarch	0.2702 (0.000) ***
	sdgarch	0.8873 (0.000) ***
	constant	0.0016 (0.000) ***

The coefficients of the equation of the model with the exception of the constant term are statistically significant at a statistical significance level of 1%. In addition, the atarch and sdgarch coefficients and the constant term of the volatility equation also appear statistically significant at a statistical significance level of 1%.

Since the abarch coefficient is not statistically significant, the Threshold SDGARCH model cannot be accepted with certainty as being appropriate to explain the behaviour of TRX cryptocurrency although it has been extracted as the most appropriate based on the AIC and BIC criteria. Any further conclusion should be taken into consideration with particular attention by the reader.

There is evidence towards the direction that TRX currency is complementary to the BTC, ETH, XRP key cryptocurrencies, with positive correlation with them, and is primarily influenced by ETH, then XRP, and ultimately by BTC. In particular, one should expect respective increases (decreases) in TRX return by about 0.35, 0.45, and 0.43 points to an increase (decrease) of BTC, ETH, and XRP by 1 unit, respectively.

Power GARCH – NEO

Table 3j denotes the estimated coefficients of the Power GARCH model for the NEO coin currency.

Table 3j – NEO best expressed by Power GARCH specification

	COEFFICIENT	NEO
Mean Equation	BTC	0.1982 (0.000) ***
	ETH	0.5874 (0.000) ***
	XRP	0.4163 (0.000) ***
	constant	-0.0029 (0.000) ***
Variance Equation	parch	0.0235 (0.000) ***
	pgarch	0.9257 (0.000) ***
	constant	0.1229 (0.283)
	power	-0.6794 (0.000) ***

All coefficients of the equation of mean and of the equation of variance, with the exception of the constant of the latter, are statistically significant at a statistical significance level of 1% whereas the NEO coinage is related to the BTC, ETH and XRP currencies and is complementary. NEO is mainly affected by ETH, then XRP, and ultimately by BTC. Specifically, the increase (decrease) in BTC, ETH, and XRP by 1 unit will lead to a decrease (decrease) in the NEO's returns by 0.20, 0.59, and 0.42, respectively.

GJR of Threshold GARCH – ETC

Table 3k denotes the estimated coefficients of GJR of Threshold GARCH for ETC.

Table 3k – ETC best expressed by GJR of Threshold GARCH specification

	COEFFICIENT	ETC
Mean Equation	BTC	0.3635 (0.000) ***
	ETH	0.4195 (0.000) ***
	XRP	0.2708 (0.000) ***
	constant	0.0006 (0.787)
Variance Equation	arch	0.4938 (0.000) ***
	tarch	-0.3501 (0.008) ***
	garch	0.6487 (0.000) ***
	constant	0.0001 (0.003) ***

The model is characterized by statistically significant coefficients of equation of mean and volatility equation to a statistical significance level of 1%, with the exception of the constant term of the equation of mean not shown statistically significant at any level.

In addition, the ETC cryptocurrency appears as a complement to the BTC, ETH, XRP key coins and is primarily influenced by ETH, after the BTC and ultimately by the XRP. Specifically, a 1-unit alteration in return of BTC, ETH, and XRP (ceteris paribus) will lead to an increase in ETC of 0.36, 0.42, and 0.27 units, respectively.

Overall, it can be seen that the majority of cryptocurrencies under scrutiny during the intensely bearish period of 2018 exhibit positive linkages with the three principal digital currencies in terms of market capitalization. Thereby, evidence tends towards the non-existence of hedging capacities among primary importance currencies in distressed times. Moreover, emphasis should be appointed to findings revealing that almost each of the cryptocurrencies investigated presents an alternative and advanced GARCH specification suitable for explaining its volatility in turbulent eras. This gives credence to the belief that digital currency market consists of highly fluctuating and bubbly assets that exhibit large variations in behaviour among them.

Conclusions

In the present study, by employing ARCH-GARCH specifications and DCC GARCH, we evaluated the behaviour of Litecoin, Tether, Monero, Cardano, Dash, IOTA, BitcoinCash, EOS, Stellar Lumens, TRON, Neo, and Ethereum Classic. Estimations were made by examining the nexus to Bitcoin, Ethereum, Ripple, which are the three most significant cryptocurrencies in terms of market capitalization. Data covering 258 days of the period 01/01/2018 - 16/09/2018 have been adopted, representing the intensely bearish period in cryptocurrency markets.

The main incentive for conducting this research is to cast light on an innovative perspective of the highly-arousing interest concerning cryptocurrencies. Increasing popularity of digital currencies among central planners, academics, analysts, investors, speculators, brokers and economic agents in general, is due to their sophisticated and decentralized character. In this paper, we focus on the particular features of high volatility among highly liquid cryptocurrencies during the bearish market and their implications about profit-making and hedging capabilities in distressed eras.

According to the AIC and BIC criteria, the variability of Litecoin and Dash is better than GARCH. BitcoinCash and EOS from Non-Linear Power GARCH. Stellar Lumens from Threshold ARCH. TRON by Threshold SDGARCH. Neo from Power GARCH. Ethereum Classic by GJR of Threshold GARCH. Tether's by APGARCH. Cardano from Non-linear GARCH with one shift, IOTA from Non-linear GARCH, and Monero from ARCH (AIC) and Nelson's EARCH (BIC). The results show that most of the cryptocurrencies under scrutiny exhibit a positive nexus with Bitcoin, Ethereum, and Ripple and are complementary to them, so no efficient hedging can be made during distressed times. It should be noted that Ethereum and Ripple exhibit a remarkably high influence on returns of alternative important cryptocurrencies in comparison to the highest appreciable Bitcoin currency.

Although there have been studies using GARCH models for studying cryptocurrencies, there has been no research into the effects of the three largest coins on the remaining digital currencies and investigation of their hedging abilities in times of crisis. This study provides an alternative look into the interconnectedness between digital coins of primary importance and very high capitalization and the rest of highly liquid cryptocurrencies during highly distressed periods. This linkage is very interesting for investors but has remained in unchartered waters up to the present. The authors' main motivation in writing this paper has been to start a fruitful discussion in the innovative aspect of volatility modelling and its economic implications in relation to alternative investments in digital currencies.

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