“The correlation strength of the most important cryptocurrencies in the bull and bear market”

AUTHORS	Sebastian Lahajnar https://orcid.org/0000-0003-4604-5223 https://www.webofscience.com/wos/author/record/P-8962-2018 Alenka Rožanec https://orcid.org/0000-0002-3258-0543 https://www.webofscience.com/wos/author/record/G-3520-2010

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Sebastian Lahajnar (Slovenia), **Alenka Rožanec** (Slovenia)

THE CORRELATION STRENGTH OF THE MOST IMPORTANT CRYPTOCURRENCIES IN THE BULL AND BEAR MARKET

Abstract

The article explores the correlation strength of the ten most important cryptocurrencies, emphasizing the examination of differences during the periods of rising and falling prices. The daily and weekly returns of selected cryptocurrencies are taken as the basis for calculating and determining the correlation strength using the Pearson correlation coefficient. The survey covers the period from the beginning of 2017 to Bitcoin's last local bottom in mid-March 2020. Research findings are as follows: 1) the most important cryptocurrencies are mostly moderately positively correlated with each other over time; 2) correlation strength decreases slightly during the bull period, but mostly remain in the range of moderate correlation; 3) correlation strength increases significantly during the bear period, with most cryptocurrencies strongly correlated with each other. The results do not change significantly if the daily or weekly cryptocurrency returns are used as the basis. A strong correlation in the period of falling prices prevents the effective diversification of the cryptocurrency portfolio, which must be considered when investing funds in the cryptocurrency market.

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Sebastian Lahajnar, Ph.D., Assistant Professor, BPMLAB, Ljubljana, Slovenia. (Corresponding author)

Alenka Rožanec, Ph.D., Assistant Professor, Faculty of Economics and Informatics, University of Novo Mesto, Novo mesto, Slovenia.

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INTRODUCTION

A cryptocurrency is defined as a digital or virtual currency that uses cryptographic algorithms to ensure security. Most cryptocurrencies are based on blockchain technology. This allows for developing distributed systems for conducting currency transactions and maintaining ledgers (Investopedia, 2019). The origin of the first cryptocurrency, Bitcoin, dates back to early 2009, when an unknown programmer, nicknamed Satoshi Nakamoto, produced the prototype of a distributed computer system for processing cryptocurrencies (Nakamoto, 2008). The great success of Bitcoin soon spurred the creation of many new cryptocurrencies, so that now, in mid-2020, thousands of cryptocurrencies could be traded with a total capitalization of more than USD 240 billion (Coinmarketcap, 2020).

The cryptocurrency market slowly picked up in 2019 after the big drop was witnessed the year before. The first half of 2020 also led to quite a few new insights, raising the question of whether investments in cryptocurrencies, particularly in Bitcoin, can, in the long run, become an alternative to investments in traditional investment assets, such as stocks and especially precious metals, the most important of which is gold. It became apparent that cryptocurrencies are not independent of what is happening in the stock markets, as their prices directly followed the fall of price indices on the most important global stock exchanges with the emergence of the COVID-19 virus pandemic. Today, Bitcoin strongly dictates the cryptocurrency market's general mood,

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accounting for more than 70% of the total market capitalization (TradingView, 2020). This gives Bitcoin an undisputed leading role, and it seems other cryptocurrencies are merely following it, not being able to make their own, independent paths by themselves.

The daily and weekly returns of selected cryptocurrencies are taken as the basis for calculating and determining the correlation strength using the Pearson correlation coefficient. Several analyses can be found on the World Wide Web that attempts to assess the correlation strength between individual pairs of cryptocurrencies, taking into consideration various time periods (mostly from one month to one year). As opposed to those analyses, which are more short-term, the study in this article focuses on a longer period of time (more than three years), with the emphasis on the examination of differences of correlation strength during the periods of rising prices (bull market) and falling prices (bear market).

1. LITERATURE REVIEW

Although blockchain technology is relatively new and cryptocurrencies have been traded extensively only for the past five years, several articles on this subject in the scientific literature address its individual aspects, both economic and technological, in more detail. Corbet et al. (2019) provide a systematic review of scientific literature, which has considered cryptocurrencies as new financial assets since 2019. Most studies are on the subject of efficiency of cryptocurrencies, finding that cryptocurrencies' efficiency has been relatively low in the past, but is slowly increasing over the years (Tran & Leirvik, 2020; Caporale, Gil-Alana, & Plastun, 2018; Kristoufek & Vosvrda, 2019). The research also shows that the importance of cryptocurrencies to the global economy will increase in the future. This prediction is contingent by several factors, the most important of which are the use of cryptocurrencies as a substitute for traditional currencies, the establishment of appropriate legislation, and the continued development of blockchain technology (Seetharaman, Saravanan, Patwa, & Meht, 2017). The popularity of cryptocurrencies, especially Bitcoin, is largely influenced by the increase of its value over the past decade, driven by growing demand (Ciaian, Rajcaniova, & Kancs, 2015). Demand is contingent on different triggers (De la Horra, de la Fuente, & Perote, 2019) – in the short run, Bitcoin behaves as a speculative asset, while speculations are not expected to have a major impact in the long run. Thus, demand is largely based on expectations about Bitcoin's future usability as a medium of exchange or preservation of financial value. In general, investors' sentiment has a high predictive power on the future of Bitcoin, and the influence of sentiment is greater in low sentiment regimes than in high sentiment regimes (Burggraf, Huynh, Rudolf, & Wang, 2020). The role of social media (on-line forums, portals, social networks, etc.), whose climate is an important predictor in determining the value of Bitcoin and other cryptocurrencies, should not be neglected (Mai, Shan, Bai, Wang, & Chiang, 2018).

Interestingly, macroeconomic data have no impact on Bitcoin's profitability (Corbet, Larkin, Lucey, Meegan, & Yarovaya, 2020). Opinions are divided on the relationship between traditional markets and cryptocurrencies. Thus, some studies suggest a relatively strong impact on Bitcoin by traditional stock market indices, such as S&P 500 and Dow Jones (Wang, Chen, & Zhao, 2020), while others (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018), based on analyses of dependence between cryptocurrencies and various other financial assets, such as gold and bonds, find that cryptocurrencies are quite isolated from other assets. However, the general finding is that the volatility of cryptocurrencies significantly exceeds traditional financial assets' volatility.

For this research, the authors are mainly interested in existing works dealing with the association between cryptocurrency pairs. Giudici and Polinesi (2019) thus find that Bitcoin prices on different cryptocurrency exchanges are strongly associated, with exchanges acting together as an effective single cryptocurrency market. The largest and most stable exchanges (such as Bitstamp) are the most important price-setters. According to their findings, Bitcoin's price is not associated with indices on traditional stock exchanges; however, volatility on traditional stock exchanges has a negative and time-delayed effect on Bitcoin

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volatility. Sifat, Mohamad, and Mohamed Sharif (2019) note that when considering the association between Bitcoin and Ethereum, based on daily and hourly data within one year, a two-way causality is indicated. The studies addressing multiple cryptocurrency pairs also confirm a strong and positive association between profitability (Katsiampa, Corbet, & Lucey, 2019; Aslanidis, Bariviera, & Martínez, 2019) and the interdependence between the Bitcoin and alternative cryptocurrency markets (Ciaian & Rajcaniova, 2018). In examining different time frames, the finding that stands out is that the price ratio between Bitcoin and alternative cryptocurrencies is significantly stronger in the short term than in the long term. However, cryptocurrencies' association strength is highly variable (Antonakakis, Chatziantoniou, & Gabauer, 2019) and ranges between 25% and 75%. It depends primarily on high or low market uncertainty, with high uncertainty corresponding to the strong association and low uncertainty corresponding to the weak association.

A quick review of basic price graphs of the strongest cryptocurrencies in terms of capital gives the impression that they are interdependent or follow the most important cryptocurrency – Bitcoin. Several analyses can be found on-line, which, using the statistical method of the correlation coefficient, scientifically confirm this impression to a high degree. For example, the Hackernoon website (Hackernoon, 2018) points out that the degree of correlation between Bitcoin and other cryptocurrencies has grown since the beginning of 2017 and stabilized in mid-2018, with the high growth of correlations also confirmed by a study of Cermak (2019), highlighting a weaker association between cryptocurrencies that use the so-called Proof of Work mechanism to validate transactions, compared to cryptocurrencies that use other consensus-building mechanisms. Similar conclusions are reached by the study published on cryptodigestnews.com (Cryptodigestnews, 2018), which takes as a basis the data on the values of ten most important cryptocurrencies for each year (from 2016 to 2018), and clearly shows an increase in the degree of cross-correlation. The analysis conducted by Binance Research (Binance Research, 2020) states that even in 2019, there is still a relatively high degree of the positive correlation between the 20 most important cryptocurrencies, with most ratios exceeding a coefficient of 0.5. The study further focuses on analyzing the relationships between degrees of correlation in individual quarters of the previous year. The largest change in correlations occurred in the third quarter of 2019, suggesting that cryptocurrencies could be more strongly correlated with unfavorable market price movements and less correlated with upward or sideways movements.

Interesting insights can also be gained by using graphs on the coinmetrics.io website (Coinmetrics, 2020). This allows us to obtain a graphical representation of the correlation strength between individual pairs of cryptocurrencies for the selected time period, correlation coefficient (Spearman, Pearson), and the period included in calculating the coefficient (90, 180, or 360 days). The graphs' analysis confirms previous findings, while a slight decline in the association strength can be detected in 2019. Another interesting website is cryptowat.ch (Cryptowat, 2020), which also provides an interactive overview of correlations between selected cryptocurrencies, with the data provided in tabular form.

2. AIMS

This article aims to investigate the correlations between cryptocurrencies with the largest market capitalization in the first half of 2020. The data from the last three years (from the beginning of 2017 to March 2020) were included in the study, with some cryptocurrencies included in the study only appearing in the second half of 2017. This article aims to explore the correlation strength of the ten most important cryptocurrencies with the largest market capitalization in the first half of 2020.

3. METHODS

The calculation of the correlation strength between individual pairs of cryptocurrencies is based on the statistical method of the Pearson correlation coefficient. This is the most commonly used measure of linear association of two numerical variables, requiring the use of at least the interval type of both analyzed variables and their linear association. The coefficient ranges between –1 and 1 and is calculated using both variables' covariance and standard deviations. The Pearson correlation coefficient answers whether a linear association between variables exists at all, and if so, how strong is this association. There are two possible types of association:

- a positive association exists when the values of both the first (x) variable and the second (y) variable are high or low. In such cases, the coefficient is positive and close to 1;
- a negative association exists when the first (x) variable values are high, and the values of the second (y) variable are low, or vice versa. In such cases, the coefficient is negative and close to –1.

The basis for interpreting the results of the Pearson correlation coefficient was defined by Cohen (Cohen, 1988) and upgraded by Rosenthal (Rosenthal, 1996): a coefficient of 0.1 is interpreted as a weak correlation, 0.3 as moderate, 0.5 as strong, and 0.7 as very strong. The basic scale was subsequently expanded and reworked into an interval form; the following intervals are used to interpret the results in the study:

- 0.7 to 1: very strong positive association;
- 0.5 to 0.7: strong positive association;
- 0.3 to 0.5: moderate positive association;
- 0.1 to 0.3: low positive association;
- –0.1 to 0.1: no association;
- –0.3 to –0.1: low negative association;
- –0.5 to –0.3: moderate negative association;
- –0.7 to –0.5: strong negative association;
- –1 to –0.7: very strong negative association.

The data on the values of the ten most important cryptocurrencies were taken from the Coinmarketcap website (Coinmarketcap, 2020), which provides an archive of average prices for all cryptocurrencies traded in cryptocurrency exchanges. The archive includes daily values of prices at the beginning and end of each day, the highest and lowest achieving daily value, the volume of transactions, and market capitalization. Cryptocurrencies are traded 24 hours a day, throughout the year, which means that there is no opening and closing trading value, as in the case of trading on traditional exchanges; these two values thus only represent the value of cryptocurrency in a certain time interval (the closing price of the previous day and the opening price of the next day are the same). The closing prices of cryptocurrencies are used with two time intervals – day and week – as the basis for calculations.

The correlation strength between cryptocurrencies can be most easily calculated by directly using the previously mentioned closing prices (daily or weekly) for the variables' values. The approach using levels often overestimates the strength of the correlation, which can lead to unreliable estimates. From this point of view, an approach using the mathematical concept of percentage change, which gives the rate of change over time and is often used in financial analysis, is more recommended. The percentage change is the basis for calculating the daily or weekly returns of an individual cryptocurrency, using the following formula:

$$return(t)=\left(\frac{closing\ price(t)-closing\ price(t-1)}{closing\ price(t-1)}\right)\cdot 100, \quad (1)$$

where t represents the unit of time – day or week.

The obtained daily or weekly returns recorded in percentages and rounded to two decimal places were the input data for calculating correlation coefficients between individual pairs of cryptocurrencies in selected periods (the research question dictated the testing of correlation coefficients throughout the studied period, the period of increasing and decreasing cryptocurrency prices).

The study of the correlation strengths cryptocurrencies includes the following periods:

- the entire period from the beginning of 2017 to the last local date, i.e., from 1 January 2017 to 12 March 2020. Currencies Bitcoin Cash, Eos, Binance Coin, Cardano, and Tron did not appear on cryptocurrency exchanges until later in 2017, so the calculations take into account the values from the date of registration;
- two periods of growth, specifically from 1 January 2017 to 16 December 2017, when Bitcoin reached its highest value, and from 16 December 2018 to 27 June 2019, when Bitcoin reached its last local peak;

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- two periods of decline, specifically from 17 December 2017 to 15 December 2018, when Bitcoin reached the local bottom in 2018, and from 28 June 2019 to 12 March 2020, when Bitcoin reached the last local bottom.

The following cryptocurrencies were included in the study: Bitcoin, Ethereum, Ripple, Bitcoin Cash, Litecoin, Eos, Binance Coin, Stellar, Cardano, and Tron. Tether and Bitcoin SV, which otherwise ranked fourth and sixth, were excluded from the study, while Cardano and Tron, which rank eleventh and twelfth, respectively, were included in the study. Tether (Investopedia, 2019) is a special type of cryptocurrency called a stablecoin. Its basic purpose is to maintain the price stability of cryptocurrencies, which is in stark contrast to classic cryptocurrencies' characteristics, which are characterized by high volatility. Thus, any correlation between Tether and other cryptocurrencies could not be expected, as its value hardly changes. However, the reason for excluding Bitcoin SV is its short existence, as it was created as a hard fork of Bitcoin Cash only in November 2018 (Investopedia, 2020); from this point of view, it differs significantly from other cryptocurrencies included in the study. The insufficiently long existence prevents the appropriate statistical analysis for the article, as its primary goal is to address the correlation strengths over a longer period of time.

4. RESULTS

Table 1 shows correlation coefficients between cryptocurrency pairs for the entire period in question, based on their daily return. It shows that there is a positive, mostly moderate correlation between all currencies. Assuming that Bitcoin, due to its market capitalization, has the greatest impact on the cryptocurrency market, the results are first analyzed in terms of the correlation between Bitcoin and other cryptocurrencies. The analysis results for the entire period show a strong or at least moderate association between Bitcoin and other cryptocurrencies. Ethereum and Litecoin have the strongest association with Bitcoin. These are cryptocurrencies that have been present on the market for a long time and have been included in this research for the entire period (since the beginning of 2017). There are two main reasons for the strong association: these cryptocurrencies have a similar set of supporters and investors who invest in less risky investments (relative to others), i.e., in established cryptocurrencies, and at the same time, react more thoughtfully in periods of high volatility (they are more experienced, informed); and second, a longer period of time was included in the calculation compared to other currencies. Here the year 2017 should be pointed out, which was marked by the constant growth of all cryptocurrencies, without major deviations. In 2018 and 2019, markets were more turbulent, as cryptocurrencies reacted differently to related events (regulation of the market, ban on trading in several countries, theft of coins, etc.). There is also a strong correlation with the significantly younger cryptocurrencies Binance Coin and Bitcoin Cash, with Eos, Cardano, and Tron not far behind, as they are close to the line separating moderate from strong correlation. On the other hand, a large deviation is found, especially when considering the strength of Ripple's correlation, which is almost bordering on a weak correlation. Based on the above, it can be concluded that in the long run, the two cryptocurrencies mentioned have a lower degree of correlation, which is interesting for investors who want to diversify their portfolio of investments in the most important cryptocurrencies.

For Ethereum, as the second strongest cryptocurrency in terms of capital, and even higher strength of correlation is found (although the deviations are not large, the average strength of correlation is higher by 0.028) other cryptocurrencies than for Bitcoin. Thus, Ethereum has a higher strength of correlation with all cryptocurrencies, except Litecoin and Binance Coin. The calculation of average values of correlation coefficients between each cryptocurrency with other cryptocurrencies shows that Ethereum has the highest average correlation strength at 0.516. This result is not surprising. If Bitcoin is today primarily seen as an investment asset for an extended period of time, Ethereum is often merely an intermediate step towards purchasing other alternative cryptocurrencies and initial coin offerings. This aspect directly affects the higher strength of correlation, as such transactions (from dollars via Ethereum to the desired cryptocurrency) mostly take place in narrow time frames. An interesting result was obtained with the third most powerful cryptocurrency in terms of capital, Ripple, as it deviates from the first two. Ripple has only a moderate association with other cryptocurrencies, except for Stellar and Cardano, with which the association is strong. There are several reasons for this, from its purpose and design of the support system, which is primarily intended for a narrow circle of users (banks), and a single company controls the network, to separate groups of supporters (friction between supporters of different cryptocurrencies are well known, and supporters of Ripple stand out with their zeal). The results of Litecoin correlations with other cryptocurrencies follow those of its older brother, Bitcoin (average correlation strength values differ by only 0.002), which is understandable given its similar design (Litecoin emerged as the first hard fork of Bitcoin in its early stages) and a comparable circle of supporters. Bitcoin Cash is characterized by a higher strength of correlation with Ripple than with previously discussed cryptocurrencies; however, there is a noticeable drop for the last four cryptocurrencies included in our study: Binance Coin, Stellar, Cardano, and Tron. In the case of Eos, there are no major deviations in calculated correlations, and the association is generally moderate. The correlations of Binance

Table 1. Pearson correlation coefficients between cryptocurrency pairs for the entire period (daily return)

		Correlation									
Cryptocurrency		**Bitcoin**	**Ethereum**	**Ripple**	**Bitcoin Cash**	**Litecoin**	**Eos**	**Binance Coin**	**Stellar**	**Cardano**	**Tron**
Bitcoin	Pearson correlation	1	.622**	.326**	.508**	.598**	.491**	.521**	.392**	.478**	.461**
	Sig. (2-tailed)	–	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	1166	1166	1166	963	1166	985	961	1166	893	911
Ethereum	Pearson correlation	.622**	1	.350**	.607**	.588**	.577**	.481**	.398**	.536**	.489**
	Sig. (2-tailed)	.000	–	.000	.000	.000	.000	.000	.000	.000	.000
	N	1166	1166	1166	963	1166	985	961	1166	893	911
Ripple	Pearson correlation	.326**	.350**	1	.424**	.380**	.437**	.305**	.553**	.598**	.424**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000	.000	.000
	N	1166	1166	1166	963	1166	985	961	1166	893	911
Bitcoin Cash	Pearson correlation	.508**	.607**	.424**	1	.541**	.526**	.339**	.355**	.386**	.318**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000	.000	.000
	N	963	963	963	963	963	963	961	963	893	911
Litecoin	Pearson correlation	.598**	.588**	.380**	.541**	1	.517**	.455**	.410**	.480**	.414**
	Sig. (2-tailed)	.000	.000	.000	.000	–	.000	.000	.000	.000	.000
	N	1166	1166	1166	963	1166	985	961	1166	893	911
Eos	Pearson correlation	.491**	.577**	.437**	.526**	.517**	1	.403**	.407**	.471**	.477**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	–	.000	.000	.000	.000
	N	985	985	985	963	985	985	961	985	893	911
Binance Coin	Pearson correlation	.521**	.481**	.305**	.339**	.455**	.403**	1	.312**	.390**	.352**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	–	.000	.000	.000
	N	961	961	961	961	961	961	961	961	893	911
Stellar	Pearson correlation	.392**	.398**	.553**	.355**	.410**	.407**	.312**	1	.582**	.326**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	–	.000	.000
	N	1166	1166	1166	963	1166	985	961	1166	893	911
Cardano	Pearson correlation	.478**	.536**	.598**	.386**	.480**	.471**	.390**	.582**	1	.434**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	–	.000
	N	893	893	893	893	893	893	893	893	893	893
Tron	Pearson correlation	.461**	.489**	.424**	.318**	.414**	.477**	.352**	.326**	.434**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	–
	N	911	911	911	911	911	911	911	911	893	911

Note: **. Correlation is significant at the 0.01 level (2-tailed).

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Table 2. Pearson correlation coefficients between cryptocurrency pairs for the period of increasing prices (daily return)

Cryptocurrency		Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron
		Correlation									
Bitcoin	Pearson correlation	1	.614**	.279**	.476**	.583**	.447**	.270**	.339**	.476**	.400**
	Sig. (2-tailed)	–	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	543	543	543	340	543	362	338	543	270	288
Ethereum	Pearson correlation	.614**	1	.264**	.576**	.546**	.527**	.260**	.317**	.493**	.425**
	Sig. (2-tailed)	.000	–	.000	.000	.000	.000	.000	.000	.000	.000
	N	543	543	543	340	543	362	338	543	270	288
Ripple	Pearson correlation	.279**	.264**	1	.424**	.334**	.415**	.158**	.515**	.610**	.408**
	Sig. (2-tailed)	.000	.000	–	.000	.000	.000	.003	.000	.000	.000
	N	543	543	543	340	543	362	338	543	270	288
Bitcoin Cash	Pearson correlation	.476**	.576**	.424**	1	.501**	.471**	.159**	.285**	.345**	.205**
	Sig. (2-tailed)	.000	.000	.000	–	.000	.000	.003	.000	.000	.000
	N	340	340	340	340	340	340	338	340	270	288
Litecoin	Pearson correlation	.583**	.546**	.334**	.501**	1	.466**	.239**	.367**	.450**	.357**
	Sig. (2-tailed)	.000	.000	.000	.000	–	.000	.000	.000	.000	.000
	N	543	543	543	340	543	362	338	543	270	288
Eos	Pearson correlation	.447**	.527**	.415**	.471**	.466**	1	.230**	.360**	.424**	.455**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	–	.000	.000	.000	.000
	N	362	362	362	340	362	362	338	362	270	288
Binance Coin	Pearson correlation	.270**	.260**	.158**	.159**	.239**	.230**	1	.166**	.281**	.302**
	Sig. (2-tailed)	.000	.000	.003	.003	.000	.000	–	.002	.000	.000
	N	338	338	338	338	338	338	338	338	270	288
Stellar	Pearson correlation	.339**	.317**	.515**	.285**	.367**	.360**	.166**	1	.492**	.270**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.002	–	.000	.000
	N	543	543	543	340	543	362	338	543	270	288
Cardano	Pearson correlation	.476**	.493**	.610**	.345**	.450**	.424**	.281**	.492**	1	.421**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	–	.000
	N	270	270	270	270	270	270	270	270	270	270
Tron	Pearson correlation	.400**	.425**	.408**	.205**	.357**	.455**	.302**	.270**	.421**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	–
	N	288	288	288	288	288	288	288	288	270	288

Note: **. Correlation is significant at the 0.01 level (2-tailed).

Coin with other cryptocurrencies are even weaker, as it has a strong association only with Bitcoin and moderate associations with other cryptocurrencies, and even here, quite a few correlations are bordering on weak. As it turns out, the average value of correlation strength is lowest in Binance Coin among all cryptocurrencies included in the study, at 0.395. Other cryptocurrencies are generally more strongly associated with the strongest cryptocurrencies in terms of capital, and less so to each other. The exception that proves the rule is the pair of Cardano and Stellar, where a strong correlation is found.

The results change to some extent if only the period of growth of cryptocurrency prices (Table 2) is included in the calculation. It is generally accepted that the rate of correlation between Bitcoin and other cryptocurrencies falls during periods of price growth. Thus, Bitcoin has a strong association only with Ethereum and Litecoin, moderate with most other cryptocurrencies and weak with Ripple. Therefore, the results suggest that alternative cryptocurrencies have a lower correlation with Bitcoin during periods of price growth, although the differences are not large. This pattern can also be detected when comparing the strength of correlations between alternative cryptocurrencies. Thus, in the case of Ethereum, correlation strength between Ethereum and other cryptocurrencies decreases in all cases, while still maintaining its top position with the average value (0.447). On the other hand, Binance Coin, on average, turns out to be the least associated with other cryptocurrencies, as the average correlation value remains at 0.23, representing only a weak correlation. Therefore, if it intends to balance the investment portfolio of the most important cryptocurrencies during the general growth trend, it makes sense to invest a larger share of funds in Binance Coin.

In a period of decreasing prices (Table 3), the strength of Bitcoin's correlation with other cryptocurrencies increases significantly, and in most cases, even achieves a very strong association. In the case of Litecoin, Ethereum, Bitcoin Cash, and Binance Coin, the value is very close to 1, which represents a perfect correlation. The strong correlation of these five cryptocurrencies indicates that their movement in the bear period is very similar, so the portfolio's diversification does not result in any advantage. Similar is true for Eos and Cardano, whereas Tron and Ripple deviate from this slightly (although the strength of their correlation with Bitcoin is still very strong or strong). Of the cryptocurrencies examined, Stellar proves to be an exception, where the strength of the correlation with Bitcoin slightly decreases during the period of falling prices, but remains within the range of moderate correlation. During this period, Stellar deviates from the cryptocurrencies included in the study, as it has a strong correlation only with Ripple and Cardano, moderate correlation with other cryptocurrencies, and a weak correlation with Binance Coin. Summarizing the authors' findings, it can be concluded, that during the bear period, cryptocurrencies are generally (very) strongly positively correlated with each other, with individual exceptions. These exceptions give us room for maneuver and the necessary information to decide how to allocate the investments during periods that are not the most profitable for investing in the cryptocurrency market.

Further is the analysis of the differences in the correlation strength coefficients between price growth periods and drop for an individual currency pair (Table 4). Green fields show pairs with a rising index (positive value), and red fields show pairs with a decreasing index (negative value). The table unequivocally confirms the conclusions reached in examining correlation coefficients by individual periods. An increase in the correlation strength is practically unambiguous and surprisingly high in most pairs (except for the pair of Litecoin and Stellar, where the strength of correlation decreased slightly). On average, the correlation strength increased by 0.35, with the largest increase occurring in the pair of Bitcoin Cash and Binance Coin, amounting to as much as 0.8. Binance Coin has the highest average increase (0.55), whereas most others increase by about 0.38, while Ripple (0.18) and Stellar (0.09) have the lowest changes. Therefore, the latter two cryptocurrencies maintain a similar strength of correlations with other most important cryptocurrencies regardless of the period in question (growth or decline).

The results presented earlier are based on the calculation of daily return for an individual cryptocurrency. The correlation strengths between cryptocurrencies, using their weekly returns as the basis, are examined in Table 5, which shows the correlation coefficients between pairs of cryptocurrencies for the entire period weekly. Table 6 shows the differences in the value of correlation coefficients for the entire period, using daily and weekly returns. It turns out that there are certain differences between the two calculations, which means that returns on a daily and weekly basis between individual pairs of cryptocurrencies are not fully aligned. If the average difference in the case of the two strongest cryptocurrencies (Bitcoin and Ethereum) is less than 0.1, it increases to 1.5 for most other cryptocurrencies, and even to over 2 for Tron.

By studying the correlation strength of cryptocurrencies based on weekly returns for the entire period, the findings regarding the correlation strength of cryptocurrencies based on daily returns can be fully confirmed, despite the mentioned differenc-

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Table 3. Pearson correlation coefficients between cryptocurrency pairs for the period of decreasing prices (daily return)

Correlation											
Cryptocurrency		**Bitcoin**	**Ethereum**	**Ripple**	**Bitcoin Cash**	**Litecoin**	**Eos**	**Binance Coin**	**Stellar**	**Cardano**	**Tron**
Bitcoin	Pearson correlation	1	.973**	.517**	.972**	.982**	.901**	.968**	.356**	.911**	.744**
	Sig. (2-tailed)	–	0.000	.000	0.000	0.000	.000	0.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Ethereum	Pearson correlation	.973**	1	.581**	.968**	.975**	.921**	.949**	.421**	.935**	.765**
	Sig. (2-tailed)	0.000	–	.000	0.000	0.000	.000	0.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Ripple	Pearson correlation	.517**	.581**	1	.502**	.510**	.601**	.448**	.712**	.671**	.588**
	Sig. (2-tailed)	.000	.000	–	.000	.000	.000	.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Bitcoin Cash	Pearson correlation	.972**	.968**	.502**	1	.978**	.904**	.962**	.333**	.901**	.727**
	Sig. (2-tailed)	0.000	0.000	.000	–	0.000	.000	0.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Litecoin	Pearson correlation	.982**	.975**	.510**	.978**	1	.901**	.974**	.334**	.911**	.728**
	Sig. (2-tailed)	0.000	0.000	.000	0.000	–	.000	0.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Eos	Pearson correlation	.901**	.921**	.601**	.904**	.901**	1	.869**	.460**	.901**	.763**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	–	.000	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Binance Coin	Pearson correlation	.968**	.949**	.448**	.962**	.974**	.869**	1	.275**	.876**	.685**
	Sig. (2-tailed)	0.000	0.000	.000	0.000	0.000	.000	–	.000	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Stellar	Pearson correlation	.356**	.421**	.712**	.333**	.334**	.460**	.275**	1	.582**	.449**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	–	.000	.000
	N	625	625	625	625	625	625	625	625	625	625
Cardano	Pearson correlation	.911**	.935**	.671**	.901**	.911**	.901**	.876**	.582**	1	.762**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	–	.000
	N	625	625	625	625	625	625	625	625	625	625
Tron	Pearson correlation	.744**	.765**	.588**	.727**	.728**	.763**	.685**	.449**	.762**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	–
	N	625	625	625	625	625	625	625	625	625	625

Note: **. Correlation is significant at the 0.01 level (2-tailed).

Table 4. Difference in value of correlation coefficients between the periods of increasing and decreasing prices (daily return)

Cryptocurrency	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron	Mean	St. dev
Bitcoin	0.000	0.359	0.237	0.496	0.399	0.454	0.698	0.017	0.436	0.344	0.382260129	0.186095186
Ethereum	0.359	0.000	0.317	0.392	0.429	0.394	0.688	0.104	0.442	0.340	0.385026565	0.15155248
Ripple	0.237	0.317	0.000	0.078	0.176	0.185	0.289	0.197	0.061	0.180	0.191290665	0.085112086
Bitcoin Cash	0.496	0.392	0.078	0.000	0.477	0.433	0.803	0.048	0.557	0.523	0.422804786	0.234712337
Litecoin	0.399	0.429	0.176	0.477	0.000	0.435	0.735	–0.033	0.461	0.371	0.383266179	0.212106933
Eos	0.454	0.394	0.185	0.433	0.435	0.000	0.639	0.100	0.477	0.308	0.380764096	0.161881496
Binance Coin	0.698	0.688	0.289	0.803	0.735	0.639	0.000	0.109	0.595	0.383	0.548813674	0.234388633
Stellar	0.017	0.104	0.197	0.048	–0.033	0.100	0.109	0.000	0.090	0.179	0.0902295	0.072775587
Cardano	0.436	0.442	0.061	0.557	0.461	0.477	0.595	0.090	0.000	0.341	0.384372303	0.1895486
Tron	0.344	0.340	0.180	0.523	0.371	0.308	0.383	0.179	0.341	0.000	0.329935632	0.104739259

es. The Table 5 shows a positive, mostly moderate correlation between all cryptocurrencies. The strength of correlation between Bitcoin and other cryptocurrencies is mostly moderate or strong, with Eos surprising weekly, as it is even more strongly correlated with Bitcoin than Litecoin and Ethereum. On the other hand, the cryptocurrencies Ripple and Stellar are on the line between moderate and weak association. When examining Ethereum, a higher degree of correlation is ob-

Table 5. Pearson correlation coefficients between cryptocurrency pairs for the entire period (weekly return)

Cryptocurrency		Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron
		Correlation									
Bitcoin	Pearson correlation	1	.565**	.291**	.376**	.619**	.669**	.375**	.302**	.446**	.359**
	Sig. (2-tailed)	–	.000	.000	.000	.000	.000	.000	.000	.000	.000
	N	166	166	166	137	166	140	136	166	127	129
Ethereum	Pearson correlation	.565**	1	.287**	.551**	.502**	.724**	.338**	.273**	.558**	.552**
	Sig. (2-tailed)	.000	–	.000	.000	.000	.000	.000	.000	.000	.000
	N	166	166	166	137	166	140	136	166	127	129
Ripple	Pearson correlation	.291**	.287**	1	.307**	.620**	.595**	.226**	.463**	.711**	.738**
	Sig. (2-tailed)	.000	.000	–	.000	.000	.000	.008	.000	.000	.000
	N	166	166	166	137	166	140	136	166	127	129
Bitcoin Cash	Pearson correlation	.376**	.551**	.307**	1	.464**	.448**	.329**	.313**	.301**	.235**
	Sig. (2-tailed)	.000	.000	.000	–	.000	.000	.000	.000	.001	.007
	N	137	137	137	137	137	137	136	137	127	129
Litecoin	Pearson correlation	.619**	.502**	.620**	.464**	1	.674**	.255**	.550**	.675**	.674**
	Sig. (2-tailed)	.000	.000	.000	.000	–	.000	.003	.000	.000	.000
	N	166	166	166	137	166	140	136	166	127	129
Eos	Pearson correlation	.669**	.724**	.595**	.448**	.674**	1	.225**	.685**	.659**	.587**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	–	.008	.000	.000	.000
	N	140	140	140	137	140	140	136	140	127	129
Binance Coin	Pearson correlation	.375**	.338**	.226**	.329**	.255**	.225**	1	.196*	.666**	.694**
	Sig. (2-tailed)	.000	.000	.008	.000	.003	.008	–	.022	.000	.000
	N	136	136	136	136	136	136	136	136	127	129

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Table 5. (cont.) Pearson correlation coefficients between cryptocurrency pairs for the entire period (weekly return)

Cryptocurrency		Correlation									
		Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron
Stellar	Pearson correlation	.302**	.273**	.463**	.313**	.550**	.685**	.196*	1	.759**	.676**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.022	–	.000	.000
	N	166	166	166	137	166	140	136	166	127	129
Cardano	Pearson correlation	.446**	.558**	.711**	.301**	.675**	.659**	.666**	.759**	1	.729**
	Sig. (2-tailed)	.000	.000	.000	.001	.000	.000	.000	.000	–	.000
	N	127	127	127	127	127	127	127	127	127	127
Tron	Pearson correlation	.359**	.552**	.738**	.235**	.674**	.587**	.694**	.676**	.729**	1
	Sig. (2-tailed)	.000	.000	.000	.007	.000	.000	.000	.000	.000	–
	N	129	129	129	129	129	129	129	129	127	129

Note: **. Correlation is significant at the 0.01 level (2-tailed), *. Correlation is significant at the 0.05 level (2-tailed).

served with other cryptocurrencies weekly than Bitcoin and is most strongly correlated with Eos, while the degree of correlation weekly is slightly reduced in general. Ripple is also interesting, as its correlation strength with quite a few cryptocurrencies increases greatly weekly and even reaches a very strong level with Cardano and Tron. In the case of Bitcoin Cash, there are no major changes, while the correlation strength of Litecoin and Eos with other cryptocurrencies mostly increases significantly weekly, which means that the two cryptocurrencies achieve very similar results as others. Binance Coin is characterized by a decrease in strength of correlation with most other cryptocurrencies, especially with the strongest ones in terms of capital, while not exceeding the weak association with as many as four others. With Cardano and Tron, the situation is reversed – the strength of correlation is mostly increased when using weekly returns, whereas no clear conclusions can be drawn for Stellar.

The analysis of differences in the value of correlation coefficients between the periods of increasing and decreasing prices for an individual cryptocurrency pair, using weekly returns, is shown in Table 7. It also shows that correlation coefficients increase for most cryptocurrency pairs, with a decrease occurring only in individual cases. Similar to the examination daily, Binance Coin (0.55) has the largest average increase weekly, while the order of other cryptocurrencies changes. It is directly followed by Tron and Litecoin, with most cryptocurrencies having a change rate between 0.35

Table 6. Difference in value of correlation coefficients for the entire period, using daily and weekly returns

Cryptocurrency	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron	Average (Abs(x))
Bitcoin	0.000	–0.058	–0.035	–0.131	0.021	0.177	–0.147	–0.090	–0.032	–0.102	0.088
Ethereum	–0.058	0.000	–0.062	–0.056	–0.085	0.147	–0.143	–0.125	0.022	0.063	0.085
Ripple	–0.035	–0.062	0.000	–0.117	0.240	0.158	–0.079	–0.090	0.112	0.314	0.134
Bitcoin Cash	–0.131	–0.056	–0.117	0.000	–0.077	–0.078	–0.010	–0.042	–0.084	–0.083	0.075
Litecoin	0.021	–0.085	0.240	–0.077	0.000	0.156	–0.200	0.139	0.194	0.260	0.153
Eos	0.177	0.147	0.158	–0.078	0.156	0.000	–0.178	0.278	0.187	0.110	0.163
Binance Coin	–0.147	–0.143	–0.079	–0.010	–0.200	–0.178	0.000	–0.116	0.276	0.342	0.166
Stellar	–0.090	–0.125	–0.090	–0.042	0.139	0.278	–0.116	0.000	0.177	0.349	0.156
Cardano	–0.032	0.022	0.112	–0.084	0.194	0.187	0.276	0.177	0.000	0.295	0.153
Tron	–0.102	0.063	0.314	–0.083	0.260	0.110	0.342	0.349	0.295	0.000	0.213

Table 7. Difference in value of correlation coefficients between the periods of increasing and decreasing prices (weekly return)

Cryptocurrency	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin	Eos	Binance Coin	Stellar	Cardano	Tron	Average (Abs(x))
Bitcoin	0.000	0.411	0.156	0.578	0.379	0.148	0.798	0.014	0.421	0.861	0.419
Ethereum	0.411	0.000	0.301	0.375	0.567	0.236	0.858	0.209	0.518	0.999	0.451
Ripple	0.156	0.301	0.000	0.266	–0.298	–0.052	0.324	0.290	0.574	0.049	0.239
Bitcoin Cash	0.578	0.375	0.266	0.000	0.508	0.493	0.667	0.075	0.576	0.695	0.406
Litecoin	0.379	0.567	–0.298	0.508	0.000	0.288	1.010	–0.424	0.383	0.742	0.469
Eos	0.148	0.236	–0.052	0.493	0.288	0.000	0.862	–0.090	0.390	0.822	0.359
Binance Coin	0.798	0.858	0.324	0.667	1.010	0.862	0.000	0.297	0.777	0.132	0.547
Stellar	0.014	0.209	0.290	0.075	–0.424	–0.090	0.297	0.000	–0.060	0.551	0.222
Cardano	0.421	0.518	0.574	0.576	0.383	0.390	0.777	–0.060	0.000	0.813	0.454
Tron	0.861	0.999	0.049	0.695	0.742	0.822	0.132	0.551	0.813	0.000	0.534

and 0.46. The largest increases occur in the pairs of Litecoin and Binance Coin (1.01) and Ethereum and Tron (0.999). Interesting results are observed particularly in Litecoin, where, in two cases, the correlation strength is significantly reduced (in the pair with Ripple by almost 0.3, and the pair with Stellar by more than 0.4). This contrasts with the results obtained in the examination based on daily return, where the decrease in Stellar was negligible, while the calculation showed an increase in the pair with Ripple.

5. DISCUSSION

Comparing the results of this study to data found on cryptowat.ch and coinmetrics.io (showing the strength of correlations between pairs of cryptocurrencies for a period of at least one day to a maximum of one year in tabular or graphical form) shows that Bitcoin is more weakly associated with other cryptocurrencies than stated by these websites. The research in several scientific papers also suggests a mostly strong association between both Bitcoin and alternative cryptocurrencies (Katsiampa, Corbet, & Lucey, 2019; Ciaian & Rajcaniova, 2018), while the authors, when examining the whole period, noticed predominantly moderate strength of correlation. A similar finding can be made for other pairs of cryptocurrencies included in the study. The reason for this lies in the fact that this study covers a time period of more than three years (for some currencies, this is the entire period of their existence), while the cryptowat.ch and coinmetrics.io websites are limited to a maximum period of one year. It can be concluded that this study at the level of all major cryptocurrencies confirms the findings made for Bitcoin by Antonakakis et al. (2019), specifically that in the short run, cryptocurrencies are significantly more strongly correlated with each other than is the case in the long run. The results do not change significantly even if the weekly returns of cryptocurrencies are taken as the basis for the calculation instead of the daily returns.

A detailed examination of the correlation graphs on the coinmetrics.io website for a multi-year period suggests that over time the strength of correlations between individual pairs of cryptocurrencies varies greatly (for example, in 2018, the strength of correlations between Bitcoin and Litecoin varied between 0.8 and 0.48). Similar results for 2019 are also provided by the study conducted by Binance.com (Binance Research, 2020), which examined changes in correlation coefficients by individual quarters. A longer research timeframe thus reduces the extreme values (extremely strong or insignificant correlation) that can be observed in shorter periods (e.g., 1 month), which ultimately leads to more balanced results (smaller differences between pairs of cryptocurrencies). However, the authors were interested in how the strength of correlations between cryptocurrencies differs between periods of rising and falling prices. The results, both with daily and weekly returns, are undoubtedly interesting as they suggest large differences in the strength of correlations between the two periods. If cryptocurrencies are mostly

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only moderately correlated during the bull market period, the strength of correlation between them increases significantly during the bear market period. The differences are significant: on average, the strength of correlation increased by 0.35, and the largest increase reached a value of 0.8. The increase is present, with rare exceptions, in all cryptocurrency pairs, which means that it is a common phenomenon that should be given full attention when planning the initial portfolio of cryptocurrencies and in its management over time.

Generally, any portfolio diversification reduces financial risk for investors, ensuring better results if investment assets are as uncorrelated as possible. Our study shows that there is always a certain degree of the positive correlation between cryptocurrencies, with at least moderate association even in the long run. Investors who invest all their assets only in the cryptocurrency market are thus exposed to extremely high risks, which were also demonstrated in practice in 2018 when the prices of most cryptocurrencies fell by more than 80%. To some extent, the risk can be reduced by a diversification of the portfolio by including weakly associated pairs of cryptocurrencies; however, this approach does not prove effective in a period of falling prices, which is usually the most critical. Thus, this research findings confirm the generally accepted belief that investors should allocate their assets to various types of investments (real estate, stocks, precious metals, etc.), with cryptocurrencies representing only a part of the portfolio. How much should be invested in cryptocurrencies depends on the type of investor, their willingness to take risks, the long-term nature of the investment, and, last but not least, their confidence in the future of blockchain technology.

CONCLUSION

In this article, the results of a study that aims to determine the strength of correlation between the ten most important cryptocurrencies in the last three years or since their inception are presented. The article contributes a new piece to the mosaic of existing scientific and expert contributions examining the issue of association strength between cryptocurrencies themselves and between cryptocurrencies and other investment assets. The key finding is that the strength of correlations between cryptocurrencies is significantly higher during a period of falling prices than during a period of rising prices. Exceptions are quite rare (e.g., EOS), so the cryptocurrency investment portfolio's effective diversification is very difficult to achieve. However, generally, the study results confirm previous findings, which indicate at least a moderate, if not already strong, positive correlation between cryptocurrencies. The differences in the results are primarily due to a longer period included in the calculation than other studies. Thus, the positive correlation is characteristic of all cryptocurrency pairs examined, regardless of whether daily or weekly returns are included in the calculation.

In the future, the research will be expanded to a larger number of cryptocurrencies (50 or 100), while the authors will continue to strive to include the longest possible research period. It would be interesting to know whether the results can also be confirmed in the case of correlation between weaker cryptocurrencies in terms of capital, which have generally been present on the market only for the last two to three years. Potentially different results (weaker association in a period of falling prices) would allow us to change how the investments in cryptocurrencies are viewed in the long run, which could result in the identification of alternative investment strategies. However, until then, the following unwritten rule still applies: Invest in cryptocurrencies only that part of your portfolio that you are also willing to lose.

AUTHOR CONTRIBUTIONS

Conceptualization: Sebastian Lahajnar.
Data curation: Sebastian Lahajnar, Alenka Rožanec.
Formal analysis: Sebastian Lahajnar, Alenka Rožanec.
Investigation: Sebastian Lahajnar, Alenka Rožanec.

Methodology: Sebastian Lahajnar.
Project administration: Sebastian Lahajnar, Alenka Rožanec.
Supervision: Alenka Rožanec.
Software: Sebastian Lahajnar.
Validation: Sebastian Lahajnar, Alenka Rožanec.
Writing – original draft: Sebastian Lahajnar, Alenka Rožanec.
Writing – review & editing: Sebastian Lahajnar, Alenka Rožanec.

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