COMPARISON OF CRYPTO-ASSETS MARKET RISK PROXIES*

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Abstract: In early 2021, the cryptoasset market capitalization exceeded $1.5 trillion, and there were more than 300 exchanges in the world where over 8,000 tokens could be traded. As part of research related to mature segments of the financial market (e.g. the stock market in the United States), scientists and practitioners have been trying to identify key risk factors for several decades, thanks to which it is possible to explain the equity risk premium for an investment in a given asset class. In recent years, there have been an increasing number of researchers trying to identify these factors for cryptoassets. The aim of this article was to analyse popular cryptoasset indices in order to identify those that can be used as a proxy of the market portfolio in order to estimate this risk factor premium. The research results indicate that the market risk factor is an important element of the market under study, and the indices that best reflect it are an index consisting of all cryptoassets weighted by capitalization and Coin100 which contains only the 100 largest cryptoassets.

Keywords: cryptoassets, digital tokens, blockchain, cryptocurrency, systematic risk, CAPM.

1. Introduction

Cryptoassets are digital representations of values or rights that can be transferred and stored electronically using distributed ledger technology or similar technology (Proposal for a Regulation…, 2019). In recent years, cryptocurrency and blockchain technology have attracted millions of investors. In early 2021, the cryptocurrency market capitalization exceeded $1.5 trillion, and there were over 300 exchanges in the world where over 8,000 digital tokens could be traded.[1] According to some researchers and practitioners, blockchain technology and cryptoassets can improve the lives of millions of people (Iansiti & Lakhani, 2017). Examples of the challenges which may be faced include a lack of access to basic financial services for 2 billion people worldwide (Larios-Hernández, 2017) and a lack of access to any register of the 5 billion people who own cryptoassets (Soto de, 2017). On the other hand, the cryptoasset market is widely unregulated and as such, opponents of cryptoassets argue that digital tokens often become the subject of speculation or even manipulation (Gandal, Hamrick, Moore, & Oberman, 2018; Li, Shin, & Wang, 2018).

Basic information on blockchain technology and its potential can be found in the publications by Dwyer (2015), Underwood (2016) and Larios-Hernández (2017). The discussed technological solutions may have development potential in various spheres of the economy, including organization management, finance and accounting, and sales and marketing (Tapscott & Tapscott, 2017). Other potential applications are contracting, auditing and verification of products (e.g. food) and so on (Fanning & Centers, 2016).

Scientific research on the cryptoasset market has been conducted for only a few years, but the number of publications is increasing, as confirmed by statistics from the Web Of Science and Scopus databases. The subject of the first articles was most often the so-called cryptocurrencies (falling under the definition of cryptoassets) with the largest market capitalization, such as Bitcoin, Ethereum, Ripple and so on. At first, less attention was paid to much smaller projects using blockchain technology, which also issued digital tokens with different characteristics and applications.

In research related to mature segments of the financial market (e.g. the stock market in the United States), scientists and practitioners have been trying to identify key risk factors for decades, thanks to which it is possible to explain the so-called equity risk premium for an investment in a given asset class. The possibility of determining this parameter is also an important element in the process of valuating many financial instruments. The capital asset pricing model (CAPM) was the first model independently proposed by Treynor (1962) and Sharpe (1964) based on earlier work by Markowitz (1952) and was used to explain the size of the equity risk premium. In this model, the only factor was the so-called market risk factor.

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[1] https://coinmarketcap.com/ (as of 18 February 2021).

Numerous studies conducted in the following decades clearly indicate that this model should be supplemented with other factors, such as the size of the company, the relations between the book value and market value, profitability and historical trends. The key research in this area was published by Fama and French (1992). According to them, the one-factor model should be completed with two other factors related to the size of the company (SMB factor) and the book-to-market ratio (HML factor), which is often referred to as the Fama-French three-factor model (Fama and French, 1992). In the following years, many authors proposed models with even more factors. Empirical research has been presented, among others, in the publications of Fama and French (2013; 2015), Nichol and Dowling (2014), Chiah, Chai, Zhong, & Li (2016), as well as Fabozzi and Wang (2016). As part of the research conducted in Poland, they have been verified by Urbański (2007), Kowerski (2008), Czapkiewicz and Skalna (2010), Waszczuk (2013), Zaremba (2014) and Czapiewski (2016), among others.

After the publication of the first research focusing on Bitcoin price changes, it became clear that it is used more as a speculative asset than as a means of payment (Baur, Hong, & Lee, 2018; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018), but it can be an attractive diversification tool (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Dyhrberg, 2016). In light of other studies, the cryptoasset market provides the opportunity to use numerous active investment strategies due to the emerging inefficiencies. For example, studies show that the use of stop-loss orders reduces the volatility of investments in individual cryptoassets by almost half (Białkowski, 2020). Other studies that focus on the effectiveness of the cryptoasset market include: Urquhart (2016), Gandal et al. (2018), Nadarajah and Chu (2017), Bariviera (2017), Cheah and Fry (2015), and Corbet, Lucey, and Yarovaya (2017).

Referring to the CAPM and its developments, an attempt has been made to identify the key risk factors, thanks to which it is possible to explain the realized rates of return on a wide range of cryptoassets. In their studies, Coelho (2020) as well as Liu and Tsyvinski (2018) have analysed the possibility of using the Fama-French three-factor model. A significant influence of factors related to the momentum and capitalization on the rates of return on cryptoassets has also also been demonstrated (Liu, Tsyvinski, A., & Wu, 2019). Long, Zaremba, Demir, Szczygielski, and Vasenin (2020) conducted research indicating the occurrence of seasonal phenomena. Excess returns were also examined by Zhang and Li (2020) and Borri and Shakhnov (2018).

The abovementioned works describe empirical studies referring to the concept of the decomposition of the observed rates of return into factors that determine them, including the market beta. Nevertheless, the time series representing the market risk factor is often chosen arbitrarily despite the fact that many cryptoasset market indices have emerged in recent years. For example, Long et al., (2020) and Zhang and Li (2020), in the single and multi-factor models, used a portfolio consisting of all cryptocurrencies weighted by capitalization. In other works, the benchmark was the

rates of return on investments in Bitcoin (e.g. Borri and Shakhnov, 2018). **The aim of this article was to compare popular cryptoasset indices in order to select those that may reflect the market risk factor. For this purpose, eight indices and two cryptocurrencies with the largest capitalization – Bitcoin and Ethereum – are compared.** This study is a continuation of the research conducted by Mercik and Cupriak (2019).

This article is divided into four chapters. Chapter 2 describes the sources of the data obtained and the research methodology. Chapter 3 discusses the results obtained. Chapter 4 is a summary supplemented with the perspective of the research conducted.

2. Source material and research methods

The main source of data in the study was https://coinpaprika.com/, which publishes prices from the most liquid digital token exchanges in the world. The analysed time series covered the period from January 2017 to the end of January 2021 (49 months in total). Such a period was selected mainly because of data availability – before January 2017 the number of digital tokens was too small to perform a broad market study, moreover data for a large number of cryptoassets prominent before 2017 are unavailable now due to delisting from data aggregating platforms.

Data were obtained in the open, high, low, close, volume (OHLCV) format for 4,963 projects. However, for 172 projects no capitalization data were available for any period, so these projects were excluded from further analysis. It should be emphasized that only small projects and those characterized by low liquidity did not have data on capitalization. In those 4,791 projects with data on capitalization, a sub-group of 2,793 projects built with the use of blockchain networks from other projects (e.g. Ethereum) were identified. These kinds of projects are referred to as 'tokens' for the purposes of this article, in contrast to projects using a proprietary network called 'coins', 1998 of which were identified. In the course of the study, 42 projects were identified that contained errors in their time series in the data about the closing price or market capitalization. Due to the inability to determine the appropriate values for these data, these projects were excluded from the analysis.

To conduct the study it was necessary to prepare monthly rates of return on three additional indices that represent the entire cryptoasset market (4,791 projects called the "CoinMarket" in this study), the entire market of tokens issued in the existing networks such as the Ethereum network, which is the most popular platform (the so-called "TokenMarket", 2,793 projects) and 100 cryptoassets with the highest capitalization ("Coin100"). Moreover, five cryptoasset indices existing on the market were selected for comparison: CRIX (Trimborn & Härdle, 2018), CCI30 (Rivin & Scevola, 2018, p. 3), CMC200 (Crypto200 Index by Solactive, n.d.), CCMIX (Crescent Crypto Market Index, n.d.) and Crypto20 (Schwartzkopff, Schwartzkopff, Botha, Finlayson, & Cronje, 2017). The monthly rates of return on the indices are shown in Figure 1.
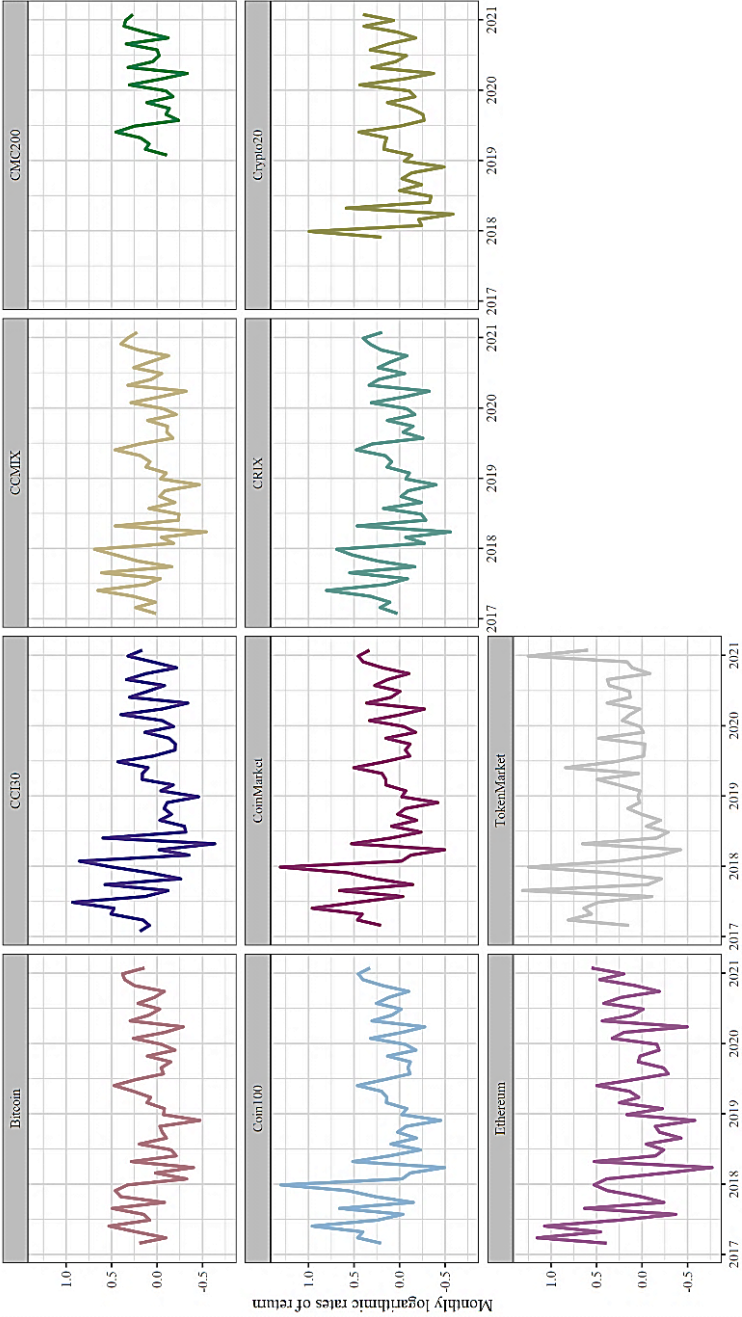
Fig. 1. Monthly logarithmic rates of return of selected cryptoasset indices

Source: own study.

According to the definition, the market portfolio (which is the basis of the CAPM model) is on the efficient frontier, whose ratio of the excess return over the return on risk-free instruments to the risk taken (measured by the standard deviation of the rates of return) is the largest (Jajuga & Jajuga, 2004). Thus, one of the crucial criteria that a potential market portfolio proxy should meet is a high risk-return efficiency. A graphical interpretation of the market portfolio is shown in Figure 2.
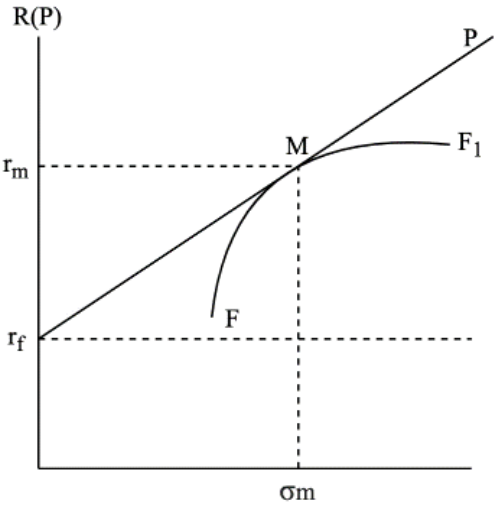

Fig. 2. Market portfolio and the efficient frontier

Source: own study.

In the figure, the symbol R(P) represents the rate of return on the portfolio, r_f – the risk-free rate, r_m – the rate of return on the market portfolio, σ_m – standard deviation of the market portfolio, M – the point where the market portfolio is located, P – the capital market line, the curve represents the efficiency curve, and F and F_1 are examples of portfolios on this curve.

The study verified ten instruments that may constitute an appropriate approximation of the rates of return on the market portfolio. These were the rates of return on: Bitcoin, Ethereum, CoinMarket, TokenMarket, Coin100, CRIX (Trimborn & Härdle, 2018), CCI30 (Rivin & Scevola, 2018, p. 3), CMC200 (Crypto200 Index by Solactive, n.d.), CCMIX (Crescent Crypto Market Index, n.d.) and Crypto20 (Schwartzkopff et al., 2017). To indicate the index that best suits the role of a market portfolio proxy, two main characteristics had to be tested: risk-return efficiency, as the market portfolio is by definition efficient in this regard, and high correlation with all other assets in the market due to the fact that the market portfolio has to reflect all systemic changes in the market as a whole.

The research procedure was divided into three stages. First, the mean, standard deviation, skewness and kurtosis of monthly logarithmic rates of return were calculated for all the analysed indices. Then the ratio of the average implemented monthly logarithmic rates of return to risk (standard deviation) was calculated and

the index with the highest value was indicated. Moroever, a number of basic statistical tests were carried out for each index to assess the statistical characteristics of each time-series. These included: the Augmented Dickey-Fuller test, which tests the presence of the unit root in the autoregressive model; the KPSS test, which aims to verify the null hypothesis that an observable time series is stationary; the Ljung-Box test, which checks the autocorrelation of a time series; the Wald-Wolfowitz Runs test, which verifies the randomness of the sample; and the ARCH test, which verifies the effect of the autocorrelation of the squared rates of return. At the second stage, the share of tokens statistically significantly correlated with each index was estimated for each index. This approach is aimed at identifying tokens whose rates of return can be explained using each of the indices. Then, the obtained results were visualized by presenting the distribution of correlation coefficients in a strip chart. Finally, at the third stage of the study, the correlation matrix was estimated for all ten indices in order to identify those that differed insignificantly from each other. At the end of the research procedure, an index was indicated that could satisfactorily reflect the market risk factor and thus explain the price changes of many other instruments on the cryptoasset market.

3. Results of empirical research

Table 1 shows the basic descriptive statistics for the ten analysed indices. Additionally, the Shapiro-Wilk test was performed for a number of rates of return. This recognized test checks the normality of the distribution of a random variable (Shapiro & Wilk, 1965), which was chosen because of its high test power (Razali & Wah, 2011). The TokenMarket index has the highest realized risk to profit ratio. Each of the analysed indices is characterized by different values of the rates of return over time (the first quartiles are negative in each case, and the third quartiles are three times higher than the

Table 1. Descriptive statistics of selected indices

Index	Sample size	Mean [%]	First quartile [%]	Third quartile [%]	Standard deviation [%]	Skewness [%]	Kurtosis [%]	Mean-to-risk [%]	Shapiro-Wilk test [%]
Bitcoin	48	7.4	-8.1	25.0	23.8	-6.5	245.2	30.86	98.17
CCI30	49	6.9	-15.8	18.9	32.3	52.3	323.2	21.20	97.45
CCMIX	49	7.2	-10.7	23.5	27.1	24.3	287.3	26.58	98.35
CMC200	25	7.8	-9.8	26.4	21.4	-2.1	193.7	36.42	96.50
Coin100	48	13.8	-8.4	30.7	33.1	104.8	514.9	**41.58**	93.73
CoinMarket	48	14.9	-6.6	33.8	33.5	98.7	485.9	**44.55**	94.33
CRIX	49	8.2	-9.6	24.1	28.7	25.1	282.2	28.72	98.87
Crypto20	39	1.4	-19.3	16.7	31.4	74.3	395.4	4.36	96.58
Ethereum	48	10.0	-19.0	38.9	39.2	35.0	328.4	25.55	97.80
TokenMarket	48	23.3	-1.9	40.6	39.2	109.4	396.0	**59.33**	91.01

Source: own study.

average). Moreover, the rates of return on the indices are characterized by high volatility, and the lowest standard deviation value is as high as 27.1%. With the exception of Bitcoin and the CMC200, the rates of return on the indices are leptokurtic and right-skewed. Based on the Shapiro-Wilk test, the hypothesis about the normality of the distribution of the monthly logarithmic rates of return for the analysed indices cannot be rejected.

Table 2 shows the results of a series of basic tests: the Augmented Dickey-Fuller test, the KPSS test, the Ljung-Box test, the Wald-Wolfowitz Runs test and the ARCH test, while Table 3 contains the p-values for these tests. The results obtained indicate that the time series which are the basis for further research can be considered stationary. In the case of two indices (Crypto20 and Ethereum), there is a unit root in a series of rates of return. The ARCH effect was observed for the Coin100 index. No autocorrelation of the rates of return was observed in the analysed indices.

Table 2. Results of statistical tests for selected indices

Index	ADF [H]	KPSS [H]	Ljung-Box [H]	Runs [H]	ARCH test [H]
Bitcoin	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
CCI30	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
CCMIX	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
CMC200	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
Coin100	Stationary	Stationary	No autocorrelation	Random sample	ARCH effect present
CoinMarket	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
CRIX	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect
Crypto20	Nonstationary	Stationary	No autocorrelation	Random sample	No ARCH effect
Ethereum	Nonstationary	Stationary	No autocorrelation	Random sample	No ARCH effect
TokenMarket	Stationary	Stationary	No autocorrelation	Random sample	No ARCH effect

Source: own study.

Table 3. P-values for statistical tests for selected indices

Index	ADF p-value	KPSS p-value	Ljung-Box p-value	Runs p-value	ARCH test p-value
Bitcoin	39%	10%	31%	24%	81%
CCI30	36%	10%	66%	55%	20%
CCMIX	52%	10%	64%	55%	57%
CMC200	66%	10%	59%	57%	37%
Coin100	34%	10%	14%	10%	4%
CoinMarket	36%	10%	12%	8%	7%
CRIX	40%	10%	62%	53%	37%
Crypto20	5%	10%	84%	93%	17%
Ethereum	3%	10%	25%	16%	7%
TokenMarket	54%	10%	58%	49%	99%

Source: own study.

Table 4 shows the share of projects (excluding Bitcoin, Ethereum and Crypto20 projects due to their presence in the group of analysed indices) statistically significantly correlated with the selected indices. The obtained results indicate that the Crypto20 index, whose token can be compared to an index fund unit of the 20 cryptocurrencies with the highest capitalization (excluding the so-called stablecoins), is characterized by the highest share of significantly correlated projects. Moreover, the Ethereum and CoinMarket indices are characterized by a high share of significantly correlated projects. It should be noted that the CMC200 and Crypto20 indices have smaller research samples than the other indices, which may explain the differences in the share of significantly correlated projects.

Table 4. Share of statistically significant correlation coefficients between projects and selected indices

Index	Number of significantly correlated projects	Share of significantly correlated projects
Bitcoin	1,281	38.33%
CCI30	210	6.28%
CCMIX	1,489	44.55%
CMC200	774	23.16%
Coin100	1,491	44.61%
CoinMarket	**1,519**	**45.45%**
CRIX	1,438	43.03%
Crypto20	**1,567**	**46.89%**
Ethereum	**1,551**	**46.41%**
TokenMarket	1,211	36.24%

Source: own study.

Figure 3 shows a strip chart of the correlation coefficients for the studied indices. Each point on the chart shows the correlation coefficient between a given index and a single project from the database (excluding Bitcoin, Ethereum and Crypto20 projects due to their presence in the group of analyzed indices). The large colour-coded dots indicate the mean correlation coefficient, and the coloured lines indicate a range of 1.5 standard deviations from the mean. With the exception of the CCI30 index, which on average is least correlated with projects, for each index, all the values within 1.5 standard deviations from the mean are greater than 0.25 and lower than 0.675.

An interesting phenomenon is the negative correlation in some projects, which are often called 'stablecoins'. By definition, these tokens should not be subject to price fluctuations or their price volatility should be minimal. In some cases, their value corresponds to the dollar value in a 1:1 ratio. Examples include the Tether USDT (https://tether.to) and TrueUSD projects (https://www.trusttoken.com/).
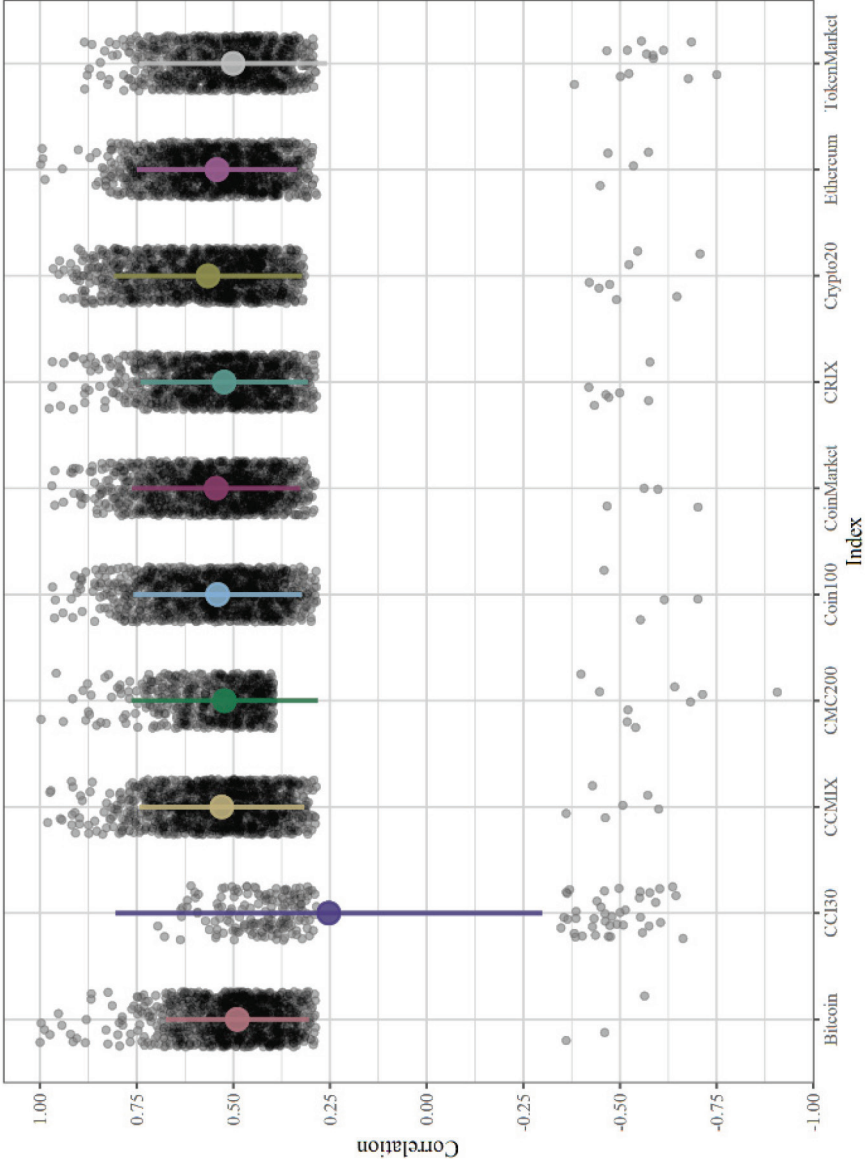
Fig. 3. Strip chart of selected indices' correlation coefficients

Source: own study.

Table 5 shows the statistics describing the distribution of correlation coefficients for the studied indices. Except for the CCI30 index, the interquartile distribution of the correlation coefficients for each index ranges from 0.406 to 0.559. The medians of the correlation coefficients for each of the analysed indices, except for CCI30, are over 0.48, which proves a relatively high degree of correlation between the studied indices and individual cryptoassets. The Crypto20, Ethereum, CoinMarket and Coin100 indices have the highest correlation coefficient medians.

Table 5. Descriptive statistics of statistically significant correlation coefficients between projects and selected indices

Index	5% Percentile	First quartile	Median	Third quartile	95% Percentile
Bitcoin	0.333	0.406	0.480	0.559	0.680
CCI30	-0.551	0.310	0.378	0.461	0.595
CCMIX	0.345	0.439	0.521	0.620	0.754
CMC200	0.406	0.450	0.511	0.602	0.721
Coin100	**0.348**	**0.441**	**0.533**	**0.637**	**0.776**
CoinMarket	**0.348**	**0.444**	**0.535**	**0.639**	**0.782**
CRIX	0.341	0.431	0.520	0.613	0.743
Crypto20	**0.360**	**0.453**	**0.553**	**0.672**	**0.825**
Ethereum	**0.346**	**0.444**	**0.537**	**0.637**	**0.762**
TokenMarket	0.335	0.418	0.499	0.592	0.715

Source: own study.

The table in Appendix 1 shows the correlation matrix for ten tested time series. Except for the CCI30 index, all indices are correlated in a statistically significant manner. The highest correlation was noted between the CoinMarket and Coin100 indices, suggesting that the creation of the index based on only the 100 largest projects gives results similar to the analysis of all instruments.

The analysis is supplemented by the figure in Appendix 2, which contains a diagram showing the correlations between the studied rates of return. As can be seen, the CCI30 is characterized by the lowest values of the correlation coefficient with other indices. The diagram was also supplemented with regression lines, for illustrative reasons only (hence a separate table with parameters was not included). The upper half of the diagram lists the correlation coefficients between the indices and statistical significance markers (three stars means significance at 1%, two at 5%, and no stars means the coefficient is statistically non-significant). Histograms of the monthly index returns are plotted on the diagonal of the diagram.

4. Conclusion

The aim of this article was to compare Bitcoin, Ethereum and popular cryptoasset indices in order to select the best reflection of the market risk factor. As a result of the study, it can be concluded that Coin100, CoinMarket and TokenMarket are indices with the best risk-to-return ratio. In this respect, by far the worst instruments are Ethereum, Crypto20, CCI30 and CRIX, which means that only portfolios containing a large amount of cryptoassets ensure the adequate elimination of risk specific to individual assets.

The instruments that are significantly correlated with a substantial part of the individual tokens are: CCMIX, Coin100, CoinMarket, Crypto20 and Ethereum – from 44.55 % to 46.89 % of projects are statistically significantly correlated with these indices. The least attractive instruments in this respect include CCI30 (6.28 %) CMC200 (23.16 %), TokenMarket (36.24 %) and Bitcoin (38.33 %). In all cases, except for CCI30, the studied indices are significantly and strongly correlated with each other; for CoinMarket and Coin100, the correlation coefficient is 0.995.

To summarise, CoinMarket and Coin100 are the indices that best reflect the market risk factor due to their satisfactory performance in regard to risk-return efficiency and correlation to individual assets in the market. It is worth noting that in many practical situations it is much easier to build an index based on the 100 tokens with the highest capitalization than to attempt to aggregate thousands of tokens listed on over 300 exchanges. For this reason, the optimal solution is to choose an index based on 100 tokens. These findings can now be used in future studies of market models for the cryptoasset sphere as well as developing asset pricing methods.

Systematic risk is an important element of the analyzed market. It seems that many investors in the market under study treat digital tokens as a homogeneous asset class. Although the purpose of tokens issued as part of the development of various projects is different, the token price changes are quite similar. In general, it can be said that using overall trends, one can explain a significant number of the price changes of individual projects.

Appendices

Appendix 1. Correlation matrix of chosen indices

| | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 | Variable 6 | Variable 7 | Variable 8 | Variable 9 | Variable 10 |
	CCI30	**CCMIX**	**CRIX**	**Bitcoin**	**Ethereum**	**Coin100**	**CoinMarket**	**TokenMarket**	**Crypto20**	**CMC200**
CCI30	1	0.0545	0.0672	-0.0272	0.2164	0.2179	0.2470	0.2548	0.0292	0.2149
CCMIX	0.0545	1	0.9832	0.9422	0.7959	0.9339	0.9313	0.7440	0.9401	0.9268
CRIX	0.0672	0.9832	1	0.9336	0.7912	0.9245	0.9230	0.7384	0.9092	0.9234
Bitcoin	-0.0272	0.9422	0.9336	1	0.6458	0.8134	0.8081	0.5851	0.8188	0.8956
Ethereum	0.2164	0.7959	0.7912	0.6458	1	0.8294	0.8299	0.7350	0.8616	0.8398
Coin100	0.2179	0.9339	0.9245	0.8134	0.8294	1	0.9948	0.7984	0.9215	0.9303
CoinMarket	0.2470	0.9313	0.9230	0.8081	0.8299	0.9948	1	0.8074	0.9272	0.9319
TokenMarket	0.2548	0.7440	0.7384	0.5851	0.7350	0.7984	0.8074	1	0.7685	0.6902
Crypto20	0.0292	0.9401	0.9092	0.8188	0.8616	0.9215	0.9272	0.7685	1	0.8474
CMC200	0.2149	0.9268	0.9234	0.8956	0.8398	0.9303	0.9319	0.6902	0.8474	1

P-value for correlation coefficients

| | Variable 1 | Variable 2 | Variable 3 | Variable 4 | Variable 5 | Variable 6 | Variable 7 | Variable 8 | Variable 9 | Variable 10 |
	CCI30	**CCMIX**	**CRIX**	**Bitcoin**	**Ethereum**	**Coin100**	**CoinMarket**	**TokenMarket**	**Crypto20**	**CMC200**
CCI30		71.01%	64.62%	85.46%	13.95%	13.67%	9.05%	8.06%	85.97%	30.23%
CCMIX	71.01%		0.00E+00	0.00E+00	1.37E-11	0.00E+00	0.00E+00	1.36E-09	0.00E+00	2.93E-11
CRIX	64.62%	0.00E+00		0.00E+00	2.20E-11	0.00E+00	0.00E+00	2.10E-09	1.33E-15	4.80E-11
Bitcoin	85.46%	0.00E+00	0.00E+00		7.16E-07	2.14E-12	3.84E-12	1.26E-05	1.90E-10	1.48E-09
Ethereum	13.95%	1.37E-11	2.20E-11	7.16E-07		3.26E-13	3.06E-13	2.71E-09	1.91E-12	1.52E-07
Coin100	13.67%	0.00E+00	0.00E+00	2.14E-12	3.26E-13		3.06E-13	1.06E-11	0.00E+00	1.69E-11
CoinMarket	9.05%	0.00E+00	0.00E+00	3.84E-12	3.06E-13	0.00E+00		4.12E-12	0.00E+00	1.30E-11
TokenMarket	8.06%	1.36E-09	2.10E-09	1.26E-05	2.71E-09	1.06E-11	4.12E-12		1.12E-08	0.01%
Crypto20	85.97%	0.00E+00	1.33E-15	1.90E-10	1.91E-12	0.00E+00	0.00E+00	1.12E-08		9.09E-08
CMC200	30.23%	2.93E-11	4.80E-11	1.48E-09	1.52E-07	1.69E-11	1.30E-11	0.01%	9.09E-08	

Source: own study.

Appendix 2. Dependence diagram of selected indices
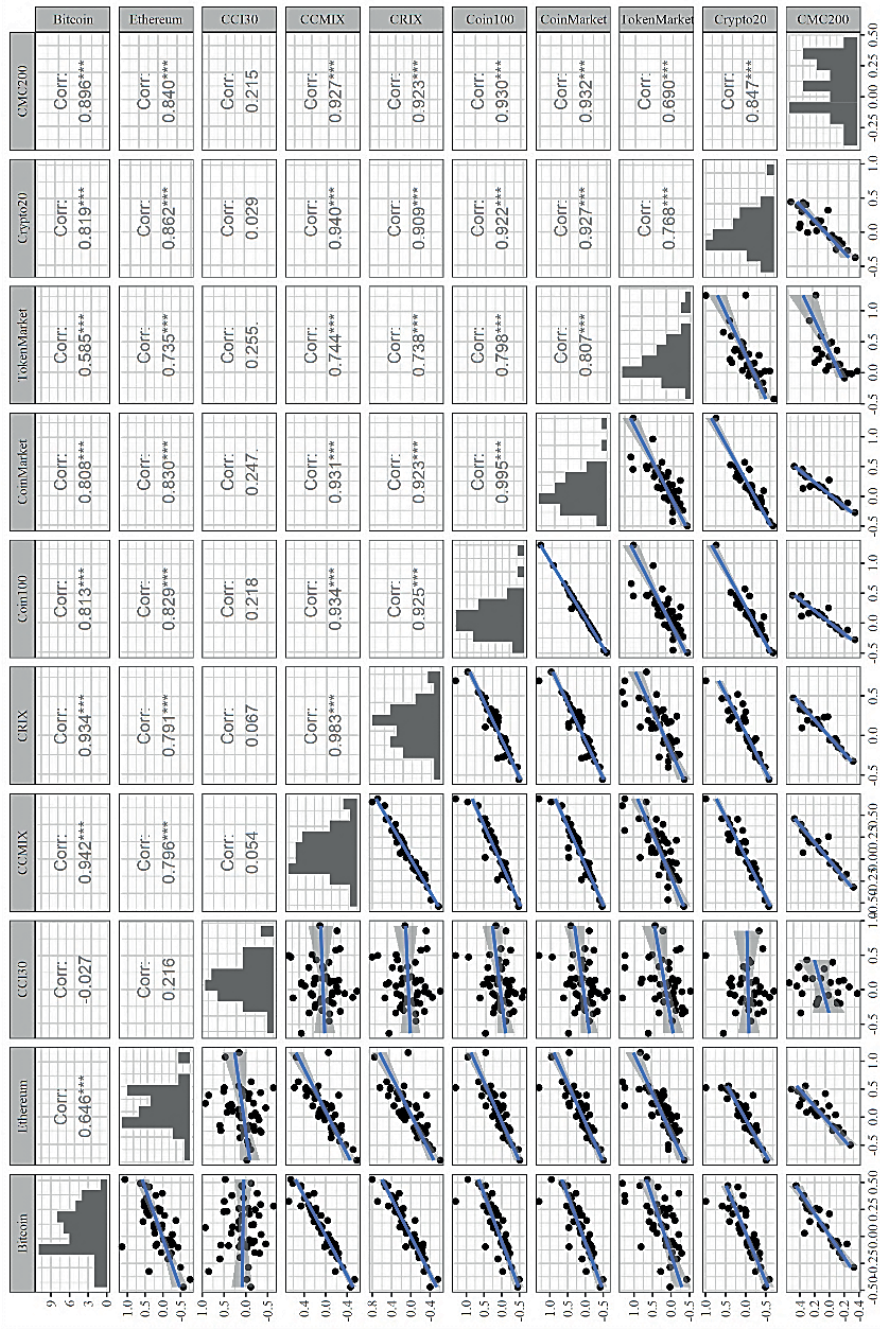
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ANALIZA RYZYKA RYNKOWEGO NA RYNKU KRYPTOAKTYWÓW. PORÓWNANIE INDEKSÓW CYFROWYCH AKTYWÓW

Streszczenie: Na początku 2021 r. kapitalizacja rynku kryptoaktywów przekroczyła 1,5 bln USD, a na świecie funkcjonowało ponad 300 giełd, na których można było handlować ponad 8 tys. tokenów. W ramach badań związanych z dojrzałymi segmentami rynku finansowego (np. rynek akcji w Stanach Zjednoczonych) naukowcy i praktycy od kilkudziesięciu lat starają się zidentyfikować kluczowe czynniki ryzyka, dzięki którym możliwe jest wyjaśnienie premii za ryzyko kapitałowe inwestycji w daną klasę aktywów. W ostatnich latach wzrasta liczba badaczy próbujących zidentyfikować te czynniki dla kryptoaktywów. Celem niniejszego artykułu była analiza popularnych indeksów kryptoaktywów i zidentyfikowanie tych, które mogą być wykorzystane jako *proxy* portfela rynkowego do oszacowania wspomnianej premii za czynniki ryzyka. Wyniki badań wskazują, że czynnik ryzyka rynkowego jest istotnym elementem badanego rynku, a indeksami, które najlepiej go odzwierciedlają, są indeks składający się ze wszystkich kryptoaktywów ważonych kapitalizacją oraz Coin100, który zawiera tylko 100 największych kryptoaktywów.

Słowa kluczowe: kryptoaktywa, tokeny cyfrowe, łańcuch bloków, kryptowaluta, syatematyczne ryzyko, metoda wyceny aktywów kapitałowych.