Trading Model for Actively Managed Investment Funds in the Crypto Asset Market Kirill Vokulov*

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Abstract:

The investment portfolio is mainly exposed to two types of risk: systematic and idiosyncratic. Therefore, the task can be divided into two parts. The first part of the task is to implement the effective set of possible investment portfolios by Gary Markowitz (Sharpe W.F., 2022). However, according to research results, an author's adjustment "Scam coefficient" should be added in order to increase the efficiency. The second part of the task is to construct an oscillator to reduce systematic risk. The first part is designed to reduce the idiosyncratic risk of the portfolio. Adding a special index is simply necessary since the crypto asset market is affected by many more factors than classical financial markets.

Keywords: Crypto Assets, Centralized Exchange, Active Management Strategy, Oscillator, Markowitz Theory, Methods Of Quantitative Analysis, BTC, DeFi.

1. Introduction

In response to the 2008 banking crisis, an absolutely new class of assets was formed - crypto assets, which began to offer investors completely original properties based on distributed ledger technology. Their own infrastructure and various markets began to form around these assets, where investors can exchange these assets. Over the 15 years of its existence, this class of assets has caused a lot of controversy, but at the beginning of 2024, more and more countries are adopting regulation of this type of assets, and they are gradually integrating into the global economy. Thus, in January 2024, the first 9 spot Bitcoin ETFs were launched on the American markets, in addition, futures on crypto assets have been traded since 2017. Despite such widespread adoption, the crypto asset market is still in a emerging state and it will take a lot of time to develop rules and standards for professional participants in this market and build financial models for completely new types of instruments.

Before a fund manager starts managing clients' assets, he needs to answer four questions to build a trading strategy:

- 1. At what point in time to make purchases and sales on the market;
- 2. In what proportion should assets and stablecoins be in the portfolio at the time of purchase or sale;
- 3. What assets need to be bought or sold;
- 4. In what proportion should these assets be.

The first two questions can be answered by developing an oscillator and finding the optimal proportions of assets and stablecoins in the portfolio through empirical tests. To answer the third question, it is necessary to evaluate assets in order to find out which assets are undervalued and will allow the fund to outperform the market in terms of profitability. There are a huge number of different assets in the crypto asset market, so this paper will look at the centralized exchange sector.

2. Asset selection model

In order to understand how crypto asset prices are formed, it is necessary to construct a model or build a theory. This requires simplifications that allow the modeler to abstract from the entire complexity of the situation and consider only its most important elements. For this purpose, certain assumptions are formulated about the object of study. These simplifying assumptions are designed to provide a degree of abstraction that allows the model to be built. The validity of these assumptions is not of great importance. What matters is the ability of the model to help in understanding and predicting the process being modeled.

The assumptions underlying the proposed asset valuation model are:

- 1. Over time, investors will have the same access to coins and tokens on centralized crypto asset exchanges as they do to COIN stocks (Coinbase Global Inc);
- 2. The Binance crypto asset exchange coin, BNB, is fairly valued by the market because it has the largest trading volume in the industry (CoinMarketCap);
- 3. Crypto asset exchanges earn their main income from fees on the spot section of the exchange;
- 4. Investors value investment portfolios based on expected returns and their standard deviations over the holding period;
- 5. The crypto asset market has a low degree of efficiency;
- 6. When choosing between two portfolios, investors will prefer the one that, all other things being equal, provides the highest expected return;
- 7. When choosing between two portfolios, they will prefer the one that, all other things being equal, has the smallest standard deviation;
- 8. If desired, the investor can buy a part of the asset below the 16th digit after an integer;
- 9. Taxes and operating costs are not significant.

In order to evaluate assets, it is necessary to first select a benchmark. In this model, we assume the use of two benchmarks. The first instrument from the world of classical finance is the COIN shares of the Coin Base company. This benchmark was not chosen by chance, since the model assumes that over time, investors will have access to investing in crypto assets. Thus, COIN shares are the most liquid and, as a result, the most correctly estimated asset. The second benchmark is the BNB coin of the Binance exchange, since it is the most liquid asset in the industry (Drop Stab). The second benchmark is necessary for assessing assets in the shorter term.

According to the third assumption, exchanges receive their main income from trading fees on the spot section. Therefore, the income for crypto exchange can be judged by the trading volume, since the exchange receives its income from each dollar traded on it. Thus, it is not necessary to calculate the precise amount of money that the exchange received from the trading operations of clients; it is enough to compare the trading volumes themselves. However, in this assumption, it is necessary to take into account that in addition to users, there are also market makers on the exchanges who perform the dealer function. These organizations also trade the volume, which then goes into the overall count, but do not pay a commission to the exchange for this. In order to isolate these volumes from the total, we used the Spot Exchange Score provided by CoinMarketCap. CMC crypto exchanges ranks are based on the following metrics: web traffic ratio; average liquidity; volume, as well as the confidence that the volume reported by the exchange is legitimate. The above factors are assigned weights, and the spot exchange is assigned a score from 0.0 to 10.0. We then convert this into a deflator to adjust trading volume, using the following formula:

$$D_i = \frac{SES_i}{10}$$

where D_i - trading volume deflator and 【SES】_i - Spot Exchange Score for the i-th exchange.

Next, to find the trading volume from which the exchange received a commission, the following formula is used:

$$Vol_i = FVol_i \times D_i$$

where <code>[Vol] _i</code> - trading volume traded by users of the i-th exchange and <code>[FVol] _i</code> - the recorded trading volume of this exchange.

Therefore, before valuing assets, it is necessary to calculate the net trading volume from which the exchange receives commissions. Then, the current capitalization for each asset, measured in US dollars, is taken as a measure of value.

Another point to consider when dealing with the crypto asset market is token inflation. Often, tokens and coins have an inflationary structure, i.e., initially, more tokens were announced to be issued than are currently in circulation. The missing number of tokens will eventually enter the market, which, all other things being equal, will reduce the price of a token or coin. Thus, instead of price, capitalization was taken in order to build several price forecasts for different numbers of issued tokens at each point in time.

Next, based on the 4 components for each asset (capitalization, circulating supply, total supply, adjusted volume), three asset valuations model were developed that imply different values.

- Fair Price This estimate means how much a token or coin should cost if investors had the same access to the crypto asset market as the NASDAQ exchange. This price can be considered as a long-term valuation of the asset;
- Price relative to the crypto market this price shows the undervaluation or overvaluation of the asset taking into account the BNB benchmark, given that the emission will be completely in the market. This price can be considered as a medium-term valuation of the asset;
- Price relative to the crypto market given the available supply this price shows whether the asset is undervalued or
 overvalued given the BNB benchmark at that particular point in time, without taking into account the dilution of the
 market cap. This valuation can be interpreted as an arbitrage opportunity.

To calculate the fair price, the net trading volume is compared to the trading volume of the Coinbase exchange, then based on this ratio, the capitalization of the asset is found, and the final step is to divide the resulting capitalization by the total emission of the token or coin, according to the following formula:

$$P_{fpi} = \frac{\frac{Vol_i}{Vol_{COIN}} \times Cap_{COIN}}{MaxS_i}$$

where P_{fi} - fair price of the i-th asset, [Vol] _COIN - Coinbase exchange trading volume, [Cap] _COIN - Coinbase exchange capitalization and [MaxS] _i - total emission of the i-th asset.

To calculate the price relative to the crypto asset market, it is necessary to determine the crypto market deflator. This concept is based on the ratio between the monitored BNB benchmark and the calculated fair price for the BNB coin. This deflator shows the current lag of the crypto asset market from the classic financial market in terms of access to liquidity and lack of regulation. Following formula is used to calculate it:

$$Df_{BNB} = \frac{P_{BNB}}{P_{fpBNB}}$$

where [Df] BNB - crypto market deflator and PBNB - current market price of BNB coin (CoinMarketCap).

Next, the price relative to the crypto asset market is calculated for the asset being considered using the formula:

$$P_{ci} = P_{fpi} \times Df_{BNB}$$

where P_ci - the relative market price of crypto assets of the i-th asset.

To calculate the price relative to the crypto asset market taking into account the circulating supply, it is necessary to use both the crypto asset market deflator and the circulating supply of the asset being assessed. This valuation is calculated using the formula:

$$P_{ai} = \frac{\frac{Vol_i}{Vol_{COIN}} \times Cap_{COIN}}{CS_i} \times Df_{BNB}$$

where P_{ai} - price relative to the crypto asset market taking into account the available supply and $[CS]_{i}$ i – circulating supply for the i-th asset.

Thus, three price value estimates were developed for different trading strategies based on the objective and investment horizon of the strategy.

3. Automatization of asset allocation model

Automatization of the algorithm for calculating an investment portfolio and quantitative assessment of tokens and coins of crypto asset exchanges begins with the process of collecting data from the network in real time, then data is processed according to the described mathematical models and the Markowitz portfolio theory is implemented to find an effective portfolio.

An initial task is dealing with software automation. Manual "parsing" of data for one portfolio consisting of 5 tokens takes about 3 minutes, respectively, collecting information for a portfolio consisting of 100+ assets will take more than an hour. To avoid this, automation can be used. For automatization, the Python programming language is utilized, as well as a number of libraries that are used to "parse" data from sites for further calculations.

To perform the automation process, Python version 3.8 or higher is required. The following libraries are used in this work:

- Requests a library that allows to interact with web applications;
- Bs4—a library for parsing HTML and XML documents. It provides a simple and convenient way to extract data from web pages, and also makes it easier to work with this data;
- Pandas a library for processing and analyzing structured data;
- Tkinter a cross-platform Python graphical interface that allows to work with the Tk library. It contains elements of
 the graphical user interface (GUI) with which you can create various applications;
- Numpy a library designed to support multidimensional arrays (including matrices); support for high-level mathematical functions;
- Matplotlib a library needed for data visualization. It allows to build two-dimensional and three-dimensional graphs;
- Re a tool required for working with regular expressions;
- Json the json module allows to encode and decode data.

After connecting all the libraries, the logic of the algorithm was developed. The data collection algorithm is as follows:

- 1. It is necessary to collect data for the asset from the website "coinmarketcap.com":
 - Price;
 - Circulating supply;
 - Total supply.
- 2. From the same site it is needed to collect data for exchanges, but using a different link by CoinMarketCap:
 - Score:
 - Spot Trading Volume(24h).

Stage one. First, it is obliged to define the site markup to parse the necessary information. Required data:

- Site URL (1 shown in Figure 1);
- Data that needs to be "parsed" (2 shown in Figure 1);
- Page Layout (3 shown in Figure 1).

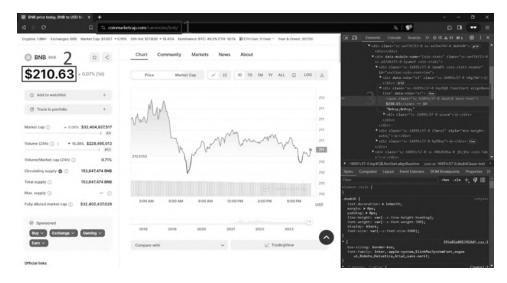


Figure 1: Page Layout

Then it is necessary to insert the markup into the code to get the result, as shown in Figure 2.

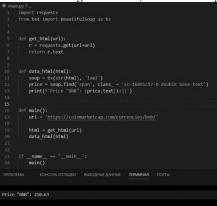


Figure 2: Python code for data collection

Stage two. Determining the site markup and the necessary information for "parsing". Required data:

- Site URL (1 shown in Figure 3);
- Data that needs to be "parsed" (2 shown in Figure 3);
- Page Layout (3 shown in Figure 3).

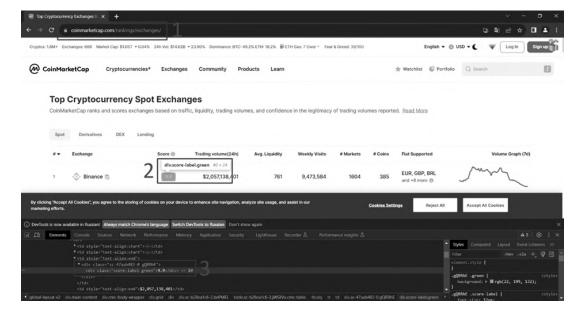


Figure 3: Page Layout

Then update the program code by inserting new data that was received on the site to obtain a new result as shown in Figure 4. Thus, with the help of the code, data can be collected from the site automatically, without spending much time.

```
.,
import requests
from bs4 import BeautifulSoup as bs
       get_html(url_active, url_score, url_exchange):
    r_active = requests.get(url=url_active)
    r_score = requests.get(url=url_score)
    r_exchange = requests.get(url=url_exchange)
    return r_active.text, r_score.text, r_exchange.text
        -r ntml_active:

soup = bs(str(html_active), 'lxml')

price = soup.find('span', class_ = 'sc-16891c57-0 dxubiK base-text')

if html_score:

soup = bs(starts
            itml_exchange:
    soup -bs(str(html_exchange), 'lxml')
    price_binance = soup.find('span', class_='sc-4984dd93-0 cwfNhn priceText')
    print(f'Price "Binance": {price_binance.text}')
 def main():
    url_active = 'https://coinmarketcap.com/currencies/bnb/'
    url_score = 'https://coinmarketcap.com/enkings/exchanges/'
    url_exchange = 'https://coinmarketcap.com/exchanges/binance/
        html_active, html_score, html_exchange = get_html(url_active,
                                                                                                       url_exchange)
        data_html(html_active, html_score, html_exchange)
         КОНСОЛЬ ОТЛАДКИ ВЫХОДНЫЕ ДАННЫЕ ТЕРМИНАЛ ПОРТЫ
"Binance": 9.9
"Binance": $4,279,335,549.31
```

Figure 4: Python code for data collection

The problem of choosing assets for an investment portfolio is that crypto companies do not have to report their income to investors. Some projects operate entirely on-chain and investors can see all cash flows through the protocol themselves. However, this does not apply to centralized exchanges that do not disclose any information about themselves publicly. To solve this problem, this section examines an algorithm that allows to calculate the exchange level of yield for the quarter. After that, using a comparative analysis with the COIN exchange, the fair price of the exchange's token or coin can be calculated, since COIN is a public company, whose shares are traded on the NASDAQ exchange.

Therefore, it is worth considering assets for purchase that meet one of the following conditions:

```
 \begin{split} \bullet & \quad P_i < P_{fpi} \ \& \ P_i > P_{ci} \ \& \ P_i < P_{ai}; \\ \bullet & \quad P_i < P_{fpi} \ \& \ P_i < P_{ci} \ \& \ P_i < P_{ai}. \end{split}
```

•
$$P_i < P_{fni} \& P_i < P_{ci} \& P_i < P_{gi}$$

Ignore assets that satisfy the following condition, as these assets are priced at equilibrium relative to COIN stock:

•
$$P_i < P_{fpi} \& P_i > P_{ci} \& P_i > P_{ai}$$
;

Assets that meet the following conditions may be candidates for short selling:

•
$$P_i > P_{fpi} \& P_i > P_{ci} \& P_i > P_{ai}$$
;

4. Market position control model

To achieve maximum efficiency, it is necessary to develop an oscillator that will include various methods of quantitative market analysis. For these purposes, technical and fundamental analysis indicators, as well as behavioral finance methods, were used.

Oscillators are tools used to analyze technical market information. They measure the speed and direction of price changes and determine levels at which the market may be considered overbought or oversold. Traders and analysts use oscillators to determine when to enter and exit the market, predict future prices, and identify market trends.

However, oscillators are not universally applicable tools and require a comprehensive approach to market analysis in combination with other tools, such as trading volume or news factors. To create a universal indicator that can take into account all input parameters, it is necessary to determine the indicators, the logic of the oscillator and conduct thorough testing of the obtained result. Firstly, there are many different indicators that investors and traders focus on. Further information is given about them. By classifying them, three main categories can be distinguished:

- Indicators based on technical analysis (including various types of moving averages, resistance levels, overbought or
 oversold indicators, and more) have a special characteristic their versatility. These indicators are used in both stock
 markets and crypto assets and are mainly based on the expectations of traders;
- 2. Indicators that rely on the analysis of investor sentiment and interest in specific assets are a common tool. An example of such an indicator is the "Fear and Greed" index, which can be used in both the crypto asset market and traditional markets:
- 3. The third set of indicators is related to the characteristics of the crypto asset market, such as the number of active wallets, the level of mining difficulty, the cost of transactions and their total number, and other parameters.

Then it is necessary to decide which specific indicators will be included in the oscillator. In this work, 18 different indicators were selected, which are presented in Table 1.

Table 1 - Indicators used in the oscillator

Name of the indicator	Brief description of the indicator
Active Address	This indicator belongs to the third block of indicators and compares the 28-day change in the
Sentiment Indicator	price of a crypto asset with the standard deviation of the 28-day change in active addresses. When
	the price changes, line goes beyond the standard deviation from bottom to top, we assume that
	the asset is overheated/overbought. If from top to bottom, the asset is considered undervalued
	(Look Into Bitcion).
SOPR	The idea behind this indicator is to analyze bitcoin transfers within the network, assuming that
	each transaction is a reason for a sale. Thus, the indicator chart fluctuates around the number 1
	(Medium).
Real Yield 5-year US	This indicator can be attributed to the second group, since it shows the difference between the
Treasuries	yield on 5-year US government bonds and expected inflation; if the value is positive, investors'
	interest will be turned towards a less risky asset (bonds), if the value is negative, towards a riskier
	one.
Correlation with Russell	A classic example of trading two highly correlated assets, as of February 18, 2023, the correlation
2000	coefficient was 91%, suggesting that if the price of Bitcoin rose during the period considered,
	and the price of Russell 2000 fell, then it can be assumed that Bitcoin is overvalued.
Quantitative Qualitative	Shows the exponential moving average RSI with a factor of 5, but with the addition of the
Estimation	volatility parameter (ATR). This indicator belongs to the 1 block of indicators (Trading View).
FED Rate Indicator	This indicator belongs to the second block and also shows the market sentiment. The idea of the
	indicator is the dynamics of the change in the US key rate.
RSI Divergence	The indicator is based on RSI, but it finds divergence, that is, a situation of divergence between
DGI	RSI and price, its main disadvantage is its 2-day delay.
RSI	A standard indicator of oversold/overbought asset conditions, which is constructed based on an
CEPI	exponentially weighted moving average over a period of 14 days.
S5FI	The indicator, based on the analysis of stocks included in the S&P500, determines the number of
	stocks trading below the 50-day MA, if the proportion of such assets exceeds 92% - overbought,
ATR Normalized and	less than 2% - oversold (Stock Charts).
%R Normanzed and	The indicator analyzes two values. The first one is related to the normalized ATR, which measures the volatility in the market, the second one is related to the Williams percentage, which
/0K	shows overbought/oversold conditions.
Williams Alligator	An indicator based on three moving averages (periods of 5, 8 and 13 days). If the short moving
Williams Amgator	average crosses the longest one and at the same time within 4 days the average crosses the long
	one from top to bottom, this is a signal to buy, from top to bottom, to sell.
T3 CCI and MACD	Evaluates the CCI indicator smoothed by the T3 average and the MACD indicator, if the
15 cei and Whiteb	smoothed CCI takes a negative value, while the MACD value, which is calculated by subtracting
	the short exponential moving average (period 12) by the long exponential average (period 26),
	should go from a positive value to a negative value, then a sell signal is triggered, but if the T3
	should go from a positive value to a negative value, then a sen signal is triggered, but it the 13

	CCI value falls below -146, in this case a buy signal is triggered, MACD is not needed in this
	case.
EMA20+EMA50	An indicator for the intersection of a short and long exponential moving average. If the short one crosses the long one from bottom to top, it is a buy signal; if it crosses the long one from top to bottom, it is a sell signal.
Hash Ribbons	The Hash Ribbon indicator identifies periods when Bitcoin miners are in distress and may capitulate. It is suggested that such periods may occur when the BTC price is at major lows and therefore may represent a good opportunity to buy on the dip (Look Into Bitcoin).
2-Year MA Multiplier	An indicator based on two moving averages over a period of 2 years, one of which is multiplied by 5. Two situations are considered, when the price of Bitcoin is higher than the moving average multiplied by 5 and when the price is lower than the 2-year moving average, respectively, in the first case we consider the state of overbought, and in the second case - the situation of oversold asset.
Puell Multiple	Another on-chain indicator, the Puell Multiple indicator was developed to estimate the Bitcoin market price in relation to the daily average Bitcoin mining price. It is based on the assumption that the Bitcoin market price is closely related to the mining volume, i.e. the number of new Bitcoins generated by miners (Look Into Bitcoin).
MVRV Z-Score	This indicator uses blockchain analysis to identify periods when Bitcoin is extremely overvalued or undervalued compared to its "fair value" (Look Into Bitcoin).
FGI	One of the most important indicators on the market assesses the mood of traders, whether they are in fear and sell or in euphoria and buy. This indicator is based on 5 sources of information: volatility, trading volumes, analysis of social networks for the dominance of positive reviews/comments or negative, analysis and tracking of bitcoin dominance on the market, analysis of trending queries in Google using special programs, popular queries are analyzed and conclusions are made. Each of the 5 indicators has a weight, depending on the change in each, the overall value of the Fear & Greed index changes (Alternative).

The next step in developing an oscillator is to define its operating logic. Considering the different methods of oscillator operation, we can distinguish three main approaches: the first is to activate a common signal when a certain number of indicators are triggered. However, this approach has drawbacks, as some signals are activated too often, and some are rare, which leads to uneven influence of individual indicators on the oscillator. The second approach is to define the oscillator's confidence area, which gives an opportunity to estimate the level of signal reliability depending on the period. Although this method is more attractive, it is not necessary to do constant monitoring of the confidence level. Therefore, the third approach, based on a combination of the first and second, is the most preferable. It will monitor each indicator, but will make a decision based on the coefficients assigned to each indicator.

One of the key steps was to establish the coefficients for each indicator. First, the analysis was done on the model using the least squares method to approximately determine these coefficients. The results are presented in Table 2.

Table 2 - Least squares method for determining coefficients

Indicator	AASI	SOPR	Real Yield US Bond	Russel 2000
Coefficient	-12.09	-3.23	-0.93	0.9
Indicator	QQE	FED Interest Rate	RSI Divergence	RSI
Coefficient	-19.58	-8.97	-9.35	-0.78
Indicator	S5FI	ATR%R	William Alligator	T3CCI
Coefficient	-8.48	5.7	-7.43	-17.89
Indicator	EMA20 + EMA50	Hash Ribbons	2MA Multiplier	Puell Multiple

Indicator	AASI	SOPR	Real Yield US Bond	Russel 2000	
Coefficient	5.75	15.93	0.9	-1.17	
Indicator	MVRV	Z-Score	FGI		
Coefficient	-1	1.45	-5.45		

The analysis was conducted by looking at a 30-day period and identifying the indicators that were activated during this time. The results demonstrate that some indicators are more likely to trigger when the market is falling, while others are activated when the market is rising, indicating that they follow the trend. However, it should be noted that some indicators with a high coefficient are triggered too often. For a more accurate analysis, additional parameters have been added, presented in Table 3.

Table 3 - Analysis of coefficients for each indicator

Indicator	Number of buy signals	Average result per purchase, %	Number of sell signals	Average result per sell, %	The condition for triggering the signal is met
AASI	25	2.74	21	-8.35	Yes
SOPR	20	9.62	27	-8.36	No
Real Yield US Bond	6	12.49	6	0.4	No
Russel 2000	15	7.43	16	-14.9	No
QQE	34	0.67	37	-10.72	No
FED Interest Rate	5	-7.89	13	5.09	Yes
RSI Divergence	13	6.92	26	-13.91	No
RSI	26	11.3	47	-12.77	No
S5FI	6	17.22	5	10.74	Yes
ATR%R	7	0.46	-	-	Yes
William Alligator	22	6.22	22	0.28	No
T3CCI	39	5.58	43	-0.15	No
EMA20 + EMA50	15	4.04	15	-1.142	No
Hash Ribbons	8	15.8	-	-	Yes
2MA Multiplier	7	7.11	3	-59.16	No

Indicator	Number of buy signals	Average result per purchase, %	Number of sell signals	Average result per sell, %	The condition for triggering the signal is met
AASI	25	2.74	21	-8.35	Yes
Puell Multiple	52	2.08	3	30.33	No
MVRV Z-Score	10	-3.41	2	-10	Yes
FGI	21	5.63	15	-5.46	Yes

The last column in the table is worth paying attention to, as it indicates whether the signals were triggered during periods of strong decline or at the peak of the market. This allows to highlight more significant indicators.

Thus, having combined two tables with the data and having conducted experiments with different variations of the coefficients, but within the designated limits, the following parameters were obtained: AASI = 3, SOPR = 2, Real Yield US Bond = 2, Correlation with Russell 2000 = 2, QQE = 2, FED Interest rate = 3, RSI Divergence = 1, RSI = 1, S5FI = 7, ATR%R = 5, William Alligator = 3, T3CCI and MACD = 2, EMA20 + EMA50 = 3, Hash Ribbons = 5, 2MA Multiplier = 4, Puell Multiple = 2, FGI = 7, MVRV Z-Score = 2.

The oscillator functioned as follows: for 30 days, the activations of the indicators were considered taking into account their coefficients, after which they were summed up to obtain the final value. To determine this parameter, an analysis of the entire period of the oscillator's operation was carried out, the main activation zones were identified and all the indicators that worked during this period were considered. This data is presented in the last column of Table 3. Taking into account the coefficients, the minimum values for the indicator to work were determined: 13 for a buy and sell signal, as well as 35 and 30 for strong buy and sell signals. The latter values differ due to the presence of two indicators that are activated only when buying, which led to an increase in the overall indicator.

After creating the oscillator, a difficult task arose to determine the most efficient allocation for each type of signal. The total number of share distribution options for the four types of signals is 100 million. To simplify the task, it was decided to start by dividing the oscillator into four separate strategies and calculate only the worst-case scenarios:

- 1. The BUY strategy assumes that at each BUY signal a purchase is made, and when the first SELL or Strong SELL signal appears, the position is closed completely and immediately;
- 2. Strong BUY strategy means that when a Strong BUY signal appears, a purchase occurs, and then when the first SELL or Strong SELL signal appears, the position is immediately closed;
- 3. The SELL strategy implies that at each SELL signal a short sale is made. Then, when the first BUY or Strong BUY signal appears, the position is closed;
- 4. The Strong SELL strategy implies that when a Strong SELL signal appears, a short sale occurs. The position is closed when the first BUY or Strong BUY signal appears.

After that, backtests were conducted for each of the four strategies on the BTC/USD BITSTAMP and CRYPTOCAP:TOTALDEFI (TradingView) pairs. The choice of these instruments is not accidental. Bitcoin is the first crypto asset and serves as a benchmark for the entire market. The pair was chosen from the BITSTAMP exchange due to its extensive data volume. TOTAL DEFI is used as an indicator of the broad market and is calculated on the Tradingview platform. This index contains a large number of assets and data (TradingView). However, it is worth noting that TOTAL DEFI does not take into account the emission of new tokens and includes Wrapped BTC, the growth of capitalization of which is not pure profit. However, this is the best option for comparing strategies and assessing their effectiveness. The DEFI index is also necessary for testing the oscillator on crypto assets other than Bitcoin and comparing the management results of Bitcoin and the broad market of crypto assets. The same principle was used to select the backtest period, which was from July 22, 2017 to January 22, 2023. Backtesting of strategies on BTC/USD BITSTAMP taking into account stated return, Figure 5.



Figure 5: BTC/USD stated return results for 4 strategies

5. Results

- 1. BUY strategy maximum efficiency is achieved at 100%;
- 2. SELL strategy maximum efficiency is achieved at 5%;
- 3. Strong BUY strategy maximum efficiency at 100%;
- 4. Strong SELL strategy maximum efficiency at 100%;

The backtest outcomes showed that the SELL strategy was ineffective. This is because markets usually grow in the long term. The crypto asset market, as a reflection of classic markets, is also subject to this trend. This conclusion is based on the analysis of the relationship between the American S&P500 index and the BTC price. To achieve maximum accuracy, the S&P500 index calculated by TVC-SPX and BTC futures from the CME-BTC1! exchange were used (TradingView). It is important to choose trading instruments whose sessions coincide to avoid errors caused by differences in quotes. Thus, over a three-year period, the correlation coefficient was 0.8.

As a result of backtesting and correlation analysis, the solution was found to determine allocation shares for the BUY, Strong SELL, Strong BUY signals. Then, based on the known values, backtests were conducted to evaluate possible value options for the SELL signal.

Selecting indicators based solely on simple returns would be too simplistic. It was therefore decided to determine the allocation share based on three ratios: effective return, a risk measure expressed as the standard deviation of returns over the study period, and the Sharpe ratio. The Sharpe ratio was calculated using returns on three-month discounted US Bills by WSI. The risk-free rate was determined using the following formula and was 8.3%.

$$\prod_{i=1}^{n} (1+r_i)^{\left(\frac{3}{12}\right)}$$

where n - number of three-month periods, r - rate of return and i - element number.

After backtesting the BUY strategy, the following results were obtained, presented in Figure 6. The maximum efficiency, measured by the effective return over the period, reaches its maximum at 76%. The maximum value of the Sharpe ratio, which evaluates the efficiency of the strategy taking into account risk, is reached at values from 45% to 52%. From these results, conclusions can be drawn. Based on the indicators of return over the period, values up to 76% are considered efficient. However, the Sharpe ratio takes into account risk and shows that efficient values are in the range from 45% to 52%.

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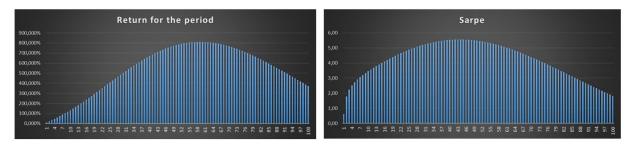


Figure 6: Effective Yield and Sharpe Ratio Result BTC/USD BUY Strategy

The results of the backtest of the Strong BUY strategy are presented in Figure 7. The maximum efficiency, measured by the effective return over the period, reaches 100%. The maximum value of the risk-adjusted Sharpe ratio is also reached at 100%. Both efficiency indicators point to the same optimal value (100%).

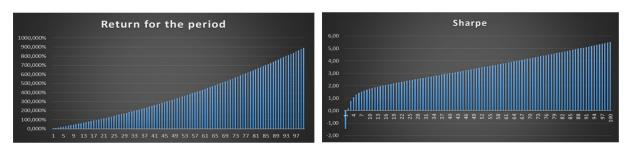


Figure 7: Effective Yield and Sharpe Ratio Result BTC/USD Strong BUY Strategy

The results of the backtest of the Strong SELL strategy are presented in Figure 8. The maximum efficiency, measured by the effective return over the period, also reaches 100%. The maximum value of the Sharpe ratio is 1.04 and is also reached at 100%. And in this case, both efficiency indicators point to the same optimal value (100%).

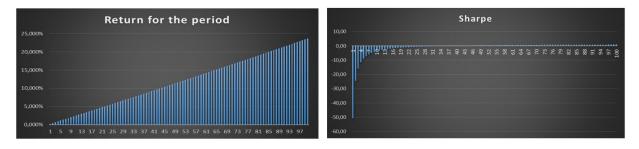


Figure 8: Effective Yield and Sharpe Ratio Result BTC/USD Strong SELL Strategy

The following research results refer to backtest of strategies on TOTALDEFI. Backtest of 4 strategies taking into account stated return is presented in Figure 9. The BUY strategy achieves maximum efficiency at 74%. The SELL strategy achieves maximum efficiency at 0%. The Strong BUY strategy achieves maximum efficiency at 100%. The Strong SELL strategy achieves maximum efficiency at 100%. According to the backtest results, the zone of effective values for the BUY signal narrows from 1% to 74%. The SELL strategy has shown its inefficiency.

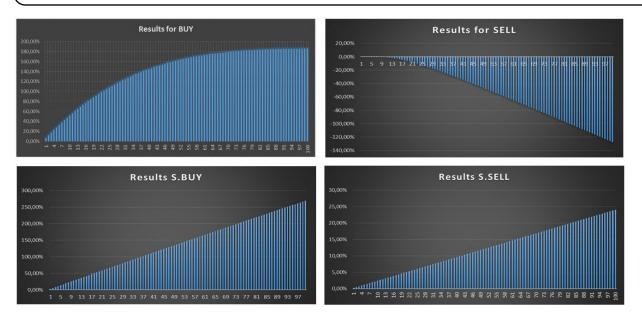


Figure 9: TOTALDEFI stated return results for 4 strategies

After the backtest, the BUY strategies results are presented in Figure 10. The maximum efficiency, measured by the effective return over the period, reaches 59%. The maximum value of the Sharpe ratio over the period, amounting to 5.56, is achieved at values of 43% and 44%.

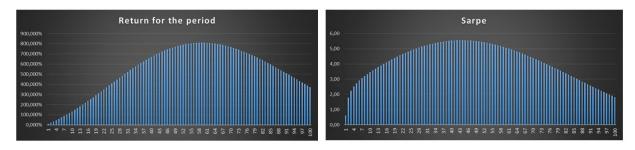


Figure 10: Effective Yield and Sharpe Ratio Result TOTALDEFI BUY Strategy

The results of the backtest of the Strong BUY strategy are presented in Figure 11. The maximum efficiency, measured by the effective return over the period, reaches 100%. The maximum value of the Sharpe ratio over the period, equal to 5.5, is also achieved at 100%.

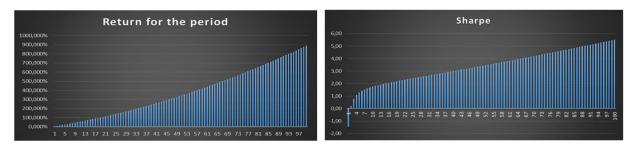


Figure 11: Effective Yield and Sharpe Ratio Result TOTALDEFI Strong BUY Strategy

The results of the backtest of the Strong SELL strategy are presented in Figure 12. The maximum efficiency, measured by the effective return over the period, reaches 100%. The maximum value of the Sharpe ratio over the period, equal to 0.97, is also achieved at 100%.

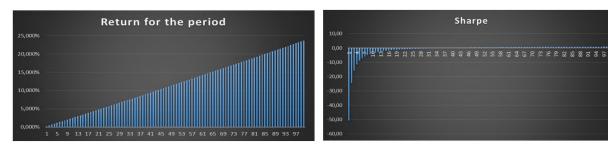


Figure 12: Effective Yield and Sharpe Ratio Result TOTALDEFI Strong SELL Strategy

As a result of the calculations, the range of possible variants of allocation shares distribution was reduced to 800. The indicators for the Strong BUY and Strong SELL signals confirm their reliability and accuracy. Based on the calculations for the SELL signal, it was decided to strengthen the sell signal by adding a signal to the oscillator indicating the direction of the current trend. This led to the division of the SELL signal into the SELL Bull trend and SELL Bear trend shown in Figure 13.



Figure 13: Displaying the oscillator on the chart

Different coefficients were also implemented for these two signals.

SELL Bull trend:

$$X \times \frac{c}{aep}$$

where X - allocation share, c - price quotation on the day of the SELL Bull trend signal is received and aep - average entry price.

SELL Bear trend:

$$X \times (1 + \frac{c}{p})$$

where X - allocation share, c - price quotation on the day of the SELL Bear trend signal is received and p - price quotation on the day of trend change.

Therefore, the Bull trend ratio will increase sales volume during a bullish trend when the market is rising, while the Bear trend ratio will decrease sales volume when the market is falling.

The next part discuses modification of the oscillator. Initially, the oscillator represented only the values for buying and selling, which led to the problems mentioned earlier. To introduce a trend, it is necessary to calculate it, and for this the SuperTrend indicator developed by Olivier Seban is used (Seban O., 2012). The formula for calculating:

$$Upper/LowerBand = \frac{(High + Low)}{2} \pm (m * ATR_n)$$

where High – maximum candle price, Low – minimum candle price, m - volatility multiplier measured by ATR and 【ATR】 n - asset volatility indicator.

Using the formula presented above, the upper and lower points can be determined, and when the next candle crosses the lower/upper trend line, it can be considered that a trend change has occurred. Taking into account all of the above, a modified oscillator was developed that makes allowances to the trend direction and the trend change point (Figure 14).

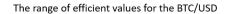


Figure 14: Displaying the modified oscillator on the chart

Next, it is necessary to evaluate the effectiveness of the oscillator taking into account the trend lines. After making changes to the oscillator, a new unknown value appears that needs to be determined. The formula for the SELL Bear trend coefficient uses the price quotation value on the day of the trend change (p). During the day, you can get 4 values that can be used in this coefficient: opening of the daily candle, closing of the daily candle, minimum price quotation value during the day, maximum price quotation value during the day. Thus, the number of possible effective options for the BTC/USD BITSTAMP strategy is reduced to 3200.

For the TOTALDEFI strategy, it was also decided to conduct additional research for the p value from formula for SELL Bear trend. In the first option, SuperTrend was applied to the BTC/USD BITSTAMP chart, while in the second one, it was applied to TOTALDEFI. Thus, the number of possible effective variants for TOTALDEFI was reduced to 1600.

The backtest results for the BTC/USD BITSTAMP strategy are presented in Figure 15. The backtests provided the following values, which can be considered the most effective for this oscillator: BUY - 52%; SELL - 18%; Strong BUY - 100%; Strong SELL - 100%. The p value is the minimum price quotation value on the day of the trend change.



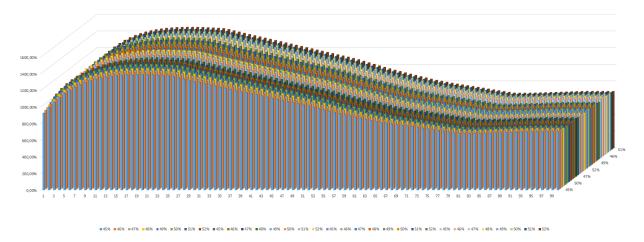
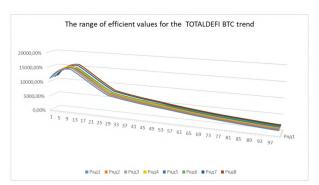


Figure 15: The range of efficient values for the BTC/USD BITSTAMP strategy

The backtest results for the TOTALDEFI strategy are presented in Figure 16. The backtests provided the following values, which can be considered the most effective for this oscillator: BUY - 44%; SELL - 11%; Strong BUY - 100%; Strong SELL - 100%. The p value is the minimum price quotation value on the day of the trend change according to the BTC/USD BITSTAMP trading pair.



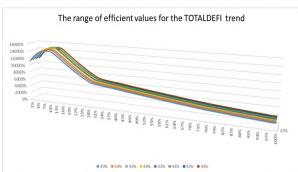


Figure 16: The range of efficient values for the TOTALDEFI strategy

A comparison of the strategy indicators is presented in Table 4.

Table 4 - Results of the strategies

Ratios	BTC/USD BITSTAMP	TOTAL DEFI
Return on investment over the holding period	701.95%	7417.27%
Strategy return	1455.05%	15572.27%
Risk-free rate for the period	8.06%	8.06%
Standard deviation over the period	146.61%	270.61%

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Quarterly Sharpe Ratio	0.5	0.58
Multiplicator	2.07	2.10
Standard deviation per quarter	31.99%	59.05%
Max return per quarter	72.42%	144.74%
Max loss per quarter	-26.6%	-40.55%
Average quarterly return	17.33%	36.17%

Based on the results obtained, it can be concluded that both strategies demonstrated high efficiency compared to the benchmark. However, it is especially noteworthy that the risk expressed by the Sharpe ratio for the TOTALDEFI strategy was higher than for the BTC/USD BITSTAMP strategy. This indicates that in the future it is more appropriate to focus on developing the TOTALDEFI strategy and improving its efficiency.

6. Determining the optimal weights of instruments in a crypto asset portfolio

The next step is to put together a portfolio of crypto assets that will be most preferable for investment. To do this, Markowitz's portfolio theory which is based on the risk-return ratio of a portfolio of securities was used. In this case, instead of securities crypto assets were utilized.

In the middle of the 20th century, the American economist Harry Markowitz wrote an article "Portfolio selection", in which he described the basic principles of his theory, which was subsequently developed and improved (Markowitz H.M., 1952). This work uses the main assumptions from it. Precisely, the risk is not considered separately, but as a whole for the portfolio, and only efficient portfolio combinations are taken into account, that is, those that are on the efficient frontier (Figure 17).

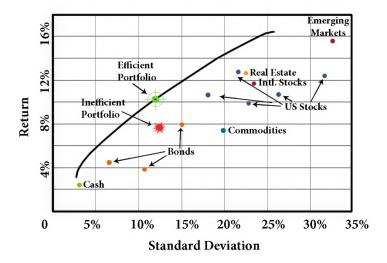


Figure 17: Efficient Frontier of a Set of Portfolios

Combining different levels of profitability and risk of crypto assets, it is possible to achieve any result in terms of risk-return ratio. In this work 500 different portfolio combinations were simulated. The obtained result is presented in Figure 18.

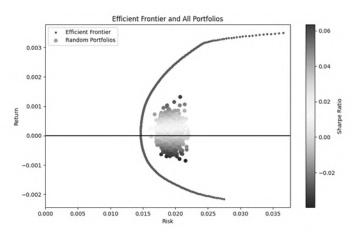


Figure 18: Markowitz's efficient frontier

The received outcomes will help understand what combination of crypto assets is necessary to choose in order to be on the efficient frontier. However, they do not tell us anything about which portfolio to choose. In some cases, when building multiple portfolios, the one that suits in terms of risk and return was opted for. But in this paper, the main interest is how to directly select the required portfolio, among many acceptable ones. To do this, additional criteria to the portfolio will be applied. In particular, its ratio of return without taking into account the risk-free rate on US government bonds for a period of 3 months to the standard deviation will be evaluated, which is also known as a risk measure.

In other words, the Sharpe ratio will be calculated. Its formula is as follows:

$$SPI = \frac{R_p - R_f}{\sigma_p}$$

where R_p – portfolio return, R_f – risk-free rate (WSI) and σ_p - standard deviation of portfolio returns. Applying this formula to 500 portfolios, the graph of the Sharpe ratio value was obtained, presented in Figure 19.

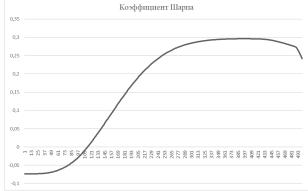


Figure 19: Sharpe Ratio for 500 Portfolios

The highest daily Sharap ratio was achieved by a portfolio with a distribution of crypto assets in the proportions presented in Table 5:

Table 5 - Distribution of crypto assets in the portfolio							
BNB	KO	CS	LEO	НТ	G	T	CRO
0%	0.	%	0%	33.29%	0.7	7%	0%
OKB	MX		BIT	BGB	BN	ЛX	EXM
0%	31	3%	2.83%	22.19%	9.6	8%	0.79%
Return	Return		Risk	$R_{ m f}$			SPI
0.79%			2.63%	3% 0.0122%		0.2962	

Next, a calculation of such a portfolio was made for the period up to the beginning of August 2023, taking into account that no portfolio rebalances were applied for a period of 4 months, starting from April and ending at the beginning of August, the result of the return is presented in Figure 20.

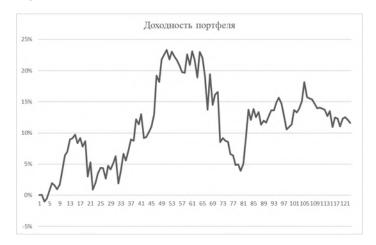


Figure 20: Return on a portfolio compiled according to Markowitz portfolio theory for the period from 01.04.2023 to 01.08.2023 Thus, a portfolio was found whose yield was 11.593% over 4 months. However, at the very beginning, the problem was identified that the crypto asset market is not similar to the securities market, which is why the assessment of its effectiveness is not always similar to the classic market. To do this, it is necessary to modify the portfolio assessment formula by adding the "Scam Coefficient" to the risk assessment, its formula is presented below:

the below:
$$C_s = w_i \times \frac{\sum_{i=0}^{N} reports}{10 \times N}$$

where w_i - weight of the i-th crypto asset and reports - full report value for 6 parameters. The values of the full report on 6 parameters include:

- The level of development and growth of the project;
- Analysis of the community sentiment towards the project;
- Community activity in interaction with the crypto asset;
- Awareness of the project, that is, its transparency, the level of trust and reliability in the crypto asset;
- The volume of project income as an indicator of the maturity of the project;
- The reliability to pay its obligations.

By implementing the "Scam coefficient" into the Sharpe formula, increasing the risk expressed by the standard deviation by the "Scam coefficient", while taking into account that the higher this ratio is, the less additional risk must be used, so it is necessary to take the inverse of this ratio, so the modified Sharpe formula will look the following way:

$$SPI_{modified} = \frac{R_p - R_f}{\sigma_p \times \frac{1}{C_s}}$$

Thus, applying the new formula to 500 portfolios, the new values presented in Figure 21 were obtained.

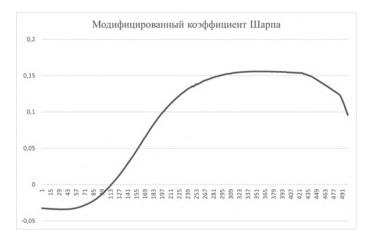


Figure 21: Modified Sharpe Ratio

Selecting the portfolio with the highest modified Sharpe ratio, a portfolio with the parameters presented in Table 6 was obtained.

Table 6 - Allocation of crypto assets in a portfolio taking into account the modified Sharpe ratio

BNB	KCS	LEO	HT	GT	CRO	OKB	MX	BIT
0%	0%	0%	31.15%	7.09%	0%	0%	26.25%	1.41%
BGB	BMX	EXM	Return	Risk	R_{f}	SPI	Cs	SPImodified
18.94%	15.18%	0%	0.69%	2.29%	0.0122%	0.2951	0.5284	0.1559

It can be noticed that the portfolio with both the classic Sharpe ratio and the modified one are similar, however, due to the increased risk, the portfolio with a lower return, but also with a lower risk was chosen. The return of such a portfolio for 4 months is shown in Figure 22.



Figure 22: Portfolio Return with Modified Sharpe

As it can be seen, the return of the two portfolios does not differ much, but the second portfolio outperformed the first in return by 0.253%, which is 0.759% per annum. It is also important to consider other parameters of the two portfolios, which are presented in Table 7.

Table 7 - Performance indicators of two portfolios

Portfolio with maximu	m SPI	Portfolio with maximum S	SPI _{modified}
BTC return	4.36%	BTC return	4.36%
Portfolio return	11.593%	Portfolio return	11.846
Risk-free rate	1.486	Risk-free rate	1.486
Standard deviation for period	1.902	Standard deviation for period	1.9014
SPI	0.2962	SPI	0.2951
Multiplier	2.6589	Multiplier	2.717
Maximum return per day	5.5645%	Maximum return per day	9.1246%
Maximum los per day	-6.9068%	Maximum los per day	5.9247%
Average return per day	0.108%	Average return per day	0.1096%
$\mathrm{SPI}_{\mathrm{modified}}$	0.1551	$\mathrm{SPI}_{\mathrm{modified}}$	0.1559

The table shows that the second portfolio with the modified Sharpe ratio for the "Scam coefficient" outperforms the first portfolio in all respects, from higher returns to lower risk, i.e. lower potential losses.

Accordingly, it can be said that the "Scam coefficient" can be used to analyze portfolios and identify the most effective one. Obviously, analyzing each portfolio would be a very long process, it would be much more convenient to create a ready-made program/interface that would output the values of the portfolio with the highest SPI indicator modified by the "Scam coefficient" automatically. In this regard, a portfolio evaluation program was developed. Visual display of the results is provided by the toolkit of the previously described "Tkinter" library. The main reason for creating a graphical display is the problem of complex interaction with the calculation results in the terminal. The starting interface of the finished product is displayed as shown in Figure 23.



Figure 23: Graphical display of the launch panel

When clicking the "Collect portfolio" button, the process of "parsing" the data and processing it according to the mathematical models described above begins, which ultimately leads to visualization of the data in the form of a table (Figure 24).

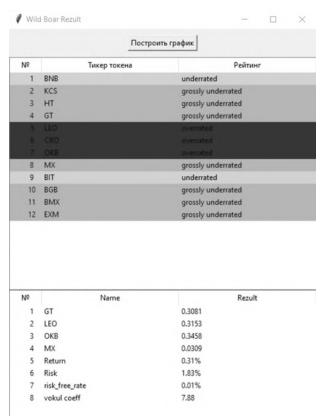


Figure 24: Visualization of asset valuation and efficient portfolio with its parameters

The top part of Figure 24 shows the valuation of all assets initially set by the manager. Where:

- Overrated corresponds $P_i > P_{cui} \& P_i > P_{ci} \& P_i > P_{ai}$;
- Low spread corresponds $P_i < P_{cii} \& P_i > P_{ci} \& P_i > P_{ai}$;
- Underrated corresponds $P_i < P_{cii} \& P_i > P_{ci} \& P_i < P_{ai}$;
- Grossly underrated corresponds $P_i < P_{cui} \& P_i < P_{ci} \& P_i < P_{ai}$.

The bottom of Figure 24 shows the efficient portfolio that the manager needs to assemble. It shows the assets and their shares in the efficient portfolio, as well as:

- Return average daily return of the asset portfolio;
- Risk daily risk of the asset portfolio, expressed as standard deviation;
- Risk-free rate risk-free rate one day ahead calculated on three-month US Treasury bills;
- Vokul Coef "Scam coefficient" for the found asset portfolio.

Additionally, the manager receives a graph of efficient portfolios (Figure 25) to assess the general position of the adjusted efficient frontier and the market position at the current moment of time.

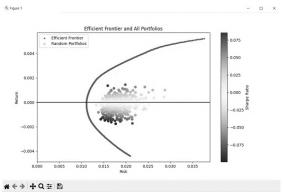


Figure 25: adjusted efficient frontier

In this part, the approach to assessing crypto assets was considered using the example of tokens and coins of centralized exchanges. It was based on a comparison of the income of exchanges without listing their tokens / coins on the financial market and the income of CoinBase. Also, to improve the accuracy of the data, the income expressed in the trading volume was cleared of the volumes of market makers. Based on the data obtained, a portfolio was built that meets the highest efficiency according to the Sharpe ratio. However, crypto assets cannot be assessed in the same way as classic instruments, since they have risks that are not typical for other instruments, in connection with which the "Scam coefficient" was developed, which, depending on the quality of the project, increases the risk by a certain level. In addition, as backtests have shown, the new portfolio is not only less risky, both when collecting and in practice, it showed a smaller drawdown compared to the first one, but also turned out to be more profitable, which suggests that adding this coefficient turned out to be the best option.

However, the process of processing and analyzing data takes quite a lot of time, which is why a unique algorithm was invented for collecting the necessary data and calculating all indicators with a visual display of the obtained result.

7. Conclusion

The paper addressed the problem of constructing a model for determining the price of exchange tokens and coins and constructing a trading strategy with an optimal risk-return ratio. For this purpose, the overall risk of the strategy was divided into idiosyncratic and systematic risks. The model for assessing the fair price of exchange tokens and coins is responsible for reducing the idiosyncratic risk. The model was also automated using Python code, which made it possible to reduce further efforts for applying such a model in practice. Next, an oscillator was designed to reduce systematic risk. For this purpose, 18 indicators of fundamental, technical and behavioral analysis were selected, then the optimal weights for the indicators were found using the multiple regression method. After that, the optimal shares of allocation of funds in the market for each type of oscillator signal were calculated using the empirical analysis method using the Sharpe ratio. Based on the data obtained, a portfolio was built that met the highest efficiency according to the Sharpe ratio. However, crypto assets cannot be assessed in the same way as classic instruments, since they have risks that are not typical for other instruments, in connection with which the "Scam coefficient" was developed, which, depending on the quality of the project, increases the risk by a certain level. In addition, as backtests showed, the new portfolio is not only less risky, both during collection and in practice, it showed a smaller drawdown compared to the first, but also turned out to be more profitable, which suggests that adding this coefficient turned out to be the best option. However, the process of processing and analyzing data takes quite a lot of time, in connection with which a unique algorithm was invented for collecting the necessary data and calculating all indicators with a visual display of the result obtained.

Thus, a model for determining the fair value of CEX tokens and coins, a portfolio construction method, and an oscillator that allows reducing systematic risk were constructed and tested. Both approaches have proven their effectiveness compared to benchmarks, which makes this study useful for extracting additional profits from the market.

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