Journal of Business Economics and Management
ISSN 1611-1699 / eISSN 2029-4433
2023 Volume 24 Issue 3: 527–550
https://doi.org/10.3846/jbem.2023.19118

STYLIZED FACTS, VOLATILITY DYNAMICS AND RISK MEASURES OF CRYPTOCURRENCIES

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Received 9 March 2023; accepted 26 April 2023

Abstract. This study explores the stylized facts, volatility clustering, other highly irregular behaviour, and risk measures of cryptocurrencies' returns. By analysing bitcoin, ripple, and ethereum daily data we establish evidence of strong dependencies among analysed cryptocurrencies. This paper provides new insights about cryptocurrency behaviour and the main measures of risk and detailed comparative analysis with tech-stocks. Comprehensive research on stylized facts confirmed high risk for both cryptocurrencies and tech-stocks with cryptocurrencies being even riskier. Empirical research findings are useful in developing dependence and risk strategies for investment and hedging purposes, especially during more volatile periods in the markets as there was confirmed existence of volatility clusters when high volatility periods are followed by low volatility periods. Sensitivity analysis and measures of Value-at-Risk (VaR) and Expected Shortfall (ES) show the amount of losses investors can expect in the worst case scenario. Our results confirm the existence of predictability, volatility clustering, and possibilities for arbitrage opportunities. Findings could be beneficial for investors and policymakers as well as for scientific purposes as findings give us a better understanding of the behaviour of cryptocurrencies.

Keywords: cryptocurrency, risk measures, volatility clustering, stylized facts, value-at-risk, expected shortfall.

JEL Classification: G1, G12, G17.

Introduction

Cryptocurrencies have attracted enormous attention from investors, regulators, and the media since bitcoin was introduced in 2008. The cryptocurrency market is expanding extremely fast however still there are many topics underexplored academically. Novel empirical research concludes that the best-known bitcoin cryptocurrency acts more like a financial asset than a currency but has attractive features as a medium of exchange, as well (Katsiampa et al., 2022). There is no doubt that bitcoin represents a unique financial instrument having its advantages

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and disadvantages (Polasik et al., 2016). Cryptocurrencies differ in their functionality and mainly they can be used as a medium of exchange which allows investors and speculators to include cryptocurrencies in their investment portfolios. There are extensive studies on how bitcoin and other cryptocurrencies can be used in a diversified portfolio as a hedge against losses (Salisu et al., 2019; Fakhfekh & Jeribi, 2019). However, what remains a sore point of analysis is the question of how risky are cryptocurrencies and whether could we predict the volatility of cryptocurrency returns to be prepared to take action before big volatility periods.

Wang et al. (2022) studies asymmetric contagion effects between stock and cryptocurrency markets. Le et al. (2021) uncover that the connectedness among green bonds, fintech, and cryptocurrencies is very high. Symitsi and Chalvatzis (2019) employ an asymmetric multivariate VAR-GARCH model to study spillover effects between Bitcoin and energy and technology companies. Empirical researches make clear that financial markets are extensively analyzed and compared with the cryptocurrency market. However, scientific literature has not yet covered the comparison between one of the most popular cryptocurrencies and tech-stocks by performing stylized facts analysis covering the evaluation of risk measures, and volatility dynamics of returns.

Even though research about Bitcoin is evolving, the existing literature lacks any test about volatility clustering and periods of large, recurrent arbitrage opportunities occurring in high-intensity periods. This paper provides a systematic review of the empirical literature based on the major topics that have been associated with the market for cryptocurrencies. Evaluation of stylized facts, volatility, and risk remains the key point for a better understanding of cryptocurrencies and their behavior. Our results indicate the existence of similar behavior between cryptocurrency and tech-stock markets. Both markets are sensitive to shocks and are considered to be risky with cryptocurrencies being even riskier. However, it does not appear that those markets are correlated. These results suggest bitcoin may offer diversification benefits for investors against technology sector risk. Research gives relevant insights for investors as it explores measures of risk which have to be considered before investing. For scientists, our results give a better understanding of cryptocurrency behavior in the cryptocurrency adoption phase as it's still a very new and growing asset class.

This paper explores stylized facts of different functionality cryptocurrencies, naming bitcoin, ethereum and ripple, compares them with tech-stocks, and gives significant contributions. First, we started our analysis with a systematic analysis of scientific literature. We gave a detailed comparative analysis of information and evaluated descriptive statistics. We explored stylized facts such as autocorrelation, volatility clustering, normality, and outliers, measured extreme values and tails dependency, calculated correlation coefficients over time, cross-correlations with different lags, and rolling correlations through all the periods between different cryptocurrency pairs. We evaluated the similarity between tech-stocks and cryptocurrencies using rolling correlations. Finally, we estimated Value-at-Risk (Var) and Expected Shortfall (ES) with historical, modified, and gaussian methods for both cryptocurrencies and tech-stocks. We checked the accuracy of modeling using a back-testing technique. Logical analysis is used to summarize the results.

The paper is organized as follows. Section 1 is devoted to the scientific literature review. Section 2 sets out the methodology and describes the data. Section 3 interprets the results of cryptocurrency stylized facts analysis, extensive correlation analysis, and sensitivity analysis of VaR and ES risk measures. Backtesting is used to evaluate the accuracy of modeling. Section 3 provides a comparison with tech-stocks and tech-stocks sensitivity analysis. The last section gives conclusions and points out the main findings.

1. Literature review

Risk and volatility are usually associated with the efficiency of the market. As cryptocurrencies are considered to be the riskiest financial instrument, scientists usually explore the efficiency of the cryptocurrency market (Makarov & Schoar, 2020; Tran & Leirvik, 2020; Urquhart, 2017). Efficiency topic leads to arbitrage which was particularly precisely analysed by Chaim and Laurini (2019), Elendner et al. (2016), Ji et al. (2019), and Sifat et al. (2019). All these papers demonstrate that the cryptocurrency market is a developing market with arbitrage potential as prices are inefficient. More specific actual and not potential arbitrage analysis was done by Bruzgė and Šapkauskienė (2022) who gave valuable insights into arbitrage topic. Scientists explored high frequency unique arbitrage data in thirteen cryptocurrency exchanges and found that investors can mitigate their trading risks by knowing which exchanges are attractive for arbitrage trading. However, high frequency trading comes with additional risks which have to be taken into account before investing. There are different high frequency trading (HFT) strategies which were analyzed and tested by Vaitonis and Masteika (2021) who created the testing method for the automated HFT strategies and confirmed that daily closing price statistical arbitrage strategies can be effectively applied in HFT. Moreover, cryptocurrency market is unique as cryptocurrencies are connected to Bitcoin and there exists long-term memory dependency on Bitcoin. Jiang et al. (2018) offered a new efficiency index with a rolling window used for testing the existence of long-term memory in the Bitcoin market. The results support other scientists' findings that the bitcoin market is inefficient (Bariviera, 2017; Chuen et al., 2018; Corbet et al., 2018). Also, a time-varying approach used by Jiang et al. (2022) makes an advantage when used for tracking the dynamic efficiency. One of the main reasons why efficiency is not maintained is the lack of reasonable pricing mechanisms and irrational behavior of investors. An effective market cannot have any mispricing. If there exists any possibility for mispricing it leads to arbitrage that increases investors' interest and leads to stronger deviations, uncertainty, and volatility. Makarov and Schoar (2020) performed extensive research on bitcoin arbitrage topics and found that bitcoin experiences big recurring deviations in prices across different exchanges. Another finding is that price deviations usually exist among countries or regions but not within the same country. Price differences between geographical regions were confirmed by other scientists, as well (Omane-Adjepong et al., 2019; Thaqeb & Algharabali, 2019). Cryptocurrency markets exhibit periods of large, recurrent arbitrage opportunities across exchanges due to the high volatility associated with risk.

Bitcoin becomes not just attractive for arbitrage but also could work well as a diversifier for hedging speculators' investments. Comprehensive research on extreme values was made by Borri (2019) who explored conditional tail-risk and found that idiosyncratic risk can be reduced, and portfolios of cryptocurrencies could offer attractive returns and hedging properties when included in investors' portfolios. Also, Gkillas and Katsiampa (2018) by investigating the extreme value theory analyzed the behavior of the returns of the five largest cryptocurrencies and found that bitcoin cash has the highest potential for gain and loss. Canh et al. (2019) as well as Beneki et al. (2019) dived deeper into the volatility topic and explored systematic risk and found that volatility spillovers exist with strong positive correlations among cryptocurrencies which offers diversification benefits and hedging abilities within the cryptocurrency market itself. As research by Makrichoriti and Moratis's (2016) show Bitcoin is fully independent of external factors coming from the capital, bond, and commodity market. Those results lead to the conclusion that cryptocurrencies can be used as hedging. Evidence by Corbet et al. (2018) further justifies bitcoin as a potential risk factor in the maximization of returns of conventional financial assets. It means that by including bitcoin investors not only can hedge their investment portfolio but also maximize the returns. Salisu et al. (2019) claim that bitcoin price exhibits such predictive powers that investors and policymakers can exploit such information when making future decisions which may minimize risks and uncertainties associated with financial assets.

Risks were precisely analyzed in the scientific literature by evaluating such risk measures as Value-at-Risk (VaR) and Expected Shortfall (Hrytsiuk et al., 2019; Likitratcharoen et al., 2018; Pele & Mazurencu-Marinescu-Pele, 2019; Trucíos et al., 2019). Besides the function of risk evaluation these measures of risk increase the accuracy of forecasting (Jiang et al., 2022; Görgen et al., 2022; Müller et al., 2022). Jiang et al. (2022) used a method capturing the stylized facts and found that including analysis of stylized facts in the analysis is useful for capturing sudden changes in the density of cryptocurrency returns. Müller et al. (2022) suggested that the main driver for the returns of cryptocurrencies is the conditional standard deviation and not the distribution of the error term. Görgen et al. (2022) compared VaR with random forest and showed that the random forest method significantly improves the forecasting performance and helps more clearly to access risks of cryptocurrencies that are prone to speculation and hypes and have the most active users. Furthemore, empirical findings by Qian et al. (2022) showed that bitcoin's price is affected by different volatility regimes. In our paper, by taking into the account the main risk measures and stylized facts we will broaden the existing research by exploring the volatility clusters.

Due to technological nature bitcoin and other cryptocurrencies are usually compared with tech-stocks. Chu et al. (2021) explored bitcoin comparing it which tech-stocks and found that individuals see bitcoin more as an investment than a technology. Abakah et al. (2023) explored bitcoin and artificial intelligence stocks and found that portfolio investors can benefit by including these assets in their diversified portfolios. Wang et al. (2022) found dependences between stock and cryptocurrency markets and their results help to predict the development trend of the high-tech industry. In this paper, we compare bitcoin with tech-stocks by extending existing research from an individual perspective to the research on volatility topic.

Literature analysis showed that cryptocurrency market is inefficient compared with gold and stock markets. Stronger deviations, uncertainty, and volatility are the results of the irrational behavior of investors. This confirms the need for scientists to fill the research gap and give a better understanding of cryptocurrencies. Literature analysis shows that cryptocurrencies offer diversification benefits and can work as a hedge in the investment portfolio. Scientific research explores volatility clustering and seasonal patterns in the cryptocurrency market, however, still there is a lack of empirical research which performs sensitivity analysis of both cryptocurrencies and tech-stocks and gives valuable insights into the volatility clustering and the risk in these markets.

2. Methodology

2.1. Data

In this study, we analyze daily closing data for the 3 cryptocurrencies bitcoin, ripple and ethereum. Cryptocurrencies have different functionality which is why it is interesting to compare how they react to each other and to external factors. Bitcoin is a purely peer-to-peer version of decentralized digital currency, while ethereum is used for smart contracts functionality and ripple is the first global real-time gross settlement network (RTGS) which enables banks to send real-time international payments across networks. Data for each cryptocurrency is taken from the earliest date publicly available online at https://coinmarketcap.com. Data used for bitcoin starts from 2013-04-29, for ethereum starts from 2013-08-04 and for ripple starts from 2015-08-08. All cryptocurrencies have data until 2021-12-31. All figures and tables in our empirical research are created by authors using the data we have, R programming language and Microsoft Excel.

2.2. Methods

The empirical analysis is based on daily returns, calculated as the difference in the log of prices. For each cryptocurrency, daily returns were computed by

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \times 100, \tag{1}$$

with P_t being the closing on day *t*.

We explored stylized facts such as outliers, autocorrelation, volatility clustering and normality.

In first step, we excluded the biggest outlier for each cryptocurrency to give more reasonable results.

We tested the normality of cryptocurrency returns using the Jarque-Bera and Shapiro-Wilk tests. The Jarque-Bera test is based on skewness and kurtosis and is defined as:

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right), \tag{2}$$

where *S*, *K*, and *N* represent the skewness, the kurtosis, and the sample size. The Shapiro–Wilk test is defined as:

$$SW = \frac{\left(\sum_{i=1}^{n} a_i X_{(i)}\right)^2}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}, \tag{3}$$

where $X_{(i)}$ are the ordered random sample values, $\overline{X}$ is sample mean, a_i is constants that derived generated from the means, variances and covariances of the order statistics of a sample of size n from a normal distribution. When the p-value is less than or equal to 0.05, the test rejects the normality hypothesis.

Autocorrelation analysis provides information about the presence of a significant periodic component in the data set. The correlation between returns separated by τ periods is evaluated by the autocorrelation of a set of n observations with lag τ:

$$\widehat{\rho_{\tau,r}} = \sum_{t=1}^{n-\tau}\left(r_t - \overline{r}\right)\left(r_{t+\tau} - \overline{r}\right) / \sum_{t=1}^{n}\left(r_t - \overline{r}\right)^2, \ \tau > 0, \tag{4}$$

where $\overline{r}$ the sample mean of all *n* observations, $\hat{\rho}$ indicates that the sample statistic estimates a correlation parameter ρ of a stochastic process when the data come from a stationary process. The two subscripts τ and *r* respectively state the lag and the series that provide the estimates.

The Ljung-Box statistic shows the existence of significant first-order autocorrelation in the residuals. In general, the Ljung-Box test is defined as:

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k}, \tag{5}$$

where $\hat{r}_k$ is the estimated autocorrelation of the series at lag k, and m is the number of lags being tested.

If p-value of the test is less than 0.05 with 95 percent confidence level we can reject the null hypothesis of the test, that the model does not exhibit lack of fit, and conclude that the data values are dependent which means that returns data is suitable for ARCH modelling. The ARCH-LM test is a Lagrange multiplier test to evaluate the importance of autoregressive conditional heteroskedastic (ARCH) effects.

We evaluated correlation, cross-correlation and rolling correlation coefficients. Correlation measures the degree to which two variables move in relation to each other. Cross-correlation show the similarities in the movement of two factors over time and rolling correlations are simply applying a correlation between two time series over time.

After comprehensive data analysis, we performed sensitivity analysis, measured Value-at-risk (VaR) and Expected Shortfall (ES) on year by year basis in 2016–2021 and back-tested results.

Sensitivity analysis of the cryptocurrency returns started from an interpretation of summary statistics and evaluation of its historical changes. Estimation of two major tail risk measures Value-at-Risk (VaR) and Expected Shortfall (ES) give a good understanding of the risk of cryptocurrency returns. VaR is a function of two parameters: the time horizon (n days) and the confidence level (α%). It is the loss level over N days that has a probability of only (100-α) % of being exceeded. The most simple way to define VaR, according to McNeil et al. (2015) is to imagine, that the VaR of our portfolio at the confidence level $\alpha \in (0, 1)$ is given by the smallest number l such that the probability that the loss L exceeds l is no larger than (1 – α). It is defined as given in (6) formula:

$$VaR_\alpha = \inf\left\{l \in R : P(L > l) \le 1-\alpha\right\} = \inf\left\{l \in R : F_L(l) \ge \alpha\right\}. \tag{6}$$

The historical method of VaR is a non-parametric VaR estimation method using the historical distribution and the probability quantile of the distribution. The return at the correct quantile (usually 95% or 99%), is the non-parametric VaR estimate. This method assumes that all possible future variations have been experienced in the past and that the historically simulated distribution is identical to the return's distribution over the forward-looking risk horizon.

Modified VaR measure incorporates skewness and kurtosis via an analytical estimation using a Cornish Fisher (a special case of a Taylor) expansion. The resulting measure is referred to variously as "Cornish Fisher VaR".

According to Artzner et al. (1999), the expected shortfall is the conditional expectation of loss given that the loss is beyond the VaR level. Yamai and Yoshiba (2005) define the expected shortfall as given in (7) formula:

$$ES_\alpha(X) = E|X|X \ge VaR_\alpha(X), \tag{7}$$

where X is a random variable denoting the loss of a given portfolio.

The expected shortfall indicates the average loss when the loss exceeds the VaR level.

Back-testing is the practice of evaluating risk measurement procedures by comparing ex-ante estimates/forecasts of risk measures with ex-post realized losses and gains. It tests how well risk estimates would have performed in the past. It allows us to evaluate whether a model and estimation procedure produce credible risk measure estimates. Methodologies fall into three categories: coverage tests, distribution tests and independence tests.

Coverage tests assess whether the frequency of exceedances is consistent with the quantile of loss a VaR measure is intended to reflect. Distribution tests are goodness-of-fit tests applied to the overall loss distributions forecast by complete VaR measures. Independence tests assess whether results appear to be independent of one period to next. Our empirical research use coverage tests as a back-testing technique.

Also, by using rolling correlations we compared how bitcoin is correlated with tech-stocks and performed the same sensitivity analysis for tech-stocks.

3. Results

3.1. Data analysis – descriptive statistics and quantiles

We started our analysis with descriptive statistics as it summarizes the characteristics of a data set. We evaluated measures of central tendency for bitcoin, ethereum and ripple and analysed measures of variability to provide basic information about variables in a dataset. From descriptive statistics, we can see that our data are following big variations.

Table 1. Descriptive statistics of bitcoin daily returns per all analysed period and different years from 2013 to 2021

	Variance	SD	Min	Max	Mean	Skew	Kurt	Median
BTC_Price	14388863	3793.27	68.43	19497.4	3126.08	1.26	0.82	736.52
BTC_Ret_all	0.0018	0.0427	–0.2337	0.4297	0.0026	0.5049	9.7027	0.0018
BTC_Ret_2013	0.0047	0.0685	–0.2337	0.4297	0.009	0.8921	8.1305	0.0073
BTC_Ret_2014	0.0015	0.0391	–0.1887	0.1929	–0.0016	–0.0239	5.6712	–0.0017
BTC_Ret_2015	0.0013	0.036	–0.2115	0.1782	0.0015	–0.868	7.8131	0.0012
BTC_Ret_2016	0.0006	0.0252	–0.1533	0.1195	0.0025	–0.279	8.8065	0.0018
BTC_Ret_2017	0.0025	0.05	–0.1874	0.2525	0.0085	0.4385	3.8035	0.0088
BTC_Ret_2018	0.0018	0.0425	–0.1685	0.1322	–0.0026	–0.2119	1.7405	0.0008
BTC_Ret_2019	0.0013	0.0356	–0.1409	0.1736	0.0023	0.5648	4.6202	0.0012
BTC_Ret_2020	0.0014	0.0377	–0.3717	0.1819	0.0046	–2.1970	27.9693	0.0027
BTC_Ret_2021	0.0018	0.0421	–0.1377	0.1875	0.0022	0.1127	1.5231	0.0013

By analysing descriptive statistics of bitcoin (BTC), ripple (XRP) and ethereum (ETH) we can see that the first year of analysis was the early stage of the crypto market and it followed big variations (Tables 1–3). Another high-intensity period was 2017 booming at the end of the year. We can see that 2017 was extremely high in daily returns for ripple which had the biggest loss in daily returns and a lot of larger positive returns (Table 2). Returns were positively skewed with the biggest positive value and it had an extremely high kurtosis value.

Table 2. Descriptive statistics of ripple daily returns per all analysed period and different years from 2013 to 2021

	Variance	SD	Min	Max	Mean	Skew	Kurt	Median
XRP_Price	0.1	0.317	0.003	3.38	0.189	3.932	24.818	0.015
XRP_Ret_all	0.007	0.082	–0.46	1.794	0.004	6.339	109.457	–0.003
XRP_Ret_2013	0.022	0.148	–0.338	0.81	0.02	1.811	7.254	0.008
XRP_Ret_2014	0.004	0.065	–0.401	0.291	0.002	–0.041	6.6	–0.001
XRP_Ret_2015	0.002	0.045	–0.151	0.258	–0.003	0.952	5.797	–0.004
XRP_Ret_2016	0.001	0.037	–0.103	0.393	0.001	4.344	37.406	–0.004
XRP_Ret_2017	0.021	0.144	–0.46	1.794	0.024	6.262	65.955	0
XRP_Ret_2018	0.005	0.068	–0.298	0.38	–0.003	0.698	5.259	–0.005
XRP_Ret_2019	0.001	0.037	–0.126	0.257	–0.001	0.959	7.707	–0.003
XRP_Ret_2020	0.006	0.080	–0.327	0.560	0.007	1.557	10.048	0.002
XRP_Ret_2021	0.002	0.047	–0.195	0.211	–0.004	0.166	3.785	–0.004

Table 3. Descriptive statistics of ethereum daily returns per all analysed period and different years from 2015 to 2021

	Variance	SD	Min	Max	Mean	Skewness	Kurtosis	Median
ETH_Price	58257.01	241.36	0.43	1396.42	203.34	1.82	3.62	149.02
ETH_Ret_all	0.0042	0.065	–0.2706	0.5103	0.0054	1.1909	7.5799	–0.0008
ETH_Ret_2015	0.0129	0.1137	–0.728	0.5103	0.0006	–0.4891	15.02	–0.009
ETH_Ret_2016	0.0048	0.0693	–0.2633	0.3536	0.0082	0.7657	4.253	–0.0025
ETH_Ret_2017	0.0053	0.0731	–0.2706	0.3366	0.0151	1.0223	3.8806	0.0039
ETH_Ret_2018	0.0031	0.0561	–0.1869	0.1807	–0.0032	–0.0244	1.1324	–0.0026
ETH_Ret_2019	0.0017	0.0411	–0.1674	0.156	0.0006	–0.1169	3.2202	–0.0008
ETH_Ret_2020	0.003	0.056	–0.272	0.259	0.006	0.009	3.418	0.006
ETH_Ret_2021	0.002	0.041	–0.148	0.114	–0.004	–0.283	0.886	0.000

Another common thing seen from the results about all analysed cryptocurrencies is that the mean of analysed cryptocurrencies was negative (Tables 1–3). Even though bitcoin had more than half positive daily returns, data was negatively skewed and maximum return was the lowest in all periods analysed. All these points show that after booming at the end of 2017, traders lost their trust in bitcoin. However, another common point highlighted for those cryptocurrencies is that all of them became more stable in 2019 as price fluctuations for all of them had the lowest values and the minimum loss value was the lowest, as well. Bitcoin, ethereum and ripple had a higher mean of returns value in 2019 compared with 2018 (Tables 1–3).

Almost in all periods ethereum and ripple had 50% values of negative daily returns while bitcoin results were positive (Tables 4–6). Even though half of the returns of ripple and ethereum were negative almost in all periods but 75% quantile showed that ripple an ethereum tend to reach higher positive returns, for example, bitcoin's 75% quantile value is 0.184, ripple's is 0.0197 and ethereum's is 0.0276. Given findings lead to the conclusion that it is necessary to evaluate periods in which prices are changing separately as daily closing prices do not show the exact returns of market participants.

Table 4. Quantiles of bitcoin daily returns per all analysed period and different years from 2013 to 2021

Quantiles	0%	25'%	50%	75%	100%
BTC_Price	68.43	378.48	736.52	6308.52	19497.4
BTC_Ret_all	–0.2337	–0.0126	0.0018	0.0184	0.4297
BTC_Ret_2013	–0.2337	–0.0168	0.0073	0.0327	0.4297
BTC_Ret_2014	–0.1887	–0.0169	–0.0017	0.0133	0.1929
BTC_Ret_2015	–0.2115	–0.011	0.0012	0.0171	0.1782
BTC_Ret_2016	–0.1533	–0.0055	0.0018	0.0098	0.1195
BTC_Ret_2017	–0.1874	–0.014	0.0088	0.0327	0.2525
BTC_Ret_2018	–0.1685	–0.0229	0.0008	0.0159	0.1322
BTC_Ret_2019	–0.1409	–0.0126	0.0012	0.0152	0.1736
BTC_Ret_2020	–0.3717	–0.0094	0.0027	0.0177	0.1819
BTC_Ret_2021	–0.1377	–0.0218	0.0013	0.0252	0.1875

Table 5. Quantiles of ripple daily returns per all analysed period and different years from 2013 to 2021

Quantiles	0%	25'%	50%	75%	100%
XRP_Price	0.0028	0.0066	0.0147	0.3001	3.38
XRP_Ret_all	–0.4600	–0.0224	–0.0028	0.0197	1.7937
XRP_Ret_2013	–0.3382	–0.0503	0.0084	0.0726	0.8095
XRP_Ret_2014	–0.4013	–0.0257	–0.0015	0.0284	0.2909
XRP_Ret_2015	–0.1511	–0.0220	–0.0039	0.0140	0.2580
XRP_Ret_2016	–0.1032	–0.0132	–0.0039	0.0090	0.3929
XRP_Ret_2017	–0.4600	–0.0232	–0.0006	0.0335	1.7937
XRP_Ret_2018	–0.2967	–0.0380	–0.0053	0.0226	0.3799
XRP_Ret_2019	–0.1256	–0.0160	–0.0026	0.0126	0.2568
XRP_Ret_2020	–0.4233	–0.0180	0.0016	0.0193	0.3971
XRP_Ret_2021	–0.3272	–0.0303	0.0023	0.0335	0.5601

Table 6. Quantiles of ethereum daily returns per all analysed period and different years from 2015 to 2021

Quantiles	0%	25'%	50%	75%	100%
ETH_Price	0.4348	11.3525	149.0150	286.4175	1396.4200
ETH_Ret_all	–0.2706	–0.0235	–0.0008	0.0276	0.5103
ETH_Ret_2015	–0.7280	–0.0406	–0.0090	0.0339	0.5103
ETH_Ret_2016	–0.2633	–0.0257	–0.0025	0.0353	0.3536
ETH_Ret_2017	–0.2706	–0.0174	0.0039	0.0366	0.3366
ETH_Ret_2018	–0.1869	–0.0305	–0.0026	0.0245	0.1807
ETH_Ret_2019	–0.1674	–0.0181	–0.0008	0.0183	0.1560
ETH_Ret_2020	–0.4235	–0.0159	0.0053	0.0297	0.1894
ETH_Ret_2021	–0.2720	–0.0223	0.0059	0.0368	0.2595

3.2. Stylized facts

In order to evaluate accurate returns, we chose to calculate continuously compounded logarithmic daily returns for cryptocurrencies as it shows overall returns through the analysed period. Bitcoin is the first and best-known cryptocurrency with the largest capitalization. However, when analysing logarithmic returns, we can see that bitcoin's returns are not larger than 0.2, while for both ripple and ethereum it could reach 0.4 (Figure 1). Ethereum had significant returns just at the beginning of the analysed period, but it is clear that ripple has the largest returns spikes. Ripple and bitcoin had similar spikes at the end of 2017. Otherwise, ripple and ethereum look more stable in 2019 than bitcoin.

Figure 1 presents that there could exist some correlations of returns as well as clusters of volatility when lower volatility periods are followed by higher volatility periods. In order to make any conclusions about cryptocurrencies volatility clustering, we need to start with the analysis of stylized facts. Stylized facts are relevant statistical measures used for traditional financial instruments. In our empirical research, we analysed four main stylized facts such as distribution of outliers, autocorrelation, volatility clustering and normality.

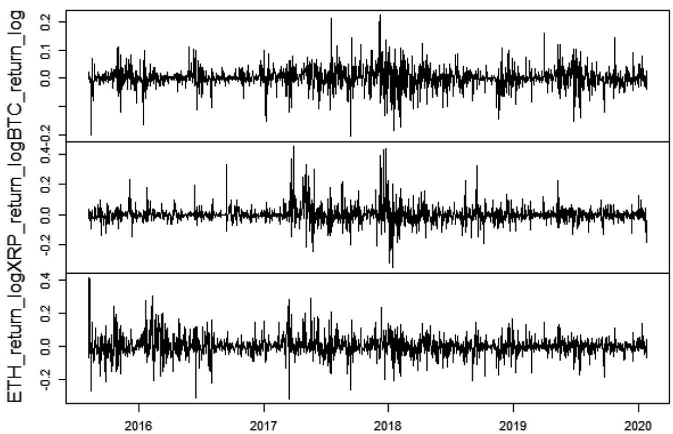

Figure 1. Logarithmic daily returns of bitcoin, ripple and ethereum cryptocurrencies per all analysed period

3.2.1. Outliers

Outlier analysis showed that all analysed cryptocurrencies have at least one big outlier. Ripple has a big positive outlier, bitcoin and ethereum have a big negative outlier which is associated with Covid-19 pandemic. After removing the biggest outlier for each cryptocurrency we see that ripple has the biggest range from –0.6 to 0.6, showing that ripple has more extreme values. Returns of all cryptocurrencies are around zero, boxplot of bitcoin and ethereum looks quite similar and accordingly goes from –0.2 to 0.2 and from –0.3 to 0.3 (Figure 2).

3.2.2. Normality

Next, we checked normality using Jacque-Bera and Shapiro-Wilk tests (Table 7). As per given results, data distribution follows a non-normal distribution. As there was previously analysed bitcoin is more skewed to the left which shows that there are more negative than positive returns.

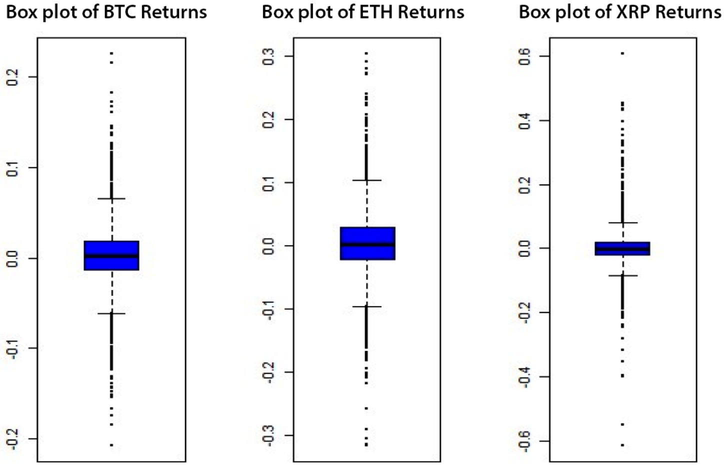

Figure 2. Box plots of bitcoin, ripple and ethereum logarithmic returns

Table 7. Bitcoin, ripple and ethereum normality tests results

Cryptocurrency	Normality test	Shapiro-Wilk	Jarque Bera
BTC	Chi-squared	0.888	6195
	p-value	0	0
XRP	Chi-squared	0.76	90911
	p-value	0	0
ETH	Chi-squared	0.917	2005
	p-value	0	0

3.2.3. Autocorrelation

Autocorrelation was checked using the Ljung-Box test. As p-value of the test in all cases is less than 0.05 with 95 percent confidence level we can reject the null hypothesis of the test and conclude that the data values are dependent which means that returns data is suitable for ARCH modelling (Figure 3). Next, we perform the ARCH Lagrange multiplier test of no conditional heteroskedasticity against an ARCH model. As p-value of the test in all cases is less than 0.05 with 95 percent confidence level we can reject the null hypothesis of the test and conclude that a series of residuals exhibit conditional heteroscedasticity.

The ARCH test is a vital tool for examining the time dynamics of the second moments. The presence of a significant excess kurtosis is not indicative of time-varying volatility, but the reverse is true: a significant ARCH effect identifies time-varying conditional volatility, volatility clustering, and, as a result, the presence of a fat-tailed distribution.

Table 8 represents that for ripple and ethereum, p-values of the test are equal or close to zero. Autocorrelation of bitcoin logarithmic returns shows that data is uncorrelated with itself previous returns (p-value = 0.33 > 0.05).

However, the ACF of squared logarithmic and absolute returns show that there exist higher-order dependencies which could be modelled. Figure 4 graphically shows that there are clear ARCH effects for bitcoin, ripple and ehereum squared logarithmic and absolute

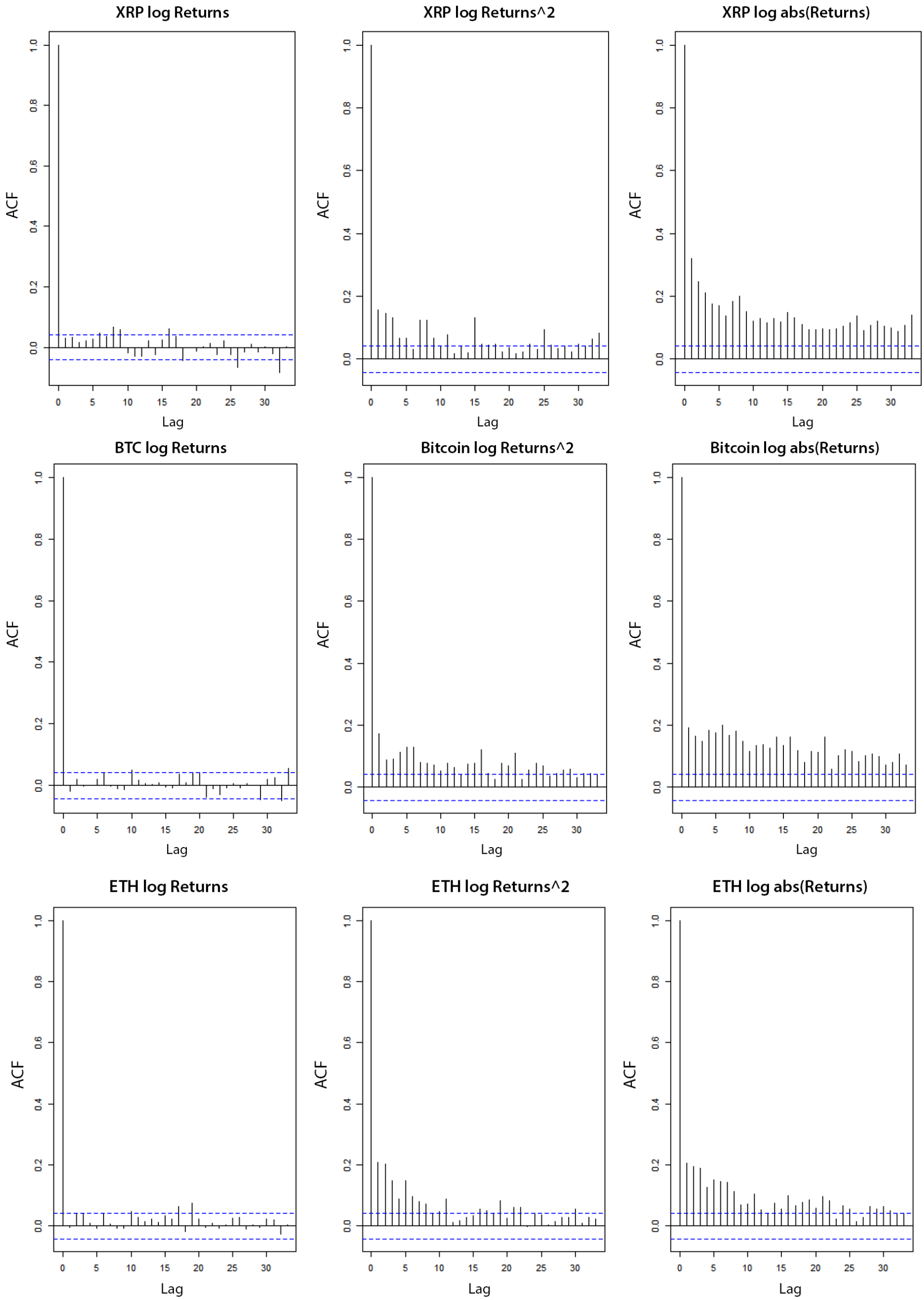

Figure 3. Autocorrelation of bitcoin, ripple, ethereum logarithmic, squared, and absolute returns

returns, so they can be easily used for prediction. According to Gyamerah (2019) results of Ljung box and LM test can be concluded that the volatility ARCH effect is very much present in the return series. The p-value of the Box-Ljung test is almost zero, which indicates a failure to reject the no ARCH effects null hypothesis.

Table 8. Bitcoin, ripple and ethereum autocorrelation results of Box-Ljung test for logarithmic, squared, and absolute returns. ARCH LM test results for all period

	BTC		ETH		XRP	
Box-Ljung test	Chi-squared	p-value	Chi-squared	p-value	Chi-squared	p-value
ret_log	31.755	0.33	53.014	0.01	74.155	0
ret_log^2	444.38	0	482.12	0	386.41	0
ret_abs	1222.4	0	713.54	0	1477.9	0
ARCH LM-test	139.36	0	215.15	0	162.37	0

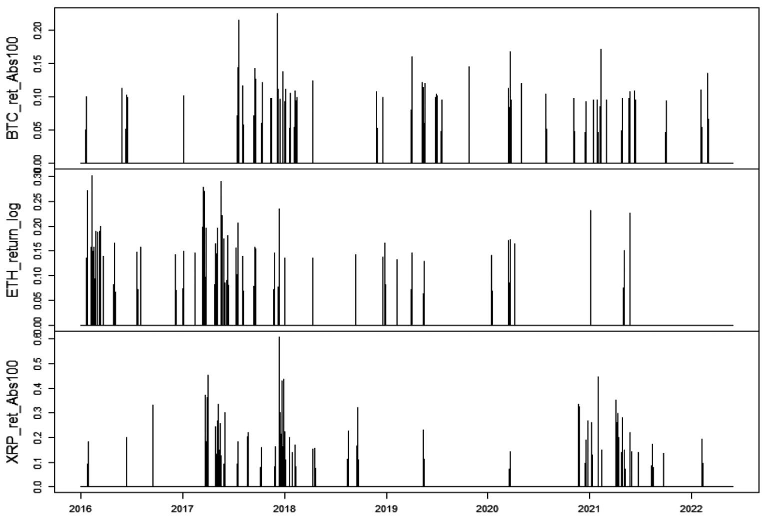

Figure 4. Bitcoin, ripple, ethereum volatility clusters in 2016–2021

3.2.4. Volatility clusters

After all the informative analysis of relations between cryptocurrency pairs, it becomes clear that some pairs are strongly related and follow each other. Other cryptocurrency pairs occasionally reflect changes with some delayed effects. Figure 4 gives visual evidence of volatility clustering with all the cryptocurrencies. There are some periods of extreme volatility of the daily returns that are followed by the sharp rise and falls in returns while periods with no such sharp movements tended. The volatility clustering graph shows that the series of returns exhibit conditional heteroskedasticity and here exist some fluctuation clusters with high and low returns.

3.2.5. Extreme values dependency

Extreme values are things that the most attract speculators at the same time being one of the biggest challenges for scientists. Previous descriptive statistics analysis confirmed that there

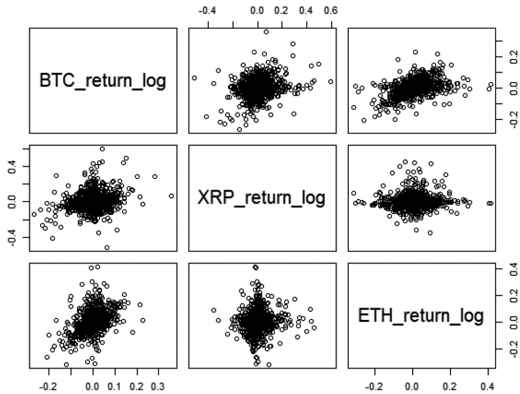

Figure 5. Heavy tails of ethereum and ripple, bitcoin and ethereum, bitcoin and ripple pairs

exist outliers and that kurtosis values support the idea of heavy tails. Outliers and extreme values are parts of cryptocurrency data, so for further analysis, it is obligatory to manage how to deal with them. After graphically evaluating the dependency of extreme deviations we see that some tail dependency exists, especially between bitcoin and Ethereum (Figure 5). That means if bitcoin reaches high values, ethereum could follow as tails are dependent on each other.

Stylized facts analysis confirmed finding that we deal with highly volatile data and dependent cryptocurrency pairs which have delayed effects.

3.2.6. Dependencies across cryptocurrencies

After a graphical evaluation of the return data, it becomes clear that there exist some relations between analysed cryptocurrencies. It is well-known that correlation analysis could be efficiently used in financial markets. If there exist any negatively correlated cryptocurrencies, investors could easily profit from them by taking advantage of hedging their portfolio and reducing market risk due to volatility.

According to correlation coefficients, there is medium strength linear relationship between cryptocurrency pairs (Table 9). However, correlation gives generalized results, so we looked further at cross-correlations and rolling correlations.

Table 9. Bitcoin, ripple and ethereum correlation matrix results

	XRP_return_log	BTC_return_log	ETH_return_log
XRP_return_log	1	0.53	0.58
BTC_return_log	0.53	1	0.59
ETH_return_log	0.58	0.59	1

3.2.6.1. Cross correlation

We evaluated cross correlation considering the degree of similarity between two time series in different lagged periods. Cross correlation value showed there is a medium-strength relation between bitcoin and ripple price. Figure 6 shows results by including time lag.

From time to time their values increase more than the accepted interval from –0.05 to 0.05. Findings from cross-correlation between bitcoin and ripple show that if one changes

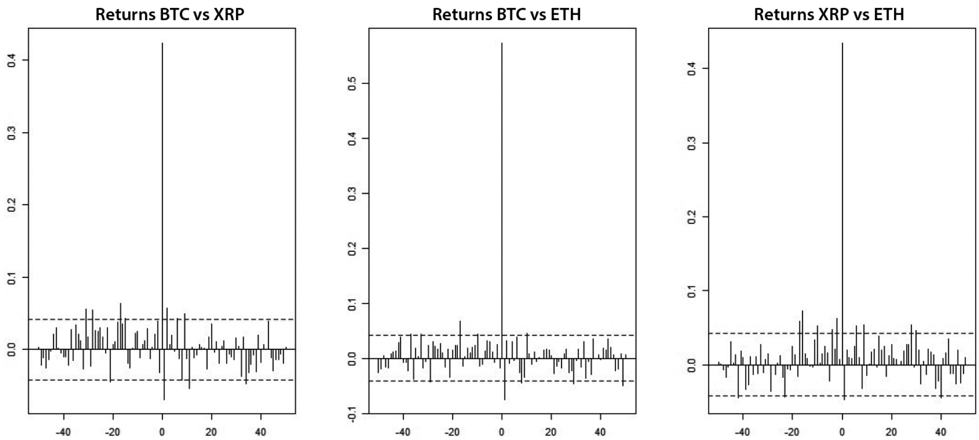

Figure 6. Cross-correlation of bitcoin, ripple and ethereum with 50 lag

per 1 point, another reacts to that change and moves the same direction after about 17 and more than 35 days. Also, it reacts negatively after one day. When evaluating the correlation coefficient between bitcoin and ethereum there is only reaction after 17 days and a negative reaction after 1 day. After measuring cross-correlations for ripple and ethereum it could be easily visually seen that cross-correlation usually occurs after a few days as cross-correlation values breach the given tolerance interval from –0.05 to 0.05.

3.2.6.2. Rolling correlation

Finally, another type of correlation is a rolling correlation which measures the volatility of returns through all periods. Figure 7 shows the rolling correlations of the cryptocurrencies log-returns series available at each period. Rolling correlations are calculated over a backwards-looking window of 30 days. Despite that rolling correlation between bitcoin and ethereum was unstable until 2018, there is a unique change from the well-known spike at the end of 2017. We can see that after big bitcoin price movements in the end of 2017, 2018

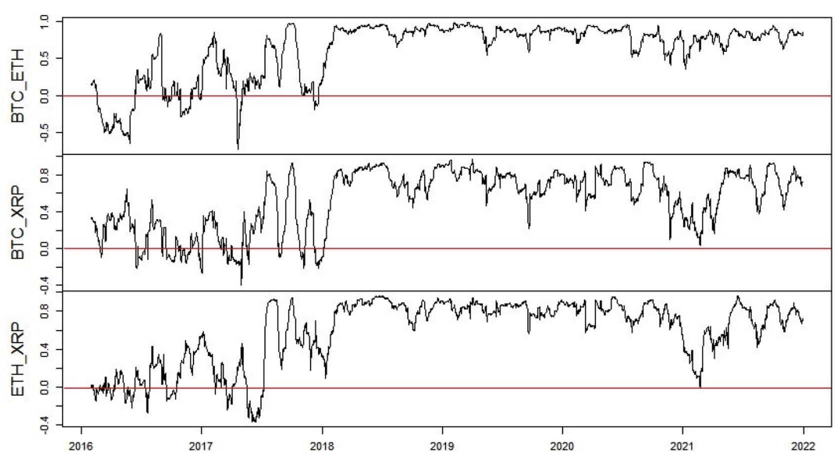

Figure 7. Rolling correlation for ethereum and ripple, bitcoin and ethereum, bitcoin and ripple pairs

started with strong correlation between all analysed cryptocurrency pairs and it remains until the beginning of 2022. Only correlation between ethereum and ripple started to weaken in the end of 2020 but it continue to be strong from the middle of 2021. These results show that cryptocurrencies are strongly related to each other.

According to De Pace and Rao (2022), correlations are natural to understand because cryptocurrencies are, in general, independently created and are based on slightly different platforms, technologies, and protocols. Thus, they exhibit different features, characteristics, and limitations. Findings based on correlation analysis lead to the conclusion that cryptocurrencies are related to each other. Extreme values on the main bitcoin cryptocurrency may tend to affect other cryptocurrencies with a delayed effect. Also, correlations are changing over time, so in order to achieve the best results and make predictions, it is necessary to evaluate how they change.

3.2.7. Comparison with tech-stocks

By looking at rolling correlations between tech-stocks and bitcoin we can see that it follows some cycles (Figure 8). However, even if in some periods correlation coefficient shows medium strength linear dependency with coefficient value of 0.5 or 0.6, soon correlation goes to zero, or even negative value and cycles changes. Overall, by looking at the graph we can see that there is no correlation between tech-stocks and bitcoin as correlation coefficient between them usually fluctuates around zero. As bitcoin, ripple and ethereum are not correlated with tech-stocks, they can be used together with tech-stocks in a diversified portfolio.

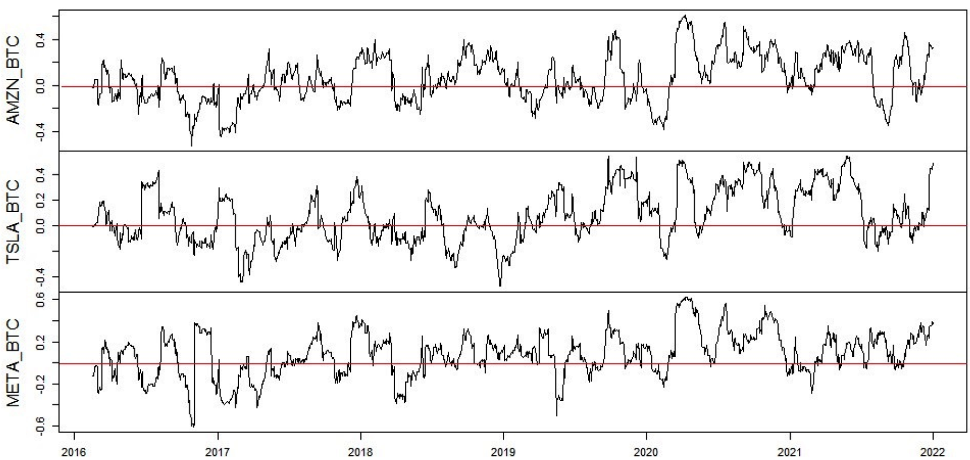

Figure 8. Rolling correlation for Amazon and bitcoin, Tesla and bitcoin, Meta and bitcoin pairs

4. Evaluation of risk measures

A further empirical sensitivity analysis follows with the best-known risk estimation measures of Value-at-Risk (VaR) and Expected Shortfall (ES). VaR modelling determines the potential for loss in the entity being assessed and the probability of occurrence for the defined loss. The empirical analysis included nonparametric methods for VaR estimation as logarithmic returns are non-stationary, there is no normal distribution and outliers exist. There were used historical, modified and gaussian methods. VaR gives the maximum loss on a portfolio over a specific time period for a certain level of confidence.

4.1. Bitcoin, ethereum and ripple – VaR, ES

Sensitivity analysis for Value-at-Risk and Expected Shortfall shows that results are almost the same for bitcoin in all exchanges using historical, modified and gaussian methods (Figure 9). However, in all cases, the modified method gives not reliable results as with increasing confidence level risk measures steadily go down until some point after which risk measures become smaller. This shows that the modified method is not suitable for evaluating ES. In order to check if the results are accurate, we used well-known back-testing technique.

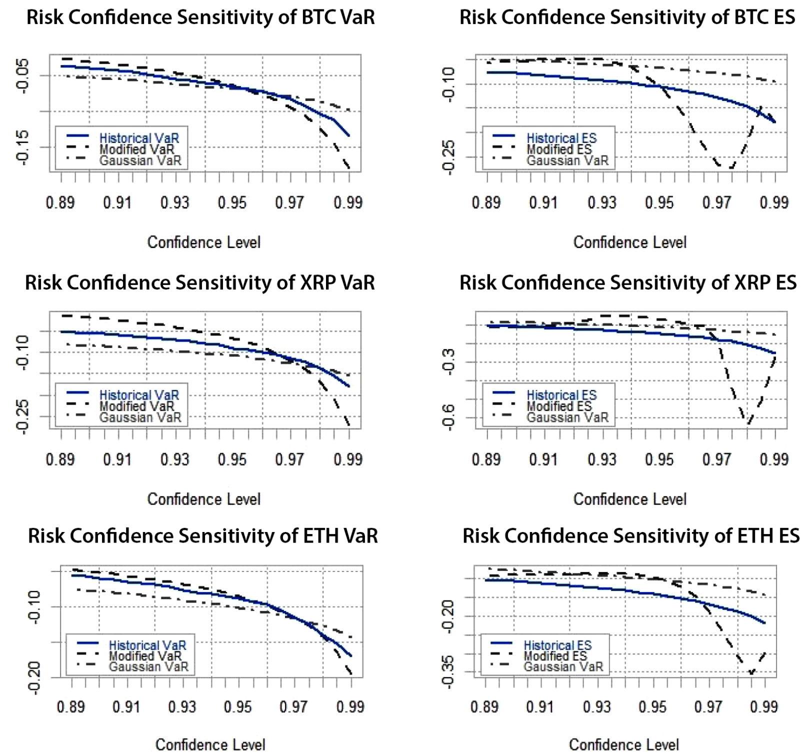

Figure 9. Risk confidence sensitivity for bitcoin, ripple, ethereum Value-at-Risk and Expected Shortfall

An analysis is based on evaluation with confidence levels of 95%. We determined one-day VaR for bitcoin in 2021 is equal to 6.4% with historical method (Table 10). This means that with a 95% confidence level the worst daily loss will not exceed 6.4% for bitcoin. Ripple and ethereum experience larger VaR values of 9.8% and 7.9% accordingly. It is clear that with a 95% confidence level gaussian method gives larger VaR values while the historical method shows the smallest VaR value. Bitcoin is still considered the least risky cryptocurrency as VaR values with all methods are smaller than for other cryptocurrencies.

Back-testing determines the exceedance amount of a VaR model by involving the comparison of the calculated VaR measure to the actual losses (or gains) achieved. Value shows how many times values exceeded the expected VaR level (Table 10). In this case, the smaller the exceedance amount the better and we can see that most of the time best results are achieved using the historical method.

Table 10. VaR for bitcoin, ripple, ethereum with 95% confidence levels using Historical, Modified and Gaussian methods

	BTC			XRP			ETH		
	Historical	Modified	Gaussian	Historical	Modified	Gaussian	Historical	Modified	Gaussian
2016	0.027	0.036	0.039	0.042	0.023	0.052	0.081	0.084	0.105
Exceed	11	20	19	10	16	22	17	23	30
2017	0.073	0.063	0.073	0.094	0.030	0.162	0.083	0.077	0.105
Exceed	28	29	33	6	21	18	13	23	23
2018	0.077	0.073	0.072	0.099	0.094	0.115	0.099	0.094	0.095
Exceed	16	20	16	14	19	20	22	23	20
2019	0.047	0.047	0.056	0.057	0.056	0.058	0.066	0.066	0.067
Exceed	13	22	24	17	24	19	17	22	19
2020	0.045	0.041	0.046	0.073	0.065	0.097	0.065	0.058	0.065
Exceed	18	27	22	12	31	28	17	26	21
2021	0.064	0.066	0.066	0.098	0.070	0.125	0.079	0.082	0.086

Expected Shortfall is defined as the average of all losses which are greater or equal than VaR. It gives the expected value of an investment in the worst case (Table 11). For bitcoin, using historical method this value with a 95% confidence level is equal to 9.4% and for ripple is equal to 16.4%. It shows that in the worst-case loss in bitcoin would be 9.4% which is less than 16.4% for ripple. The difference between VaR and ES for bitcoin is equal to 3 % and for ripple this difference is 6.6%. That means that in worst case ripple is more likely to evidence losses.

Table 11. ES for bitcoin, ripple, ethereum with 95% confidence levels using Historical, Modified and Gaussian methods

	BTC			XRP			ETH		
	Historical	Modified	Gaussian	Historical	Modified	Gaussian	Historical	Modified	Gaussian
2016	0.061	0.089	0.050	0.059	0.109	0.072	0.146	0.138	0.134
2017	0.107	0.107	0.094	0.170	0.091	0.190	0.135	0.109	0.132
2018	0.111	0.117	0.092	0.161	0.166	0.145	0.141	0.143	0.121
2019	0.081	0.070	0.071	0.087	0.054	0.077	0.104	0.120	0.085
2020	0.064	0.049	0.060	0.144	0.205	0.127	0.094	0.092	0.084
2021	0.094	0.097	0.085	0.164	0.100	0.155	0.127	0.163	0.111

Finally, graphs for predicted values and backtesting results for bitcoin, ripple and ethereum are presented in Appendix A.1, A.2, A.3 given in the external Mendeley Data repository (Bruzgė, 2023).

4.2. Amazon, Tesla and Meta – VaR, ES

As explored in literature analysis, scientists find some significant relationships between cryptocurrency and the stock market. In our empirical research, we decided to compare cryptocurrency results with traditional financial assets. As cryptocurrencies are usually compared with tech-stocks, we picked 3 of the best-known tech-stocks such Tesla, Amazon and Meta. We did the same sensitivity analysis for tech-stocks (Tables 12–13).

Table 12. VaR for Tesla, Meta and Amazon with 95% confidence levels using Historical, Modified and Gaussian methods

	TSL			META			AMZN		
	Historical	Modified	Gaussian	Historical	Modified	Gaussian	Historical	Modified	Gaussian
2016	0.039	0.043	0.039	0.026	0.010	0.026	0.028	0.027	0.028
Exceed	15	11	11	15	15	9	11	10	8
2017	0.035	0.036	0.035	0.016	0.017	0.016	0.016	NA	0.019
Exceed	12	13	12	14	10	10	13	8	9
2018	0.052	0.051	0.060	0.032	0.034	0.034	0.042	0.037	0.036
Exceed	12	13	9	18	18	18	18	8	21
2019	0.050	0.050	0.050	0.024	0.023	0.027	0.023	0.023	0.023
Exceed	12	10	10	14	12	10	10	9	10
2020	0.077	0.089	0.084	0.043	0.048	0.047	0.038	0.035	0.037
Exceed	12	11	8	11	11	7	12	11	12
2021	0.051	0.048	0.054	0.032	0.030	0.030	0.026	0.026	0.025
Exceed	12	11	9	14	13	11	12	10	12

Table 13. ES for Tesla, Meta and Amazon with 95% confidence levels using Historical, Modified and Gaussian methods

	TSL			META			AMZN		
	Historical	Modified	Gaussian	Historical	Modified	Gaussian	Historical	Modified	Gaussian
2016	0.060	0.069	0.050	0.038	0.010	0.036	0.044	0.038	0.037
2017	0.050	0.051	0.044	0.025	0.029	0.020	0.024	0.008	0.025
2018	0.078	0.061	0.075	0.052	0.053	0.043	0.056	0.057	0.046
2019	0.079	0.095	0.063	0.036	0.027	0.034	0.033	0.034	0.029
2020	0.136	0.153	0.108	0.068	0.084	0.059	0.049	0.047	0.046
2021	0.071	0.062	0.069	0.041	0.040	0.037	0.033	0.041	0.031

Value-at-Risk sometimes was couple of times lower for tech-stocks than for cryptocurrencies. However, still, chosen stocks experienced some shocks and were sensitive for big news. As historic prices show losses could be even bigger in practice but still lower than in the cryptocurrency market.

Graphs for predicted values and back-testing results for Tesla, Meta and Amazon are presented in Appendix A.4, A.5, A.6 given in the external Mendeley Data repository (Bruzgė, 2023).

Discussion

Almeida et al. (2022) found that cryptocurrencies may have safe haven properties. Their empirical research of cryptocurrency market show that during the pandemic uncertainty increased but risk decreased. Additionally, extensive systematic literature review performed by Almeida and Gonçalves (2022) indicated that cryptocurrencies can be used as a hedge against stocks, fiat currencies and geopolitical risks. Our research confirms the safe haven properties as we showed that cryptocurrencies can be used as a hedge as they are not correlated with tech stocks. We explored the same cryptocurrencies as Melki and Nefzi (2022) for the same purpose as they did but additionally from Almeida et al. (2022), Almeida and Gonçalves (2022) and Melki and Nefzi (2022) our research was broadened by including analysis of stylized facts and value at risk measures from which we gave novel results about the existing volatility clustering in the cryptocurrency market.

Value at risk were mainly used by scientist as source to increase the accuracy of forecasting (Jiang et al., 2022; Görgen et al., 2022; Müller et al., 2022). However, in our paper we did not forecast the returns of cryptocurrencies. We used this risk measures additionally with stylized facts analysis to determine the volatility clusters and we found that there exists volatility clustering in the cryptocurrency market when active and highly volatile periods are followed by minimal activity periods.

Conclusions

Literature analysis showed that the cryptocurrency market is inefficient compared with gold and stock markets. Stronger deviations, uncertainty, and volatility are the results of the irrational behaviour of investors. Inefficiency leads to arbitrage potential, however big returns and losses, as well. An investor must be educated about the risk that he takes before investing in financial instruments with less efficiency, naming cryptocurrency and tech-stocks. Literature analysis shows that cryptocurrencies offer diversification benefits and can work as a hedge in the investment portfolio. Scientific research explores volatility clustering and seasonal patterns in the cryptocurrency market, however, still there is a lack of empirical research which performs sensitivity analysis of both cryptocurrencies and tech-stocks and gives valuable insights into the volatility clustering and the risk in these markets. Scientific literature confirm that cryptocurrency market is a unique laboratory for studying due to its' unique features and arising opportunities because of existing volatility clustering.

The overall analysis covered in this empirical research confirms that there exists some volatility clustering in bitcoin, ethereum and ripple returns. Descriptive statistics showed that bitcoin, ethereum and ripple developed through the analysed period as all of them became more stable in 2019, but were still very sensitive to shocks and were heavily influenced by the Covid-19 pandemic shock. Despite that, price fluctuations decreased and the mean for all of them remained positive. Bitcoin looks the most stable compared with ripple and ethereum. Despite that ripple was introduced earlier than ethereum, it remains less predictable as there were some periods with a high level of price shocks.

Stylized facts analysis showed that there are many outliers or extreme deviations, data is not normally distributed. After evaluation of extreme values, it was confirmed that there exists some tail dependency between different cryptocurrency pairs. Autocorrelation results confirmed that there exists higher-order dependency on squared logarithmic and absolute returns that can be modelled in predicting volatility clustering. Following that, it was confirmed existing ARCH effects for all cryptocurrencies in all analysed periods which confirms the existence of volatility clusters.

The further work provided a comprehensive and detailed analysis of the correlation between cryptocurrencies and confirmed that cryptocurrencies are strongly correlated. Comparison of rolling correlations with tech-stocks showed that there is no correlation between cryptocurrencies and tech-stocks. It confirms that cryptocurrencies can be used as a hedge in a diversified portfolio as they are not correlated with stocks. Sensitivity analysis by evaluating key risk measures of VaR and ES showed that cryptocurrencies are riskier than tech-stocks, however both cryptocurrencies and tech-stocks are sensitive to shocks in the market. While being one of the riskiest financial instruments cryptocurrencies represent a unique financial asset class which has an anti-inflationary mechanism and other advantages when comparing them with stocks.

Our results confirmed the existence of volatility clusters and showed that tech-stocks are not correlated with cryptocurrencies so based on these findings there are possible implications for businesses and policymakers. Businesses could create some diversified cryptocurrency/tech-stock high risk indexes for risk prone investors. As cryptocurrencies are decentralized, policymakers cannot regulate cryptocurrencies, but they can regulate cryptocurrency exchanges with the indirect effect for cryptocurrencies. New regulations should indicate that exchanges must maintain given requirements in order to offer trading opportunities. More requirements would lower the emergence of new exchanges as well as fraudulent ones. As a result risk coming from the high frequency trading and fraudulent activity would be minimized. Volatility clustering showed us periods of high volatility which increase risk. Policymakers could add requirements for exchanges to keep investors informed when risk in the market increases as market goes into the bigger volatility period.

Research gave a broad view and analysis of the volatility clustering topic but the main limitation is a lack of detailed analysis of volatility clusters. That's why our future direction is to expand the analysis of volatility clusters even further by finding the factors which indicates when the volatility period starts or ends and explore periods of high and low volatility more in detail.

Funding

This research has received funding from European Regional Development Fund (project No 13.1.1-LMT-K-718-05-0006) under grant agreement with the Research Council of Lithuania (LMTLT). Funded as European Union's measure in response to Cov-19 pandemic.

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