Practical Risk-adjusted Cryptocurrency Portfolio Optimization Framework

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Abstract:

Cryptocurrencies represent a new type of digital financial asset that still cannot be linked to the fundamental and systematic factors of the traditional capital market. When creating a portfolio, investors have to consider the dynamics of asset returns in order to identify and quantify the best risk measure and to achieve the best possible portfolio performance. Given the possibility of portfolio optimization that includes different risk measures, this paper will formally identify and define whether standard deviation or Conditional VaR (CVaR) best suit the dynamics of cryptocurrency market by developing and employing a practical framework. For this purpose, we test two optimization targets: MaxSR and MaxSTARR. The obtained portfolio optimization results are compared among each other and to the performance of the CRIX index in the same observation period. The overall results suggest that 80% of randomly created portfolios performed better if they use the MaxSTARR portfolio optimization framework.

Keywords: CVaR, MaxSTARR, MaxSR, cryptocurrency, portfolio optimization JEL classification: E49, G11, P45

إطار عملي لتحسين محفظة العملات المشفرة معدلة حسب المخاطر

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المستخلص العربي:

تمثل العملات المشفرة نوعًا جديدًا من الأصول المالية الرقمية التي لا يزال من غير الممكن ربطها بالعوامل الأساسية والمنهجية لسوق رأس المال التقليدي. فعند إنشاء محفظة، يتعين على المستثمرين النظر في ديناميكيات عائدات الأصول من أجل تحديد وتحديد أفضل مقياس للمخاطر وتحقيق أفضل أداء ممكن للمحفظة. نظرًا لإمكانية تحسين المحفظة التي تتضمن مقاييس مخاطر مختلفة، ستحدد هذه الورقة وتحدد رسميًا ما إذا كان الانحراف المعياري أو القيمة المشروطة المعرضة للخطر يناسب ديناميكيات سوق العملات المشفرة من خلال استخدام إطار عملي. لهذا الغرض، نختبر هدفين للتحسين: MaxSR وMaxSTARR ، تتم مقارنة نتائج تحسين الحافظة التي تم الحصول عليها بأداء مؤشرCRIX في نفس فترة المراقبة. تشير النتائج الإجمالية إلى أن ٨٠٪ من المحافظ التي تم إنشاؤها عشوائيًا كان أداؤها أفضل إذا استخدمت إطار MaxSTARR.

الكلمات المفتاحية: العملة المشفرة، تحسين المحفظة، القيمة المشروطة المعرضة للخطر.

1. Introduction

As a largely unintended consequence of the development of Internet and IT, over the last couple of years, ideas of digital assets, digital currencies and even central bank digital currencies are gaining traction. The beginning of the journey can be traced to year 2008 and the publication of the seminal paper titled: "Bitcoin: A Peer-to-Peer Electronic Cash System". What followed was the release of the Bitcoin protocol in January 2009. This created the first known infrastructure supporting a new type of asset, a digital asset called bitcoin. The goal of this new technology was to enable instantaneous transactions, low cost of executing transactions while having intermediary to keep records and execute transactions.

Cryptocurrencies represent a new type of digital asset class that does not fall into any of the existing definitions and classification categories of financial instruments. For a detailed discussion on what is Bitcoin and how is it viewed from a financial standpoint see e.g. Glaser et. al. (2014). Looking at cryptocurrencies from the aspect of issuing standard financial instruments, it is possible to come to wrong conclusion. Namely, cryptocurrencies are not and do not have to be exclusively related to the business success of the company that issued them - as is the case with stocks. Cryptocurrencies are based on open source software that is free to the public and is hosted on one of the collaboration platforms. If a public blockchain is observed, there are different incentives to maintain such an ecosystem. In the example of the Bitcoin platform, for each new created block of transactions, the nodes in the network, in addition to the transaction fee, are rewarded with a new number of bitcoins. In other words, after raising the capital needed for initial costs, once the blockchain becomes active and public, it is the community that largely influences its success through consensus between developers.

Due to its dynamics cryptocurrency market is perceived as a risky but attractive investment opportunities. Besides the lack of classical regulation another troubling point for investors is the lack a methodology to calculate an approximate fundamental or intrinsic value that would serve as a benchmark of the price momentum for a particular cryptocurrency. That being said, the cryptocurrency market and its entire infrastructure is continuously developing. Due to its availability, opportunities it provides and affordability compared to some of the other financial assets an increasing number of people invest in cryptocurrencies, which is why there is a need for research we conduct in this paper in order to define investment opportunities, but also the best risk measure for cryptocurrency portfolio optimization.

The aim of this paper is to explore the feasibility of constructing a cryptocurrency portfolio using different optimization objectives to identify the most suitable risk measure for the investment selection process.

The objectives of this paper are to: a) Compare the performance of different optimization strategies; b) Compare the performance of employed optimization strategies in relation to CRIX index representing the movement of the general cryptocurrency market

The paper is divided in five sections. After the Introduction, we provide a literature review of portfolio optimization with the emphasis of research dealing with optimization of cryptocurrencies. In Section 3 we present the analysed data and the methodology we employ. Section 4 presents and interprets the obtained optimization results. The last Section draws the implications and provides recommendations for future research in the field of cryptocurrency optimization.

2. Literature review

One the first research studies on optimization of cryptocurrencies was performed by (Trimborn, 2015). He optimized the portfolio constituents of the CRyptocurrency IndeX - CRIX index, benchmarking the whole crypto market, with the minimal variance as the optimization target. Chuen et al. (2017) and later Trimborn et al. (2019) conducted research where they introduce a number of cryptocurrencies into the existing portfolio composed of traditional financial instruments. In case of Chuen et al. (2017) the cryptocurrencies were optimized together with gold, stock indexes and real estate market index while Trimborn et al. (2019) used only stock indexes. Both research papers came to the same conclusion that portfolios containing cryptocurrencies performed superiorly to the ones without them. Continuing on their research was the paper by Petukhina et al. (2021). In their investigation, the authors categorized existing standard and recent optimization models into four distinct strategies: risk-oriented, return-oriented, risk-return-oriented, and combination strategies. Their results demonstrated the potential benefits of incorporating cryptocurrencies into a portfolio alongside traditional assets. However, it was observed that raising the limits on the units controlling liquidity resulted in lower cumulative returns for the same portfolios. The opportunities provided by constructing a portfolio of financial assets and cryptocurrencies during market downturn during the COVID-19 pandemic was investigated by Goodell and Goutte (2021) and Conlon et al. (2020). Both studies reached similar conclusions, indicating that cryptocurrencies are not reliable safe havens for the majority of tested equity markets. Additionally, cryptocurrencies were found to offer limited diversification benefits during bearish market conditions. Nevertheless, both studies acknowledged that the cryptocurrencies pegged to the value of the US dollar, could serve as a safe haven investment during times of market turmoil but this speaks much more to the characteristic of a US dollar as a safe haven currency rather than to the safe haven status of cryptocurrencies as such.

Starting the branch of research papers examining Bitcoin's contribution to a portfolio of traditional assets were (Briere et al., 2015) and (Eisl et al., 2015). They conclude that Bitcoin contributes to a portfolio of traditional assets with its higher risk being more than compensated by higher expected returns. The utility of Bitcoin in global portfolios of traditional assets is analysed in (Kajtazi and Moro, 2018).

(Kajtazi and Moro, 2018) as well as (Symitsi et al., 2019) come to a similar conclusion that adding Bitcoin to a traditional portfolio improves the risk-reward ratio. (Lee Kuo Chuen et al., 2018) based their approach to valuing the introduction of cryptocurrencies into a traditional financial portfolio on sentiment analysis. They optimized a portfolio of ten cryptocurrencies together with traditional assets including stock indices, real estate market index and gold. They conclude that cryptocurrencies raise the effective limit of possible portfolios, thereby improving the reward-risk ratio. They report that their sentiment analysis based strategy yields higher cumulative returns thus supporting the notion of significant sentiment driven dynamics in the cryptocurrency market. Klein et al. (2018) is a rare example of research results going contrary to the above mentioned papers. Klein et al. (2018) first selected traditional global financial indices and then created two more portfolios for each index, one adding gold and the another adding Bitcoin into the mix. Based on the obtained results they concluded that Bitcoin does not have the same characteristics as gold, with gold being a more important and actually significant addition to the traditional portfolio of assets as opposed to Bitcoin.

Since the secondary cryptocurrency market is a distinct novel financial market it warrants an examination of the possibility of constructing efficient portfolios exclusively composed of cryptocurrencies with varying allocation objectives. Researchers such as Liu (2018), Brauneis, Mestel (2018), Platanakis et al. (2018), Tomić (2020), Čuljak, Tomić, Žiković (2022) and Tomić, Žiković, Jovanović (2022) investigated optimization opportunities possibilities by creating portfolios with different optimization goals of risk minimization, returns maximization, and return to risk ratio maximization. They all came to very similar conclusions, indicating that none of the tested optimization strategies can outperform a simple equally weighted cryptocurrency portfolio.

Tomić (2020) analysed various optimization objectives, while taking into account the systematic impact of Bitcoin on the behaviour of the whole cryptocurrency market. He finds that by controlling for the Bitcoin, superior portfolio performance is achieved by higher return to risk reward ratio. Čuljak, Tomić, Žiković (2022) investigated the benefits of cryptocurrency portfolio optimization by dividing cryptocurrencies into sectors. Thy conclude that diving cryptocurrencies into sectors such as business services, transaction/exchange and financial sector yields superior results to the case when all cryptocurrencies, regardless of their intended uses are treated equally. Tomić, Žiković, Jovanović (2022) investigated the performance of randomly selected cryptocurrencies portfolios compared to CRIX index which represents a benchmark of the cryptocurrencies market. CRIX index is weighted by individual cryptocurrency market capitalization with the liquidity adjustment. Their results show the superior performance of the CRIX index compared to the randomly generated portfolios, especially in the area of significantly lower risk values.

The usual approach that most research papers dealing with cryptocurrencies portfolio optimization take is either analysing whether they contribute to better performance of the portfolios composed of classical financial assets or even financial indices or simply finding an optimal cryptocurrency portfolio under the Modern portfolio theory framework. We focus on the later but given the proven and very pronounced non-normal behaviour of cryptocurrencies' returns visible through their skewness and leptokurtosis we move beyond the classical modern portfolio theory framework. There is a gap in the literature regarding the performance of alternative optimization objectives such as minimizing other risk metrics besides variance, be it VaR, CVaR or maximum drawdown. Besides testing the "alternative" measures of risk there is also an often overlooked question of beating the cryptocurrency market with optimization schemes i.e. can optimizing random portfolio perform better than the general cryptocurrency market.

3. Data and Methodology

In the aforementioned research papers examining the possibility of portfolio optimization in the cryptocurrency market, different optimization goals are being implemented, but only on one sample of potential portfolio constituents. Such methodology is desirable when one wants to highlight the possibilities of different optimization goals, but does not provide an answer to an important question, which is the risk measure that best suits the dynamics of changes of the cryptocurrency market. In our research, ten random portfolios each consisting of twenty randomly selected components from a population of predefined seventy cryptocurrencies. The sample of these seventy cryptocurrencies is selected by their respective market capitalization. For this purpose, the results of the portfolio of two optimization strategies that define the optimal reward-risk ratio (tangency portfolio) from the efficient frontier of possible portfolios will be considered. The main difference between those two optimization strategies is that the first optimization strategy uses Standard Deviation as a risk measure (STDEV), and the second optimization strategy uses Conditional Value at Risk (CVaR) as a risk measure. Using this approach, it is possible to extend on the previous researches by defining a risk measure that is more suitable for the construction and cryptocurrency portfolio optimization.

We use cryptocurrency daily price data from the Coinmarketcap - CMC platform. The observation period used is from 25.01.2018 to 01.08.2019, forming a sample of 554 daily observations i.e. 553 daily discrete returns. This observation period was used on purpose to test the behaviour of risk measures during a volatile market regime for cryptocurrencies. We formed two portfolios with maximization of return and risk ratios optimization target: Maximize Sharpe Ratio (MaxSR) and Maximize Stable Tail-Adjusted Return Ratio (MaxSTARR). 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 Conlon et al. (2020), Čuljak, Tomić, Žiković (2022) and Tomić, Žiković, Jovanović (2022). Optimization is performed out of sample (backtesting), with the equal parameters for each optimization target. The assessment of initial parameters and portfolio weights was performed on a time period of $k = 30$ days and we applied a 95% confidence level. Given the dynamics of the cryptocurrency market, a more frequent monthly rebalance of $K = 30$ days was chosen with the rolling window approach. For each period $k + 1$, portfolio returns are extracted with respect to the results of the allocation optimization in the previous k and $k + K$ moment, respectively.

For the starting optimization model we use the classical Modern Portfolio Theory approach developed by Markowitz (1952) also known as mean-variance (M-V) model. In its classical form the model is set up to minimize the variance of a portfolio given the expected return. The basic form of the Markowitz formulation in linear form is given as:

$$\min_{w} \quad \sigma_p^2\,(w) = w^{\mathrm{T}}\hat{\Sigma}w \tag{1}$$
$$s.t. \quad \mathbf{1}_N^{\mathrm{T}}w = 1, \qquad x^T w \geq \mu, \qquad w_i \geq 0$$

where σ_p^2 is the variance of a portfolio, $w = (w_1, w_2, \dots, w_N)^T$ are assets' weights, $\hat{\Sigma}$ is the estimated covariance matrix of assets N and returns T. There are three constraints in this model: $\mathbf{1}_N$ is a $(Nx1)$ vector where the sum of portfolio weights has to be equal to 1, x is the $(Nx1)$ vector of expected returns whose sum has to be equal or greater than the desired total portfolio return μ. The final restriction refers to the requirement that all portfolio holdings have to be positive in size i.e. no short selling allowed. In case where the constrain of the required rate of return is omitted from equation (1), portfolio optimization becomes a global minimum variance of portfolio – GMV strategy. This approach is attractive to an investor that wants to find the composition of individual assets that minimizes the total variability of the portfolio.

One of the main statistical problems with equation (1), is the assumption of a Gaussian distribution of asset returns. Studies by e.g. (Briere et al., 2015) and (Lee Kuo Chuen et al., 2018), prove the presence of heavier tails than normal in cryptocurrencies. For this reason, we use the approach employed by e.g. (Eisl, 2015), (Petukhina et al., 2018) and Tomić, Žiković, Jovanović (2022), that is actually based on the Conditional VaR - CVaR methodology by (Rockafellar and Uryasev, 2000). Due to not having limitations of normal distribution assumption as well as being a coherent risk measure (unlike VaR) CVaR can be considered as a more robust risk measure.

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

$$\Psi(w, \zeta) = P\{y | f(w, y) \leq \zeta\} \qquad (2)$$

Where w is a vector of portfolio weights, ζ loss associated with vector w and y uncertainties (usually macro market variables) that impact the loss. For a specific confidence level α, Value at Risk (VaR_α) of a portfolio is:

$$VaR_\alpha(w) = min\{y | \Psi(w, \zeta) \geq \alpha\} \qquad (3)$$

If $f(w, y)$ exceeds the VaR, the expected value of the loss (CVaR) is given by:

$$\mathrm{CVaR}_\alpha(w) = \frac{1}{1-\alpha} \int_{y(w) \leq VaR_\alpha(w)} y f(y|w)\, dy \qquad (4)$$

The modification from using variance as in the M-V model to using CVaR turns our model to Mean-Conditional Value at Risk (M-CVaR) model:

$$\min_{w} \quad \mathrm{CVaR}_{\alpha}(w) \tag{5}$$
$$s.t. \;\; \mathbf{1}_N^{\mathrm{T}} w = 1, \qquad w_i \geq 0$$

Taking the expected return of the portfolio and its standard deviation forms the Sharpe ratio. In the classical Modern Portfolio Theory set up the portfolio with the highest Sharpe ratio is the optimal portfolio, i.e. the tangent portfolio used in this paper:

$$\max_{w} \;\; \left\{\frac{w^{\mathrm{T}}\mu - \bar{r}_f}{\sqrt{w^{\mathrm{T}}\hat{\Sigma}w}}\right\} = \left\{\frac{w^{\mathrm{T}}\mu}{\sqrt{w^{\mathrm{T}}\hat{\Sigma}w}}\right\} \tag{6}$$
$$s.t. \;\; \mathbf{1}_N^{\mathrm{T}} w = 1, \qquad w_i \geq 0, \qquad i = 1, \dots, N$$

$\bar{r}_f$ represents the risk-free interest rate adjusted for the observation period, $\mathbf{1}_N$ 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. For the purposes of this research, the risk-free interest rate is omitted.

If CVaR is used in the denominator of equation (4) instead of the standard deviation, the Sharpe ratio turns into Stable Tail-Adjusted Return Ratio (STARR) and is given by (7). The optimization goal is to maximize the STARR ratio:

$$\max_{w} \left\{\frac{w^{\mathrm{T}}\mu - \bar{r}_f}{\mathrm{CVaR}_{\alpha}(w)}\right\} = \left\{\frac{w^{\mathrm{T}}\mu}{\mathrm{CVaR}_{\alpha}(w)}\right\} \tag{7}$$

$$s.t.\ \ \mathbf{1}_N^{\mathrm{T}} w = 1, \qquad w_i \geq 0, \qquad i = 1, \dots, N$$

The results of several different absolute measures of return and risk: geometric return ($R_{G,i}$), cumulative return (CY) with initial wealth of 1 USD, standard deviation ($\sigma_{a,i}$), VaR, CVaR, worst drawdown (WD), as well as relative measures of performance: Sharpe ratio (Sharpe, 1963), MSquared (Modigliani and Modigliani, 1997), Regression alpha, Jensen's alpha (Jensen, 1968) and Information ratio (Bacon, 2008), are presented in order to evaluate the success of each optimization strategy, where values are calculated annually and refer to the total time series of portfolio returns, except for the beta regression between portfolio returns and the CRIX index.

Sharpe ratio:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{8}$$

where $R_p$is the return on portfolio, $R_p$is the risk-free rate of return and $\sigma_p$is the standard deviation of the portfolio excess returns.

MSquared:

$$MS^2 = \left(R_p - R_f\right) \times \frac{\sigma_M}{\sigma_p} + R_f \tag{9}$$

where σ_B is the standard deviation of the excess returns for a benchmark portfolio usually representing the market, (in this case it is the CRIX index).

Jensen's alpha:

$$\alpha_J = (R_{p-}R_f) - \beta_{p,M}(R_M - R_f) \tag{10}$$

where R_M is the return of the market (CRIX), $\beta_{p,M}$ is the beta of the portfolio.

Information ratio:

$$IR = \frac{R_p - R_M}{TE} \tag{11}$$

where TE is the Tracking Error i.e. the standard deviation of difference between portfolio and market returns.
For realized portfolio return annual geometric average return is used $R_{Gi} = prod(1 + R_{d,i})^{\frac{scale}{n}} - 1$, where $R_{d,i}$ represents the daily realized return of portfolio i in period t, n is the number of observations and $scale$ is set to 252, representing the number of trading days in a year. Standard deviation and CVaR are transformed into annual values by applying the square root of time to their daily values.

4. Results and discussion

In this section we present and interpret out-of-sample backtesting results for each of the implemented optimization targets. The success of each strategy is estimated by comparing its results to the performance of the CRIX index representing a benchmark of the crypto market. The results are interpreted in two steps. Firstly, the results are compared and interpreted at the level of the asset allocation model and compared with the CRIX index for the optimization strategy separately. Secondly, in order to define the best risk measure for portfolio optimization, the results are compared between portfolios that differ in risk measure during optimization. Table 1 comparatively shows the results of performance measures for the MaxSR optimization strategy. The structure of the table is as follows: the first column shows the absolute and relative performance measures used with the corresponding notations. The next 10 columns show the results of implemented performance measures on the returns of 10 portfolios in accordance with the optimization strategy, and the last column shows the results of performance measures for the CRIX index as a benchmark of the cryptocurrency market.

The first two rows of the table present the parameters of the fitted regression line, illustrating the relationship between the portfolio returns as the dependent variable and the CRIX index as the independent variable. The negative value of the beta parameter for all portfolios indicates that they moved in the opposite direction compared to the movement of the CRIX index. This suggests that the strategy is less volatile in terms of systemic risk than the CRIX index.

However, it is essential to note that only two portfolios, on average, achieved higher returns than the CRIX index, indicating a regression alpha. This implies that, on average, the portfolios attained negative returns when the CRIX index remained stagnant. The realization of geometric and cumulative returns of the portfolios also supports this observation, where none of the portfolios achieved a higher return than the CRIX index.

In terms of risk measures, the CRIX index outperformed the created portfolios, as it achieved lower values for all implemented risk measures during the observed period. Similarly, relative performance measures favour the CRIX index throughout the observed period. All values, except for the N-2 portfolio, where the MSquared value is less negative relative to the CRIX index, indicate that the CRIX index is a more favourable choice compared to the MaxSR optimization strategy, particularly during turbulent periods - the timeframe used in this study.

Table 1: Performance measures results for MaxSR optimization strategy

Performance Metrics		Asset Allocation										Index
		10 portfolios of 20 randomly selected cryptocurrencies										
		N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	CRIX
Beta	β_i	-0.18	-0.18	-0.18	-0.20	-0.26	-0.13	-0.22	-0.23	-0.22	-0.18	1.00
Annualized Alpha	$a_{a,i}$	-0.49	0.18	-0.12	-0.45	0.25	-0.09	-0.24	-0.09	-0.38	-0.66	0.00
Annualized Return	$R_{G,i}$	-0.68	-0.21	-0.44	-0.67	-0.32	-0.45	-0.60	-0.37	-0.59	-0.77	-0.18
Cumulative Return	CY	0.10	0.61	0.30	0.10	0.45	0.30	0.15	0.38	0.16	0.05	0.66
Annualized Std Dev	$\sigma_{a,i}$	0.96	0.90	0.97	1.06	1.14	1.00	1.24	0.87	0.90	0.88	0.63
Annualized VaR	$VaR_{a,i}$	1.62	1.46	1.60	1.78	1.85	1.64	2.06	1.43	1.51	1.51	1.04
Annualized CVaR	$CVaR_{a,i}$	2.03	1.84	2.01	2.23	2.33	2.06	2.58	1.79	1.89	1.98	1.31
Worst Drawdown	WD	0.96	0.90	0.88	0.97	0.94	0.90	0.98	0.92	0.92	0.96	0.78
Sharpe Ratio	$SR_{d,i}$	-0.70	-0.24	-0.46	-0.64	-0.28	-0.45	-0.49	-0.43	-0.65	-0.88	-0.29
MSquared	M^2	-0.45	-0.15	-0.29	-0.40	-0.18	-0.28	-0.31	-0.27	-0.41	-0.56	-0.18
Jensen's Alpha	α_i	-0.71	-0.24	-0.48	-0.71	-0.37	-0.47	-0.64	-0.41	-0.63	-0.80	0.00
Information Ratio	IR	-0.41	-0.03	-0.22	-0.38	-0.10	-0.22	-0.29	-0.16	-0.34	-0.51	/

Source: Author's calculation

Table 2 comparatively shows the results of performance measures for the MaxSTARR optimization strategy, with the same structure as in Table 1. In relation to the CRIX index, the presented results are similar to the previous ones. All portfolios achieved a negative value of the beta parameter, but in this case four portfolios on average achieve a higher return than the CRIX index which indicates alpha regression, which is indicative compared to the previous MaxSR strategy. As before, no portfolio achieved higher geometric and cumulative returns than the CRIX index, and for all risk measures the CRIX index achieved lower values in the observed period. Relative performance measures favour the

CRIX index as well. Apart from the N-5 portfolio where the MSquared value is less negative relative to the CRIX index, all values indicate the superiority of the CRIX index over randomly created portfolios optimized by the MaxSTARR strategy.

Table 2: Performance measures results for MaxSTARR optimization strategy

Performance Metrics		Asset Allocation										
		10 portfolios of 20 randomly selected cryptocurrencies										Index
		N-1	N-2	N-3	N-4	N-5	N-6	N-7	N-8	N-9	N-10	CRIX
Beta	β_i	-0.17	-0.17	-0.38	-0.26	-0.21	-0.17	-0.21	-0.21	-0.20	-0.17	1.00
Annualized Alpha	$a_{a,i}$	-0.43	0.06	-0.10	0.52	0.13	-0.17	0.32	0.13	-0.07	-0.48	0.00
Annualized Return	$R_{G,i}$	-0.66	-0.39	-0.42	-0.40	-0.31	-0.53	-0.48	-0.21	-0.44	-0.65	-0.18
Cumulative Return	CY	0.11	0.36	0.32	0.35	0.46	0.21	0.26	0.61	0.30	0.12	0.66
Annualized Std Dev	$\sigma_{a,i}$	1.01	1.13	0.96	1.65	1.03	1.15	1.61	0.86	1.05	0.88	0.63
Annualized VaR	$VaR_{a,i}$	1.70	1.88	1.61	1.50	1.68	2.03	2.63	1.40	1.73	1.52	1.04
Annualized CVaR	$CVaR_{a,i}$	2.12	2.35	2.02	1.88	2.11	2.54	3.30	1.76	2.17	1.90	1.31
Worst Drawdown	WD	0.94	0.89	0.90	0.97	0.92	0.93	0.97	0.83	0.90	0.90	0.78
Sharpe Ratio	SR	-0.65	-0.35	-0.44	-0.24	-0.31	-0.46	-0.30	-0.25	-0.42	-0.73	-0.29
MSquared	M^2	-0.41	-0.22	-0.28	-0.15	-0.20	-0.29	-0.19	-0.16	-0.27	-0.47	-0.18
Jensen's Alpha	α_i	-0.69	-0.42	-0.45	-0.45	-0.36	-0.57	-0.52	-0.25	-0.48	-0.68	0.00
Information Ratio	IR	-0.37	-0.15	-0.19	-0.12	-0.11	-0.25	-0.17	-0.02	-0.20	-0.40	/

Source: Author's calculation

Comparing the results of performance measures between two optimization strategies implemented on equal components of the portfolio, the following observations stand out. There is no significant difference between the values of the beta regression coefficients, all values in both tables are negative, which indicates the opposite direction of movement in relation to the CRIX index. On the other hand, seven portfolios on average achieve a higher return if optimized with the MaxSTARR strategy, presented through a regression alpha. Similarly, eight portfolios optimized by the MaxSTARR strategy achieved higher geometric and cumulative returns than the portfolios optimized by the MaxSR strategy. In terms of risk, the MaxSTARR strategy is slightly riskier than the MaxSR strategy, but this is compensated by the higher realized portfolio return. On the other hand, the worst drawdown also favours the MaxSTARR optimization strategy. Of the 10 portfolios observed, eight portfolios have smaller worst drawdowns, and one N-4 portfolio has the same. The results of relative performance measures are in line with previous relationships. Only three portfolios N-2, N-5 and N-6 achieved worse values of relative performance measures if the portfolios are optimized by MaxSTARR optimization strategy.

5. Conclusion

This paper primarily focuses on exploring the feasibility of constructing a cryptocurrency portfolio using different optimization objectives to identify the most suitable risk measure for the investment selection process. Our methodology is presented in two steps. In the first step, individual portfolio performance results are compared to the CRIX index, serving as a market benchmark, to assess the success of each optimization strategy. In the second step, the results are compared between optimization strategies to determine a more appropriate risk measure for portfolio optimization, with the aim of avoiding excessive risk and achieving better overall portfolio performance.

The findings indicate that cryptocurrency portfolio optimization models employing Conditional Value at Risk (CVaR) as a risk measure demonstrate superior results in 80% of portfolios created from 20 randomly selected cryptocurrencies as potential components. Consequently, the MaxSTARR optimization strategy outperforms the MaxSR optimization strategy in terms of overall portfolio performance. As a result, investors are advised to prioritize the use of CVaR as a risk measure over the traditional Standard Deviation when modelling portfolios in the secondary cryptocurrency market. This methodology of creating random portfolios and evaluating the practical implications of various risk measures represents a novel scientific and practical contribution to the field of cryptocurrency market investment opportunities.

However, it is essential to emphasize the significance of a prudent initial selection of potential portfolio components, as it plays a crucial role in the construction and optimization of cryptocurrency portfolios. While the cryptocurrency market is subject to substantial systematic risk associated with bitcoin as the leading factor, no matter which allocation model is used, achieving perfect portfolio optimization may be challenging. To achieve optimal results during practical implementation, careful consideration must be given to selecting portfolio components in alignment with investor preferences. This finding underscores the possibility of constructing and modelling portfolios solely composed of cryptocurrencies, which creates opportunities for further scientific and professional research in exploring investment opportunities in the secondary cryptocurrency market.

As a suggestion for future research very clearly there remains the question of how to outperform the market. Our results show that by just changing the risk measures i.e. optimization objectives it will be very difficult to beat the cryptocurrency market. Although there are still possibilities in trying out different rebalance frequencies, alternative time periods for model optimization, as well other risk measures and such analysis can definitively further enhance our understanding of effective strategies in the dynamic cryptocurrency market it is not very likely it will solve this issue. One of the possible and promising lines of research in this regard is incorporating sentiment analysis as one of the indicators since the cryptocurrency market is notorious for reacting violently to changes in the general sentiment.

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