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Benefits of sectoral cryptocurrency portfolio optimization

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ABSTRACT

When creating a portfolio, investors should consider the dynamics of the income ratio of the selected portfolio asset in order to identify and quantify the investment risk. This research paper formally identifies and describes the benefits of sectoral cryptocurrency classification portfolio optimization and its performance. Six optimization targets will be tested: MinVar, MinCVaR, MaxSR, MaxSTARR, MaxUT and MaxMean. We compare the obtained portfolios with the performance of the CRIX index (representing the crypto market) over the same period. Our results show that five out of six portfolio strategies performed better if they included sectoral cryptocurrencies, namely from financial, exchange and business services sectors.

1. Introduction

Bitcoin, the computer program or protocol, was released to the public on 9 January 2009, creating the world's first cryptocurrency – bitcoin. Its technology enabled almost instantaneous transaction execution, with negligible fees without intermediaries or the central body, which attracted great attention, as well as a large number of users. An important characteristic of the Bitcoin protocol is its open source system, the system whose initial code is open and free to the public. This means that anyone who is interested can freely study and work on the system; if their suggestions are in the direction of improvement, the community will accept the changes and improve the protocol. Again, this also means that anyone who wants can freely take the existing protocol, modify it, change it or adapt to their needs in some context, create a new cryptocurrency and release it to the public. The latter allowed the creation of a number of new cryptocurrencies with various characteristics and the spread of their use, firstly in payment transactions and then in the context of their trading on the new secondary market.

2. An overview of the current research

In this paper, we investigate the relationships among cryptocurrencies and cryptocurrency sectors with the aim of constructing and modeling superior portfolios, in the sense that such portfolios can beat the market. The cryptocurrency market and its entire infrastructure is continuously growing year on year. Due to their availability, an increasing number of institutional and individual investors of various profiles invest and trade in cryptocurrencies, slowly making cryptocurrencies a legitimate asset class in investors' view. Since cryptos are entering the mainstage, the need for serious financial analysis and continued research is increasing.

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One of the first studies on this topic was conducted by Trimborn (2015), who in his work optimizes the cryptocurrency portfolio of constituents of the CRyptocurrency IndeX – CRIX, with the aim of minimizing variance. From a volatility point of view, the results of the approximated data portfolio favor an optimized portfolio where volatility is lower than CRIX. On the other hand, when excluding the estimated data, the results favor the CRIX index where volatility is lower and cumulative return is higher.

Trimborn et al. (2019) conducted research into the existing cryptocurrency portfolios with an individual market capitalization of more than USD 1 million and incorporated them with traditional instruments – stocks, components of the S&P 100 and DAX30 indexes, shares listed on the Portuguese stock exchange, and ran a minimal variance optimization. Optimization is carried out with and without liquidity limitation on units and the performance of the portfolio is compared. The inclusion of cryptocurrencies in the portfolio improves the reward-risk ratio. Equity-constrained portfolios of equities and cryptocurrencies produce better cumulative returns than non-restricted portfolios.

One of the most comprehensive studies examining the performance of a portfolio created from cryptocurrencies and traditional assets was conducted by Petukhina et al. (2021). The authors group the existing standard and recent optimization models into four strategies: risk-oriented strategies, return-oriented strategies, risk-return-oriented strategies and combination strategies. The authors apply the selected models to portfolios composed of 55 selected cryptocurrencies and 16 variables represented by 5 types of traditional assets. The performance of all the portfolios indicates the usefulness of including cryptocurrencies in a portfolio along with traditional assets. The same portfolios achieved a lower cumulative return in case when the limits on the units controlling the liquidity were raised.

Chuen et al. (2017) model market sentiment as the average return of a historical return series and create a portfolio strategy based on a performed sentiment analysis. The authors optimized a portfolio of ten selected cryptocurrencies along with traditional assets consisting of stock indices, real estate market index and gold. The inclusion of cryptocurrencies in the portfolio raises the effective limit of possible portfolios, thereby improving the reward-risk ratio. In addition, the strategy created on a sentiment analysis achieved a far higher cumulative return than comparative portfolios, thus confirming the significant sentiment dynamics in the cryptocurrency market.

The secondary cryptocurrency market can be viewed as a separate asset class and it is therefore desirable to examine the possibility of constructing an efficient portfolio made up solely of cryptocurrencies with different allocation goals. One of the first papers examining such a possibility is Liu (2018). The observed sample consists of ten cryptocurrencies with a market capitalization of more than USD 1 billion. Other than the portfolio with minimal variance, none of the optimization models met their target. The author concludes that in the cryptocurrency market sophisticated models cannot beat the performance of portfolios with equal weights – observing them from the viewpoint of a rational investor.

Analysis of the options for the optimization and diversification of risk in the cryptocurrency market was also conducted by Brauneis and Mestel (2018). Their results confirm the previous research. The highest expected return, as well as the Sharpe ratio, was achieved by the portfolio with equally weighted assets, regardless of the frequency of rebalancing. It concludes that a portfolio with equal allocations is the best choice when creating and modeling a portfolio in the cryptocurrency market.

The performance analysis of a sophisticated portfolio optimization model in relation to the passive approach of equal allocations in the cryptocurrency market was also conducted by Platanakis et al. (2018). Given the results of performance measures that do not favor either of the models, the authors also conclude that passive (naive) diversification with equal allocations is a better choice for portfolio construction in the cryptocurrency market.

In all the research papers described above, the cryptocurrency market was viewed as one separate market in which cryptocurrencies have equal characteristics. Each cryptocurrency represented an input variable with equal probability of being selected as a component of the portfolio, with its potential allocation in the portfolio defined by the optimization goal. In other words, the initial selection of portfolio components is either conditioned by an existing framework, such as the CRIX cryptocurrency index, or left to the choice resulting from the portfolio optimization of several different cryptocurrencies, most often cryptocurrencies with high market capitalization. Such an approach implies that all cryptocurrencies are equal in all their properties and capabilities, which is highly questionable. In this paper we test this common belief and approach the problem from a different angle. Cryptocurrencies can be categorized in six basic categories: payment currencies, blockchain economies, utility tokens, privacy coins, stablecoins and others. Each category is specific and offers certain advantages over the other. Since utilization tokens provide a specific purpose in the practical application of a product or service, they are by far the most created on decentralized computer platforms, i.e. blockchain economies. Accordingly, the cryptocurrency market can also be viewed through sectoral division according to the utilization properties of cryptocurrencies. Comparing portfolio performance with and without sectoral cryptocurrency selection will determine the usefulness of applying such an approach. In addition, cryptocurrencies that have a lower market capitalization and do not represent input variables in previous papers will now be considered. In other words, cryptocurrencies that are undervalued by their fundamentals will be easier to spot by sectoral observation of the cryptocurrency market. Such an approach is necessary and desirable to eliminate the subordinated position of potential investors, that is, to contribute more to the performance of the investor portfolio in the cryptocurrency market. Moreover, with the aim of evaluating their performance, the performance of the resulting portfolios will be compared with the performance of the CRIX index over the same time period. The described methodological approach has not been considered so far and represents a significant scientific contribution in the field of research of investment opportunities in the cryptocurrency market.

3. Data and methodology

For the purpose of this study, we used publicly available daily price data (in USD) for a total of 65 cryptocurrencies collected from the Coinmarketcap – CMC platform pages. Data was collected for the period from 8/26/2019 to 02/22/2020, creating a sample of 146 daily observations, or 145 daily returns for 65 time series.

To test the utility of cryptocurrency sectoral division, an existing portfolio consisting of the top 50 cryptocurrencies by market capitalization includes additional 15 cryptocurrencies, 5 leading cryptocurrencies by each of the three leading utilization sectors by market capitalization: finance, exchanges and business services. Sectoral cryptocurrencies that originally entered the first 50 by market capitalization were excluded and replaced with the next utilization token by the size of market capitalization in the respective sector.

We formed multiple portfolios with different optimization goals of risk minimization, return maximization and maximization of return and risk ratios. Given the results of previous research by Briere et al. (2015); Chuen et al. (2017) as well as Goodell and Goutte (2021), and the absence of a normal distribution of returns, apart from the standard deviation, we used the conditional Value at Risk - CVaR for the risk measure, i.e. the methodology that follows the work of Rockafellar and Uryasev (2000) and Conlon et al. (2020), with a confidence level of 95 %. Our optimization goals are as follows: minimum variance (MinVar), minimum CVaR (MinCVaR), maximize sharpe ratio (MaxSR), maximize stable tail-adjusted return ratio (MaxSTARR), maximize utility function (MaxUT) and maximize mean return (MaxMean). In order to examine the benefits of treating the cryptocurrency market through sector division we conducted the research in two steps. The first step was to form and test the performance of a portfolio whose components make up the first 50 cryptocurrencies by market capitalization. In the second step, additional 15 sectoral cryptocurrencies were included in the existing data set. In order to achieve the inclusion of sector cryptocurrencies in the portfolio, in the second step, linear group constraints were created where 20 % of the total portfolio allocation must be allocated to sector cryptocurrencies according to the optimization goals. The notation of portfolio optimization goals involving sector cryptocurrencies is as follows: minimum variance-sector (MinVar-S), minimum CVaR-sector (MinCVaR-S), maximize sharpe ratio-sector (MaxSR-S), maximize stable tail-adjusted return ratio-sector (MaxSTARR-S), maximize utility function-sector (MaxUT-S) and maximize mean return-sector (MaxMean-S). Optimization is performed out of sample (backtesting), with the same parameters for each optimization goal. A time period of $k = 10$ days was used to estimate the initial parameters and portfolio allocation. Given the dynamics of the cryptocurrency market, a more frequent monthly rebalance of $K = 30$ days was chosen with the so-called extending window approach $k + K$. For each period $k + 1$, portfolio returns are drawn with respect to the results of the allocation optimization in the previous k, i.e. $k + K$ moment.

3.1. Asset allocation models

The basic optimization model used in this paper is based on the Modern Portfolio Theory (Markowitz, 1952). In its original form, the model focuses on minimizing the variance of the asset portfolio for a given level of expected return within certain theoretical assumptions, which is why it is often referred to as the mean-variance (M-V) model. The basic form of the Markowitz formulation (soft return constraints) expressed in the form of linear algebra can be written as follows:

$$\begin{aligned} &\min_{w} \sigma_p^2(w) = w^{\mathrm{T}}\widehat{\Sigma}w \\ &s.t.\ 1_N^{\mathrm{T}}w = 1,\ x^T w \geq \mu,\ w_i \geq 0 \end{aligned} \tag{1}$$

where σ_p^2 is the variance of the portfolio, $w = (w_1, w_2, \ldots, w_N)^T$ are the weights of individual assets in the portfolio and $\widehat{\Sigma}$ is the estimated covariance matrix of assets N and their returns T. The above expression involves three additional constraints: 1_N represents a $(Nx1)$ vector where all elements of the vector represent the portfolio weights and their sum must be one (full investment constraint), x is the $(Nx1)$ vector of the expected returns of the portfolio assets whose sum, with respect to individual portfolios of the portfolio assets, must be greater than or equal to the desired total portfolio return μ. The last restriction defines a constraint on short selling assets, that is, all portfolio holdings must be positive in size. By further formulation, the basic Markowitz model presented above is better adapted to the actual needs where its variants are used in this paper and described.

3.2. Global minimum variance portfolio objective

If the limit of the required rate of return is omitted from the expression (1), portfolio optimization with the aim of minimizing risk results in a global minimum variance of portolio - GMV. Such a strategy is focused only on the return covariance matrix and is based on finding the proportion of individual assets that minimizes the total variance of the portfolio. The GMV formulation used in this paper is given by expression (2), which includes a linear constraint for a sectoral cryptocurrency group. For portfolios that do not include sectors, the linear restriction is omitted.

$$\begin{aligned} &\min_{w} \sigma_p^2(w) = w^{\mathrm{T}}\widehat{\Sigma}w \\ &s.t.\ 1_N^{\mathrm{T}}w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{aligned} \tag{2}$$

L and U are the lower and upper bounds for the sector cryptocurrency group. A is the constraint matrix for the sector cryptocurrency group.

3.3. Global minimum CVaR portfolio objective

The disadvantage of the expression (2), is the assumption of a normal distribution of the portfolio's asset return for which the parameters are estimated. Considering the results of the study by Briere et al. (2015) and Chuen et al. (2017), where evidence of the presence of a heavy-tailed cryptocurrency return distribution is shown, in this study expression (3) is used (Petukhina et al. (2021) and (Eisl et al. (2015)), which is based on the CVaR methodology by Rockafellar and Uryasev (2000). We use a more reliable risk measure (CVaR) as a measure of risk so that the Mean-Variance model turns into Mean-Conditional Value at Risk (M-CVaR).

We define the cumulative distribution function of a loss function $z = f(w, y)$ as

$$\Psi(w, \zeta) = P\{yf(w, y) \leq \zeta\} \tag{3}$$

where w is fixed decision vector (i.e. portfolio weights), ζ loss associated with that vector and y uncertainties (e.g. market variables) that impact the loss. For a given confidence level α, the Value at Risk (VaR_α) associated with portfolio is given as

$$VaR_\alpha(w) = min\{y\Psi(w, \zeta) \geq \alpha\} \tag{4}$$

If $f(w, y)$ exceeds the VaR, then the expected value of the loss is defined as

$$\mathrm{CVaR}_\alpha(w) = \frac{1}{1-\alpha} \int_{y(w) \leq VaR_\alpha(w)} yf(yw)dy \tag{5}$$

Expression (5) is adapted to the optimization goal of risk minimization, with a confidence level of 95 %. For portfolios that do not include sector cryptocurrencies, their linear restriction is omitted.

$$\begin{gathered} \min_w \mathrm{CVaR}_\alpha(w) \\ s.t.\ 1_N^{\mathrm{T}} w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{gathered} \tag{6}$$

3.4. Maximize Sharpe and STARR ratio portfolio objective

By putting in a ratio, the expected return of the portfolio and the standard deviation of the portfolio, a Sharpe ratio is obtained. In this case, the optimization goal of maximizing the return for a given level of risk is implemented. The portfolio that has the highest Sharpe ratio represents the optimal portfolio, i.e. the tangent portfolio used in this paper (7). For portfolios without sector cryptocurrency, the linear restriction is omitted.

$$\begin{gathered} \max_w \left\{\frac{w^{\mathrm{T}}\mu - \bar{r}_f}{\sqrt{w^{\mathrm{T}}\widehat{\Sigma}w}}\right\} = \left\{\frac{w^{\mathrm{T}}\mu}{\sqrt{w^{\mathrm{T}}\widehat{\Sigma}w}}\right\} \\ s.t.\ 1_N^{\mathrm{T}} w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{gathered} \tag{7}$$

In the above expression, $\bar{r}_f$ represents the risk-free interest rate adjusted for the observation period. For the purposes of this research, the risk-free interest rate is omitted, as can be seen from (7) and (8).

If CVaR is used in the denominator of expression (7) instead of the standard deviation, the Sharpe ratio turns into Stable Tail-Adjusted Return Ratio (STARR) and is given by (8). The optimization goal is to maximize the STARR ratio with a 95 % confidence level and a linear limit for sector cryptocurrencies.

$$\begin{gathered} \max_w \left\{\frac{w^{\mathrm{T}}\mu - \bar{r}_f}{\mathrm{CVaR}_\alpha(w)}\right\} = \left\{\frac{w^{\mathrm{T}}\mu}{\mathrm{CVaR}_\alpha(w)}\right\} \\ s.t.\ 1_N^{\mathrm{T}} w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{gathered} \tag{8}$$

3.5. Maximize quadratic utility function portfolio objective

The disadvantage of the Sharpe ratio is the assumption that all investors are equally risk-averse, resulting in only one optimal portfolio that delivers the best reward-risk ratio. In order to derive the utility function curve, it is necessary to introduce an investor aversion parameter to risk γ. According to (9), a lower parameter value (lower risk aversion) also means a lower penalization of the portfolio risk contribution, which leads to a higher-risk portfolio, that is, a potentially higher expected return. Conversely, in the case of a higher risk aversion, higher-risk portfolios will be more penalized, leading lower-risk portfolios and lower expected returns. By gradually increasing the degree of risk aversion, a portfolio efficient frontier is derived in order to find the desired risk-return profile. The value of the parameter used in the paper is one.

$$\begin{gathered} \max_w \mu(w) - \frac{\gamma}{2} w\widehat{\Sigma}w \\ s.t.\ 1_N^{\mathrm{T}} w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{gathered} \tag{9}$$

In the above expression, γ represents the degree of investor aversion to risk.

3.6. Maximize return portfolio objective

In contrast to the strategy that minimizes variance, the study also implements an optimization strategy that maximizes expected portfolio returns, i.e. does not include a predefined level of risk. In this case, the optimization algorithm does not take into account the variance and covariance matrix, but uses the average returns of the previous period to estimate the highest expected portfolio return in the next period. The assets of the portfolio with the highest average return in the previous period will have the highest allocation in the portfolio. Since the strategy does not consider risk as an input in optimization, it is considered extremely high-risk. The formulation used in this paper to maximize the expected return is given by (10). It includes a linear constraint for a group of sectoral crypto-currencies. For portfolios without cryptocurrencies divided by sectors, the linear restriction is not included.

$$\begin{aligned} &\max_{w} \mu_p(w) = w^{\mathrm{T}} \\ &s.t.\ 1_N^{\mathrm{T}} w = 1,\ w_i \geq 0,\ L \leq \mathrm{A}w \leq U \end{aligned} \tag{10}$$

In the above expression, μ_p is the expected portfolio return.

The results of several different absolute and relative measures of success are presented in order to evaluate the success of each optimization strategy: Sharpe ratio (Sharpe, 1963), MSquared (Modigliani and Modigliani, 1997), Regression alpha, Jensen's alpha (Jensen, 1968), Treynor ratio (Treynor, 1965) and Information ratio (Bacon, 2008), where the values are calculated annually and relate to total time series of portfolio returns.

4. Results and discussion

We present and interpret the obtained empirical results in two phases. In the first phase, the results are reviewed and interpreted by a comparative method between asset allocation models according to the initial selection of the portfolio components. In addition, the success of a particular strategy is judged by the implementation of performance measures that include the CRIX index as a benchmark for the crypto market over the observation period. In the second phase, the results of allocation models are compared and interpreted between portfolios to determine the benefits of dividing and optimizing cryptocurrencies according to their appropriate sectors.

Table 1 shows the results of the previously described performance measures for six asset allocation models for 50 cryptocurrencies selected by CMC market size. Table 2 shows the results of portfolio performance measures that, in addition to the 50 cryptocurrencies per CMC, include additional 15 cryptocurrencies per related financial, exchange and business services sector. The last column in the table shows the results of the CRIX index over the same period as the benchmark of the cryptocurrency market. All values except the regression beta and worst drawdown of each optimization strategy are reported annually. In case of negative values, the Traynor ratio is omitted.

In comparison to the CRIX index, all implemented optimization goals achieved a higher cumulative return in the same observation period. However, the CRIX index achieved a lower standard deviation level in five out of six observed cases. Four portfolios have smaller worst drawdowns than the index, as well as a higher *SR*.

Fig. 1 shows the dynamics of the daily cumulative returns of individual strategies, the total daily returns of all strategies, and an underwater chart for drawdown to further illustrate the performance of different portfolio optimization goals.

By including additional 15 sectoral cryptocurrencies that would not initially be selected as components of the portfolios by their market capitalization, the results differ by all measures shown in Table 2.

Fig. 2 shows the dynamics of the daily cumulative returns of individual strategies, the total daily returns of all strategies, and the underwater chart for drawdown, further illustrating the performance of different portfolio optimization goals.

Interpreting the results also involves considering the performance of strategies between portfolios that differ in composition. The first thing to notice is the height of the regression alpha, which for all portfolios except the MinVar-S, achieved a better result if sectoral

Table 1
Asset allocation models without sectoral cryptocurrencies.

		Asset Allocation Models						
Performance Metrics		MinVar	MinCVaR	MaxSR	MaxSTARR	MaxUT	MaxMean	CRIX
Beta	β_i	0,05	−0,05	0,02	−0,014	−0.05	−0,01	1
Annualized Alpha	a_{ai}	1,12	1,91	1,16	1,53	0,97	2,29	/
Annualized Return	R_{Gi}	0,94	1,44	0,95	0,62	0,72	0,95	0,57
Annualized Std Dev	σ_{ai}	0,49	0,54	0,48	0,94	0,46	1,04	0,47
Worst Drawdown	WD	0,27	0,29	0,26	0,57	0,27	0,56	0,31
Cumulative Return	CY	1,46	1,67	1,47	1,32	1,37	1,47	1,29
Sharpe Ratio	SR	1,92	2,68	1,95	0,66	1,58	0,91	1,20
MSquared	M^2	0,91	1,27	0,92	0,31	0,75	0,43	0,57
Treynor Ratio	TR	18,69	/	59,03	/	/	/	0,57
Jensen's Alpha	α_i	0,91	1,47	0,94	0,63	0,75	0,95	/
Information Ratio	IR	0,56	1,20	0,56	0,05	0,23	0,34	/

Table 2
Asset allocation models with sectoral cryptocurrencies.

Performance Metrics		Asset Allocation Models						
		MinVar-S	MinCVaR-S	MaxSR-S	MaxSTARR-S	MaxUT-S	MaxMean-S	CRIX
Beta	β_i	0,05	0,03	−0,08	0,10	−0,12	0,22	1
Annualized Alpha	a_{ai}	0,86	2,39	1,37	3,74	1,51	10,10	/
Annualized Return	R_{Gi}	0,73	1,99	1,09	3,02	1,09	5,84	0,57
Annualized Std Dev	σ_{ai}	0,45	0,53	0,43	0,67	0,48	1,17	0,47
Worst Drawdown	WD	0,27	0,22	0,29	0,23	0,25	0,35	0,31
Cumulative Return	CY	1,37	1,88	1,52	2,23	1,53	3,02	1,29
Sharpe Ratio	SR	1,62	3,79	2,53	4,50	2,27	4,99	1,20
MSquared	M^2	0,77	1,79	1,20	2,13	1,07	2,36	0,57
Treynor Ratio	TR	14,91	76,54	/	31,22	/	26,88	0,57
Jensen's Alpha	α_i	0,70	1,98	1,12	2,97	1,16	5,72	/
Information Ratio	IR	0,26	2,04	0,77	3,09	0,74	4,31	/

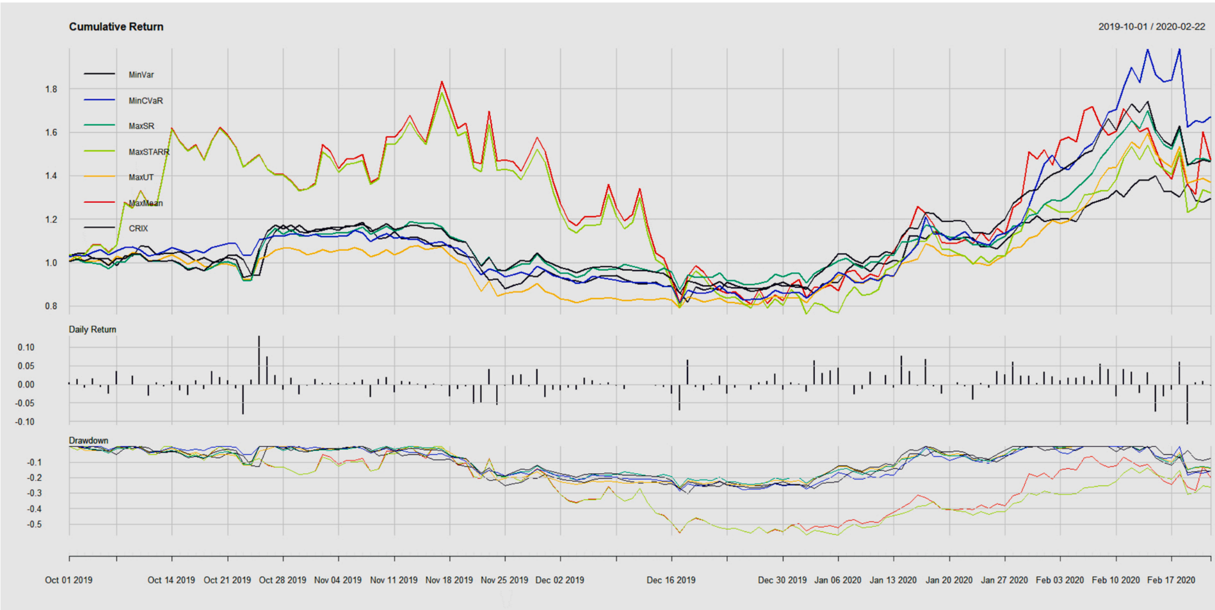

Fig. 1. Performance summary of various strategies without sectoral cryptocurrencies.

cryptocurrencies were included in the portfolio. Portfolios with sectoral cryptocurrencies earn, on average, higher returns than portfolios without sectoral components. Geometric return has the same relationships. Only the MinVar-S portfolio has a lower return than the portfolio return without sectoral cryptocurrency, thus confirming our finding and logic that there are benefits in treating the cryptocurrency market through sectoral affiliation.

In terms of risk, four strategies involving sectoral cryptocurrencies achieved a lower standard deviation than the portfolios without them. However, the higher risk was offset by the higher realized returns, implying a higher Sharpe ratio. Worst drawdown also points to the benefits of including sectoral cryptocurrencies, whereas only the MaxSR-S portfolio has a higher worst drawdown than the MaxSR portfolio.

The inclusion of sectoral cryptocurrencies also led to an increase in cumulative return for all strategies except the MinVar-S portfolio. The biggest difference was recorded by the MaxMean-S portfolio, where its cumulative return increased by 1.55. By applying a return maximization strategy and considering sectoral cryptocurrencies as components of the portfolio, it was possible to achieve a higher cumulative return (by 105 % over a 146-day period) than the same strategy that does not consider sectoral cryptocurrencies. A significant increase in cumulative return was also achieved by the MaxSTARR-S portfolio of 0.91, or 69 %, compared to MaxSTARR. The results of the Sharpe ratio and MSquared measures are consistent with the above findings. The largest increase in SR and M^2 refers to the MaxMean-S portfolio. Only the MinVar-S portfolio has a lower SR and M^2 relative to the equivalent strategy without sectoral cryptocurrencies. Given that five out of six portfolios that include sectoral cryptocurrencies had a higher geometric return and the regression beta did not increase significantly, Jensen's alpha performed better for all portfolios except MinVar-S. The

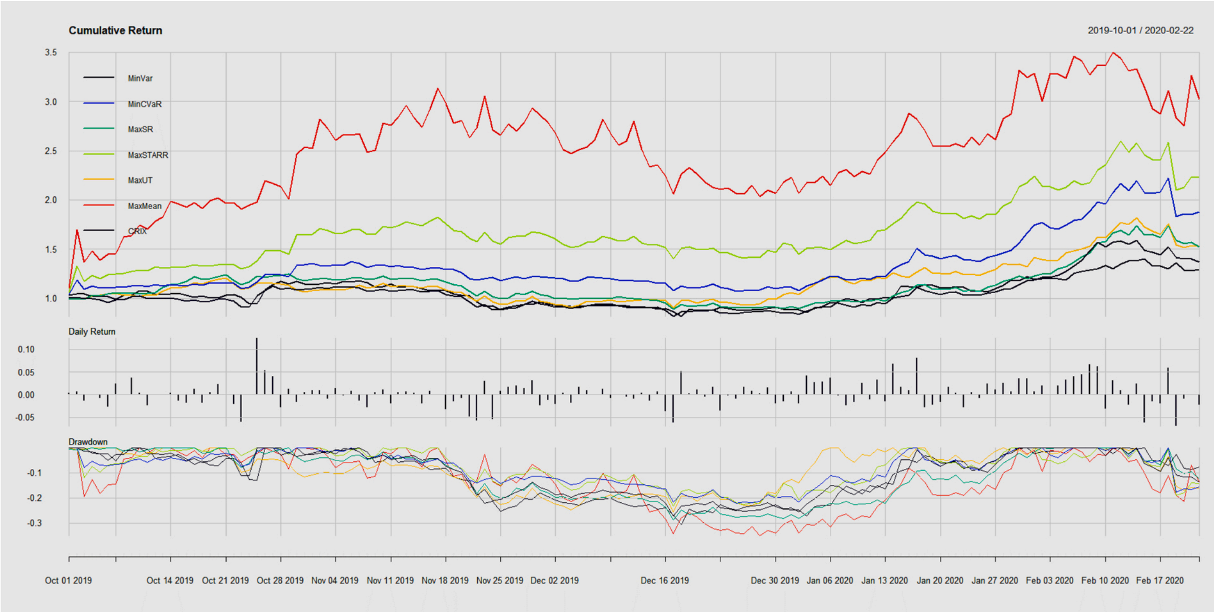

Fig. 2. Performance summary of various strategies with sectoral cryptocurrencies.

inclusion of additional sectoral cryptocurrencies in the existing portfolios contributed to the improvement of portfolio performance compared to the market represented by the CRIX index. Treynor ratio and Information ratio also performed significantly better for all sector portfolios except MinVar-S portfolios. Considering all of the above, it can be concluded that five out of six portfolios created according to different optimization goals achieved better results if they viewed the cryptocurrencies through the sectoral perspective (financial, exchange and business services). The results obtained contribute significantly to the understanding of investment opportunities in the cryptocurrency market and logic behind sectoral segmentation of cryptocurrency market.

In line with the obtained results, we have to emphasize the utility and necessity of observing the cryptocurrency market through sectoral affiliation with the aim of finding potentially "undervalued" cryptocurrencies. If portfolio components are selected solely by market capitalization, it would mean that those cryptocurrencies have already achieved the value that makes them a potential portfolio component. The possibility of price growth for such cryptocurrencies is certainly much lower than the possibility of cryptocurrency growth, which ranks much lower in terms of market capitalization. Sectorally, cryptocurrencies with lower market capitalization are emerging and investors can spot them more easily. Looking at the overall capitalization of the sector, it is easier to spot and identify current trends in the cryptocurrency market, such ss the growth trend of DeFi cryptocurrencies in 2019.

5. Conclusion

The primary goal of this paper is to examine the usefulness of observing cryptocurrencies through their sectoral affiliation when constructing a portfolio. The results of our empirical investigation are contributing to understanding and utilizing investment opportunities in the cryptocurrency market. The methodology for exploring the benefits of sectoral allocation and portfolio construction was implemented in two phases. In the first phase, the performance of the portfolio limited in composition to market capitalization is created and interpreted. In the second phase the cryptocurrencies of the three leading sectors by market capitalization—finance, exchanges and business services—are included. Consideration of the cryptocurrency market by sectoral affiliation is justified by the theoretical assumption that there are significant price trends of certain sectors in the cryptocurrency market. Such an approach easily recognizes cryptocurrencies that belong to the same sector and have lower market capitalization (higher price growth potential).

The results suggest that portfolios in which 20 % of the weight is allocated to cryptocurrencies of lower market capitalization achieve higher values across all implemented performance measures in five of the six optimization strategies. It can be concluded that it is desirable and necessary to observe the cryptocurrency market through the type or cryptocurrency utility, and such an approach can be achieved by categorizing cryptocurrencies into their sectors. Potential investors, and portfolio managers in particular, should not consider cryptocurrencies only on the basis of their market capitalization. Cryptocurrencies have characteristics and capabilities that define them according to their nominal purpose. Accordingly, portfolio managers are encouraged to consider cryptocurrencies by their characteristics (the type and purpose they provide) when constructing a portfolio, in order to eliminate their subordinate position and to contribute to portfolio performance in the cryptocurrency market.

Data availability

Data is publicly available on Coinmarketcap - CMC platform.

Author statement

Maria Čuljak: Conceptualization, Methodology, Software, Writing- Original draft preparation. Bojan Tomić: Data curation, Software, Writing- Original draft preparation. Saša Žiković: Supervision, Investigation.

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References

Bacon, C., 2008. Practical Risk-adjusted Perfomace Measurement. John Wiley & Sons, Ltd, United Kingdom.
Brauneis, A., Mestelb, R., 2018. Cryptocurrency-Portfolios in a Mean-Variance Framework. Financ. Res. Lett. 28, 259–264.
Briere, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: portfolio diversication with bitcoins. J. Asset Manag. 16 (6), 365–373.
Chuen, D.L.K., Guo, L., Wang, Y., 2017. Cryptocurrency: a new investment opportunity? J. Altern. Invest. 20 (3), 16–40.
Conlon, T., Shaen, C., McGee, R.J., 2020. Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. Res. Int. Bus. Financ. 54, 101248.
Eisl, A., Gasser, S., Weinmayer, K., 2015. Caveat Emptor: Does Bitcoin Improve Portfolio Diversication? Working Paper, WU. Available at SSRN: https://ssrn.com/abstract=2408997.
Goodell, J.W., Goutte, S., 2021. Diversifying equity with cryptocurrencies during COVID-19. Int. Rev. Financ. Anal. 76, 101781.
Jensen, M.C., 1968. The performance of mutual funds in the period 1945-1964. J. Finance 23 (2), 389–416.
Liu, W., 2018. Portfolio diversication across cryptocurrencies. Financ. Res. Lett. 29, 200–205.
Markowitz, H., 1952. Portfolio selection. J. Finance 7 (1), 77–91.
Modigliani, F., Modigliani, L., 1997. Risk-adjusted performance. J. Portf. Manage. 23 (2), 45–54.
Petukhina, A., Trimborn, S., Härdle, Wolfgang K., Elendner, H., 2021. „Investing with cryptocurrencies – evaluating their potential for portfolio allocation strategies. Quant. Finance 21 (11), 1825–1853.
Platanakis, E., Sutcliffeb, C., Urquhartc, A., 2018. Optimal vs naïve diversification in cryptocurrencies. Econ. Lett. 171, 93–96.
Rockafellar, R.T., Uryasev, S., 2000. Optimization of conditional value-at-Risk. J. Risk 2, 21–42.
Sharpe, W., 1963. A simplified model for portfolio analysis. Manage. Sci. 9 (2), 277–293.
Treynor, J.L., 1965. How to rate management of investment funds. Harv. Bus. Rev. 43 (1), 63–75.
Trimborn, S., 2015. Towards Cryptocurrency Index – Analysis of the Market. Master's Thesis. Humboldt-Universität zu Berlin.
Trimborn, S., Li, M., Härdle, Wolfgang K., 2019. Investing with cryptocurrencies - a liquidity constrained investment approach. J. Financ. Econom. 18 (2), 280–306.

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