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Original Research Article

Investigating the Effect of Futures Leverage on Constrained Cryptocurrency Portfolios Using a Mean-Semi-Variance Model and Invasive Weed Optimization Algorithm

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In financial markets, a primary concern for investors is achieving enhanced returns while effectively managing portfolio risk. Leveraged trading is one potential strategy for increasing returns; However, the main question is how to choose the best level of leverage to create the most efficient investment portfolio. This study examines the optimal leverage level of cryptocurrency futures in a diversified portfolio of digital assets, using a constrained mean semi-variance model and the Invasive Weed Optimization (IWO) algorithm .The dataset, sourced from CoinMarketCap, consists of daily returns for 10 cryptocurrencies and 5 futures contracts over the period from 2022 to 2025. The proposed model incorporates allocation constraints, wherein each asset in the portfolio is subject to upper and lower bounds on its weight. Due to the imposed constraints, the problem is not solvable via traditional quadratic programming techniques, necessitating the application of the IWO algorithm as the optimization method. Empirical results reveal that incorporating futures into a cryptocurrency portfolio does not inherently enhance its performance. While leverage may increase expected returns, it simultaneously elevates portfolio risk. Consequently, based on the Sortino ratio, the overall risk-adjusted performance of the portfolio does not necessarily improve with the use of leveraged futures.

Keywords: Portfolio Optimization, Cryptocurrency Market, Invasive Weed Optimization Algorithm, Constrained Mean Semi-Variance, Sortino Ratio
JEL Classification*:* C22, G23, G11.

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1 Introduction

In recent years, the cryptocurrency market has experienced significant growth and has become an important segment of the global financial markets. Characteristics such as exceptionally high price volatility and widespread accessibility to innovative financial instruments, including leverage trading, distinguish this market from traditional financial markets (Bajars & Reitalu, 2022). The introduction of leveraged trading and the rapid expansion of decentralized finance (DeFi) platforms have enabled investors to increase their trading volumes by assuming higher levels of risk. Nevertheless, a fundamental question arises regarding the extent to which the increased use of leverage impacts portfolio performance.

In portfolio optimization, simultaneous objectives of maximization and minimization are critical. However, with the increasing complexity, constraints, and availability of financial instruments in modern markets—such as leverage trading—the classical Markowitz mean-variance model no longer suffices (Poon, 2025). Moreover, due to the asymmetric nature of volatility in cryptocurrency markets, employing the mean semi-variance model presents a more suitable alternative to the traditional Markowitz framework (Baur & Dimpfl, 2018).

In practical applications, problem constraints are typically more complex and extensive than those encountered in standard quadratic optimization problems. Consequently, traditional quadratic programming techniques are often inadequate for addressing such issues. Under these circumstances, metaheuristic algorithms serve as effective solution approaches.

Metaheuristics are high-level algorithmic frameworks designed to solve complex and NP-hard optimization problems by emulating natural, social, or physical phenomena. They seek near-optimal solutions within vast search spaces by maintaining a strategic balance between exploration and exploitation, thus efficiently handling nonlinear, high-dimensional problems that classical methods cannot adequately model in reasonable time (Houssein et al, 2025).

The objective of the present study is to determine the optimal futures leverage ratio in combination with a constrained cryptocurrency portfolio by utilizing the mean semi-variance model and applying the weed optimization algorithm as the solution method. Furthermore, the study evaluates the performance of the resulting portfolios through the Sortino ratio.

The remainder of the paper is organized as follows: Section 2 provides a review of the literature encompassing theoretical foundations and prior research; Section 3 details the Methodology of research; Sections 4 and 5 present the empirical results and conclusion.

2 Literature Review

The cryptocurrency market, as an emerging sector in the digital financial industry, has experienced remarkable growth over the past decade. This market comprises the buying, selling, and exchanging of decentralized digital assets that are built upon blockchain technology (Vishweswaran & Padmavathi, 2025). Today, with the continuous expansion of the cryptocurrency market, numerous opportunities have opened for investors. Additionally, the availability of diverse investment instruments has significantly enhanced the attractiveness of this market. For example, the use of futures contracts in this market enables investors to employ leverage.

Leverage trading refers to the use of borrowed capital or financial instruments with leverage to increase the volume of trades and purchasing power. This tool allows traders to open larger positions with less capital, consequently magnifying their potential profits or losses (Chen et al., 2024). However, given that investment risk is an inseparable aspect of all financial markets, the need to employ portfolio models to control risk is increasingly recognized.

One of the foundational portfolio models is the Markowitz model, which minimizes risk for a given level of expected return. This approach can substantially control risk; however, one of the main assumptions of the Markowitz portfolio theory is that the returns of the securities follow a normal distribution, which is often not the case in reality. Thus, the mean semi-variance model can be a suitable alternative to this traditional model. Moreover, when constraints increase in the optimization problem, quadratic programming methods are no longer adequate to solve such complex problems. In these circumstances, metaheuristic algorithms are employed because they can efficiently solve these complex problems.

The algorithm we used in this study to solve the optimization problem is the Invasive Weed Optimization algorithm, which will be explained in detail below:

The Invasive Weed Optimization algorithm is a type of metaheuristic algorithm inspired by the growth patterns of weeds. This algorithm was first introduced by Mehrabian and Lucas in 2006. The detailed steps of the algorithm are as follows:

- Initial Population: A limited number of “seeds” are randomly dispersed in the search space.

- Reproduction: Each weed (or solution) generates a number of seeds proportional to its fitness (objective function value). That is, better solutions produce more seeds.
- Spatial Dispersion: The produced seeds are scattered around their parent's location following a normal distribution with a variable standard deviation. The standard deviation decreases nonlinearly over iterations to focus the search around more precise optima.

$$\sigma_{iter} = \frac{(iter_{Max} - iter)^n}{(iter_{Max})^n} \left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{initial}$$

  Here, $iter_{Max}$ denotes the maximum number of cycles, σ_{iter} represents the standard deviation of each new seed or weed at any cycle, and n is the nonlinear index.
- Competitive Exclusion: After seed production, the entire population (parents and offspring) is evaluated, and the best individuals are selected to remain for the next generation. This process repeats until a minimum number of iterations or stopping criteria are met.

Markowitz (1952), in his seminal paper titled *Portfolio Selection*, introduced the mean-variance model for portfolio selection. Initially, Markowitz focused on maximizing the expected return.

Estrada (2004) conducted a study comparing the mean-variance model with the mean semi-variance model. The results indicated that the mean semi-variance model is more appropriate than the mean-variance model and that semi-variance is a better risk measure than variance. Subsequently, Estrada (2004) further examined and compared the mean-variance and mean semi-variance models and proposed heuristic solutions for optimization problems involving semi-variance, finding that the mean semi-variance model outperforms the mean-variance model.

Several studies have also investigated metaheuristic algorithms for portfolio optimization, discussed as follows:

Busetti (2000) demonstrates that the traditional portfolio optimization methods lose their effectiveness when real-world constraints are incorporated into the problem, whereas metaheuristic algorithms such as Genetic Algorithm, Tabu Search, and others remain highly flexible and efficient in such environments. Hence, the invasive weed optimization algorithm has a higher performance in comparison with other methods.

Kamili and Raffi (2016) examined the bat algorithm for solving portfolio optimization problems with cardinality constraints. Using market indices from four different countries, their results showed that the bat algorithm can perform effectively in solving this problem.

Eslami Bidgoli and Tayyebi Sani (2014) studied portfolio optimization using a memetic ant algorithm. The results demonstrated that the combined algorithm outperforms the genetic algorithm alone across all tested scenarios.

Beihaqi et al. (2015) applied the bee colony algorithm to portfolio optimization, modeling expected asset returns as fuzzy returns and using semi-variance as the risk measure. Their model included weight and cardinality constraints, and their results indicated that the bee colony algorithm performed better than other algorithms examined.

Afsharirad and Mazaherifar (2018) investigated genetic and invasive weed optimization algorithms for obtaining the efficient frontier using the mean semi-variance model. For expected return forecasting, they compared the second-order autoregressive (AR) method and the simple mean, concluding that the second-order AR method predicted with less error. Furthermore, the invasive weed optimization algorithm outperformed the genetic algorithm in performance.

Research has also addressed the application of cryptocurrencies and leverage in portfolio management:

Bowala and Singh, (2022) optimized portfolios consisting of cryptocurrencies, minimizing losses and risk, providing justification for incorporating cryptocurrencies into portfolios.

Kumar et al. (2025) demonstrated that Bitcoin serves as an effective hedge against stock market volatility in the U.S., while some evidence suggests that cryptocurrency markets are influenced by gold markets.

Chen et al. (2024) examined the impact of leverage in portfolio selection, accounting for liquidity costs. The findings indicate that under liquidity cost constraints and leverage use, portfolio efficiency declines when targeting higher return levels.

Eskandari et al. (2024) investigated the hedging ability of cryptocurrencies within portfolios comprising stocks and gold coins. Their results revealed that cryptocurrency inclusion, especially during significant gold price increases, is justified for portfolio risk hedging.

Poon (2025) studied complex portfolio optimization problems with leveraged trading strategies, employing metaheuristic algorithms. Their findings indicate that metaheuristic algorithms improve risk-adjusted returns.

Alidaee et al. (2025) analyzed the inclusion of cryptocurrencies in equity portfolios and found that cryptocurrencies considerably control portfolio risk.

Xu (2025) applied reinforcement learning algorithms to cryptocurrency portfolios, showing that this approach significantly enhances return and risk control.

Chen et al. (2024) explored the role of leverage in capital market trading, demonstrating its significant influence on market dynamics.

Previous studies have primarily focused on traditional portfolio optimization and the effects of cryptocurrencies in portfolios. Recently, attention has shifted to learning algorithms and return forecasting in portfolio optimization. However, this paper advances by examining the impact of futures contracts within cryptocurrency portfolios. In this study, a constrained cryptocurrency portfolio is optimized using the mean semi-variance model, with the Invasive Weed Optimization algorithm employed as the solution method.

It should be noted that in this research, the model here relies on the mean semi-variance due to its advantages, and because traditional solution methods are incapable of handling the minimum and maximum weight constraints, the invasive weed optimization algorithm is selected as the solution method.

3 Methodology

Based on Markowitz's theory, the portfolio return can be calculated as the expected return, and the portfolio risk is measured by the portfolio variance. The optimal portfolio is the one that, for a given level of expected return, has the minimum possible risk. The original Markowitz model is formulated as follows:

$$Min\ \sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j \sigma_{i \cdot j} \tag{1}$$

Subject to:

$$\sum_{i=1}^{N} x_i \mu_i = R^* \tag{2}$$

$$\sum_{i=1}^{N} x_i = 1 \tag{3}$$

$$x_i \geq 0, \forall i \in (1,2, \dots, N) \tag{4}$$

In equation (1), xi and xj represent the weights of two stocks i and j, respectively, and σ denotes the covariance between stocks i and j. In equation (2), R* represents a specified target return. Equation (3) states that the sum of all portfolio weights must equal one, and equation (4) indicates that each stock's weight can range between zero and one, preventing short selling.

The Markowitz model, developed in 1952, uses variance as a measure of risk. However, in 1959, Markowitz himself suggested in a paper that using semi-variance as a risk measure could be more appropriate because returns above the mean are not considered risky by investors but rather desirable. To obtain the efficient frontier, the following model can be used. Instead of finding a single portfolio, this model derives the efficient frontier:

$$Minimize\ \lambda \left(\sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j S_{ij}\right) - (1-\lambda)\left(\sum_{i=1}^{N} x_i \mu_i\right) \quad (5)$$

$$Subject\ to\text{:}\ \sum_{i=1}^{N} x_i = 1 \quad (6)$$

$$x_i \geq 0 \ \ (i = 1,2,\dots,N) \quad (7)$$

In equation (5), the objective function is minimized, where semi-variance (S) is used as the risk measure. In this model, the parameter λ varies within the interval 1. When λ=0, the entire weighting coefficient is assigned to return, and regardless of risk aversion, the portfolio with the highest return is selected. Conversely, when λ=1, the entire weighting is allocated to risk aversion, and the portfolio with the lowest risk is chosen. For values of λ between these extremes, both factors influence the resulting portfolios.

Equation (6) states that the sum of the asset weights equals one. Finally, equation (7) imposes the non-negativity constraint on each asset's weight, thereby eliminating short selling.

In the above problem, Estrada's (2004) formula is used to calculate the **semi-covariance**. Estrada (2004) defined the semi-covariance between two assets under a target threshold as follows:

$$\textstyle\sum_{ijB} = E\left\{Min\,(R_i - B, 0).\,Min\big(R_j - B, 0\big)\right\} \quad (8)$$

$$= \left(\frac{1}{T}\right).\sum_{t=1}^{T}\left[Min(R_{it} - B, 0).\,Min\big(R_{jt} - B, 0\big)\right] \quad (9)$$

In this formula, B represents the benchmark return value desired by the investor. If, instead of the target return B, the average return R¯ is substituted into the formula, the resulting measure is the semi-covariance under the mean.

$$\textstyle\sum_{ijB} = E\left\{Min\,(R_i - \overline{\mathrm{R}}, 0).\,Min\big(R_j - \overline{\mathrm{R}}, 0\big)\right\} \quad (10)$$

$$= \left(\frac{1}{T}\right).\sum_{t=1}^{T}\left[Min(R_{it} - \overline{\mathrm{R}}, 0).\,Min\big(R_{jt} - \overline{\mathrm{R}}, 0\big)\right] \quad (11)$$

As financial markets become increasingly complex, additional constraints may be imposed on the portfolio selection problem. One such constraint added to this model is the weight limitation for each asset, where the weight of each asset can vary between lower (L) and upper (U) bounds according to specific requirements. The complete model considered in this study is formulated as follows:

$$Minimize\ \lambda\ (\sum_{i=1}^{N}\sum_{j=1}^{N}x_i x_j S_{ij}) - (1-\lambda)(\sum_{i=1}^{N}x_i\mu_i) \quad (12)$$

Subject to:

$$\sum_{i=1}^{N}x_i = 1 \quad (13)$$

$$L \leq x_i \leq U.\ i = 1,2,\dots,N \quad (14)$$

$$x_i \geq 0\ \ (i = 1,2,\dots,N) \quad (15)$$

In the first line of the new formula, the semi-covariance is denoted by the symbol S. All the constraints in this model are similar to the previous one, with the difference that here two parameters, L and U, are used to define the lower and upper bounds of each asset's weight. The minimum weight an asset can have is L=0.003, and the maximum weight is U=0.30.

There are no efficient exact algorithms available for solving such constrained optimization problems in mathematical programming. Therefore, in this study, the metaheuristic invasive weed optimization algorithm, a search-based method, is employed. The ultimate goal is to obtain the efficient frontier using this algorithm and to determine the optimal degree of leverage in futures trading.

Sortino Ratio

The Sortino Ratio is an investment performance metric that measures the excess return (relative to the risk-free rate) against downside risk or negative volatility. Unlike the Sharpe Ratio, which considers total volatility, the Sortino Ratio focuses solely on negative fluctuations (downside deviations) and excludes positive volatility. This provides a more accurate and realistic assessment of the risk of potential losses, aligning well with investor`s interest in portfolio risk evaluation and management using advanced statistical models and optimization algorithms.

$$SOR = \frac{(\mu - r)}{\sigma d}$$

In this formula, σd represents the semi-deviation (standard deviation of returns below the target rate) (Sortino & Price, 1994).

In this paper, the sample consists of 10 cryptocurrencies and 5 active futures contracts in the market, with daily price data spanning from June 2022 to June 2025. The software used for analysis is MATLAB.

4 Empirical Results

In this study, a cryptocurrency investment portfolio is constructed using daily returns data from 10 cryptocurrencies and 5 cryptocurrency futures contracts, covering the period from the beginning of 2022 to the beginning of 2025. The data source for all assets is CoinGeckoCap (coingecko.com), a reputable and widely used cryptocurrency market data provider.

Table 1

Mean and Variance of the 10 Studied Cryptocurrencies

Crypto Name	ada	bnb	btc	doge	eth	link	sol	steth	trx	xrp
Mean of Return	0.0006	0.0007	0.0011	0.0018	0.0005	0.0013	0.0018	0.0005	0.0017	0.0021
Variance	0.0018	0.0010	0.0008	0.0024	0.0013	0.0021	0.0028	0.0013	0.0015	0.0021

Source: Research Findings

Table 2

Mean and Variance of the Studied Futures Contracts

Futures Name	Futures_bnb	Futures_btc	Futures_eth	Futures_sol	Futures_xrp
Mean of Return	0.0176	0.0266	0.0129	0.0421	0.0515
Variance	0.5474	0.4617	0.7291	1.6099	1.2257

Source: Research Findings

In this research, leverage ranging from 1 to 4 is applied to the futures contracts as follows:

- In the first portfolio, the futures contracts have a leverage of 1,
- In the second portfolio, the futures contracts have a leverage of 2,
- In the third portfolio, the futures contracts have a leverage of 3,
- And in the final portfolio, the futures contracts have a leverage of 4.

Accordingly, four efficient frontiers are generated, each corresponding to a different level of leverage, as illustrated in the figure below. Furthermore, considering the model constraints, minimum and maximum weight limits are imposed such that the weight of each asset in the portfolio is at least 0.003 and at most 0.3.

The resulting outputs are presented as four efficient frontiers corresponding to the four leverage levels.

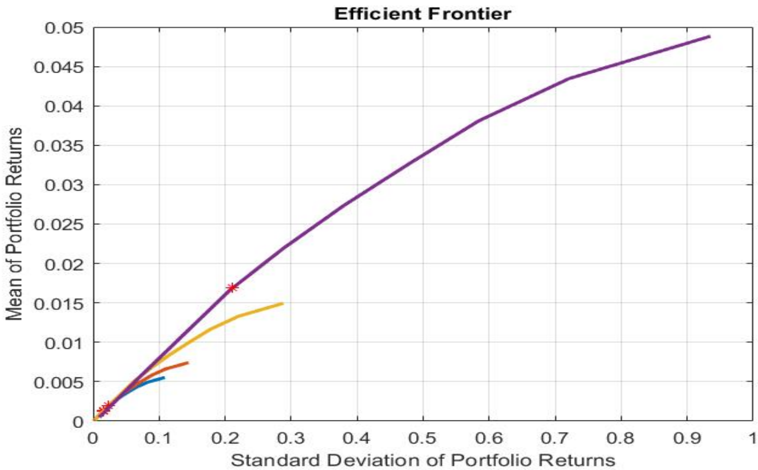

Figure 1. Efficient Frontier Obtained from Four Investment Portfolios
Source: Research findings

As illustrated in above figure, four efficient frontiers are presented herein. The smallest efficient frontier corresponds to the portfolio constructed from cryptocurrencies with a leverage factor of one. In a similar manner, the larger efficient frontiers correspond to leverage levels of two, three, and four, respectively. Consequently, the largest efficient frontier is associated with a leverage of four.

For each efficient frontier, the optimal portfolio—selected based on the Sortino ratio—is indicated by a star. It is obvious that the optimal portfolio derived from the largest efficient frontier (leverage four) has both higher expected return and higher risk relative to the optimal portfolios identified on the other efficient frontiers.

The table below displays the weight of each cryptocurrency in the optimal portfolio corresponding to each efficient frontier.

Table 3
Cryptocurrency Weights in the Optimal Portfolio for Each Efficient Frontier

Max Sortino Portfolio weight in Each Frontier Line				
Crypto`s Weights of best portfolio				
Crypto Name	Frontier 1	Frontier 2	Frontier 3	Frontier 4
ada	0.003	0.003	0.003	0.003
bnb	0.003	0.003	0.003	0.003
btc	0.003	0.003	0.003	0.003
doge	0.003	0.003	0.003	0.003
eth	0.003	0.003	0.003	0.003
link	0.003	0.003	0.003	0.003
sol	0.003	0.003	0.003	0.003
steth	0.003	0.003	0.003	0.003
trx	0.300	0.300	0.300	0.300
xrp	0.168	0.064	0.136	0.300
Futures_bnb	0.003	0.003	0.003	0.003
Futures_btc	0.003	0.003	0.003	0.003
Futures_eth	0.003	0.003	0.003	0.003
Futures_sol	0.003	0.003	0.003	0.003
Futures_xrp	0.168	0.155	0.082	0.300

Source: Research Findings

After constructing the four efficient frontiers, the best portfolio within each was identified using the Sortino ratio as the performance criterion. Finally, the Sortino ratios obtained from these four frontiers were compared.

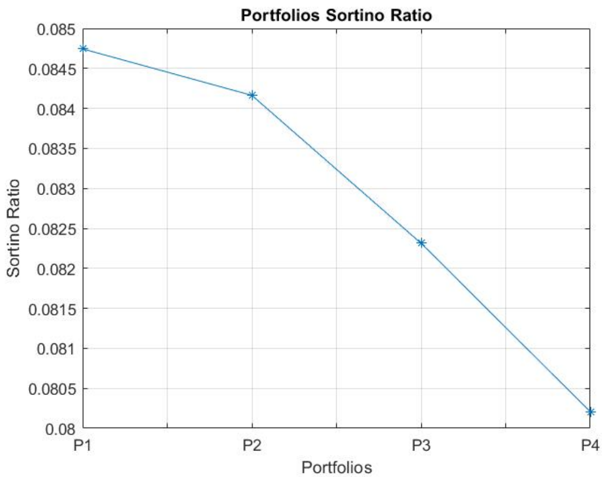

Figure 2. Sortino Ratios Obtained from Four Investment Portfolios
Source: Research Findings

Table 4
Portfolios Sortino Ration

Portfoilo	P1	P2	P3	P4
Sortino Ratio	0.0847	0.0842	0.0823	0.0802

Source: Research Findings

As illustrated in the figure 2 and table 4, the performances of the optimal portfolios obtained from the four efficient frontiers are denoted by their Sortino ratios as P1, P2, P3, and P4. Specifically, P1 corresponds to the Sortino ratio of the optimal portfolio on the efficient frontier with leverage one, P2 pertains to the optimal portfolio on the frontier with leverage two, and P4 represents the Sortino ratio of the optimal portfolio derived from the frontier with leverage four.

It is clear that the Sortino ratio of P1 exceeds those of the other portfolios, indicating that the performance of the best portfolio with leverage one surpasses that of the portfolio with leverage four. In other words, as the trading leverage increases, the performance of the existing portfolios demonstrates a declining trend.

5 Conclusion and Policy Recommendation

In this study, the optimal leverage level for futures contracts within a cryptocurrency portfolio was determined using a constrained mean semi-variance model coupled with the Invasive Weed Optimization algorithm. According to the study conducted by Busetti (2000), the traditional portfolio optimization method gradually loses its efficacy as additional constraints are incorporated into the mean semi-variance model. Consequently, this limitation justifies the adoption of the Invasive weed optimization metaheuristic algorithm in the current study. Owing to its enhanced capacity to manage complex and nonlinear constraints, this algorithm demonstrates commendable performance in environments characterized by real-world restrictions. Futures with leverage levels ranging from 1 to 4 were combined sequentially, producing one efficient frontier per leverage level. Each subsequent efficient frontier was larger than the preceding ones because increasing leverage allowed the frontier to encompass higher returns and higher risk. Consequently, the optimal portfolio on each higher-leverage frontier exhibited both greater return and greater risk compared to portfolios with lower leverage.

The results indicate that increasing the leverage degree in the investment portfolio leads to higher optimal portfolio returns, a finding that aligns with Poon’s (2025) study, which also observed that portfolio returns rise with increasing leverage. However, this study also reveals that increased leverage intensifies portfolio risk, which in turn can undermine overall portfolio performance.

Furthermore, by evaluating the optimal portfolios from each efficient frontier using the Sortino ratio, it was found that although higher-leverage portfolios achieve higher returns, their overall performance is generally poorer due to the associated increase in risk. Therefore, it can be concluded that raising the leverage level of futures in the portfolio does not necessarily translate into improved overall portfolio performance.

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