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Evaluation of Alternative Weighting Methods for the Selection of Portfolio Optimization Model

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Tartu, 2023

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Acknowledgement

We would like to express our deepest gratitude to all those who have supported and guided us throughout the completion of this master's thesis. Their invaluable contributions and unwavering encouragement have been instrumental in making this work possible. First and foremost, we would like to extend our heartfelt appreciation to my supervisors for their exceptional guidance, expertise, and continuous support. Their insightful feedback, constructive criticism, and dedication to our academic growth have been invaluable. We would also like to express our gratitude to the OpenAI team for developing and creating ChatGPT played a significant role in assisting us by providing the definitions of financial terms and formulation of mathematical formulas in LaTex during the writing data and methodology part. It is worth mentioning that the formulas presented in the subsection of Portfolio Optimization in the methodological part of this study are original contributions developed by the authors.

Abstract

This paper explores the use of technical indicators to construct alternative portfolio optimization models that balance risk and return and to evaluate the reliability and profitability of technical analysis indicator-weighted portfolios for investors. The study uses four technical analysis indicator-weighted portfolios: Moving Average Convergence Divergence (MACD)-weighted portfolio, Relative Strength Index (RSI)-weighted portfolio, Commodity Channel Index (CCI)-weighted portfolio and Stochastic Oscillator-weighted portfolio. This paper distinguishes itself by introducing a novel approach that incorporates technical indicators for the optimization and adjustment of asset weights. Notably, previous studies have not explored the utilization of technical indicators in this manner. In contrast to other researchers, our methodology involves the daily optimization of asset weights, coupled with the computation of daily portfolio performance over an extended time frame. The findings suggest that all technical indicators, except for the Stochastic Oscillator, can be used to construct diversified portfolios that offer a balance between risk and return. Based on the results, The MACD-weighted portfolio has the lowest volatility at 18.61 percent and a relatively strong Sharpe and Sortino ratio, at 0.67 and 1.01 percent, respectively, while the RSI-weighted portfolio has the second highest Calmar ratio and the lowest potential for losses. The CCI-weighted portfolio provides the second-highest annual return at 15.55 percent, but it has higher annual volatility compared to MACD and RSI. The Stochastic Oscillator-weighted portfolio has the highest risk at 159.76 percent, but also the highest potential for gains and downside risk. The optimal portfolio depends on an investor's goals, risk tolerance, and investment strategy. However, based on the metrics provided, the MACD portfolio is the optimal portfolio among the other portfolio models for investors seeking higher returns with lower risks.

Keywords:
Portfolio Optimization, Stock Market, Technical Indicator, Portfolio Management, Asset Weight Allocation

CERCS classification code: S180

We have written this master's thesis independently. Any ideas or data from other authors or sources have been appropriately referenced.

1 Introduction

Portfolio optimization is the process of selecting the optimal mix of assets for investment to achieve a specific set of investment objectives (Hongjoong, 2021). In the realm of investment management, portfolio optimization plays a crucial role in achieving a balance between risk and return. Traditional portfolio optimization models often rely on fundamental analysis, such as evaluating financial statements and economic factors, to determine the asset weights in a portfolio. However, an alternative approach gaining popularity is the use of technical indicators to guide portfolio construction. This paper delves into the exploration of technical indicators as tools for constructing alternative portfolio optimization models. The primary objective is to assess the reliability and profitability of technical indicator-weighted portfolios, offering valuable insights for investors seeking to diversify their portfolios while minimizing risk and maximizing returns. The study uses four technical indicator-weighted portfolios and determines which one can yield consistent and robust results. The findings of this study may be useful to investors looking to diversify their portfolios and minimize risk while maximizing returns. The objective of this study is to assess the robustness of the suggested portfolio models that employ technical indicators to determine the asset weights. The process involves choosing a particular set of assets and gathering their past performance data to calculate various technical indicators. These indicators are evaluated based on metrics such as Annual return, Annual volatility, Sharpe ratio, Max drawdown, Sortino, and Calmar ratios. To construct and refine the technical indicator-weighted portfolio, we utilized the selected technical indicators. The asset weights in the portfolio were predetermined using Monte Carlo simulation in order to apply those weights in the formulas we defined for an empirical part. Overall, this study contributes to the existing body of research by providing insights into the effectiveness of technical indicator-weighted portfolios. The findings can guide investors in making informed decisions about portfolio diversification, risk management, and potential returns. By understanding the robustness and reliability of these alternative portfolio optimization models, investors can navigate the complexities of the financial markets more effectively.

By creating an efficient frontier—a graph displaying the set of optimal portfolios that yield the highest return for a given level of risk or the lowest risk for a given level of return—the Mean-Variance (MV), hereinafter referred to as the MV, model by Markowitz (1952) addresses the portfolio optimization problem (Hongjoong, 2021). However, Bessler et al., 2017 discuss that the MV model has significant shortcomings for practical applications, and some enhancements are needed to address those problems. The accuracy of future stock market forecasts is particularly important for the MV model's success. Hongjoong, 2021 also emphasizes that since the stock market is influenced by a variety of factors and is primarily a nonlinear, non-stationary, volatile, and noisy structure, forecasting it can be difficult. For instance, it is argued whether capitalization-weighted indices are optimal. Stocks with high comparable prices to their fundamentals are overweighted by the market capitalization weighting technique, and equities with low relative prices to their fundamentals are underweighted. Moreover, the market capitalization weighting technique frequently results in an underdiversified portfolio due to excessive exposure to a small number of very large stocks (Finnerman and Kirchmann, 2015).

The pre-selection of high-quality stocks is vital to the effectiveness of portfolio management. In order to build a portfolio, investors must figure out the optimal weight for each company and the expected future return of their investments. The investors should calculate the optimal weight across all chosen equities in a pre-selection stage before constructing trading investment (Naik and Albuquerque, 2022). Clare et al., 2013 discovered that applying weights that monkeys may have chosen, or choosing constituent weights at random, would likewise have yielded a significantly superior risk-adjusted performance than a cap-weighted scheme.

Technical indicators are commonly used in identifying market trends and potential price reversals. Technical indicators can be used to generate trading signals and inform the selection of assets for investment. Technical trading indicators have received a lot of attention in the stock and Forex (FX) markets, but commodity and bond markets have received less attention. Dunis and Miao, 2005 applied technical rules to a wide variety of financial assets and investigated the performance of technical trading rules in the context of portfolio performance. The most popular technical indicators include the Stochastic Oscillator, Relative Strength Index (RSI), hereinafter referred to as the RSI, and Moving Average Convergence Divergence (MACD), hereinafter referred to as the MACD.

Momentum indicators, such as RSI and Stochastic Oscillator are based on the principle that asset prices tend to continue in the same direction for some time before changing direction. They measure the rate of change in asset prices over a specified period, typically 14 periods. Values above 80 are considered overbought, indicating that the asset may be due for a price correction. Values below 20 are considered oversold, meaning the asset may be due for a price rebound. Gumparthi, 2017 showed that one of the technical indicators- RSI is a strong analytical tool that assist the investor in selecting the appropriate combination of assets for their portfolio building, decreasing risk and boosting return. There are numerous methods available to help investors minimize their likelihood of suffering losses and improve returns.

Several challenges and limitations are associated with technical indicators in portfolio optimization. One of the most significant challenges is the need for high-quality data. Various factors can affect historical data, including market conditions, economic events, and company-specific factors. Another limitation of using technical indicators in portfolio optimization is the risk of relying too heavily on past performance. Past performance may not indicate future performance, and there is always the risk of unexpected events or changes in market conditions that can significantly impact asset performance.

The following is how the paper was organized: The introduction section provided an overview of the research study. The second section presented a concise summary of the related works in the field. In the third section, we described the data used in our study and explain the methodology employed for our research. Moving on, the fourth section presented the empirical findings of our study, with a focus on the different portfolio weighting models. Finally, in the fifth section, we provided a conclusion along with suggestions for further exploration.

2 Literature review

Forecasting stock market indices is a difficult task that poses a significant challenge for investors and researchers. This is primarily due to the dynamic and nonlinear nature of the stock market, which is impacted by a variety of factors, such as economic policies, government regulations, political instability, investor sentiment, and future economic conditions. The complexity of this system makes it inherently unstable, leading to difficulties in accurately predicting future trends and movements in the stock market (Chen and Hao (2017)). Investing in securities is a complex financial activity that is impacted by a multitude of factors, including political, economic, and psychological influences on investors (Wang and Kim, 2018). The changes in the stock market are nonlinear and exhibit multifractal characteristics. Due to the inherent risk associated with stock market investments, excessive price volatility or low stability can lead to uncontrollable levels of risk. Short-term financial asset returns tend to persist, but long-term returns are likely to reverse (Wang and Kim (2018)).

On the other hand, portfolio optimization has also been challenging for investors and researchers. Portfolio optimization is choosing the most suitable asset allocation that fulfills financial goals, such as maximizing returns or minimizing risks (Finnerman and Kirchmann, 2015). The MV model introduced by Markowitz in 1952 addresses the portfolio optimization problem by constructing an efficient frontier, a graphical representation of the optimal portfolios that provide the highest return for a given level of risk or the lowest risk for a given level of return (Finnerman and Kirchmann, 2015). However, the MV model has practical limitations; further enhancements are necessary to address these challenges. Past study has shown that various other weighting methods based on heuristics and optimization outperform the market capitalization weighting method (Finnerman and Kirchmann (2015)). The task of constructing a portfolio through effective stock selection is crucial for both individual and institutional investors.

Optimizing and improving portfolio performance has recently become a primary focus of modern financial research and investment decision-making. The success of portfolio selection is heavily dependent on accurate forecasts of future stock market performance, which has the potential to generate high investment returns and mitigate risks. Therefore, making reasonable and precise predictions is critical to achieving these goals (Chen et al. (2021)). For instance, Knowles (2015) introduces a novel strategic approach to quantitative investment methodology aimed at making informed decisions about asset allocation. The outcome is a set of strategies that produce improved risk-adjusted returns for the broad equity, bond, and hedge fund markets. Upon analyzing the portfolios, the authors discovered that they delivered significantly higher risk-adjusted returns across multiple market cycles. Clare et al. (2013) examined and contrasted the performance of several different indexing strategies using data on the 1,000 largest US equities for each year between 1968 and the end of 2011. They discovered that applying weights that monkeys could have chosen or

choosing constituent weights at random would have yielded a significantly superior risk-adjusted performance than a cap-weighted method. Finnerman and Kirchmann (2015) assessed how the Stockholm Stock Exchange (SIX30RX), hereinafter referred to as the SIX30RX, stacks up against portfolios built using the same stocks but different weighting strategies. The weighting method that performs the best overall in terms of return and risk-adjusted return is minimum variance. While using a straightforward algorithm, the equal-weighted portfolio outperforms and resembles the SIX30RX index in terms of features. In conclusion, all examined alternative weighting methods outperform the SIX30RX index, with the exception of those based on momentum ones.
Technical indicators, especially momentum indicators, have been widely used and addressed in several pieces of literature to evaluate whether they perform well in predicting stock market prices and optimizing portfolios. One of the most talked-about topics in finance is momentum. According to some ideas, such as the efficient market hypothesis, all information accessible to the market is contained in asset prices. Hence it should not be feasible to continue receiving abnormal returns. Several academic studies simultaneously demonstrated the existence of momentum and the profitability of methods based on it (Frytsiuk (2019)). Nedĕla (n.d.) examined the effects of several technical analysis indicators and the stochastic dominance approach on portfolio decision-making in various markets throughout various crisis periods that capture various market situations. Frytsiuk (2019) sought to backtest various methods for identifying and capitalizing on momentum in the Nordic financial market. MACD and Chaikin indicators were the foundation of active strategies. These were both less effective than passive management techniques. Chaikin strategy was outperformed by MACD strategy based on half-month and one-month holding periods in terms of efficiency and return. Wang and Kim (2018) aimed to develop an effective method for predicting the stock price trend. They compare the accuracy between a MACD histogram and a MACD-HVIX histogram and find that the accuracy of using the MACD-HVIX histogram is 55.55 percent higher than that of the MACD histogram when they use the buy-and-sell strategy. They found that the new indicator is more stable. Therefore, the improved stock price forecasting model can predict the trend of stock prices and help investors augment their return in the stock market. Rosillo et al. (2013) looked at how the indicators such as RSI, MACD, Momentum, and Stochastic performed when applied to various firms in the Spanish Continuous Market. Also, this research provided traders with solutions to their concerns related to indication discrepancy. Gumparthi (2017) computed the 14-day RSI for the selected short-term investment stocks at a future time (March 2014) and compared that value to the initial 14-day RSI to evaluate the performance of short-term investments in the Indian stock markets. In this instance, the majority of the outcomes were favorable, demonstrating the applicability of RSI in Indian stock markets. Six of the ten screenplays were chosen, and six of the ten scripts were chosen as the Price-to-Earnings (P/E) ratio is a greater predictor of profitability than Earning per share (EPS). Dunis, Miao, et al. (2006) utilized technical trading rules, the most popular forecasting method in the financial markets, to determine the best trading frequency for various

assets within the context of active asset management. The findings demonstrated that the two volatility filters and the model switch approach improve model performance in terms of annualized return, Sharpe ratio and maximum drawdown. Both the portfolio level and the level of a single asset show substantial improvement.

The research discussed in the aforementioned papers has certain gaps that warrant further investigation. Although some of the studies utilized technical indicators to develop portfolio models, the number of technical indicators employed did not exceed two and was limited in scope. Furthermore, none of the studies except for Finnerman and Kirchmann (2015) employed technical indicators to determine and adjust asset weights within the portfolio. Although Finnerman and Kirchmann (2015) employed the RSI as a means of developing an alternative weighting technique, the authors did not calculate the daily weights of the assets to assess the performance of the portfolio on a daily basis.

Therefore, additional research is required to explore the effectiveness of using a larger number of technical indicators in portfolio selection and management, as well as the benefits of incorporating technical indicators in the asset allocation process. By examining the impact of a wider range of technical indicators on portfolio performance, researchers could have provided valuable insights into the suitability of these tools for investors seeking to optimize their investment strategies. As exploring the role of technical indicators in determining asset weights within a portfolio can offer a more comprehensive understanding of their potential value in portfolio management, we incorporated popular technical indicators into the adjustment of asset weights in a portfolio based on the values of the technical indicators. The research motivation is to see how the proposed technical indicators-weighted portfolio models perform in the context of weighting assets based on the identified indicators.

3 Data and Methodology

We created multiple portfolios using technical indicators, namely the MACD, RSI, Stochastic Oscillator, and Commodity Channel Index (CCI), hereinafter referred to as the CCI. Data gathering, data preprocessing, model construction, portfolio optimization, and performance assessment were all steps in portfolio optimization. From a trustworthy financial data source - Yahoo Finance, we gathered historical data for the assets of the Financial Times Stock Exchange (FTSE 100) index, hereinafter referred to as the FTSE 100, including daily price and volume data. The data comprised pertinent elements such as opening price, closing price, high price, low price, volume, as well as a sufficiently wide time interval to assure the validity of the analysis. Preprocessing was performed on the collected data to guarantee its quality and suitability for analysis. Given that the data was obtained from a widely recognized and dependable source, we performed a single pre-processing step of data cleaning. This involved identifying and addressing issues such as missing values, outliers, and data anomalies that may affect the accuracy and reliability of the dataset.

3.1 Data

We collected data from Yahoo Finance on the FTSE 100 Index, including High, Low, Volume, Open, Close, and Adjusted Close prices. We extracted a time series from January 1, 2012, to March 10, 2023, with daily frequency. A quality check was performed on the dataset to detect any anomalies, resulting in the identification of a few assets with missing values. To fill in these missing values, we employed the linear time interpolation technique for assets with 10 and fewer missing records. Linear time interpolation is a method of filling missing values in time series data by estimating the missing values with a straight line drawn between two adjacent data points. This method assumes that the trend between two data points is linear and estimates the missing values by fitting a straight line between the available data points. The formula for linear time interpolation between two data points (t_1, y_1) and (t_2, y_2) is given by:

$$y(t) = y_1 + \frac{(y_2 - y_1)}{(t_2 - t_1)}(t - t_1) \tag{1}$$

where t is the missing time point, and $y(t)$ is the estimated value at time t. For the remaining assets with more than 10 missing values, they were excluded from the dataset.

To build the portfolio optimization models, we calculated three technical indicators using the Adjusted Close prices of the FTSE 100 assets, including the RSI, MACD, and Stochastic Oscillator indicators. The CCI indicator was calculated using the High, Low, and Close prices of the assets in the FTSE 100 Index. These indicators are commonly used to analyze trends in financial markets and can provide insights into potential trading opportunities. In the following part, we have a detailed insight into the technical indicators.

3.2 Technical Indicators

3.2.1 Relative Strength Index (RSI)

The RSI is a popular technical indicator used to measure the speed and change of price movements in financial markets. It calculates the ratio of upward price movements to downward price movements over a specified period of time, typically 14 days, and generates a value between 0 and 100. RSI values above 70 are considered overbought, suggesting a potential reversal or correction in price, while values below 30 are considered oversold, indicating a potential upward price movement. The formula for RSI is:

$$RSI = 100 - \frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}} \tag{2}$$

where:

- Average Gain is the average of all upward price movements over the selected time period
- Average Loss is the average of all downward price movements over the selected period.

3.2.2 Moving Average Convergence Divergence (MACD)

The MACD is a widely used technical indicator that helps identify potential trend reversals and generate buy or sell signals. It consists of two lines, the MACD line and the signal line, along with a histogram. The MACD line is calculated by subtracting the longer-term (26-periods) exponential moving average (EMA) from the shorter-term (12-periods) EMA, while the signal line is an EMA of the MACD line. When the MACD line crosses above the signal line, it generates a bullish signal, indicating a potential upward trend, while a crossover below the signal line suggests a bearish signal, indicating a potential downward trend. The histogram represents the difference between the MACD line and the signal line, providing further insight into the strength and momentum of the trend. We normalized the values of MACD between 0 and 100 in order to be consistent with other technical indicators. The formula for MACD is:

$$MACD = EMA_{12} - EMA_{26} \tag{3}$$

3.2.3 Commodity Channel Index (CCI)

The CCI is a technical indicator used to identify overbought and oversold levels in an asset's price. It measures the difference between an asset's current price and its average price over a specific period of time, relative to its mean deviation.The CCI is typically calculated using a 20-periods moving average of typical price (the average of high, low, and closing prices). Positive CCI values indicate prices above the average, suggesting overbought conditions, while negative CCI values indicate prices below the average, suggesting oversold conditions. Traders often use the CCI to identify potential trend reversals and generate buy or sell signals. The same normalization process of MACD values applied to CCI values to keep consistency among all technical indicators that we employed in our paper. The formula for CCI is:

$$CCI = \frac{\text{Typical Price} - \text{SMA}_{20}(\text{Typical Price})}{0.015 \times \text{Mean Deviation}} \tag{4}$$

where:

- Typical Price is the average of the high, low, and closing prices for a given period
- Mean Deviation is the mean absolute deviation of Typical Price from the Simple Moving Average (SMA) over the selected time period.

3.2.4 Stochastic Oscillator

The Stochastic Oscillator is a popular technical indicator that measures the momentum and strength of price movements. It compares the current closing price of an asset to its price range over a specific period of time (typically 14-periods). The indicator generates values between 0 and 100, with readings above 80 considered overbought and readings below 20 considered oversold. Traders often use the Stochastic Oscillator to identify potential trend reversals, confirm the strength of a trend, and generate entry or exit signals based on overbought or oversold conditions.The formula for the Stochastic Oscillator is as follows:

$$K = \frac{C - L14}{H14 - L14} \times 100 \tag{5}$$

where:

- K is the current value of Stochastic Oscillator
- C is the closing price of the asset for the current period
- L14 is the lowest price of the asset over the last 14 periods
- H14 is the highest price of the asset over the last 14 periods

3.3 Portfolio metrics

Annual return is the percentage gain or loss of a portfolio over a one-year period. It indicates the overall profitability of the portfolio during that time. Annual volatility, also known as standard deviation, measures the fluctuation or variability of returns for a portfolio over a one-year period. It indicates the risk or volatility associated with the portfolio.The Sharpe ratio is a measure used in finance to assess the risk-adjusted return of an investment or portfolio. It quantifies the excess return earned per unit of risk by comparing the average return of the investment to the volatility or standard deviation of those returns.

Annual return of portfolio:

$$R_p = \sum_{i=1}^{n} w_i R_i \tag{6}$$

where R_p is the annual return of the portfolio, w_i is the weight of the i^{th} asset in the portfolio, R_i is the annual return of the i^{th} asset, and n is the total number of assets in the portfolio.

Volatility (standard deviation) of portfolio:

$$\sigma_p = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}} \tag{7}$$

where σ_p is the volatility (standard deviation) of the portfolio, σ_i is the standard deviation of the i^{th} asset, ρ_{ij} is the correlation coefficient between the i^{th} and j^{th} assets, and all other variables are as defined above.

Sharpe ratio of portfolio:

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

where R_p is the expected portfolio return R_f is the risk-free rate of return σ_p is the standard deviation of the portfolio's excess returns

3.4 Portfolio Optimization Models

We created 4 portfolios depending on technical indicators - MACD, RSI, Stochastic Oscillator, and CCI. For each portfolio, we calculated the returns, risks, and other key performance indicators such as the Sharpe ratio, maximum drawdown, Sortino ratio, etc. We used Monte Carlo simulation to optimize the weights for each asset, with the goal of maximizing portfolio returns while reducing risks. Let $RSI_{i,t}$ be the daily RSI value of asset i on day t, where $i \in 1, 2, \ldots, 89$ and $t \in 1, 2, \ldots, 3650$, representing 10 years of daily data. Let w_i be the optimal weight obtained by Monte Carlo Simulation for asset i, where $i \in 1, 2, \ldots, 89$.

For RSI-weighted portfolio:

We can calculate the weighted RSI value for each asset on each day by multiplying the RSI value by the corresponding weight:

$$RSI_{i,t} \times w_i \tag{9}$$

To find the weighted RSI values for our portfolio over the 10-year period, we need to sum the weighted RSI values for each asset on each day:

$$\sum_{i=1}^{89} RSI_{i,t} \times w_i \tag{10}$$

This gives us the total weighted RSI value for our portfolio on each day, based on the RSI values and optimal weights for each asset. Then, to find the daily weights for our portfolio over the 10-year period, we need to divide the weighted RSI values for each day by the sum of the weighted RSI values for that day:

$$\frac{RSI_{i,t} \times w_i}{\sum_{i=1}^{89} RSI_{i,t} \times w_i} \tag{11}$$

This gives us the proportion of our portfolio that should be invested in each asset on each day, based on their RSI values and optimal weights.

After finding the daily weights for the portfolio, we can use them to calculate the weighted prices of each asset on each day. Then, to calculate the daily portfolio value, we need to sum the weighted prices for all assets on each day.

Let $P_{i,t}$ be the daily price of asset i on day t, where $i \in 1, 2, \ldots, 89$ and $t \in 1, 2, \ldots, 3650$, representing 10 years of daily data. Let $w_{i,t}$ be the daily weight for asset i on day t, where $i \in 1, 2, \ldots, 89$ and $t \in 1, 2, \ldots, 3650$.

We can calculate the weighted price for each asset on each day by multiplying the price by the corresponding weight:

$$P_{i,t} \times w_{i,t} \tag{12}$$

To find the daily portfolio value, we need to sum the weighted prices for all assets on each day:

$$\sum_{i=1}^{89} P_{i,t} \times w_{i,t} \quad \forall t \in 1, 2, \ldots, 3650 \tag{13}$$

This gives us the daily value of our portfolio over the 10-year period, based on the daily prices of each asset and the daily weights for our portfolio.

For MACD-weighted portfolio:

We can calculate the weighted MACD value for each asset on each day by multiplying the MACD value by the corresponding weight:

$$MACD_{i,t} \times w_i \tag{14}$$

To find the weighted MACD values for our portfolio over the 10-year period, we need to sum the weighted MACD values for each asset on each day:

$$\sum_{i=1}^{89} MACD_{i,t} \times w_i \tag{15}$$

By dividing the weighted MACD values for each day by the sum of the weighted MACD values for that day, we get the proportion of our portfolio that should be invested in each asset on each day, based on their MACD values and optimal weights.:

$$\frac{MACD_{i,t} \times w_i}{\sum_{i=1}^{89} MACD_{i,t} \times w_i} \tag{16}$$

The weighted price for each asset on each day by multiplying the price by the corresponding weight:

$$P_{i,t} \times w_{i,t} \tag{17}$$

Summing the weighted prices for all assets on each day:

$$\sum_{i=1}^{89} P_{i,t} \times w_{i,t} \quad \forall t \in 1, 2, \ldots, 3650 \tag{18}$$

For CCI-weighted portfolio:

We can calculate the weighted CCI value for each asset on each day by multiplying the CCI value by the corresponding weight:

$$CCI_{i,t} \times w_i \tag{19}$$

To find the weighted CCI values for our portfolio over the 10-year period, we need to sum the weighted CCI values for each asset on each day:

$$\sum_{i=1}^{89} CCI_{i,t} \times w_i \tag{20}$$

By dividing the weighted CCI values for each day by the sum of the weighted CCI values for that day, we get the proportion of our portfolio that should be invested in each asset on each day, based on their CCI values and optimal weights.:

$$\frac{CCI_{i,t} \times w_i}{\sum_{i=1}^{89} CCI_{i,t} \times w_i} \tag{21}$$

The weighted price for each asset on each day by multiplying the price by the corresponding weight:

$$P_{i,t} \times w_{i,t} \tag{22}$$

Summing the weighted prices for all assets on each day:

$$\sum_{i=1}^{89} P_{i,t} \times w_{i,t} \quad \forall t \in 1, 2, \ldots, 3650 \tag{23}$$

For Stochastic Oscillator-weighted portfolio:

We can calculate the weighted SO value for each asset on each day by multiplying the SO value by the corresponding weight:

$$SO_{i,t} \times w_i \tag{24}$$

To find the weighted SO values for our portfolio over the 10-year period, we need to sum the weighted SO values for each asset on each day:

$$\sum_{i=1}^{89} SO_{i,t} \times w_i \tag{25}$$

By dividing the weighted SO values for each day by the sum of the weighted SO values for that day, we get the proportion of our portfolio that should be invested in each asset on each day, based on their SO values and optimal weights.:

$$\frac{SO_{i,t} \times w_i}{\sum_{i=1}^{89} SO_{i,t} \times w_i} \tag{26}$$

The weighted price for each asset on each day by multiplying the price by the corresponding weight:

$$P_{i,t} \times w_{i,t} \tag{27}$$

Summing the weighted prices for all assets on each day:

$$\sum_{i=1}^{89} P_{i,t} \times w_{i,t} \quad \forall t \in 1, 2, \ldots, 3650 \tag{28}$$

The preceding section explicated the mathematical procedures utilized in constructing four various portfolios of technical indicators through the implementation of the Python programming language. The final results provide a description of the daily value of all portfolios over a period of 10 years.

4 Empirical results

The empirical results are centered around the evaluation and comparison of the portfolio optimization models. Empirical results contain four portfolio optimization models and their main results. In the end, we compared these models and chose the optimal one based on evaluation metrics.

4.1 MACD-weighted portfolio

A MACD-weighted portfolio is a type of investment portfolio where the weights of the assets in the portfolio are determined by their respective MACD signals. In a MACD-weighted portfolio, assets that have a bullish MACD signal (i.e., a positive crossover between the MACD and signal line) are assigned higher weights, while assets with a bearish MACD signal (i.e., a negative crossover between the MACD and signal line) are assigned lower weights or excluded from the portfolio altogether. The purpose of using a MACD-weighted portfolio is to capitalize on the technical of the market and take advantage of bullish trends while avoiding assets that may be in a downtrend.

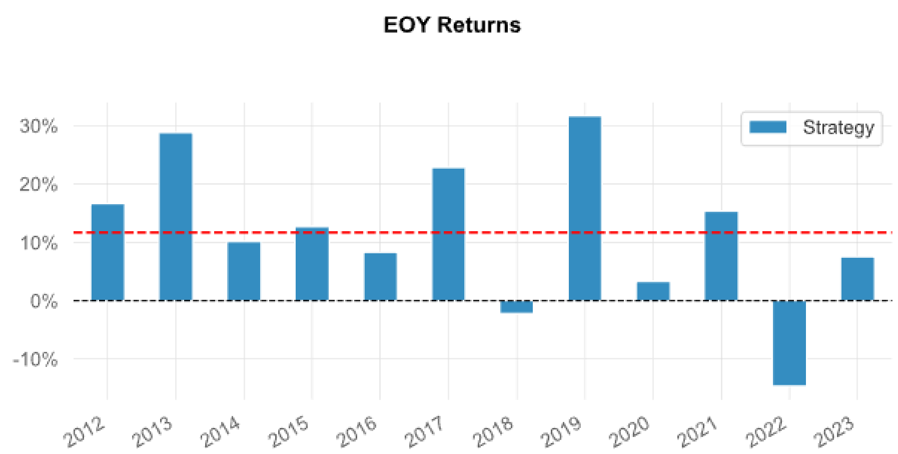

Figure 1. EOY of MACD-weighted portfolio over 2012-2023

(Graph created by the author(s))

The volatility in returns of the MACD-weighted portfolio in recent years could be attributed to a number of factors, such as macroeconomic events, changes in market sentiment, and changes in interest rates. For instance, the COVID-19 pandemic in 2020 and the Russian-Ukraine war had a significant impact on global financial markets, causing widespread panic and uncertainty among investors. This led to increased market volatility, which could have affected the returns of the portfolio.

Having considered the given numbers in Figure 1, it appears that the End of Year (EOY), hereinafter referred to as the EOY, return of the MACD-weighted portfolio has also been quite volatile over the years. The portfolio had positive returns in most years, with the highest returns in 2013 and 2019, at 28.81 percent and 31.68 percent, respectively. However, the portfolio also experienced negative returns in some years, such as in 2018 and 2022. In 2022, the portfolio experienced a significant decrease in return, with a negative return of -14.63 percent. In 2023, the portfolio had a positive return of 7.5 percent.

Overall, the MACD-weighted portfolio appears to have delivered positive returns over the long term, but its returns may be subject to significant fluctuations due to market volatility.

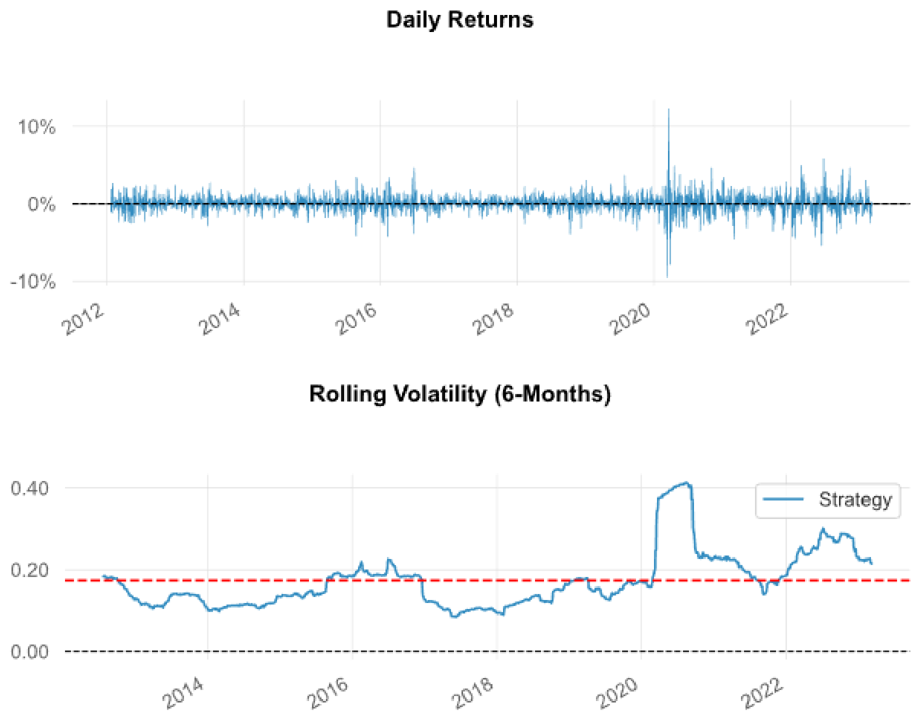

Figure 2. Daily returns and Rolling volatility of MACD-weighted portfolio over 2012-2023

(Graph created by the author(s))

We also visualized daily returns and volatilities of the proposed portfolio in Figure 2 to show a correlation between them where it is obvious that volatility which was remarkably high at the beginning of 2020 followed by the same volatility trend in 2021 affected fluctuations in returns in the same period.

The Rolling Sharpe Ratio and Rolling Sortino Ratio of a MACD-weighted portfolio are measures of risk-adjusted performance calculated over a 6-month moving time window. The higher the ratios, the better the risk-adjusted performance of the portfolio. Based on Figure 3 both ratios were higher in 2017-2018 and in 2021, indicating better risk-adjusted performance during those periods. However, in 2019 and 2022, both ratios dipped into negative territory, suggesting that the risk-adjusted performance of the portfolio worsened during those periods. In 2017, the Rolling

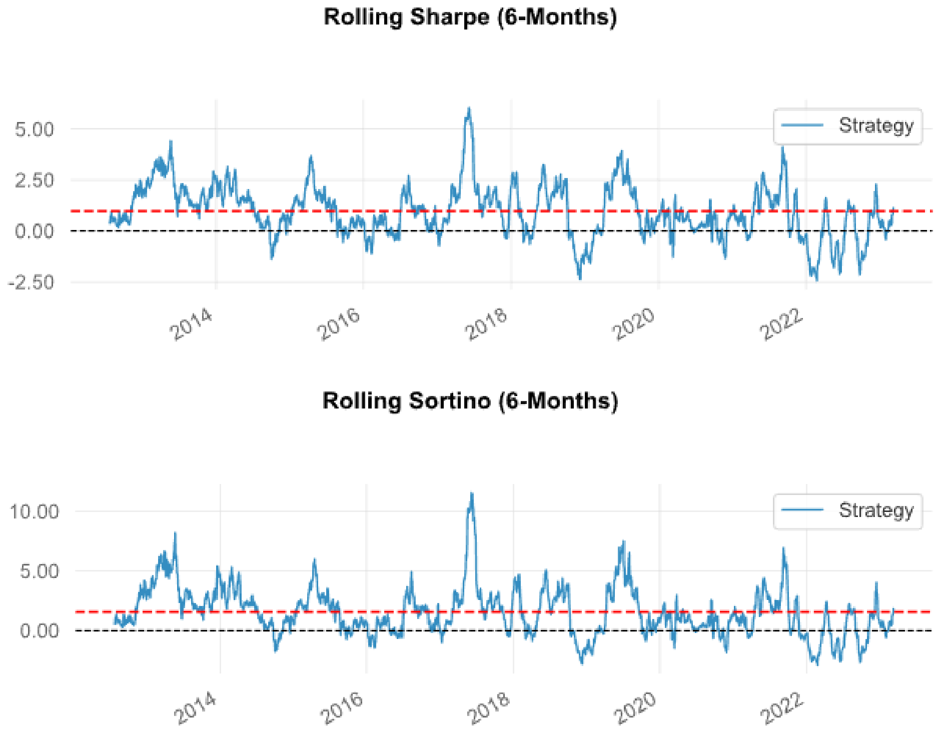

Figure 3. Rolling Sharpe and Sortino ratio of MACD-weighted portfolio over 2012-2023

(Graph created by the author(s))

Sharpe Ratio hit 5 and Rolling Sortino Ratio hit 10 during the same period. In other words, based on the value of the Rolling Sharpe ratio in 2017, the portfolio achieved a return that is 5 times greater than the amount of risk taken to achieve that return, over the 6-month period. In the same period, a higher Sortino ratio suggests that the portfolio has generated a higher return per unit of downside risk taken on. In 2022, the Rolling Sharpe Ratio dipped to -2.5, indicating that the portfolio was generating negative returns relative to its level of risk.

The correlation between the Rolling Sharpe Ratio and the Rolling Sortino Ratio of a portfolio is due to the fact that they both measure risk-adjusted performance. The Sharpe ratio measures the excess return earned over the risk-free rate, while the Sortino ratio measures the excess return earned over the downside deviation. As such, both ratios are affected by the same factors, such as the portfolio's volatility and returns.

4.2 RSI-weighted portfolio

A RSI-weighted portfolio is a type of investment portfolio where the weights of the assets are also determined by their respective RSI values. In a RSI-weighted portfolio, assets that have higher RSI values are assigned higher weights, while assets with lower RSI values are assigned lower weights or excluded from the portfolio altogether. The main goal of using an RSI-weighted portfolio is to capture the technical of the market and benefit from bullish trends while minimizing exposure to assets that may be in a downtrend. This approach is based on the idea that the RSI indicator, which is commonly used in technical analysis, can provide useful signals about the market trend and technical of individual assets. By adjusting the weights of the portfolio based on the RSI values of the assets, investors can potentially enhance the risk-adjusted returns of their portfolio. However, it is important to note that this strategy, like any other investment strategy, involves risks and may not always achieve the expected performance.

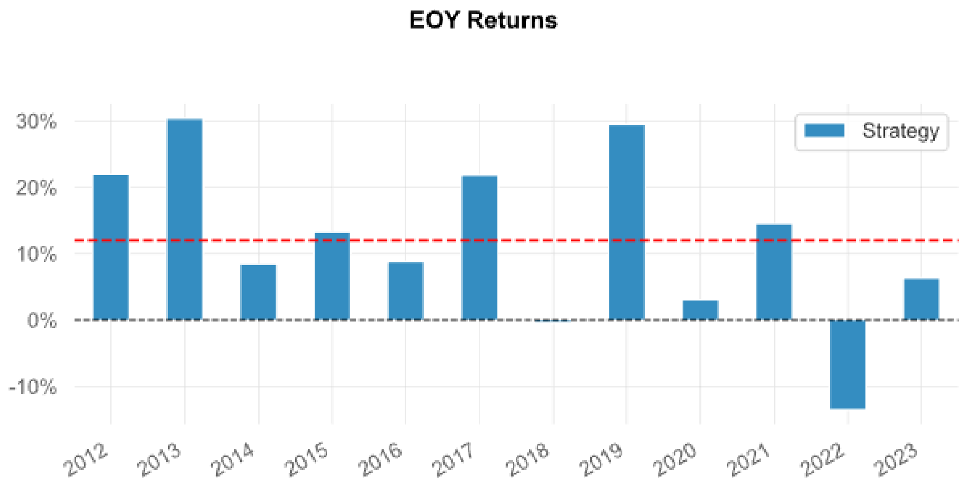

Figure 4. EOY of RSI-weighted portfolio over 2012-2023

(Graph created by the author(s))

Based on Figure 4, the EOY return of the RSI-weighted portfolio has been positive in most years, with the highest returns in 2013 and 2019, at 30.38 percent and 29.47 percent, respectively. However, the portfolio also experienced negative returns in some years, such as in 2018 and 2022. In 2022, the portfolio experienced a decrease in return, with a negative return of -13.54 percent. In 2023, the portfolio had a positive return of 6.29 percent. When comparing the RSI-weighted portfolio to the MACD-weighted portfolio, we can see that the RSI-weighted portfolio had similar returns in most years but had higher returns in 2013 compared to the MACD-weighted portfolio. The MACD-weighted portfolio had a smaller negative return in 2022 compared to the RSI-weighted portfolio.

Daily returns show the percentage change in an asset's or portfolio's price from one trading day to the next. Positive returns indicate a price increase, while negative returns indicate a decrease. The RSI-weighted portfolio experienced a shift in its daily return fluctuations from a narrow range of -5 and 5% to a wider range of almost -10 and 10% due to economic and political factors in recent years. Rolling volatility measures the variability of an asset's or portfolio's returns over a rolling window of time and helps investors understand the risk associated with investing in the asset. A

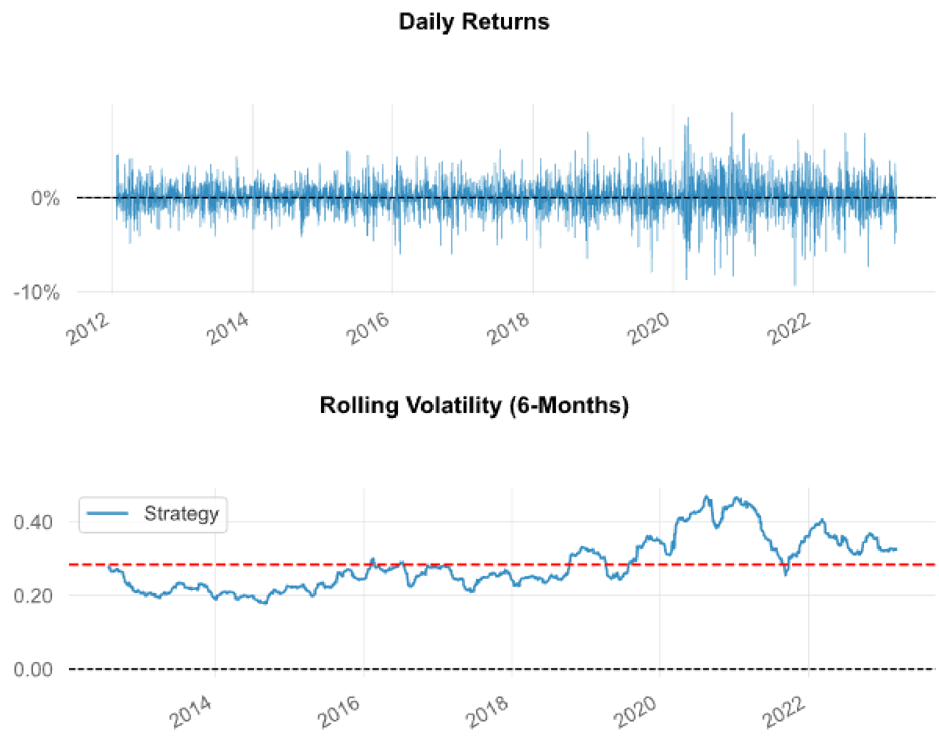

Figure 5. Daily returns and Rolling volatility of RSI-weighted portfolio over 2012-2023

(Graph created by the author(s))

high rolling volatility indicates more variability and a higher chance of significant gains or losses, while a low rolling volatility indicates more stability and a lower chance of significant gains or losses. Additionally, the 6 monthly rolling volatility of the portfolio showed an increasing trend over time, reaching a peak of 40-50% in recent years, while remaining at 30% or less in earlier years. The Figure 5 indicates that the daily return fluctuations and rolling volatility are positively correlated, displaying a similar trend and coherence with each other.

The Figure 6 demonstrates a risk-adjusted performance of a RSI weighted portfolio from 2012 to 2023. The two graphs display a strong positive correlation and a similar trend over the entire period, indicating that the portfolio's returns are consistent with its risk profile. Rolling Sharpe values exhibit peaks over 2 at seven points over the entire period, indicating high returns relative to its volatility. However, at times, Rolling Sharpe values drop to negative values, indicating poor risk-adjusted returns. On the other hand, Rolling Sortino values exhibit peaks above 4 at several points, indicating exceptional returns relative to its downside risk, but also dips to negative values, indicating poor returns when considering downside risk. The average Rolling Sharpe value of 0.6 indicates the portfolio generates returns greater than the risk-free rate, but not exceptional. The average Rolling Sortino value of 1 suggests that the portfolio's returns are greater than the risk-free rate, and its downside risk is lower than the overall risk of the portfolio. The peaks and troughs of both graphs provide insights into the portfolio's performance at different times, highlighting periods of exceptional returns and poor risk-adjusted returns.

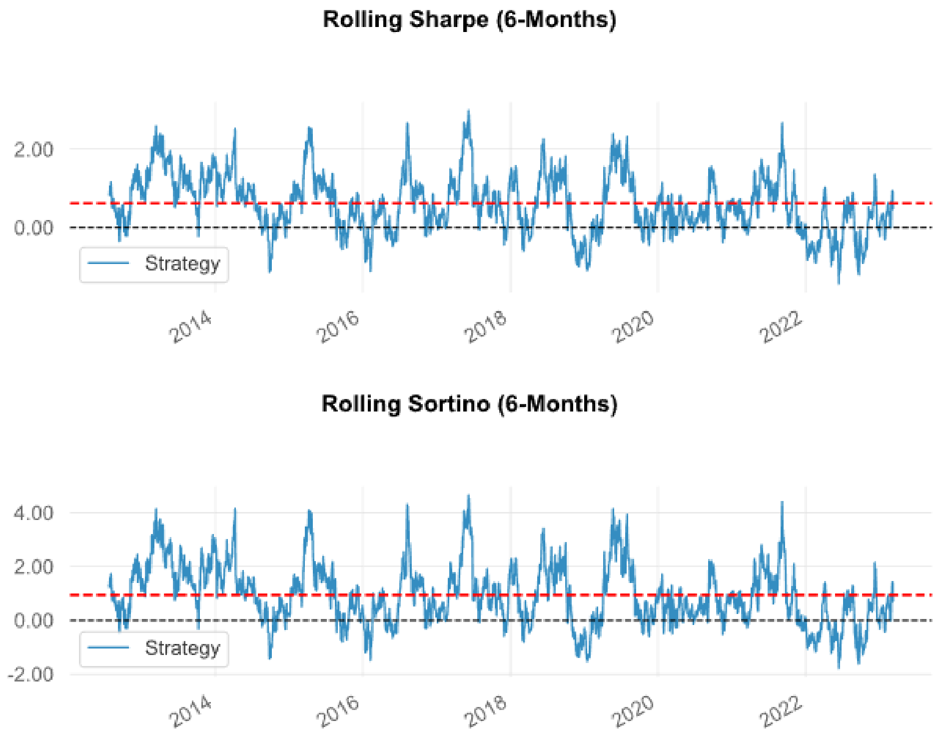

Figure 6. Rolling Sharpe and Sortino ratio of RSI-weighted portfolio over 2012-2023

(Graph created by the author(s))

4.3 Stochastic Oscillator-weighted portfolio

The Stochastic Oscillator-weighted portfolio is a type of investment portfolio that uses the Stochastic Oscillator technical indicator to determine the weightings of the securities in the portfolio. The portfolio construction process involves ranking the securities based on their Stochastic Oscillator values and then allocating a higher weight to the securities with higher values. This weighting scheme is intended to capture the technical of the securities in the portfolio. The weightings of the securities in the portfolio are constantly changing based on the Stochastic Oscillator values, which allows the portfolio to adapt to changing market conditions. technical strategies like the Stochastic Oscillator-weighted portfolio tend to be a higher risk due to their reliance on short-term price movements.

Based on Figure 7, it appears that the EOY return of the Stochastic Oscillator-weighted portfolio has been quite volatile over the years. The portfolio had positive returns in most years, with the highest returns in 2013 and 2019, at 33.71 percent and 27.78 percent, respectively. However, the portfolio also experienced negative returns in some years, such as in 2018 and 2020. In 2022, the portfolio experienced a significant decrease in return, with a negative return of -27.48 percent. However, in 2023, the portfolio had a positive return of 12.36 percent. It is important to note that a single year's return is not necessarily indicative of the long-term performance of a portfolio. It is also important to consider the risks and other factors associated with the portfolio's investments. It may be useful to analyze the portfolio's returns over a longer period of time and compare them to relevant benchmarks to determine its performance.

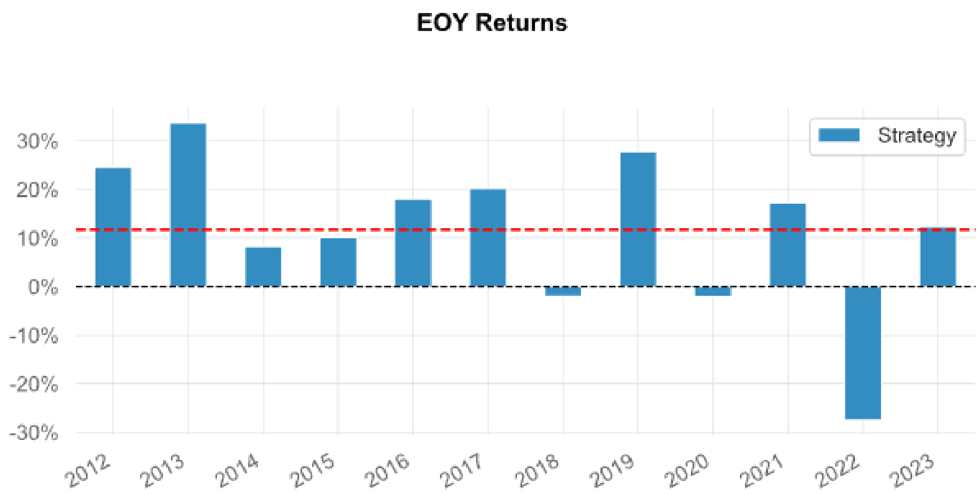

Figure 7. EOY of SO-weighted portfolio over 2012-2023

(Graph created by the author(s))

Regarding daily returns and rolling volatility figures of the portfolio in Figure 8, as in previous portfolios, due to high uncertainty in financial markets in recent years led to high volatility.

In Figure 9, we can see that both ratios had similar trends over time, with the Sortino ratio showing slightly higher values than the Sharpe ratio. The value of the Sortino ratio was around 0 to 2 while that of the Sharpe ratio was changing around 0 and 4 indicating that the portfolio was providing some risk-adjusted return. However, in the middle of 2022, we see a dip in both ratios, with both

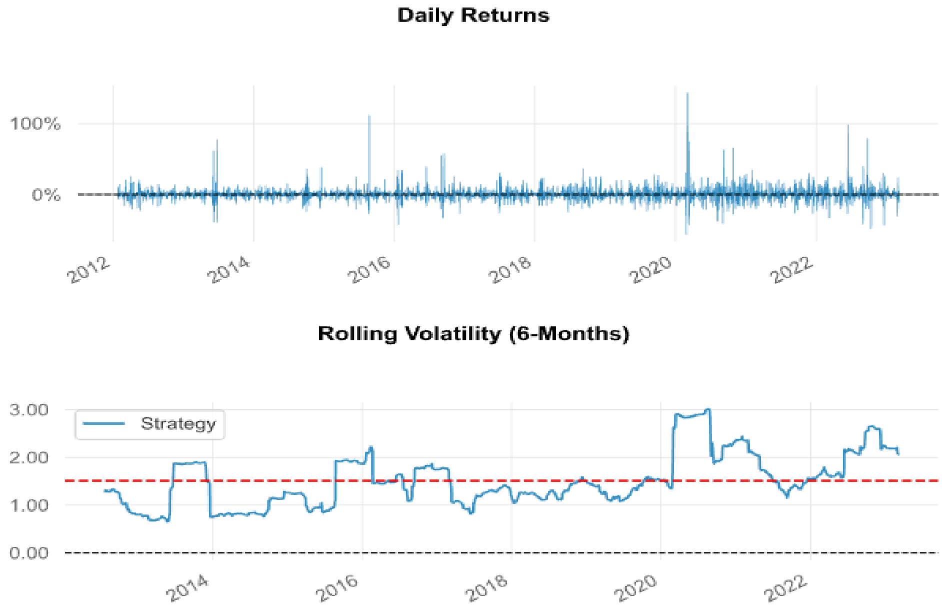

Figure 8. Daily returns and volatility of SO-weighted portfolio over 2012-2023

(Graph created by the author(s))

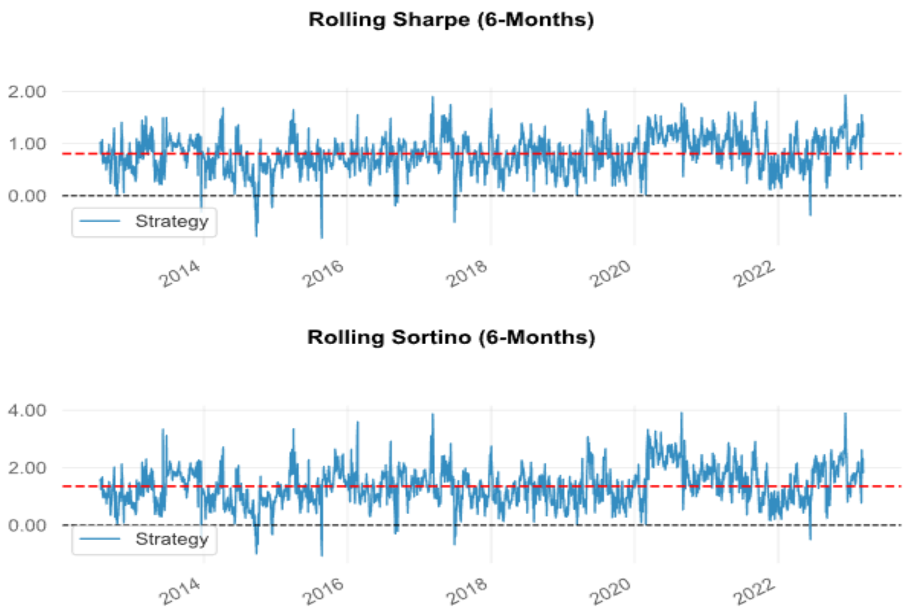

Figure 9. Rolling Sharpe and Sortino of SO-weighted portfolio over 2012-2023

(Graph created by the author(s))

going into negative territory. This indicates that the portfolio was not performing well relative to the risk taken during that period.

4.4 CCI-weighted portfolio

A CCI-weighted portfolio is an investment portfolio where the weights of the assets are determined by their respective CCI values. Higher CCI values are given to assets, while lower CCI values are given to assets that are either omitted from the portfolio or given lower weights. A CCI-weighted portfolio also capitalizes on market technical and gain from positive trends while limiting exposure to potential downtrend-related assets. The foundation of this strategy is the notion that the CCI indicator can offer insightful signals regarding the market direction and technical of specific assets. It is crucial to remember that this method, like all other investment strategies, has risks and could not always produce the results anticipated.

The Figure 10 Based on the data provided, the EOY return of the CCI-weighted portfolio has been mostly positive, with the highest returns in 2013 and 2017, at 30.32 percent and 21.64 percent, respectively. However, the portfolio also experienced negative returns in some years, such as in 2018 and 2022. In 2022, the portfolio experienced a decrease in return, with a negative return of -15.83 percent. This negative return could be due to several reasons, such as a change in market conditions, changes in interest rates or inflation, or specific events affecting the underlying assets in the portfolio. However, it is important to note that a single year's return is not necessarily indicative of the long-term performance of a portfolio. The Figure 11 shows that the CCI-weighted portfolio's rolling volatility and daily returns both exhibit consistency with one another and move in the same direction.

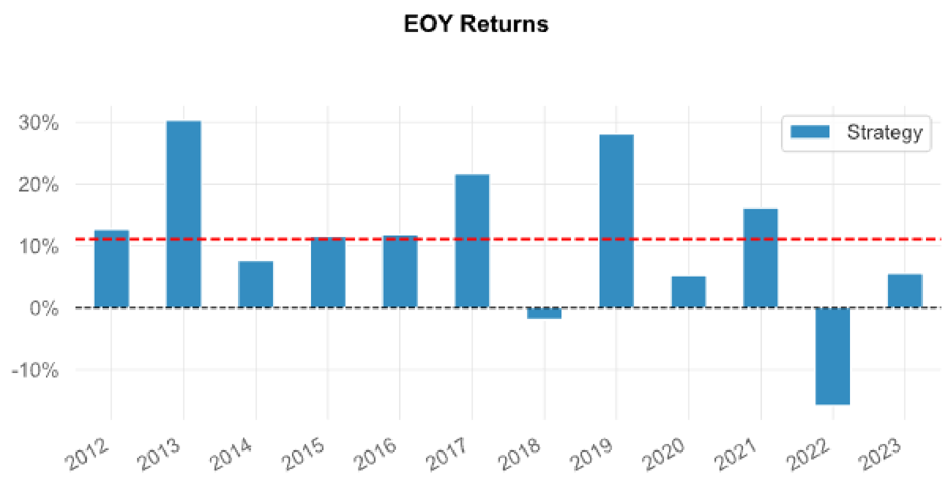

Figure 10. EOY of CCI-weighted portfolio over 2012-2023

(Graph created by the author(s))

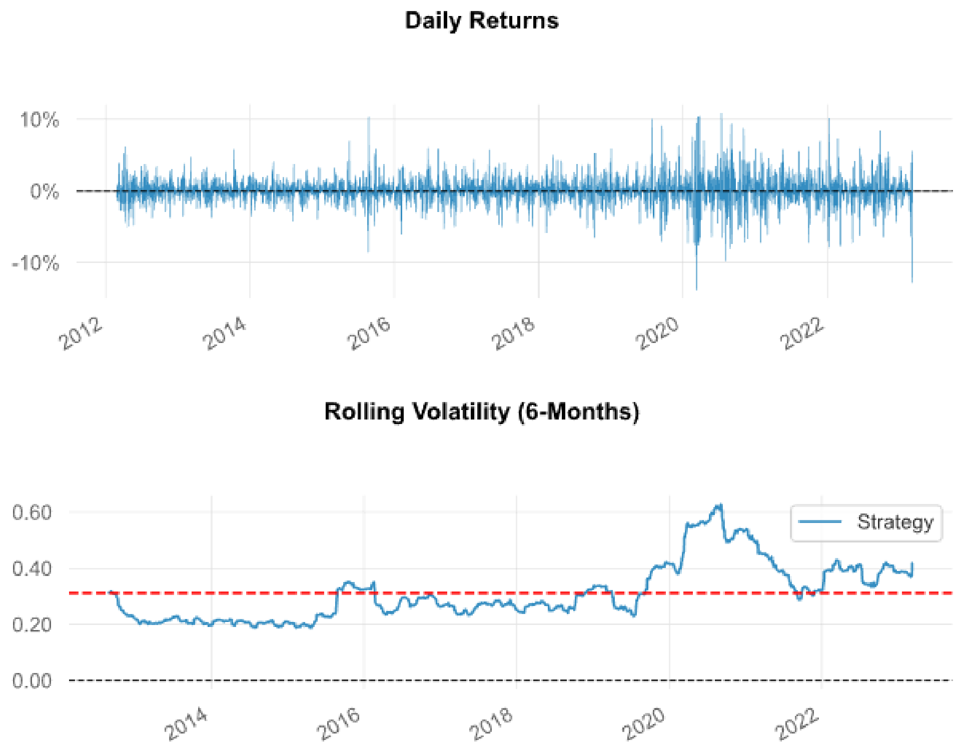

Figure 11. Daily returns and Rolling volatility of CCI-weighted portfolio over 2012-2023

(Graph created by the author(s))

The Rolling Sharpe and Rolling Sortino ratios are important measures of the risk-adjusted performance of a portfolio. The fact that both ratios follow the same trend and are highly correlated indicates that the CCI-weighted portfolio's risk-adjusted performance is consistent over time as depicted in Figure 12. The peaks in Rolling Sharpe values in 2015 and 2019 suggest that the portfolio performed exceptionally well during those years, while the negative values in 2019 and 2022 suggest that the portfolio experienced significant losses during those periods. The average value of Rolling Sharpe at around 0.7 indicates that the portfolio's risk-adjusted returns are modest. On the other hand, the Rolling Sortino values that surpassed 4 at some points indicate that the portfolio had strong upside potential and was able to generate excess returns relative to its downside risk. However, the negative values in 2016, early 2019, and 2022 suggest that the portfolio's downside risk was also significant during those periods. The average Rolling Sortino value at approximately 1 indicates that the portfolio's returns are above the risk-free rate, but the excess returns are not as high as those suggested by the peaks in Rolling Sortino values. Overall, these results suggest that the CCI-weighted portfolio's risk-adjusted performance has been consistent but not exceptional over the analyzed period. It is strongly important to note that getting different values of returns and volatilities that we have analyzed so far do not depend only on market conditions, but also on the nature of the technical indicators, meaning that each of these indicators and their corresponding portfolios can have different sensitivities to price changes and market conditions based on their unique characteristics and the way they are calculated.

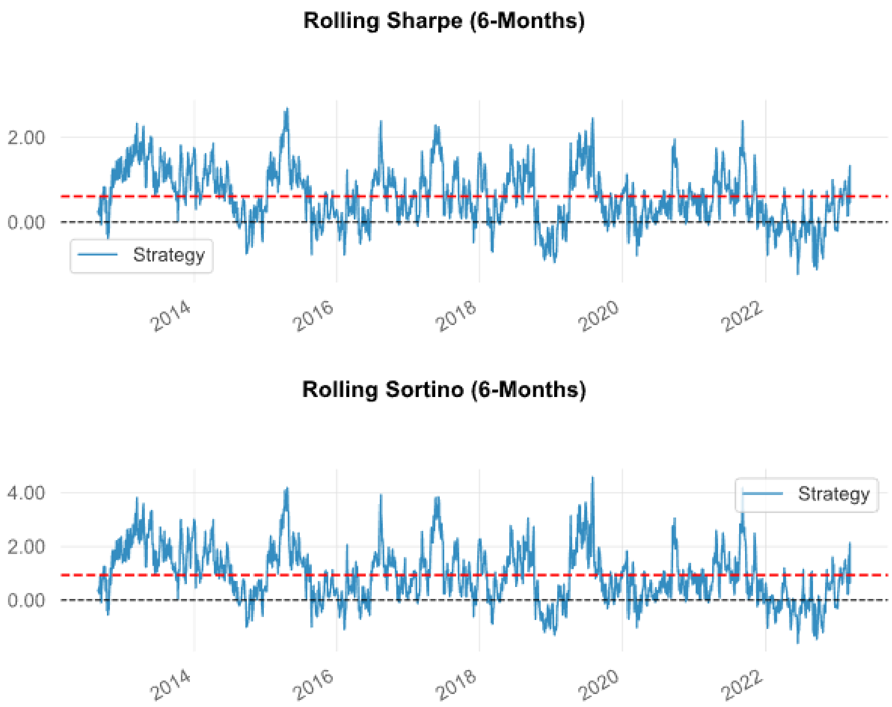

Figure 12. Rolling Sharpe and Sortino ratio of CCI-weighted portfolio over 2012-2023

(Graph created by the author(s))

Looking at the annual return on the Table 1, we can see that the Stochastic Oscillator-weighted portfolio has the highest return at 127.61 percent, followed by the CCI and RSI-weighted portfolios at 15.55 percent and 15.41 percent, respectively. The MACD-weighted portfolio has the lowest annual return at 12.46 percent.

In terms of annual volatility, the MACD portfolio has the lowest volatility at 18.61 percent, while the Stochastic Oscillator portfolio has the highest volatility at 159.76 percent. This indicates that the Stochastic Oscillator portfolio has the highest risk compared to the other portfolios.

The Sharpe Ratio measures the risk-adjusted return of an investment, and the Stochastic Oscillator portfolio has the highest Sharpe Ratio at 0.80. This is likely due to the high returns and high

Table 1. Performance of Oscillator Weighted Portfolios

Metrics	MACD	RSI	CCI	Stochastic Oscillator
Annual Return	12.46%	15.41%	15.55%	**127.61**%
Annual Volatility	18.61%	29.22%	32.87%	**159.76**%
Sharpe Ratio	0.67	0.53	0.47	**0.80**
Max Drawdown	-35.05%	-32.97%	-37.79%	**-77.48**%
Daily Value at Risk	-1.88%	-2.96%	-3.34%	**-16.04**%
Sortino Ratio	1.01	0.77	0.71	**1.36**
Calmar Ratio	0.36	0.47	0.41	**1.65**
Omega Ratio	1.13	1.10	1.09	**1.18**

(Table created by the author(s))

volatility of the portfolio. However, the MACD and RSI portfolios also have relatively strong Sharpe Ratios at 0.70 and 0.54, respectively.

The Max Drawdown measures the maximum loss from a peak to a trough of an investment, and the Stochastic Oscillator portfolio has the largest maximum drawdown at -77.48 percent. This means that the Stochastic Oscillator portfolio has the highest potential for loss compared to the other portfolios.

The Daily Value at Risk (VaR), hereinafter referred to as the VaR, measures the maximum potential loss with a certain level of confidence over a given period, and the Stochastic Oscillator portfolio has the highest VaR at -16.04 percent. This indicates that the Stochastic Oscillator portfolio has the highest potential for large losses in a single day.

The Sortino ratio is a measure of risk-adjusted return that focuses on downside risk. It is similar to the Sharpe ratio but only considers the standard deviation of negative returns. The Stochastic Oscillator portfolio has the highest Sortino Ratio at 1.36. This is likely due to the high returns and high volatility of the portfolio, as well as the high potential for downside risk.

The Calmar Ratio measures the ratio of the annualized return to the maximum drawdown, and the RSI portfolio has the highest Calmar Ratio at 0.37. This means that the RSI portfolio has the best ratio of returns to potential losses compared to the other portfolios.

Finally, the Omega Ratio measures the probability-weighted ratio of gains to losses, and all four portfolios have Omega Ratios greater than 1, indicating that the portfolios are generating more gains than losses.

In summary, the four technical-indicator weighted portfolios have varying levels of risk and return. Although the Stochastic Oscillator-weighted portfolio has the highest annual return, the best Sharpe, Sortino and Calmar ratio, it is very risky to optimize asset weights based on Stochastic Oscillator. The CCI-weighted portfolio provides the second-highest annual return, but its volatility is still higher compared to MACD- and RSI-weighted portfolios. The MACD portfolio has the lowest volatility and a relatively strong Sharpe and Sortino ratio, which gives robust results among other portfolios. Overall, the optimal portfolio will depend on an investor's specific goals, risk tolerance, and investment strategy. However, based on the metrics provided in the table, the MACD-weighted portfolio appears to be the most attractive and optimal choice for investors seeking higher returns with lower risk. The significance of the research findings lies in their potential applicability for investors, as the proposed models, with the exception of the Stochastic Oscillator, can serve as valuable tools for portfolio optimization. These findings contribute to the existing body of knowledge by providing investors with practical insights to enhance their decision-making processes and potentially improve portfolio performance.

5 Conclusion and Suggestions for Further Research

In this research, four alternative portfolio models have been analyzed. The main purpose of the study was to introduce alternative portfolio optimization models and analyze whether technical indicator-weighted portfolios are trustable and provide profitable results for investors. We came up with the following conclusion: With regard to the portfolio models, it can be concluded that the four technical indicator-weighted portfolios have varying levels of risk and return. Our study yielded significant discoveries. Primarily, we observed that investors can utilize the suggested alternative portfolio optimization models for effective portfolio management. Furthermore, our findings revealed the practicality and applicability of employing technical analysis indicators to optimize portfolios. While the Stochastic Oscillator-weighted portfolio has demonstrated the strongest performance metrics in terms of annual return, Sharpe ratio, Sortino ratio, and Calmar ratio, it is important to note that this portfolio also carries a higher level of risk by having the largest maximum drawdown and highest Daily VaR compared to the other oscillator-weighted portfolios. The optimal portfolio will depend on an investor's specific goals, risk tolerance, and investment strategy. However, based on the metrics provided, the MACD-weighted portfolio appears to be a compelling option for investors looking to achieve higher returns with lower risk. To summarize, the analysis suggests that technical indicators except for Stochastic Oscillator can be used to construct diversified portfolios that offer a balance between risk and return.

Regarding recommendations for further improvements, we came up with the followings:

Combining Machine Learning (hereinafter ML) models with portfolio optimization models could have generated more precise results. It is a fact that incorporating ML models into portfolio optimization is an approach that has shown promising results. One potential strategy is to pre-select assets for the portfolio based on the prediction performance of ML models. However, to improve the effectiveness of this approach, advanced algorithms or models for Ensemble Learning can be explored, which can increase the diversity of predictions and optimize the portfolio models further. To identify the best model for stock price prediction and pre-selection of assets, a comparative analysis of popular ML models such as Random Forest, Xgboost, Support Vector Machines (SVMs), and Neural Networks can be conducted. Moreover, it is crucial to take into account the impact of different market conditions or events on the performance of the models, such as market crashes or significant policy changes. By investigating whether the models can be adapted to such scenarios, we can assess their robustness and performance over an extended period.

Additionally, testing the robustness of the results is essential. This can be achieved by using different technical indicators or weighting schemes, as only four technical indicators were used in this study. Overall, incorporating ML models into portfolio optimization and pre-selecting assets based on the prediction performance of these models can be a promising approach. To improve the effectiveness of this approach, advanced algorithms for Ensemble Learning can be explored, and the performance of different popular ML models can be compared. Finally, it is crucial to take into account different market conditions and test the robustness of the results using different technical indicators and weighting schemes to ensure the portfolios' resilience to market shocks.

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A Appendix

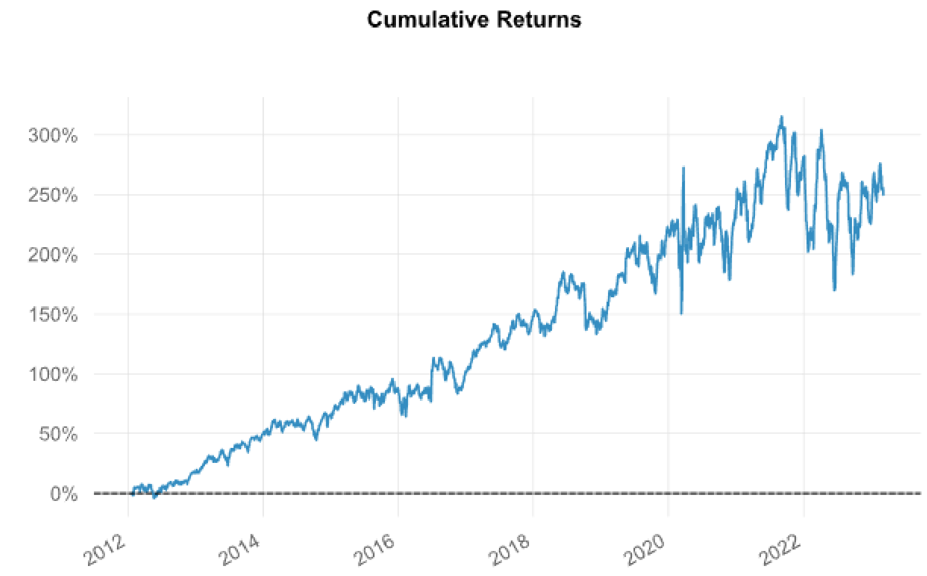

Figure 13. MACD-weighted portfolio

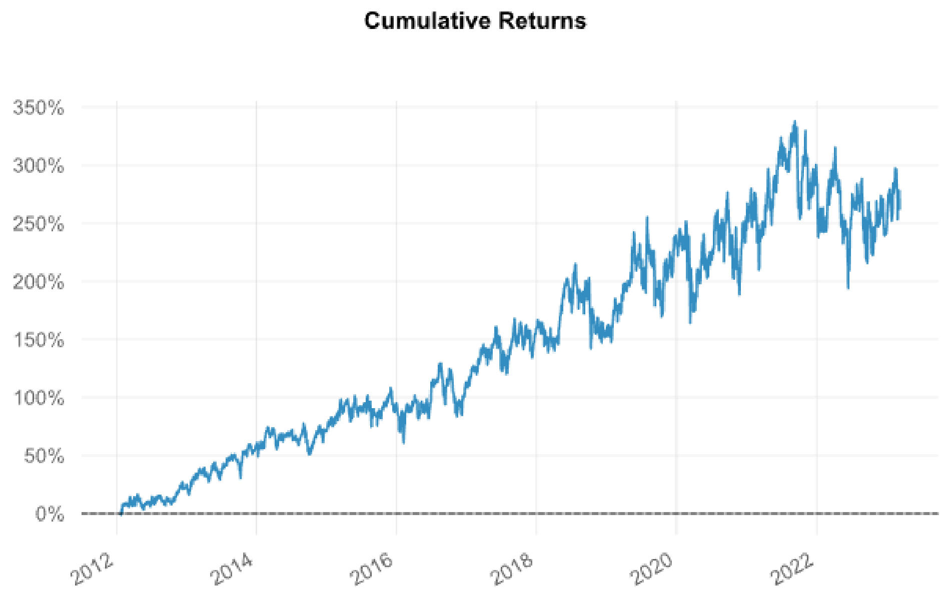

Figure 14. RSI-weighted portfolio

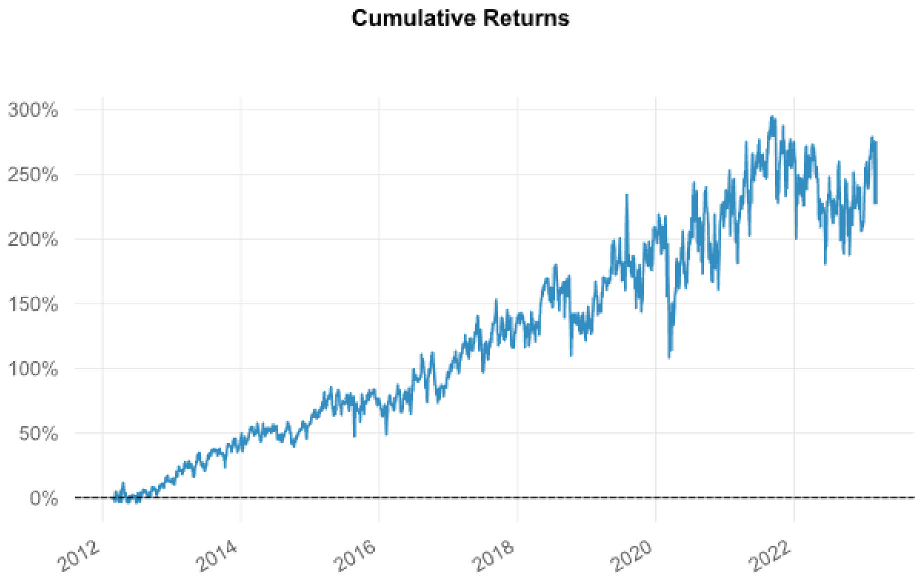

Figure 15. CCI-weighted portfolio

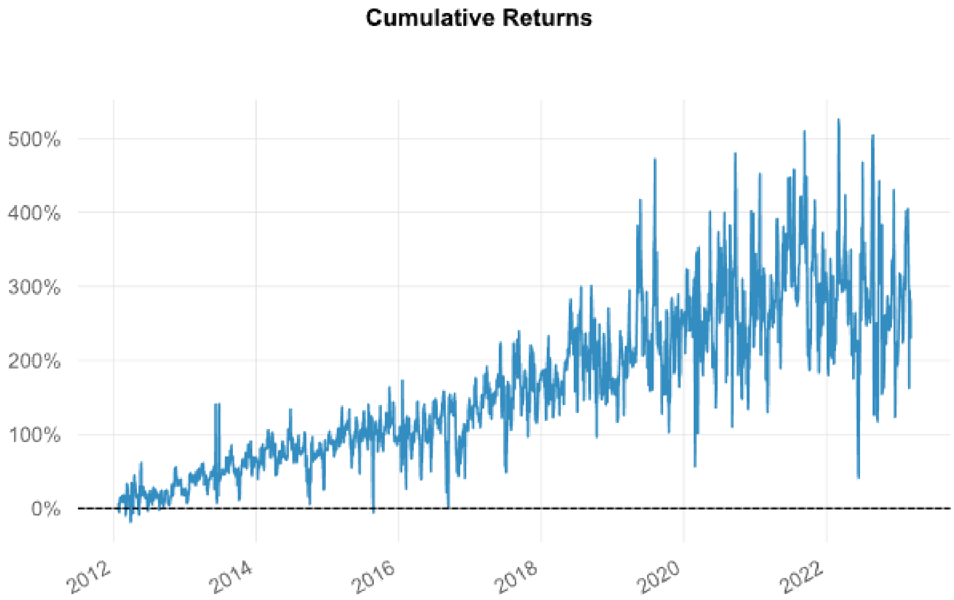

Figure 16. Stochastic Oscillator-weighted portfolio

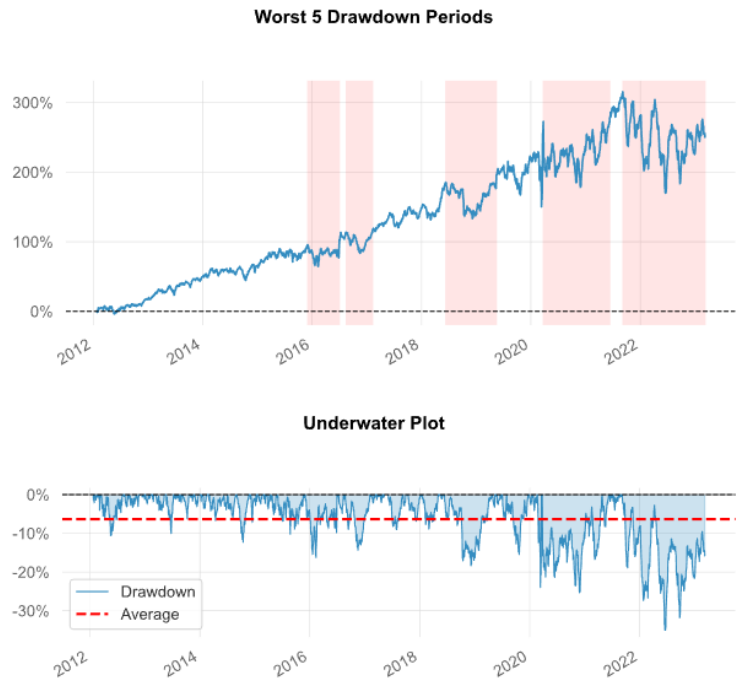

Figure 17. MACD-weighted portfolio

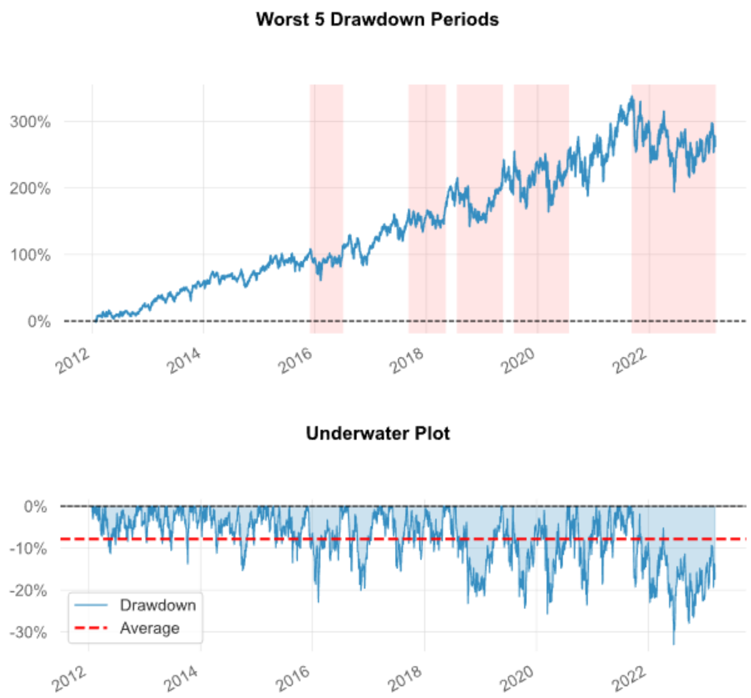

Figure 18. RSI-weighted portfolio

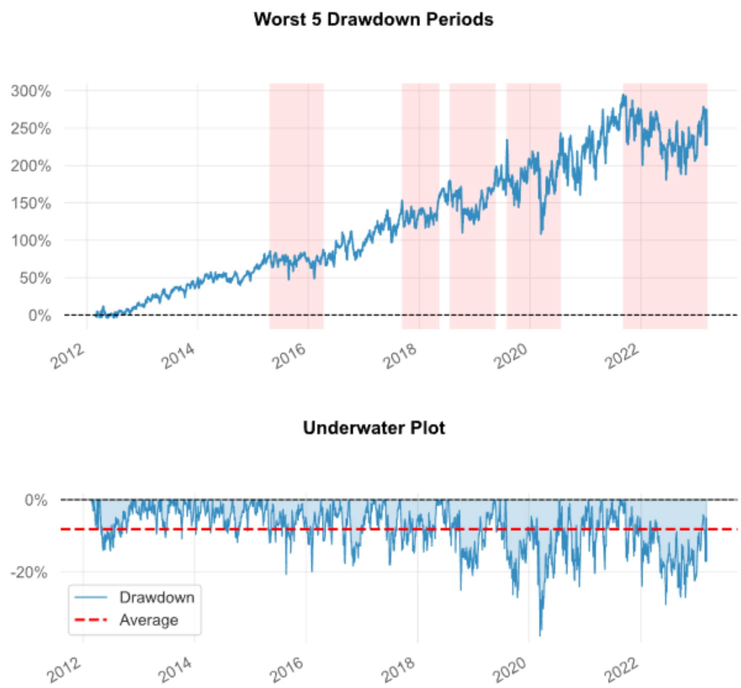

Figure 19. CCI-weighted portfolio

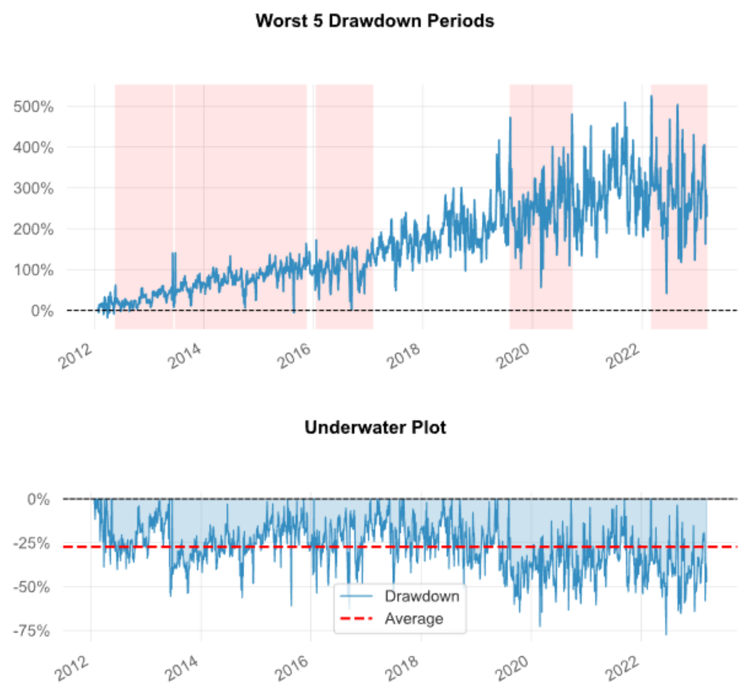

Figure 20. Stochastic Oscillator-weighted portfolio

Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2012	-0.90	5.53	-1.77	3.16	-6.37	4.24	1.19	1.79	1.08	1.32	4.58	2.22
2013	3.14	5.56	2.33	-2.01	4.16	-3.08	7.83	-0.56	0.78	5.27	0.94	1.80
2014	-0.30	7.79	-1.48	-0.81	0.99	-0.51	-2.15	4.15	-5.35	2.74	6.46	-1.01
2015	3.46	3.68	-0.02	0.97	5.25	-5.92	5.02	-2.09	-2.15	3.68	4.97	-4.01
2016	-3.88	4.97	-0.91	-3.48	2.70	7.58	3.57	-0.41	-0.86	-3.59	-3.83	7.12
2017	3.95	3.12	4.14	0.01	5.57	-4.99	-2.78	7.83	2.66	-1.10	-1.58	4.73
2018	-0.07	-4.11	0.96	3.72	11.19	-1.75	3.86	-4.48	1.43	-8.44	-4.58	1.51
2019	2.69	6.11	3.79	2.99	5.32	2.12	1.50	-1.26	-4.91	-1.32	7.61	3.86
2020	-1.45	-8.51	10.90	-2.72	6.26	-7.59	6.05	0.46	3.27	-15.20	-2.01	18.30
2021	0.75	-1.39	-1.94	12.53	0.17	7.34	-0.65	4.81	-10.53	4.42	-7.84	9.14
2022	-19.25	7.38	16.70	-4.56	-11.91	-4.03	18.42	-7.08	-9.48	4.13	9.07	-7.58
2023	6.28	3.25	-2.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 21. MACD-weighted portfolio

Monthly Returns (%)

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2012	0.40	7.45	1.13	1.08	-1.30	1.90	0.58	-1.33	0.21	0.26	11.29	-0.91
2013	2.03	6.32	3.80	-5.68	5.90	-2.92	10.14	-0.85	-1.88	6.86	4.45	-0.16
2014	0.33	8.72	-0.90	-4.27	1.38	2.45	-4.32	5.05	-9.06	5.76	5.38	-0.98
2015	3.62	4.45	0.33	-0.71	6.61	-5.08	6.48	-5.40	-1.58	4.31	5.11	-4.50
2016	-3.29	1.28	2.26	-5.75	1.77	11.50	3.32	-4.27	3.67	-6.54	-1.96	8.11
2017	6.03	0.98	5.87	-2.44	6.39	-8.23	-3.70	13.34	0.87	-1.88	-3.01	7.67
2018	0.82	-4.42	-0.63	5.13	14.71	-3.32	2.12	-2.68	2.59	-9.88	-4.75	1.93
2019	0.74	2.06	9.07	3.48	5.43	-1.30	11.90	-8.10	-7.61	5.14	2.78	4.43
2020	-2.18	-7.86	-3.56	3.68	6.78	-0.44	9.39	-4.51	5.14	-11.38	0.39	10.08
2021	0.68	-3.42	1.71	6.99	4.58	9.78	-3.25	4.36	-11.66	9.03	-7.85	5.21
2022	-9.12	5.23	5.63	-2.65	-10.38	1.85	8.57	-7.82	1.12	-5.77	8.48	-6.89
2023	5.44	-1.61	2.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Figure 22. RSI-weighted portfolio

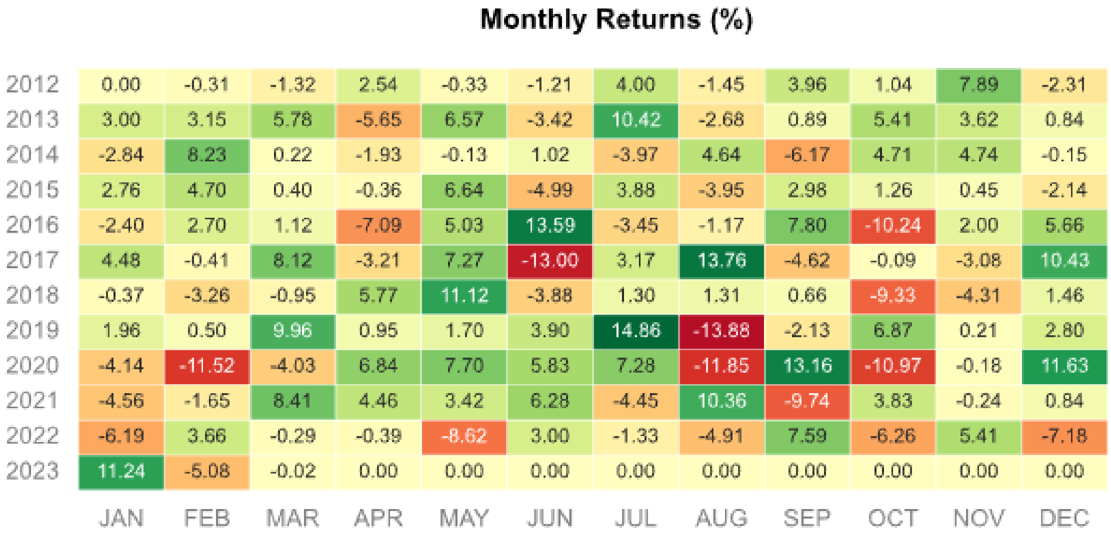

Figure 23. CCI-weighted portfolio

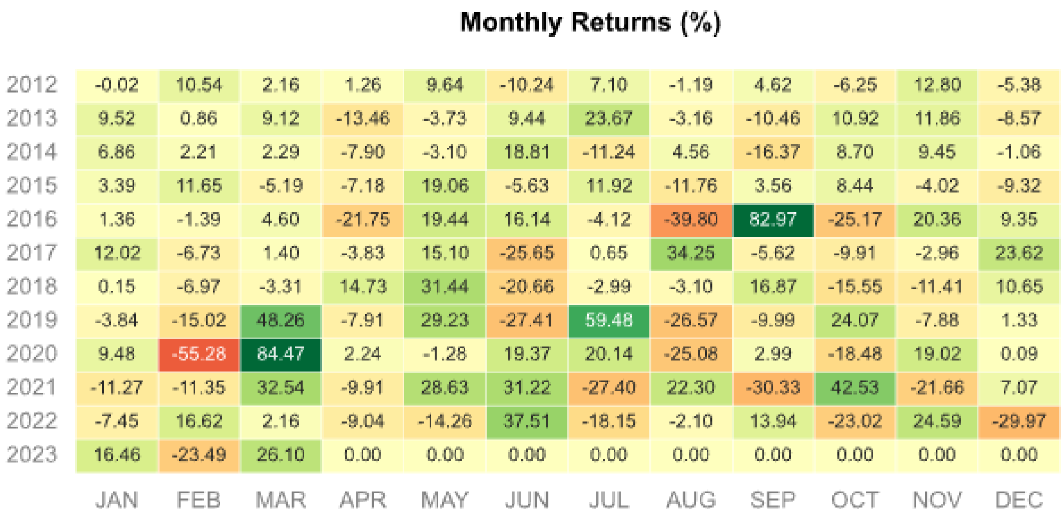

Figure 24. Stochastic Oscillator-weighted portfolio

Resümee

Evaluatsioon Alternatiivsete Kaalumise Meetodite kohta Portfelli Optimeerimine Mudeli Valiku jaoks

Käesolevas uurimuses uuritakse tehniliste näitajate kasutamist alternatiivsete investeerimisportfellide optimeerimismudelite koostamisel, mis tasakaalustavad riski ja tootlust ning hindavad tehnilise näitaja kaalutud portfellide usaldusväärsust ja kasumlikkust investorite jaoks. Uuring analüüsib nelja tehnilise näitajaga kaalutud portfelli:MACD-kaalutud portfell, RSI-kaalutud portfell, CCI-kaalutud portfell ja Stochastiline oscillaator-kaalutud portfell. See käesolev artikkel eristub end uue lähenemisviisi tutvustamisega, mis hõlmab tehniliste näitajate kasutamist varade kaalude optimeerimiseks ja kohandamiseks. Märkimisväärselt ei ole varasemad uuringud uurinud tehniliste näitajate kasutamist sel moel. Erinevalt teistest teadlastest hõlmab meie metoodika igapäevast varade kaalude optimeerimist koos igapäevase portfelli jõudluse arvutamisega pikema aja jooksul. Tulemused näitavad, et tehnilisi näitajaid, välja arvatud Stohhastiline ostsillaator, saab kasutada mitmekesistatud portfellide koostamiseks, mis pakuvad tasakaalu riski ja tootluse vahel, kusjuures RSI portfell tundub olevat investorite jaoks kõige atraktiivsem valik, kes otsivad suuremat tootlust madalama riskiga. Tulemuste põhjal omab MACD-kaalutud portfell madalaimat volatiilsust 18,61 protsendiga ning suhteliselt tugevat Sharpe'i ja Sortino suhet vastavalt 0,67 ja 1,01 protsenti, samal ajal kui RSI-kaalutud portfell omab teistest krgeimat Calmari suhet, madalaima potentsiaali kaotuste osas. CCI-kaalutud portfell pakub teist kõrgeimat aastatulu pärast Stohhastilise ostsillaatoriga kaalutud portfelli 15,55 protsendiga, kuid omab võrreldes MACD ja RSI-ga kõrgemat aastast volatiilsust. Stohhastilise ostsillaatoriga kaalutud portfell omab kõrgeimat riski 159,76 protsendiga, kuid samas ka kõrgeimat potentsiaali kasumi ja riski osas. Optimaalne portfell sõltub investori eesmärkidest, riskitaluvusest ja investeerimisstrateegiast. Siiski, analsis kasutatud mõõdikute alusel, on MACD portfell optimaalne valik investoritele, kes otsivad suuremat tootlust madalama riskiga võrreldes teiste portfellimudelitega.

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18.05.2023