Cryptocurrency Portfolio Optimization

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***Abstract*—In the latter half of 2020 and the beginning of 2021, the interest and demand for cryptocurrency skyrocketed to new records [1]. But with a plethora of cryptocurrency options, most with high levels of volatility, it is difficult to determine how to construct a viable cryptocurrency portfolio. I approached this problem comprehensively, offering a comparison of a variety of techniques including both repeated random sampling and numerical optimization techniques. Included in this analysis are 13 of the most prominent cryptocurrencies: Bitcoin, Bitcoin Cash, Litecoin, Ethereum, Tron, Binance Coin, Ripple, Cardano, Stellar, Monero, Chainlink, Dogecoin, and Polkadot.**

I. Introduction

Since its inception in 2009 the cryptocurrency asset class has drawn many critics, opponents, and confounded expectations. The underlying technology, blockchain, has been praised for its transparency, potential as a store of value, and a hedge against inflation and unstable governments [2]. Critics argue that cryptocurrencies' semi-anonymous nature benefit criminal activities, pointing to online black-markets such as the infamous Silk Road [2].

In the early days of cryptocurrency, making an investment presented a number of challenges. First, cryptocurrency could not be purchased or stored using any of the common financial firms where one would normally buy assets. Purchasing cryptocurrency required an investor to use little-known online exchanges or untrustworthy in-person ATMs [2]. Second, an investor needed to have the technical knowledge to manage a digital 'wallet'. Lastly, investors needed to have the stomach for their new investment's high level of volatility.

II. Motivation

While cryptocurrency continues to be a high-risk investment, most of the inconvenient barriers to entry have since been removed. Cryptocurrency can now be purchased, sold, and traded using a variety of established services such as Paypal, CashApp, Robinhood, and Coinbase. These services can manage your digital wallet and can link to your checking account, making it easier than ever to invest in cryptocurrency.

The increase in accessibility can, at least in part, be attributed to an increase in adoption by the financial community. In addition to niche investment firms like Grayscale, which has invested heavily in cryptocurrency, cryptocurrency investment services have been adopted by Mastercard and are being developed by JP Morgan and Morgan Stanley [1]. Cryptocurrency adoption as an investment for large companies has also begun, with Tesla purchasing 1.5 billion dollars-worth of Bitcoin. Since October of 2020, the price of Bitcoin has risen 356%, Ethereum's price has risen 572%, and an even a lesser-known alternative called Litecoin has risen in price 175% [2]. Given this new financial landscape, it is prudent to develop a strategy for optimizing a portfolio of these assets.

III. Statement of Problem

The problem I have attempted to solve is how to optimally construct a portfolio of cryptocurrency assets, utilizing a buy and hold strategy. The assets for consideration are: Bitcoin, Bitcoin Cash, Litecoin, Ethereum, Tron, Binance Coin, Ripple, Cardano, Stellar, Monero, Chainlink, Dogecoin, and Polkadot. 60 days of historical data for each of these assets was used for analysis. The goal is to optimize the selection and allocation of assets while considering both return and risk. For the purposes of this analysis short positions, or bets against an asset, were not included.

IV. Related Work

Several of the portfolio optimization approaches taken in this work are directly inspired by Harry Markowitz's work in portfolio selection. Markowitz's mean-variance approach to portfolio selection sought to find the most 'efficient' portfolios based on an analysis of their expected return and expected volatility [3]. In mean-variance analysis, the feasible set of portfolios for a given collection of assets is the set of all portfolios one could construct using a given collection of assets. The feasible set of portfolios can be found using Monte Carlo simulation, which I have used in one of my optimization approaches [3]. The optimal portfolio is then selected by finding the portfolio that has the highest ratio of expected return to expected volatility. This particular metric is called the Sharpe Ratio (1). While a portfolio that maximizes this metric could be found through simulation, additional constraints can be included and the problem can be formulated as a numerical optimization problem, as will be demonstrated in section 5.

Another concept that is integral to this work, and a common theme throughout Modern Portfolio Theory and the work of Harry Markowitz, is diversification. Diversification in portfolio allocation can be oversimplified as the idea that allocations should be spread amongst a variety of assets rather that heavily weighted in one particular area [4]. Markowitz formalized this idea mathematically through the use of the covariance matrix for a particular portfolio's returns. Markowitz sought to minimize the amount of correlation of a portfolio's assets relative to their expected returns [4]. This concept of diversification can be evaluated through a diversification ratio, and it, as well as covariance, are used in this project.

V. *Methodology*

To find a solution for this problem, 6 portfolios were constructed, each representing a different approach. The 6 portfolios considered are:

A. *Even Allocation Portfolio*

This portfolio is constructed using the exact same weight for each asset, with the weights being a fraction of the number of assets considered. Even allocation is considered as a baseline to compare the other portfolios and not as a realistic strategy.

B. *Random Allocation Portfolio*

The random allocation portfolio is constructed using a random weight for each asset. Weights are found using a Python random number generator. This portfolio is also used as a baseline.

C. *Monte Carlo Portfolio*

The Monte Carlo Portfolio is constructed by repeated random sampling. Weights are generated randomly and evaluated based on the Sharpe Ratio, the ratio of expected return to expected volatility:

$$S_a = \frac{E[R_a - R_b]}{\sigma_a} \tag{1}$$

Where R_a is the return of an asset, R_b is the risk-free return, and σ_a is the standard deviation.

This process is repeated thousands of times and the portfolio with the highest Sharpe Ratio is selected through inspection as the optimal portfolio [5].

D. *Minimum Volatility Portfolio*

As its name suggests this approach seeks to find the collection of assets that have the lowest volatility. The problem can be formulated as a quadratic optimization problem as such:

$$\begin{aligned} \underset{\mathbf{w}}{\text{minimise}} \quad & w^T \sum w \\ \text{s.t.} \quad & \sum_{j=1}^{n} w_j = 1 \\ & w_j \geq 0, j = 1, \ldots, N \end{aligned} \tag{2}$$

Where w are the weight vectors, Σ is the covariance matrix, w_j is an individual weight for an asset, and N is the number of assets [5].

E. *Maximum Sharpe Ratio Portfolio*

Similar to the Monte Carlo portfolio, maximum Sharpe ratio optimization seeks to maximize the Sharpe ratio. In contrast to the Monte Carlo approach, maximum Sharpe Ratio optimization is approached from a numerical optimization perspective. The problem can be formulated as:

$$\begin{aligned} \underset{\mathbf{w}}{\text{maximise}} \quad & \frac{\mu^T w - R_f}{(w^T \sum w)^{1/2}} \\ \text{s.t.} \quad & \sum_{j=1}^{n} w_j = 1 \\ & w_j \geq 0, j = 1, \ldots, N \end{aligned} \tag{3}$$

F. *Maximum Diversification Portfolio*

The final portfolio, maximum diversification, seeks to maximize the diversification ratio, which is a measure of given assets volatility in a portfolio relative to the total volatility for all the assets in the portfolio [5]. The objective function is the diversification ratio, and the problem was set up as follows:

$$\begin{aligned} \underset{\mathbf{w}}{\max} \quad & D = \frac{w^T \sigma}{\sqrt{w^T \sum w}} \\ \text{s.t.} \quad & \sum_{j=1}^{n} w_j = 1 \\ & w_j \geq 0, j = 1, \ldots, N \end{aligned} \tag{4}$$

G. *Solver*

All optimization problems were solved using the Scipy optimize package. The Sequential Least Squares Programming solver, a variation of the quasi-Newton method, was chosen as the solver for the numerical optimization approaches. This solver was recommended in the literature [5], and due to the complexity of the problem was sufficient.

VI. Results

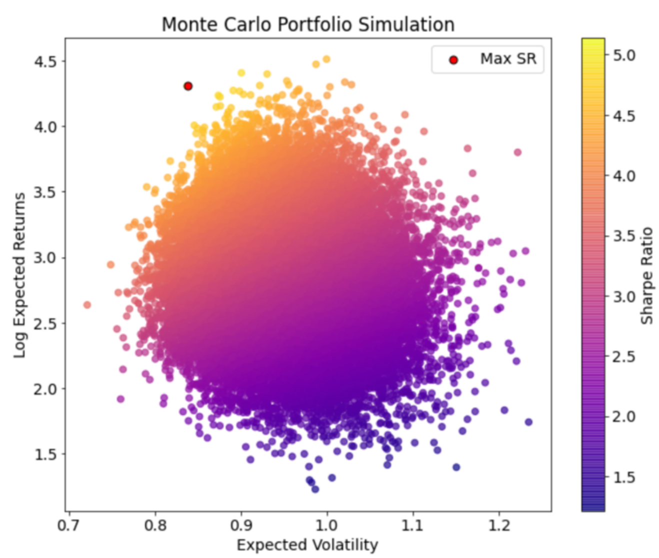

Fig. 1. Monte Carlo simulated portfolio results.

A. *Monte Carlo/Efficient Frontier*

The results of the repeated random sampling experiment were interesting given that they did not produce the traditional-looking efficient frontier curve. When the experiment was done

	BTC	BCH	ETH	LTC	TRX	BNB	XRP	ADA	XLM	XMR	LINK	DOGE	DOT
Monte Carlo	.22	.0056	.14	.21	.013	.068	.011	.0009	.025	.04	.04	.11	.11
Minimum Volatility	.33	0	.12	0	.04	.25	0	0	0	.26	0	0	0
Maximum Sharpe	.92	0	0	0	0	0	0	0	0	0	0	.06	.02
Maximum Diversification	.21	0	0	0	0	0	0	0	.08	.26	0	.15	.21

Table. 1. Optimized weights.

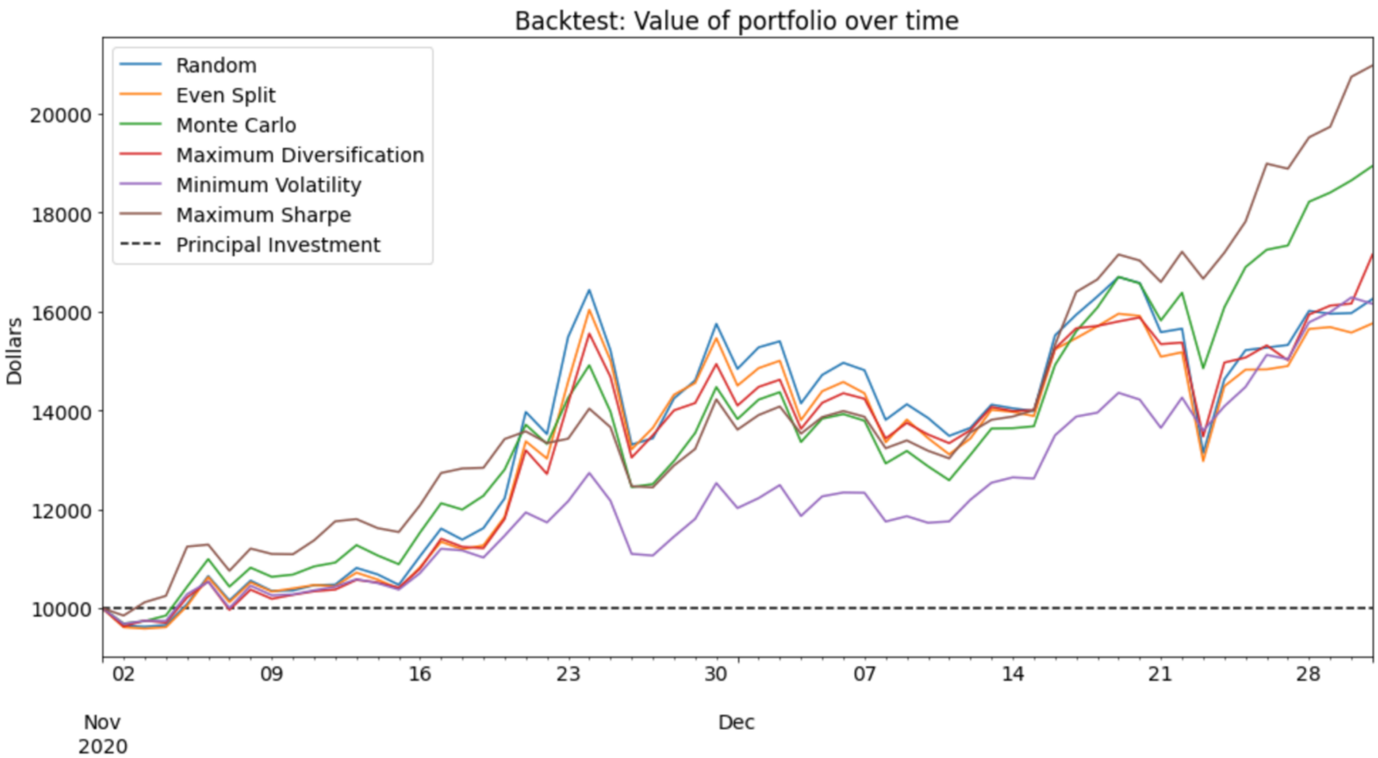

Fig. 2. Hypothetical value of optimized portfolios.

with 4 cryptocurrencies versus 13, the efficient frontier curve did emerge. I expect that these results are due to high correlation between some of the cryptocurrencies. Despite the unusual shape, the portfolio that had the best Sharp ratio was similar to the result of the numerical optimization of the Sharpe ratio.

B. Minimum Volatility

The optimal portfolio allocation for the minimal volatility approach suggested a portfolio of: Monero, Binance Coin, Tron, and Bitcoin, with modest weights for each.

C. Maximum Sharpe

The weights for this approach were by far the most exaggerated, suggesting a 92% allocation of bitcoin and the rest split between Dogecoin and Polkadot. These results are likely influenced by the massive gains that these assets have made in the last few months outweighing their volatilities.

D. Maximum Diversification

It was interesting to see that the results of the maximum diversification were not the most diverse in the classical sense of the word. In the sense of being exposed to the highest number of assets, the Monte Carlo portfolio was much more diverse. In this case these results are more a reflection of reducing correlation between assets and the found weights had some similarity to the minimum volatility approach.

E. Backtesting

The weights found from each optimization technique were tested against historical data over a 60-day period. As you can see in Fig. 2, the maximum Sharpe approach performed the best throughout most of the test period and at the end. It is unsurprising that the Monte Carlo approach was the next best considering that the best portfolio from that experiment was selected using the same metric as maximum Sharpe. It is disconcerting that the minimum volatility approach performed worse than the randomly selected portfolio and the evenly weighted portfolio. It is safe to say that minimum volatility is not the best strategy for this asset type.

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