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**Preliminary Communication**

# A TIME SERIES ANALYSIS OF FOUR MAJOR CRYPTOCURRENCIES

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**Abstract**. *Because of an increasing interest in cryptocurrency investments, there is a need to quantify their variation over time. Therefore, in this paper we try to answer a few important questions related to a time series of cryptocurrencies. According to our goals and due to market capitalization, here we discuss the daily market price data of four major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC). In the first phase, we characterize the daily returns of exchange rates versus the U.S. Dollar by assessing the main statistical properties of them. In many ways, the interpretation of these results could be a crucial point in the investment decision making process. In the following phase, we apply an autocorrelation function in order to find repeating patterns or a random walk of daily returns. Also, the lack of literature on the comparison of cryptocurrency price movements refers to the correlation analysis between the aforementioned data series. These findings are an appropriate base for portfolio management. Finally, the paper conducts an analysis of volatility using dynamic volatility models such as GARCH, GJR and EGARCH. The results confirm that volatility is persistent over time and the asymmetry of volatility is small for daily returns.*

**Key words**: *cryptocurrencies, time series, volatility*

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## 1. INTRODUCTION

Since the beginning of the web and introduction of electronic payment systems, there have existed ideas of avoiding transaction costs and payment uncertainties on the Internet. This was mainly a theoretical concept until an electronic payment system based on

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cryptographic proof was introduced. The system allowed any two willing parties to transact openly with each other without the necessity to introduce a trusted third party (Nakamoto, 2008). In such a manner, Bitcoin was first proposed as a cryptocurrency at the beginning of 2009, and lately, its block chain system for maintaining a decentralized system has been widely recognized as a new distributed platform for financial institutions. As a cryptocurrency, Bitcoin utilizes special encryption to generate money. Since 2009, numerous cryptocurrencies have been established together with several systems for maintenance and transaction recordings. Such systems are mainly based on distributed ledger tehnology (Pinna & Ruttenberg 2016). Most of the cryptocurrencies rely on decentralized concept of transactions which is supported by cryptocurrency miners. Moreover, these transactions are also anonymous which resulted in huge legislation challenges. Recently, some cryptocurrencies rely on distributed ledger technology while at the same time they have a centralized token system. Differences and challenges between decentralized and centralized cryptocurrencies are usually called K-Y paradox (Hegadekatti 2017)

According to CoinMarketCap (CoinMarketCap, 2018), at the moment there are 914 cryptocurrencies in the market. The combined market capitalization of all cryptocurrencies is approximately $371 billion, where the top 5 currencies represent over 83% of the market. Our analysis will cover four of the five top currencies in the market.

Many of cryptocurrency price properties have attracted attention. Recently, a few research papers have found some similarities between usual financial time series and time series of major cryptocurrencies (Takaishi, 2017, Chan et al., 2017 and Catania et al., 2018). Similar to equity prices, cryptocurrencies reveal time varying volatility, heavy tails and an asymmetric reaction of the volatility process to the sign of past observations.

There has been a large amount of research done about Bitcoin, as it is the most popular cryptocurrency, while other important cryptocurrencies are still neglected. Due to the similar walk of time series of other cryptocurrencies, some advanced knowledge on Bitcoin price movements could be used in analysis of other observed currencies. Hence, in this paper we briefly consider some of the most important results in popular studies. Using weekly data of Bitcoin prices, Briere et al. (2015) examine diversified investment portfolios and discover that Bitcoin is extremely volatile and demonstrates high mean returns. Kristoufek (2015) found short and long links between Bitcoin and influencing factors. Correspondingly, in the same study, Bitcoin exhibits the properties of both standard financial assets and speculative assets. Cheah and Fry (2015) confirm that the Bitcoin market is highly speculative, and more volatile and susceptible to speculative bubbles than other currencies. Therefore, an examination of its volatility is crucial for investors. If we look at the aspect of volatility of cryptocurrencies, Barivieara et al. (2017) notice that the existence of long memory and persistent volatility explains the application of GARCH-type models. Moreover, an adequate usage of the GARCH model specification suggests the significance of having both a short and long-run element of conditional variance (Katsiampa, 2017). Many extensions of GARCH have been carried out to effectively estimate Bitcoin price dynamics (Dyhrberg, 2016, Bouri et al., 2017). The asymmetry in the Bitcoin market is still significant, suggesting that Bitcoin prices were driven more by negative than positive shocks (Bouoiyour and Selmi, 2016). It suggests that the Bitcoin market is still far from being mature.

Considering previous studies, we attempt to offer some basic stylized facts about major cryptocurrency movements and potential linkages among them. Our research presented in the following paper encompasses four sections. After an adequate introduction, explanations and a literature review, we continue with the second section where we offer some basic statistical properties of the four cryptocurrencies. The third section explains the volatility dynamics of a cryptocurrency`s daily returns and introduces three GARCH type models. Finally, we conclude the paper with some remarks and recommendations.

## 2. Data and its Statistical Properties

In view of our goal, in this paper we look at the daily market price data of four major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP) and Litecoin (LTC). For the analysis, we selected to use daily market data taken from August 6th, 2015 to March 11th, 2018, or exactly 948 daily observations. A start date was chosen based on the trading release date of Ethereum cryptocurrency. Other mentioned cryptocurrencies wereréleased earlier (Bitcoin in 2009, Litecoin in 2011 and Ripple in 2013).

Table 1 contains summary statistics of daily logarithmic or continuously compounded returns of the exchange rates of four cryptocurrencies. The assumption is that the data are independent and identically distributed, have no serial correlation and have no heteroskedasticity.

**Table 1** Summary statistics

| Statistics | BTC | ETH | XRP | LTC |
|---|---|---|---|---|
| Mean | 0.0037 | 0.0067 | 0.0049 | 0.0040 |
| Median | 0.0032 | 0.0000 | -0.0015 | 0.0000 |
| Maximum | 0.2276 | 0.3830 | 1.0280 | 0.5516 |
| Minimum | -0.1892 | -0.3101 | -0.6530 | -0.3125 |
| Std. Dev. | 0.0409 | 0.0776 | 0.0976 | 0.0598 |
| Skewness | -0.2046 | 0.2243 | 1.8397 | 1.9040 |
| Kurtosis | 7.3981 | 6.4764 | 23.0633 | 18.4828 |
| Jarque-Bera | 769.85 | 484.82 | 16417.56 | 10030.9 |
| Probability | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| ρ(1) | 0.0050 | -0.0518 | -0.2066 | 0.0231 |
| ρ(2) | -0.0064 | -0.0124 | 0.0732 | -0.0368 |
| ρ(3) | 0.0085 | 0.0942 | 0.1055 | 0.0269 |
| ρ(4) | -0.0494 | -0.0689 | -0.0588 | 0.0225 |
| ADF | -30.5688 | -34.5773 | -16.1419 | -30.0424 |
| PP | -30.5683 | -34.6049 | -37.0895 | -30.0842 |
| ARCH(4) | 17.3163 | 19.0455 | 16.8507 | 10.1807 |

*Source: authors` research*

The results in Table 1 emphasize positive expected daily returns in case of all four observed cryptocurrencies. Minimum and maximum refers to the presence of extreme observations in the sample period (i.e. heavy tails of distribution). The standard deviation shows better relative stability of exchange rates in the case of Bitcoin than for the other cryptocurrencies. The findings related to normal distribution assumptions demonstrate strongly the leptokurtic feature of the data series with some signs of skewness. Bitcoin poses negative, while other cryptocurrencies show positive skewness. The generally accepted financial theory assumes that rational investors prefer positive asymmetry where big losses are less likely to appear. The argument to invest with positive skewness lies in the fact that median is more than mean. Hence, there is a better chance to yield a profit. On the other hand, negative skewness attracts investors who are ready to risk and adopt the rules of active investment management. Some interesting research on stock price skewness proves that negative asymmetry is more likely to happen to stocks with increase in trading volume, positive returns in last 36 months and bigger share in market capitalization (Chen et al., 2001). Expectedly, the Jarque-Berra statistics in all four cases refer to the hypothesis that reject the existence of normal distribution of returns of exchange rates. Serial correlation or autocorrelation $\rho(i)$, estimated at lag i for each data series, are usually small. Such results provide long term surplus profits as opposed to short term profits that do not automatically perform any possible trends in returns of cryptocurrency's exchange rates (Radovanov, Marcikić, 2017). Additionally, the results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root test show rejection of the null hypothesis of a unit root for the returns and accept the presence of stationarity in data series of returns. Table 1 contains the results of ARCH LM test for autoregressive conditional heteroskedasticity in the residuals with four lagged residuals in the model. The values of ARCH (4) confirm that there exist ARCH effects in the returns of cryptocurrencies, suggesting that the model for the conditional mean needs to be expanded with autoregressive conditional heteroskedasticity model for the conditional variance (Katsiampa, 2017). Considering all previous facts and findings, particularly serial correlation and ARCH LM test, the log returns of the exchange rates of observed four cryptocurrencies are approximately independent and identically distributed, have no serial correlation and have heteroskedasticity.

**Table 2** Correlation matrix

| | BTC | ETH | LTC | XRP |
|---|---|---|---|---|
| BTC | 1.0000 | 0.9145 | 0.9582 | 0.8292 |
| ETH | 0.9145 | 1.0000 | 0.9320 | 0.9061 |
| LTC | 0.9582 | 0.9320 | 1.0000 | 0.8752 |
| XRP | 0.8292 | 0.9061 | 0.8752 | 1.0000 |

*Source: authors` research*

Table 2 represents the correlation matrix of returns of cryptocurrency`s exchange rates. The intersection of a row and column in Table 2 shows the results of the correlation coefficient between two cryptocurrencies. Due to the level of correlation which is positive and closer to 1, we noticed similarities in movements of returns in the case of all four cryptocurrencies. Nevertheless, a risk diversified investment portfolio does not include assets with high positive correlation. Theoretically, that cannot reduce portfolio risk. What additionally substantiates the fact of a bad choice to have a portfolio with two or more mentioned cryptocurrencies, is the analysis of cross-correlations within the same data set. The results show a high degree of correlation within +/- 12 lags (days). Table 3 presents the cross-correlation coefficient between BTC and ETH. Cross-correlation results indicate the level of similarities between two time series in different moments of time. Therefore, correlation changes over time will not improve portfolio risk diversification by including two or more cryptocurrencies.

**Table 3** Cross-correlations between BTC and ETH

| i | BTC,ETH(-i) | BTC,ETH(+i) |
|---|---|---|
| 1 | 0.9053 | 0.9162 |
| 2 | 0.8968 | 0.9181 |
| 3 | 0.8883 | 0.9193 |
| 4 | 0.8795 | 0.9203 |
| 5 | 0.8713 | 0.9214 |
| 6 | 0.8627 | 0.9214 |
| 7 | 0.8533 | 0.9208 |
| 8 | 0.8444 | 0.9193 |
| 9 | 0.8359 | 0.9172 |
| 10 | 0.8287 | 0.9155 |
| 11 | 0.8217 | 0.9142 |
| 12 | 0.8148 | 0.9134 |

*Source: authors` research*

## 3. VOLATILITY OF CRYPTOCURRENCIES

Due to the dynamic nature of returns of cryptocurrencies, the GARCH-type models will be applied in this paper. Besides standard GARCH(1,1), we will present a volatility analysis by using GJRGARCH and EGARCH concerning asymmetry in volatility of returns.

Standard GARCH(1,1) (Bollerslev, 1986) contains a conditional variance equation as follows:

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

Where $\sigma_t^2$ denotes time-depending variance, $e_{t-1}^2$ is lagged error term and $\omega > 0$, $\alpha > 0$ and $\beta > 0$.

The GJRGARCH(1,1) (Glosten et al., 1993) model has the following conditional variance equation:

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma e_{t-1}^2 I_{t-1} \tag{2}$$

Where $I_{t-1} = 1$ if $e_{t-1} \le 0$ and $I_{t-1} = 1$ if $e_{t-1} > 0$.

The exponential GARCH model (Nelson, 1991) denoted by EGARCH(1,1) has a conditional variance equation as follows:

$$\ln \sigma_t^2 = \omega + \alpha \left| e_{t-1} \middle/ \sqrt{\sigma_{t-1}^2} \right| + \delta \left( e_{t-1} \middle/ \sqrt{\sigma_{t-1}^2} \right) + \beta \ln \sigma_{t-1}^2 \tag{3}$$

In all three types of GARCH models, we used the univariate AR(1) model for conditional mean equation. Table 4 presents the estimated results of the aforementioned GARCH models in the case of four cryptocurrencies.

**Table 4** Estimation results of GARCH models

| Crypto-currency | Bitcoin | | | Ethereum | | |
|---|---|---|---|---|---|---|
| Model | AR-GARCH | AR-GJR | AR-EGARCH | AR-GARCH | AR-GJR | AR-EGARCH |
| c | 0.0029*** | 0.0032*** | 0.0029*** | 0.0032** | 0.0033** | 0.0032** |
| AR(1) | -0.0173* | -0.0206* | -0.0478* | -0.0179* | -0.0180* | -0.0491* |
| ω | 0.0000*** | 0.0000*** | -0.6458*** | 0.0002*** | 0.0002*** | -0.8019*** |
| α | 0.1862*** | 0.2471*** | 0.0257*** | 0.2797*** | 0.2617*** | 0.0641*** |
| β | 0.8036*** | 0.7082*** | 0.9472*** | 0.7124*** | 0.7129*** | 0.9136*** |
| γ | - | -0.0491* | - | - | -0.0056 | - |
| δ | - | - | -0.0009 | - | - | 0.0211 |
| Crypto-currency | Ripple | | | Litecoin | | |
| Model | AR-GARCH | AR-GJR | AR-EGARCH | AR-GARCH | AR-GJR | AR-EGARCH |
| c | -0.0036* | -0.0020* | -0.0028* | 0.0014 | 0.0014 | 0.0022** |
| AR(1) | -0.1664*** | -0.1667*** | -0.1956*** | 0.0297 | 0.0022 | 0.0088 |
| ω | 0.0008*** | 0.0008*** | -1.0038*** | 0.0001*** | 0.0001*** | -0.2831*** |
| α | 0.4504*** | 0.4264*** | 0.1265*** | 0.0909*** | 0.1070*** | 0.0426*** |
| β | 0.5455*** | 0.5362*** | 0.8662*** | 0.9007*** | 0.8818*** | 0.9471*** |
| γ | - | -0.2943*** | - | - | -0.1067*** | - |
| δ | - | - | 0.1056*** | - | - | 0.0924*** |

*Source: authors` research*

Note: In Table 4 * represents the significance at the 10% level, ** represents the significance at the 5% level, while *** denotes the significance at the 1% level.

In the first two rows of each model, Table 4 presents the results of conditional mean equation estimated parameters, while the other five rows are reserved for conditional variance estimated parameters. In each estimated model, α + β is close to 1 and it indicates the persistency of volatility over time. Mostly, the larger values of β parameters mean that large changes in the volatility will affect future volatilizes for a long period of time. However, we cannot neglect the significance of ARCH effects estimated in parameter α. In GJR and EGARCH models the asymmetry of positive and negative innovations on the volatility has been involved. In the case of BTC and ETH, there is no significance in estimated parameters γ and δ, thus the effects on sign are inconsiderable. In other words, the results demonstrate a small level of volatility asymmetry for daily returns. On the other hand, asymmetry parameters in the case of XRP and LTC reveal the existence of positive asymmetry where good news increases the volatility more than bad news of the same size, which is totally different than the cases of other financial time series.

## 4. CONCLUSIONS

The cryptocurrency market has lately seen huge growth. Due to the increasing demand and interest in cryptocurrencies, Chu et al. (2017) believe that they should not be treated as more than just a novelty. The same authors are looking at cryptocurrencies in terms of financial assets, where most market participants trade them for investment purposes. However, as cryptocurrencies are both decentralized and mainly unregulated they will never behave precisely like other currencies on the market. Nevertheless, their current position on the market is somewhere between classical commodities and currency because of their decentralized nature and limited market size.

The answer about the future of cryptocurrencies lies in resolving legislation challenges since open block chains are currently not ready for usage in traditional economies. Governments and corporations worldwide already observed that they can benefit from block chain technology, and a lot of research is being conducted in order to enable block chain systems for regulated global usage. For the central bank of a country, a centralized cryptocurrency can be considered as a retail e-currency for the whole country. Finally, it can lead to a legal framework for the whole unregulated tokenized crypto exchanges, because it is much easier to organize and regulate taxation and accounting for the centralized cryptocurrency.

Examining the statistical properties and the volatility of cryptocurrencies would be mainly valuable in terms of portfolio management, risk analysis and market sentiment analysis. The results shown in this paper prove to substantially support the investment decision making process. Highlighting the importance of active investment management, the volatility modelling process demonstrates the equal importance of the short and long-run components of conditional variance. Additionally, cryptocurrencies can be used as a tool for risk-averse investors in anticipation of bad news.

## REFERENCES


Bariviera, A., Basgall, M.J., Hasperue, W. & Naiouf, M. (2017). Some Stylized Facts of the Bitcoin Market. *Physica A*, 484, 82-90.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal *of Econometrics*, 31 (1), 307-327.

Bouoiyour, J. & Selmi, R. (2016). Bitcoin: A Beginning of a New Phase?, *Economics Bulletin*, 36 (3), 1430-1440.

Bouri, E., Azzi, G. & Dyhrberg, A.H. (2017). On the Return-Volatility Relationships in the Bitcoin Market around the Price Crach of 2013. Economics: The Open-Access, Onep-Assessement E Journal, 11 (1), pp.1-16.

Briere, M., Oosterlinck, K. & Szafarz, A. (2015). Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoins. *Journal of Asset Management*, 16 (1), 365-373.

Catania, L., Grassi, S. & Ravazzolo, F. (2018). *Predicting the Volatility of Cryptocurrency Time Series. (Oslo: CAMP Working Paper Series No 5/2018.)* Retrieved from: http://brage.bibsys.no/bitstream/handle/11250/2489408/WP_CAMP_5_2018.pdf Accessed on: 15 January 2018.

Chen, J., Hong, H. & Stein, J. (2001). Forecasting Crashes: Trading Volume, Past Returns and Conditional Skewness in Stock Prices. *Journal of Financial Economics*, 61 (3), 345-381.

Chan, S., Chu, J., Nadarajah, S. & Oserrieder, J. (2017). A Statistical Analysis of Cryptocurrencies. *Journal of Risk and Financial Management*, 10 (12), 1-23.

Cheah, E.T. & Fry, J. (2015). Speculative Bubbles in Bitcoin Markets? An Emprical Investigation into the Fundamental Value of Bitcoin. *Economic Letters*, 130 (1), 32-36.

CoinMarketCap. (2018). *Cryptocurrency Market Capitalizations.* Retrieved from: http://coinmarketcap.com/coins/views/all/Accessed on: 8 March 2018.

Chu, J.. Chan, S., Nadarajah, S. & Osterrieder, J. (2017). GARCH Modelling of Cryptocurrencies. *Journal of Risk and Financial Management*, 10 (17), 1-15.

Dyhrberg, A.H. (2016). Hedging Capabilities of Bitcoin. Is It the Virtual Gold? *Finance Research Letters*, 16 (1), 139-144.

Glosten, L., Jagannathan, R. & Runkle, D. (1993). On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48 (1), 1779-1807.

Hegadekatti, K. (2017). *The K-Y Paradox: Problems in Creating a Centralised Sovereign Backed Cryptocurrency on a Decentralised Platform*. Retrieved from: https://ssrn.com/abstract=2942914 Accessed on: 30 April 2018.

Katsiampa, P. (2017). Volatility Estimation for Bitcoin: A Comparison of GARCH Models. *Economics Letters*, 158, 3-6.

Kristoufek, L. (2015). What are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLoS ONE 10*. Retrieved from: journals.plos.org /plosone/article?id=10.1371/journal.pone.0123923 Accessed on: 9 March 2018.

Nakamoto, S. (2008). *A Peer-to-Peer Electronic Cash System*. Retrieved from: http://bitcoin.org/bitcoin.pdf Accessed on 8 March 2018.

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59 (1), 347-370.

Pinna, A. & Ruttenberg, W. (2016) *Distributed ledger technologies in securities post-trading*. Retrieved from: https://bravenewcoin.com/assets/Industry-Reports-2016/European-Central-Bank-Distributed-ledger-technologies-Report.pdf. Accessed on: 17 February 2018.

Radovanov, B. & Marcikić, A. (2017). Bootstrap Testing of Trading Strategies in Emerging Balkan Stock Markets. *Ekonomie a Management*, 20 (4), 103-119.

Takaishi, T. (2017). Statistical Properties and Multifractality of Bitcoin. *Cornel University Library*. Retrieved from: http://arxiv.org/abs/1707.07618 Accessed on: 15 January 2018.

# ANALIZA VREMENSKIH SERIJA ČETIRI GLAVNE KRIPTOVALUTE

*Kako raste interes ka investiranju u kriptovalute, jasno je da postoji potreba da se kvantifikuju njihove varijacije kroz vreme. Zbog toga u ovom radu mi pokušavamo da odgovorimo na nekoliko važnih pitanja koja se odnose na vremenske serije kriptovaluta. Spram naših ciljeva i tržišne kapitalizacije, analiziramo dnevne cene četiri glavne kriptovalute: Bitkoin (BTC), Eterijum (ETH), Ripl (XRP) i Lajtkoin (LTC). U prvom delu opisujemo dnevne stope prinosa u odnosu na kurs američkog dolara posmatrajući osnovne statističke pokazatelje. Interpretacija ovih rezultata u mnogome može biti glavna smernica tokom procesa odlučivanja o ulaganju. U sledećoj fazi primenjujemo autokorelaciju sa ciljem da utvrdimo ponavljajuće obrasce ili slučajno kretanje dnevnih povrata. Sem toga, nedostatak literature koji se bavi upoređivanjem kretanja cena kriptovaluta upućuje na analizu korelacije između navedenih vremenskih serija. Zaključci ovakve analize su osnova portfolio menadžmenta. Na kraju, urađena je analiza volatilnosti koristeći GARCH, GJR i EGARCH, kao modele za dinamičnu volatilnost. Rezultati potvrđuju da je volatilnost perzistentna tokom vremena, a da je asimetričnost volatilnosti mala kada se posamtraju dnevni prinosi.*

Ključne reči: *kriptovalute, vremenske serije, volatilnost*