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DISSERTATION

CRYPTOCURRENCY TRADING

—FROM SINGLE-FACTOR MODEL TO MULTIFACTOR MODEL BY TAKING LONG-SHORT STRATEGIES

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SUPERVISION: PROF. TIAGO CRUZ GONÇALVES

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ABSTRACT

This study explored the impact of different indicator factor models on the performance of portfolios under the same trading strategy within the same time frame. The indicator factors selected were the Commodity Channel Index (CCI), Volume, and Bollinger bands (Boll count). The trading strategy employed is known as the 'Long-short pairing strategy', which involves taking a long and holding position in a single coin ranked first while short-holding a coin ranked last at the same time. 264 Coins that are traded on Binance plarforms are included in this research, and coin selection process is refreshed every 6 hours. The time frame considered for this analysis spans from September 20, 2020, to September 20, 2023. The evaluation metrics for portfolio performance are the accumulated net value, annual return, portfolio standard deviation, Sharpe ratio, maximum draw-down, information ratio, etc. The hyper-parameter of the factors was tuned by machine learning using Grid search.

The results showed that combining additional factors into the model can increase annual returns. However, reducing portfolio volatility and risk exposure is in doubt. Also, the impact of additional factors on portfolio performance and risk can vary significantly depending on the specific factors and their correlations, emphasising the importance of careful factor selection and combination in portfolio optimisation.

KEYWORD: Cryptocurrency, Market-Neutral Strategies, Commodity Channel Index, Volume, Boll

JEL Codes: C61, C63, G19.

RESUMO

Este estudo explorou o impacto de diferentes modelos de fatores indicadores no desempenho de portfólios sob a mesma estratégia de negociação dentro do mesmo período de tempo. Os fatores indicadores selecionados foram o Índice de Canal de Mercadorias (CCI), Volume e Contagem de Boll. A estratégia de negociação empregada é conhecida como 'ESTRATÉGIAS DE MERCADO NEUTRO', que envolve assumir uma posição longa e manter em uma única moeda classificada em primeiro lugar, enquanto simultaneamente mantém uma posição curta em uma moeda classificada em último lugar. 264 moedas negociadas nas plataformas Binance estão incluídas nesta pesquisa, e a seleção das moedas é atualizada a cada 6 horas. O período de tempo considerado para esta análise abrange de 20 de setembro de 2020 a 20 de setembro de 2023. As métricas de avaliação do desempenho do portfólio incluem o valor acumulado líquido, retorno anual, desvio padrão do portfólio, índice Sharpe, rebaixamento máximo, índice de informação, entre outros. Os hiperparâmetros dos fatores foram ajustados por meio de aprendizado de máquina, usando Grid search.

Os resultados mostraram que a combinação de factores adicionais no modelo tem grandes possibilidades de aumentar os retornos anuais, no entanto, as capacidades para reduzir a volatilidade da carteira e a exposição ao risco estão em dúvida.Além disso, o impacto de factores adicionais no desempenho e risco da carteira pode variar significativamente dependendo de os fatores específicos e suas correlações, enfatizando a importância da seleção e combinação cuidadosa dos fatores na otimização do portfólio.

PALAVRA-CHAVE: Criptomoeda, Estratégias neutras de mercado, Índice de canais de mercadoria, Volume, Boll

Códigos JEL: C61, C63, G19.

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest gratitude here. Completing this Master's thesis is an essential milestone in my academic career, and I would like to thank all those who supported and encouraged me on this journey.

Secondly, "I would like to express my deepest gratitude to my advisor, Professor TIAGO CRUZ GONÇALVES, for their unwavering support, guidance, and expertise throughout the entire journey of this research. I am truly fortunate to have had the opportunity to work under their supervision, and I am immensely grateful for their dedication to my success. Their encouragement and constructive feedback have been invaluable, and I couldn't have completed this work without their mentorship. I extend my heartfelt thanks to TIAGO CRUZ GONÇALVES for their belief in my abilities and for being an inspiring mentor."

Thirdly, I would like to thank my family. They have always been my strong support, and they have not hesitated to support me no matter what difficulties I faced. I would like to especially thank them for their support and understanding in my academic and personal life.

Finally, I would like to thank the digital currency research team that has participated in recent years. The digital currency space is a field of challenges and opportunities, and I have had the privilege of delving into it and achieving some results. In the process, I have made many like-minded research partners and friends, and their discussions and sharing have enriched my research experience.

In conclusion, completing this Master's thesis was a challenging and growing journey, and I would like to thank all the people who quietly supported me behind my back. Your help and encouragement mean a lot to me and I will take it to heart. Thank you!

GLOSSARY

CCI-Commodity Channel Index

Boll_Count: Count the numbers that crossing both of the lower and upper Bollinger bands

BTC: Bitcoin

USD: American Dollar

UDST: The live price of Tether USDt is $ 1.000079 per (USDT / USD) with a current market cap of USD 83.25B

CAPM: Capital Asset Pricing Model

APT: Arbitrage Price Theory

IR: The Information Ratio

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1. INTRODUCTION

Cryptocurrencies, underpinned by blockchain technology (Abadi & Brunnermeier, 2018), enable decentralised transactions. Since Bitcoin emerged in 2009, more than 50 million investors have engaged in cryptocurrency trading across over 100 global exchanges. Additionally, over 100,000 companies worldwide now accept payments in bitcoins and Bitcoin debit cards (Makarov & Schoar, 2020). Given the growing interest in cryptocurrencies, their investment potential has become a significant subject of scrutiny, with researchers and industry professionals exploring their utility beyond speculative purposes.

Trading cryptocurrencies to make a profit seems either difficult or easy. The difficulties derive from its huge volatility and non-intrinsic value, leading to emotional trading errors (Cheah & Fry, 2015). However, due to its market inefficiency, it can be easy to create significant digital asset price dispersion, which offers scope for arbitrage opportunities (Ahmed et al.,2020). Factor research, whose underlying thought is using multifactors to explain stock returns, was also researched in the cryptocurrency market. Several factors, such as low volatility, mean-reversion factors (Rabener, 2017), short-term momentum factors (Hubrich Rabener, 2017), volume and size factors (Trimborn et al., 2016), were studied in the cryptocurrency market and proven to be efficient in getting returns. Among them, the Volume factor and one of the momentum factors of the Commodity Channel Index (CCI) were helpful in recent years. Davies (2015) optimised the probability opportunities by adding Bollinger bands (Boll count) with CCI. Besides, from the Capital Asset Pricing Model (CAPM) to the Arbitrage Price Theory (APT) model and from the Fama-French three-factor model that expands to the Fama-French five-factor model, several studies have identified that multifactor models, incorporating multiple-factor, offer improved explanatory power for security returns.

Furthermore, multifactor models can also find applications in risk management. However, it is important to note that these findings have predominantly been verified within the context of the securities market. Consequently, this raises a pertinent question：

1. *Does a multiple-factor Portfolio generate better annual returns while minimising the risks than a single-factor portfolio under the same trading strategy?*

Cryptocurrencies are hazardous and volatile assets (Pelster et al., 2019; Chaim & Laurini, 2018), so a technical trading strategy should guide rational trading (Fang et al., 2020). The two strategies that would be used for the cryptocurrency market are the buy-hold and long-short strategies. Compared to the two, the Long-short strategy has been one of the most influential and active methods because it provides a more comprehensive range of opportunities for generating returns, regardless of the broad market direction. Applying a long-short strategy in constructing a trading portfolio seems valid to get an excess return. Thus, this raised another question:

2. *Does a single or multiple-factor portfolio using a Long-short strategy generate abnormal returns while minimising the risks compared to a Buy-Hold strategy?*

From the two research questions, this study aims to explore the impact of different indicator factor models on the performance of the portfolios under the same trading strategy within the same time frame. The indicator factors selected were the Commodity Channel Index (CCI), Volume, and Bollinger bands (Boll count). The trading strategy employed is the 'Long-short pairing strategy', which involves taking a long and holding position in a single coin ranked first while short-holding a coin ranked last simultaneously. Coin selection is re-balanced every 6 hours, which considers the high volatility of cryptocurrency market. Prices can experience significant fluctuations within short time intervals. Rebalancing every 6 hours allows researchers to capture and respond to rapid price changes, ensuring that the portfolio remains aligned with the intended strategy. The time frame considered for this analysis spans from September 20, 2020, to September 20, 2023 because the cryptocurrency market is known for its rapid evolution and changing dynamics. By selecting a time frame that spans several years, it can potentially capture different market conditions, including bull and bear markets, regulatory changes, and technological advancements. The evaluation metrics for portfolio performance are the accumulated capital net value , annual return, portfolio standard deviation, Sharpe ratio, maximum draw-down, information ratio, etc. The hyper-parameter of the factors was tuned by machine learning using Grid search. The result of this research showed that combining additional factors into the model can increase annual returns. However, reducing portfolio volatility and risk exposure is in doubt. Also, the impact of additional factors on portfolio performance and risk can vary significantly depending on the specific factors and their correlations, emphasising the importance of careful factor selection and combination in portfolio optimisation.

By addressing these elements, the dissertation makes a significant contribution to the field of cryptocurrency investment and portfolio management, shedding light on strategies and factors that can potentially optimize returns and minimize risks in a high-volatility and evolving market.

The dissertation started with the literature review, delving into the previous studies of factors, technical indicators, long-short strategies, and machine learning models in cryptomarket research. Then, the research methodology is outlined, encompassing terminology, factor selection, portfolio construction, hyper-parameter optimization, and performance evaluation. The section 4 of Exploration and Result focuses on data analysis, including factor correlation, portfolio performance, and benchmarking against Bitcoin. The dissertation concludes with a comparative discussion, offering insights into cryptocurrency investment and trading strategies.

2. LITERATURE REVIEW

The basis of Factor investing derives from the development of the Capital Asset Pricing Model (CAPM) and Arbitrage Price Theory (APT), in which the underlying thought is to use multifactors to explain stock returns (Ross, 1976; Fama,1970). Fama and French (1992, 1996) developed the Fama-French three-factor model, which was expanded to the Fama-French five-factor model. Over time, there has been a significant increase in the number of variables that possess explanatory capabilities, resulting in an extensive range of dozens to hundreds of factors (Harvey et al., 2016).

The lack of regulations in the cryptocurrency market can indeed lead to challenges in assessing the value of cryptocurrencies and can influence investor behavior (Ahinefficientmed et al., 2020). Besides, cryptocurrency markets, are not always perfectly efficient. As a result, trading strategies underlying factors such as momentum, value, and size can help traders reducing exposure to specific risks and enhance the portfolio's risk-adjusted returns, as well as exploit market inefficiencies to generate excess returns (Yang, 2019; Caporale et al., 2018). Although the optimal factor model for the cryptocurrency market is still debatable, several factors influence cryptocurrencies' return.

In the study by Liu et al. (2022), they identified specific risk factors that account for the fluctuations in the returns of factor portfolios and formulated a three-factor model tailored to the cryptocurrency market. Rabener (2017) conducted an analysis of factors related to low volatility and mean-reversion within the cryptocurrency market. The study of Liu and Tsyvinski (2020) highlights that cryptocurrency returns can be predicted by two cryptocurrency-market factors: momentum and investor attention. Wang & Vergne (2017) found the positive returns of cryptocurrencies caused by the increasing demand promoted by the news publications or "buzz" on social media in the short term. Gunay (2019) explored the impact of Twitter posts on the price of

Ripple in their study.. Liu & Tsyvinski (2022) conducted tests to assess whether cryptocurrency returns are influenced by factors like the 5-Fama and French models and the CAPM (Capital et al. Model). Their findings observed that proxies for investor attention, such as the count of Twitter posts mentioning Bitcoin, exhibit a strong predictive power for cryptocurrency returns. Also, they indicate a robust time-series cryptocurrency momentum effect. Elendner and colleagues (2018) discovered a notable positive alpha associated with short-term momentum in their research. Besides the momentum factor, Volume and size also matter (Trimborn et al., 2016). Balcilar et al. (2017) and Jermann (2021) regarded transaction volume to be an effective predictor of cryptocurrency returns, and small-cap cryptocurrencies generate returns that surpass the average performance in the market (Elendner et al., 2016).

Among the above-studied factors, momentum and Volume factors can be associated with applying technical indicators. Technical indicators are derived from technical analysis; they involve predicting future price movements by analysing historical price data, including metrics like opening prices, closing prices, and trading volumes (Farias Nazário et al., 2017). Past research has demonstrated that technical analysis can enhance investment strategies and outperform a straightforward buy-and-hold strategy (Dai et al., 2020). This research highlights the potential utility of technical analysis and its associated indicators in making informed investment decisions.

Momentum indicators quantify the rate at which prices are altering within a specified time frame for the momentum factor and volume factor. In contrast, volume indicators reveal whether there is a predominance of sellers or buyers in the market. Three momentum indicators were often used: Moving Average Convergence Divergence (MACD), Commodity Channel Index (CCI), and Relative Strength Index (RSI), . (Nazário et al., 2017). The Commodity Channel Index (CCI) has been regarded as helpful in recent years. Besides, traders must consistently and accurately forecast three critical aspects of the underlying asset for a successful trade: price, the direction in which the price will move, and the duration it will take to reach the anticipated changes (Davies, 2015). Davies (2015) proposed a system combining the use of Bollinger bands with CCI, and it is convinced that the combined indicators ensure a higher probability of timing in the anticipated price reversal correctly, leading to optimised trading opportunities. These Three-Factor-associated indicators were selected for further research.

Portfolios that leverage multiple factors have shown the capacity to produce returns that differ significantly from what would be anticipated in a standard or traditionally expected market environment. Previous research has indicated that portfolios constructed based on specific criteria have exhibited superior performance compared to portfolios comprised of cryptocurrency market indexes (Koedijk et al., 2016). The construction of a portfolio depends on which strategy that will be used. Buy-hold strategy or Long-short strategy are the two strategies used for the cryptocurrency market (Ahmed et al., 2020). A Buy-Hold strategy represents a long-term, passive investment approach where investors maintain a stable portfolio over an extended period. In contrast, a Long-Short strategy involves taking a long position in undervalued assets and a short position in overvalued assets, with the aim of achieving a positive expected return while keeping net exposure to systematic or market risk at zero (Shubert, 2006). It's important to note that cryptocurrencies are not subject to the constraints associated with short-selling, making both Buy-Hold and Long-Short strategies feasible in this context. However, long-short portfolios have been one of investors' most effective methods over time (Shubert, 2006; Beaver et al., 2016). A study by Nair (2021) compared the buy-and-hold and long-short strategies for four cryptocurrencies from January 1, 2018, to December 31, 2019. The findings indicated that the long-short pairs trading strategy consistently outperformed the conventional buy-and-hold strategy in the cryptocurrency markets. Similarly, Liu et al. (2020) implemented long-short strategies with sorting periods ranging from 1 to 4 weeks across a dataset of 1583 coins, revealing excess returns of 2.7%, 3.3%, 4.1%, and 2.5%, respectively. Additionally, Tzouvanas et al. (2020) also observed that the long-short strategy yielded the highest profitability, with weekly returns of 19.396% (32.004%) for 12 (6) cryptocurrencies.

As the demand for effective analytical methods in cryptocurrency price prediction continues to rise, a multitude of deep-learning models have been developed and introduced. The performance of data prediction using deep learning is significantly influenced by user-defined model settings, referred to as hyperparameters (Kin & Sung, 2022). Hyperparameter optimisation, or hyperparameter tuning, represents a critical phase in the training of machine learning models, directly impacting their performance (Nakisa et al., 2018). Various optimisation algorithms have been proposed to identify these hyperparameters, including Genetic Algorithms, Bayesian Optimization, Randomized Grid search, and Grid search (Chan & Treleaven, 2015). Among these options, random search is an algorithm that autonomously selects values for each parameter using a probabilistic distribution (Chan & Treleaven, 2015).

Grid search is a method that systematically explores a predefined section of the hyperparameter space associated with the specific algorithm comprehensively (Chan & Treleaven, 2015).

Unlike random search, which can be time-consuming, *Grid search* is widely employed for comprehensively exploring specific parameter values within a model. Many research studies favour this method due to its simplicity compared to alternative techniques. For instance, in their study on predicting Bitcoin's daily closing price, Rostami et al. (2021) utilised the Grid search method to yield superior performance with lower errors. Similarly, Fadil et al. (2021) employed the Grid search Method to determine optimal parameters for Support Vector Regression. However, it's worth noting that this approach may be less suitable when dealing with many hyperparameters, and its rigidity can limit its ability to achieve higher accuracy.

The literature review reveals a growing body of research on the multifaceted nature of cryptocurrency investments and trading strategies. While numerous factors have been identified as influential in cryptocurrency returns, the debate surrounding the most effective factor model for the cryptocurrency market persists. The extant literature underscores the significance of portfolio management based on these factors and trading strategies, particularly the Buy-Hold and Long-Short strategies. However, the question of whether a portfolio constructed using multiple factors can offer better annual returns with reduced risks compared to a single-factor portfolio remains unanswered. Additionally, in the dynamic and volatile cryptocurrency market, it is essential to investigate whether a Long-Short strategy, whether single or multiple-factor-based, can generate abnormal returns while mitigating risks compared to the traditional Buy-Hold strategy. These questions represent critical gaps in the existing knowledge that this dissertation seeks to address, aiming to provide insights into optimizing cryptocurrency portfolio management and trading strategies within this rapidly evolving and relatively unregulated asset class.

Therefore，the two research questions of this research are:

1. Does a multiple-factor Portfolio generate better annual returns while minimising the risks than a single-factor portfolio under the same trading strategy?

2. *Does a single or multiple-factor portfolio using a Long-short strategy generate abnormal returns while minimising the risks compared to a Buy-Hold strategy?*

3. METHODOLOGY

This chapter begins with the definitions and descriptions of proprietary terms, factors and the long-short strategy involved in constructing the model. Subsequently, it introduces the specific steps and rules for cryptocurrency selection and how the model is constructed. As model backtesting or forecasting requires confirmation of factor parameters, this study also elaborates on how machine learning techniques are employed to determine the optimal combination of hyper-parameters for a given model, specifically through Grid search and creating a list of values for each factor. Finally, this research defines and describes the metrics used for portfolio performance evaluation. Additionally, it presents information regarding data and the foundational Python research setup indicators.

3.1 General Definitions and Abbreviation

The below indexes will be utilised throughout this written work:

t = a specific interval in time

i = a specific cryptocurrency

* Offset means a defined period; different offset means the different period

- **The offset returns ($r_{i,t}$) :** obtained as a ratio of the cryptocurrency prices at the end of the previous offset ($p_{i,t-1}$), the cryptocurrency price at the end of the current offset

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}} \text{.......... ...... 1)}$$

- **The portfolio return ($r_{portfolio}$) :** The calculation involves using the compounded annual growth rate (CAGR) to determine the performance of the created Portfolio. It measures the growth of an initial investment (IV) of one unit to its final value (FV) over the period spanning from September 1, 2021, to September 1, 2023, for the Portfolio.

$$r_{portfolio} = \left(\frac{IV}{FV}\right)^{(\frac{1}{3})} - 1 \ldots\ldots\ldots\ldots 2)$$

- **The market return ($r_{m,t}$):** obtained as the offset returns ($r_{i,t}$) of the Index. Bitcoin is the leader in the cryptocurrency market, so Bitcoin price and market performance are often used as an Index for the entire market. Bitcoin price indices, such as Bianca's BTC Index, can be used to track general market trends.

- **Risk-free rate:** This research selected the yield on the benchmark 10-year U.S Treasury yield as the risk-free rate, which is 4.72% at 2023/09 (Bloomberg, 2023)

3.2 Select Factor and Technical Indicators

Following Feng et al. (2020) and, Liu et al. (20222), Jermann (2021), this research took two factors of momentum and Volume into the study, which then momentum indicators suggested by Davies (2015) combining Bollinger bands with CCI, as well as the Volume are considered.

- **Commodity Channel Index (CCI):** a momentum indicator determining whether a trading instrument may be oversold or overbought (Maitah et al., 2016). In most cases, the CCI (Commodity et al.) indicator should ideally fall within the range of -100 to +100. When it deviates from this range, it indicates overbought or oversold conditions. The formula of CCI is as follows:

$$TP = \frac{(P_{Max} + P_{Min} + P_{close})}{3} \ldots\ldots.3)$$

$$MA = \frac{Sum(Close, N)}{N} \ldots\ldots\ldots\ldots.4)$$

$$ATP = SMA(TP, N) \ldots\ldots\ldots\ldots\ldots\ldots.5)$$

$$MD = MAD_N(TP) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.6)$$

$$CCI = \frac{TP - ATP}{0.015 * MD} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.7)$$

[1]

- **Volume:** the total number of shares or contracts exchanged for a particular security. A lower volume value in the cryptocurrency market denotes fewer recent transactions. Additionally, it demonstrates how little this coin is worth on the market. Coins with a lower market capitalisation are more susceptible to price changes, which can lead to greater profits. The mathematical equation is:

Volume = Number of Shares (or Contracts) Traded

- **Boll_Count:** Bollinger Bands technical analysis tool is used to access price volatility and identify potential buy or sell signals. The formula of Bollinger band is:

---

[1] 'TP' refers to 'Typical Price,' which denotes the arithmetic average of the highest, lowest, and closing prices for a given day.
'ATP' represents 'Average Typical Price,' representing TP's N-day simple moving average.
'AD' represents 'Absolute Deviation,' which refers to the absolute difference between TP for each day and the ATP calculated over a specified period.
'MD' represents 'Mean Deviation,' which is the average of these absolute deviations (AD).

$$BOLD = MA(TP,n) - m*\sigma[TP,n] \quad \text{.......... 9)}$$

Where

$$BOLU = Upper\ Bollinger\ Band \quad \text{.......... 10)}$$

$$BOLD = Lower\ Bollinger\ Band \quad \text{.......... 11)}$$

$$MA = Moving\ \ Average \quad \text{.......... 12)}$$

$$TP(typical\ price) = (High + Low + Close)/3 \quad \text{.......... 13)}$$

$$n = Number\ of\ days\ in\ smoothing\ period(typically 20) \quad \text{.......... 14)}$$

$$m = Number\ of\ Standard\ Deviations(typically 2) \quad \text{.......... 15)}$$

$$\sigma[TP,n] = Standard\ Deviation\ Over\ Last\ n\ Period\ of\ TP \quad \text{..... 16)}$$

Boll_Count is used to calculate the number of times a financial asset's price crosses the upper or lower Bollinger Bands within a specified time frame.

3.3 Portfolio Construction Under Long-short Strategy

Several long-short portfolios are construed from using single-factor, two-factors, and three-factors. The Portfolio was constructed based on the following setting:

3.3.1 Single-Factor Portfolios

The single-factor portfolios, constructed using signals from a sole component, represent the more rudimentary form of portfolios. An initial ranking process is conducted to determine the decision rule for selecting cryptocurrencies to go long or short. The ranking system assigns a rank (Rankfactor, i,t) to each cryptocurrency, taking into account the various factors, the ranking process involves assigning ranks according to the magnitude of their respective values, which are the product value of average price and value of hyper-parameters.(Sample results as shown in Figure 1), with the highest value receiving the first rank and the lowest value receiving the final rank while considering a single offset at a time.

candle_begin_time	offset	symbol	avg_price	Next_avg_price	Cci[3]	Cci[5]	Volume_[3]	Volume_[5]
2022/10/18 0:00	0	BTC-USDT	19550.47889	19545.13609	0.731556756	0.660127156	806187323.5	1239256715
2022/10/18 1:00	1	BTC-USDT	19581.97513	19622.97225	0.66551267	0.816084346	936020111.3	1289269927
2022/10/18 2:00	2	BTC-USDT	19526.0408	19657.66189	1.123287948	0.977172478	656331160.8	1317025585
2022/10/18 3:00	3	BTC-USDT	19488.01476	19509.25405	-0.390318968	0.24430568	724496332.2	1382990937
......	......	......	......	......	......	......	......	......
2022/10/18 0:00	0	ETH-USDT	1331.333099	1331.532821	0.732302488	0.950863491	635264142.2	1044956512
2022/10/18 1:00	1	ETH-USDT	1337.407738	1334.917245	0.723574105	0.967171484	878290402.4	1253707317
2022/10/18 2:00	2	ETH-USDT	1332.144446	1336.742603	0.882070319	0.978876803	710761203.2	1218257645
2022/10/18 3:00	3	ETH-USDT	1327.471212	1319.22213	-0.03563317	0.714714728	742752755.6	1234756454
......	......	......	......	......	......	......	......	......

FIGURE 1: Sample Data That Calculated for the Rank

$$rank_{factor,i,t} =$$

$$\{1 \mid \mathrm{factor}_{i,t} = \text{highest}; 2 \mid \mathrm{factor}_{i,t} = \text{second highest}; \ldots; n \mid \mathrm{factor}_{i,t} = \text{nth highest}\}$$

In constructing a portfolio, constructing single-factor portfolios at a single offset involves investing in equities according to their ranks. It acquires long-short portfolios for each specific factor at a single offset by longing the coins that ranked first while shorting the coins that ranked last. As a result, the $r_{i,t}$ for each offset by both long and short positions will be obtained.

For example, to select CCI as the Single-Factor to construct a long-short strategic Portfolio, it first set up a ranking system calculating the values of CCI of different currencies under the same parameter and put them in order from the highest value to the lowest based on the previous performance. Then, long the coin ranked first, while short the coin ranked bottom in the current offset. Based on the selection, it can get a coin selection list for each 6 hour as required. Also, the return as the long-short position for the selected coin in an offset can be calculated. Then, the annual return and accumulated net value can also be calculated.

3.3.2 Equally Weighted Two-factor and Three-factor Portfolios

The construction of equally weighted 2-factors and three-factor portfolios follows a progression from single-factor portfolios.

The weights assigned to the N-factor portfolio (W_N, i, t) are derived from the composition of weights assigned to the N-factors portfolios. The weights indicate how much of each single-factor portfolio is included in the composition. If 2 factors included, the weight is 1/2 for each, and if there includes 3 factors, the weight if 1/3.

$$W_{multifactor\,i,t} = \frac{1}{N} * \sum_{factor} \left(W_{factor,i,t}\right) \text{ ....18)}$$

For factors 1=(CCI, VOLUME), For factors 2=(VOLUME, BOLL_COUNT), and For factors 3=(CCI_COUNT), For factors 4=(CCI, VOLUME, BOLL_COUNT)

Portfolios are constructed by summarising the coins in long-short positions in each offset over the time horizon from September 20, 2020, to September 20, 2023. The rule is the same as indicated in the Single-factor portfolios: Taking long positions in cryptocurrencies ranked first and short positions ranked last.

3.3.3 Portfolio and Hyper-parameter Based on Grid search for Model Tuning

To account for variations in the predictive strength of each factor, distinct models are constructed with the factors (CCI, VOLUME, BOLL_COUNT) serving as independent variables, while the dependent variable, return ($r_{i,t}$), is examined separately in each model. The factor coefficients ($bcc_{i,t}$, $bvolume_{i,t}$, $bboll\_count_{i,t}$) then function as the base for the return estimates ($r_{i,t}$). The models under Single-Factor and multiple-factor are as follows:

$$R^{e}_{i,t,} = b_0 + b_{cci,c} * CCI \quad \text{......19)}$$

$$R^{e}_{i,t,} = b_0 + b_{volume,t} * Volume \quad \text{......20)}$$

$$R^{e}_{i,t,} = b_0 + b_{boll\_count} * Boll\_count \quad \text{......21)}$$

$$R^{e}_{i,t,} = b_0 + b_{cci,c} * CCI + b_{volume,t} * Volume \quad \text{......22)}$$

$$R^{e}_{i,t,} = b_0 + b_{cci,c} * CCI + b_{boll\_count} * Boll\_count \quad \text{......23)}$$

$$R^{e}_{i,t,} = b_0 + b_{volume,t} * Volume + b_{boll\_count} * Boll\_count \quad \text{......24)}$$

$$R^{e}_{i,t,} = b_0 + b_{cci,c} * CCI + b_{volume,t} * Volume + b_{boll\_count} * Boll\_count \quad \text{......25)}$$

- **Model Tuning**

A machine learning model is equipped with multiple hyperparameters that impact the network's architecture, such as the number of hidden units and the training process, including the optimiser selection. The model's performance can exhibit notable variations based on the particular set of hyperparameters chosen. This research employed the Grid search method to discover the most suitable hyperparameters for our cryptocurrency price dataset. This procedure systematically explored all possible hyperparameter combinations, guided by the dataset.

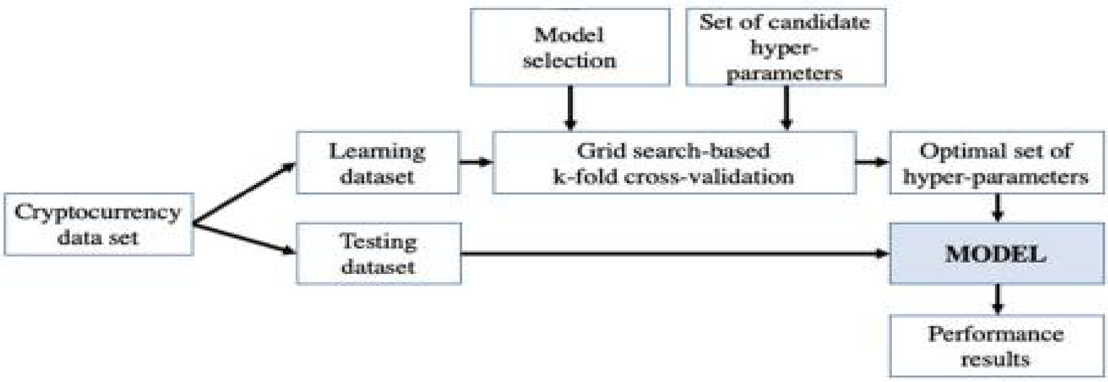

FIGURE 2: Model Tuning processes (Source from: Kwon et al., 2019, P.700)

Figure 1 illustrates the comprehensive process of identifying the optimal set of hyperparameters and validating the models with these optimal settings. The cryptocurrency price dataset is initially divided into training and testing data subsets. Subsequently, a cross-validation procedure based on Grid search is executed. This cross-validation process is iterated K times, and the outcomes are averaged to determine a single set of optimal hyperparameters. The chosen model is then retrained using these optimal hyperparameters, and its performance is subsequently assessed using the test data. The specific performance evaluation metrics will be elaborated upon in the following section.

It's worth noting that the effectiveness of data prediction hinges on appropriately configuring the hyperparameters. As highlighted by Larochelle et al. (2007), testers need to specify either a list of values to test or a range specification for each hyperparameter. Examples include '5 values evenly spaced between 30 and 80' or '8 values logarithmically spaced between 1 and 1000'."

In this research, it sets hyper-parameter values in a non-continuous or non-regularly spaced manner, and the set value are as following:

set a list of values for each factor to find a given model's best hyper-parameter combination. They are:

Boll_Count: n_list = [3, 5, 8, 13, 21, 34, 55, 89, 144]

CCI: n_list = [3, 5, 8, 13, 21, 34, 55, 89, 144]

Volume: n_list = [3, 5, 8, 13, 21, 34, 55, 89, 144]

The reasons of this setting are: Firstly, setting a non-linear sequence allows for a balance between a comprehensive search and computational efficiency. It may not be necessary to explore every possible hyper-parameter value, especially if some values are very similar in terms of performance. Non-regularly spaced values enable efficient coverage of a broad range while focusing on significant points. Secondly, Irregularly spaced values help assess the sensitivity of the model to hyper-parameter changes. This can reveal whether small changes in specific hyper-parameters have a significant impact on model performance, aiding in a better understanding of the model's behavior. Thirdly, the choice of non-continuous or non-regularly spaced values in hyper-parameter tuning is benefit for computational efficiency, which allows for a more effective search for the best hyper-parameter combination.

3.4 Portfolios' Performance Evaluation

When formulating factor portfolios, the model utilizes readily accessible data, encompassing details such as the opening price, highest price, lowest price, closing price, trading volume, and market capitalization of each cryptocurrency. Various performance indicators and ratios are employed to assess the performance of the portfolios created based on individual factors or combinations of factors. The computation of all these performance evaluation metrics is carried out using the Python programming language.

- **Accumulated Net Value:** The total or cumulative value of an investment or Portfolio over a specified period.

- **Annualized Returns:** This term denotes the expected rate of return over a one-year investment horizon.

$$Annualized\ Rrturns = \left(\frac{P_{end}}{P_{start}}\right)^{365/n} - 1 ....26)$$ [2]

- **Annualized standard deviation:** The standard deviation is expressed as a percentage and reflects the variability in the investment returns.

- **Sharp Ratio:** aim to quantify a return adjusted for risk. It achieves this by comparing the difference between the annualised portfolio return($R_{Portfolio}$) and the annualized risk-free return (r_f) to the portfolio's annualized standard deviation ($\sigma_{portfolio}$). $\bar{r}_p$ represents the portfolio's mean (average) return rate during the backtesting period (Sharpe, 1966).

$$Sharpratio_{portfolio} = \frac{r_{portfolio} - r_f}{\sigma_{portfolio}} .... .27)$$

$$Volatility = \sigma_{portfolio} = \sqrt{\frac{365}{n} \sum_{i=1}^{n} (r_p - \bar{r}_p)} .... 28)$$

- **Max draw-down:** The maximum draw-down is when the price suddenly drops to its lowest point within a specific period.

$$MaxDrawdown = \max(1 - \frac{P_x}{P_y}).........29)$$ [3]

- **The Information Ratio (IR):** Assesses how a portfolio performs relative to its

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[2] The choice of 'n' as the number of backtesting trading days is based on 365 days, given that the cryptocurrency market operates throughout the year.
'Pstart' and 'Pend' respectively represent the net values at the beginning and end of the portfolio.

[3] Px and Py represent the total value of assets (cryptocurrencies and cash) held at some point each day, with y being more significant than x.

benchmark by considering the standard deviation of the return ($\sigma_{rportfolio} - r_{benchmark}$) differences between the portfolio and the benchmark ($r_{benchmark}$).

$$IR_{portfolio} = \frac{r_{portfolio} - r_{benchmark}}{\sigma_{r_{portfolio}} - r_{benchmark}} \text{..........30)}$$

Benchmark return: This denotes the reference standard annualised rate of return. This research calculates benchmark returns using a simple buy-and-hold portfolio for Bitcoin.

$$Benchmark\ \mathrm{Re}turns = (\frac{M_{end}}{M_{start}})^{365/n} - 1 \text{...........31)}$$ [4]

- **Alpha & Beta:** Alpha is a metric used to measure the excess return generated by a portfolio or asset relative to its level of risk. Where σ_{m2} represents the variance of market portfolio returns, beta represents the returns within a portfolio that are correlated with market fluctuations, measuring the Portfolio's sensitivity to market volatility.

$$Alpha = \partial = R_P - r_f - \beta(R_m - r_f) \text{.........31)}$$

$$Beta = \frac{Cov(R_m, R_f)}{\sigma_m^2} \text{............................32)}$$

3.5 Data and Configuration Setting

The used sample consists of all currently traded cryptocurrencies in the Binance platform due to the consideration of market significance, diversity, computational, and

4 The benchmark is set as a Bitcoin portfolio.

market capitalization threshold. Thus, a total of 264 coins are included. The list of the names of coin can be seen in Appendix TABLE 8.

All the data that retrieved from the Binance cryptocurrency platform covering the period from September 1, 2020, to September 1, 2023 because the cryptocurrency market is known for its rapid evolution and changing dynamics, by selecting a time frame that spans several years, it can potentially capture different market conditions, including bull and bear markets, regulatory changes, and technological advancements.

The number of coins that are selected for each offset is 1 for long while 1 for short due to the consideration of analytical Simplicity, managing one coin for each offset simplifies the execution and management of the strategy, especially when dealing with a large number of coins. It can be computationally more efficient.

Coin selection is re-balanced every 6 hours, which considers the high volatility of cryptocurrency market. Prices can experience significant fluctuations within short time intervals. Rebalancing every 6 hours allows researchers to capture and respond to rapid price changes, ensuring that the portfolio remains aligned with the intended strategy.

Regarding the leverage, the neutral strategy is particularly volatile. It is not recommended to open leverage twice because it is easy to hit a position due to a draw-down of about 40%-50%.

The offset is set as 0, that means during each 6 hours that starts from 0:00 am, coins are selected only once. Coins are only selected once at 0:00 am, 6:00am, 12:00pm, 18:00 pm, while they were not selected at any other offset time, such as selected at 1:00 am, 7:00 am, etc. The reasons is that this research focuses on capturing relative price movements and aims to generate returns based on the assets' relative performance, not on the overall market direction. The more offset is set, the returns will be smoother because the risk is evenly distributed due to the equal allocation of capital for each offset."

TABLE 1 summarized the configuration setting for this research.

Name	**Setting**
Period frame	2020-09-20 to 2023-09-20
Filtering and Number of coins	1
Holding period	6H
Leverage	1 time, Long 50%, Short 50%
Offset	0
Initial Capital	100

TABLE 1: Configuration Setting

4. Exploration and Result

This chapter starts with the correlation analysis among the Three-Factors and then analyses the portfolios under each single or multiple factor. Finally, a table summarised with the research questions' results is discussed.

TABLE 2 summarized the best 3 results of each factor model with optimal hyperparameters regarding annual return

Model	**FACTORS WITH SET HYP**	**Name**
Single-Factor Model	*Boll_Count* (144)	*Portfolio 1*
	'Volume (21)	*Portfolio 2*
	'CCI (34)	*Portfolio 3*
Two factor Model	CCI(55) Volume (21)	*Portfolio 4*
	Boll_Count (144) CCI(89)	*Portfolio 5*
	Boll_Count (144) *Volume (13)*	*Portfolio 6*
Three Factor Model	*Boll_Count* (144) CCI(89) *Volume (13)*	*Portfolio 7*
	Boll_Count (34) CCI(89) Volume (21)	*Portfolio 8*
	Boll_Count (144) *Volume (13)* CCI (55)	*Portfolio 9*

TABLE 2: The Best 3 results of Each Factor Model that with Optimal Hyperparameters Regarding Annual Return

4.1 Factor Correlation Analysis

This research first examines the correlation between each factor. It employed the scipy. Stats. Spearman function to compute the Spearman rank correlation coefficients between pairs of factors, yielding the following results:

	Boll_count	**CCI**	**Volume**
Boll_count	1	0.14	0.63
CCI	0.14	1	0.55
Volume	0.63	0.55	1

TABLE 3: Spearman Correlation Between Factors

Coefficient close 1 indicates a strong positive correlation between two variables, implying that the other tends to increase as one variable increases, resulting in a positive rank relationship. Examining the results, the Spearman rank relationship between Boll_Count and CCI does not exhibit a robust correlation. Their ranks have no evident monotonic relationship, suggesting a relatively weak association. Conversely, the Spearman correlation is 0.55 between CCI and Volume and 0.63 between Volume and Boll_count, suggesting moderate to strong positive correlations. That means when the value of CCI increases, Volume also tends to increase. Similarly, when the value of Volume increases, Boll_Count also tends to increase, with a relatively strong positive rank relationship.

4.2 Single-Factor Portfolio

In constructing a portfolio, constructing single-factor portfolios at a single offset involves investing in equities according to their ranks. A total of 50 sets of hyperparameter groups were obtained through the hyperparameter tuning using Grid search by Python.

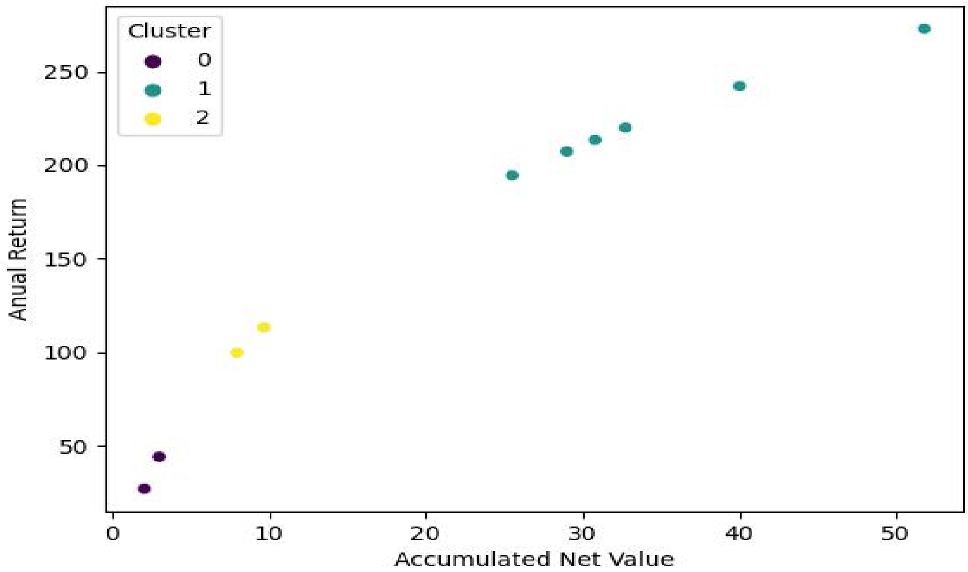

FIGURE 3: Cluster Plot of The Top 10 Single-Factor Model of Annual Return

Figure 2 describes a clustering plot of the top 10 data points. It can be observed that among these 10 data points where the Accumulated Net Value exceeds 25 and the Annual Return exceeds 200%, 6 data points meet these criteria. Notably, the parameter value of Boll_Count had significantly impacts the cumulative net value and annualised returns. Among the top 6 factors, 5 of them belong to the "Boll_Count" category, with parameter value of 144. Additionally, one of the factors is "CCI", with parameter value of 34.

The Figure 3and Figure 4 shows the sharp ratios, standard deviations, annual return of the 3 portfolios. Firstly, Portfolio 1 exhibited the highest Accumulated Net Value and Annual Return among the three single-factor models. Its accumulated net value reached 44.61, with an annual return of 254.77%. Although the annual return rate is relatively high, its standard deviation is 48, and the Sharpe ratio is -0.08%. These results suggest that the Portfolio under this single-factor model may be assuming a relatively high level of risk while generating low average excess returns, even falling below the risk-free rate. This indicates the need to reassess and optimise the investment strategy to ensure better risk-adjusted performance. The Portfolio under this single-factor model experienced the highest draw-down from November 9, 2022, at 21:00:00 to August 10, 2023, at 09:00:00, with a draw-down ratio as high as -86.51%. However, the return-to-draw-down ratio for this Portfolio was the highest among the three single-factor combinations at 2.94.

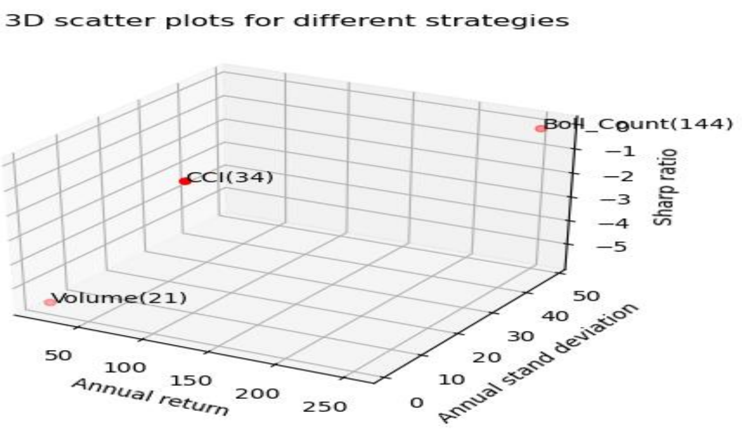

FIGURE 4: 3D Scatter For The TOP 3 Single-Factor Model of Annual Return

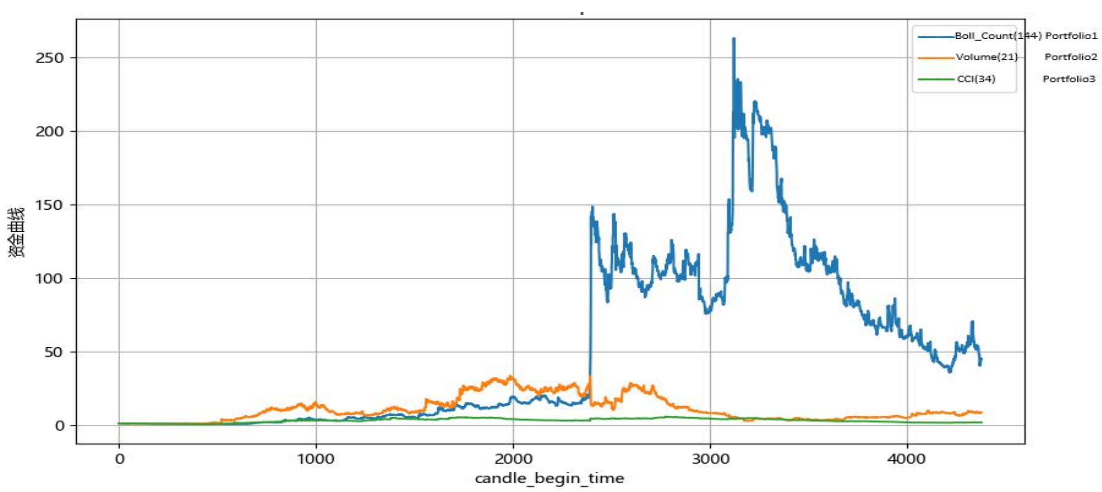

FIGURE 5: Return Curve For The TOP 3 Single-Factor Model of Annual Return

Secondly, considering the Portfolio 2, it also exhibited a negative Sharpe ratio, with a relatively high standard deviation, suggesting a potential exposure to higher volatility and risk without commensurate returns to support such risk. This Portfolio also experienced a draw-down of -75.45% from August 16, 2022, at 22:00:00 to August 13, 2023, at 10:00:00, with returns barely covering the draw-down.

Lastly, Portfolio 3 had an annual return rate of 102.18% and a standard deviation of 8.4365, with a Sharpe ratio also in negative territory at 0.5369%. This result indicates that while the Portfolio's annual return rate is high, its excess return seems insufficient relative to the risk assumed. This may be attributed to the high standard deviation, indicating significant portfolio volatility and risk. Unlike the first two combinations, the draw-downs for this single-factor model were concentrated mainly in late 2022 and 2023, with the draw-down period occurring primarily from February to November 2022.

Considering the highest cumulative net value and annualised returns, Portfolio 1 at various offsets is decisive but may carry substantial risk. Portfolio 3 at offset 0 also performed well in cumulative net value and annualised returns but exhibited high risk. As single-factor portfolios appear highly volatile, further optimisation is studied to improve risk-adjusted performance by combining each factor.

4.3 Two Factors Portfolio Performance

In constructing the model, two pairs of factors were combined. Portfolios were created by summarising coins in long-short positions for each offset over the time horizon from September 20, 2021, to September 20, 2023. A total of 84 sets of hyperparameter groups were obtained through the hyperparameter tuning using Grid search by Python.

Below, this research presents the three optimal parameters and model results for each two-factor pair.

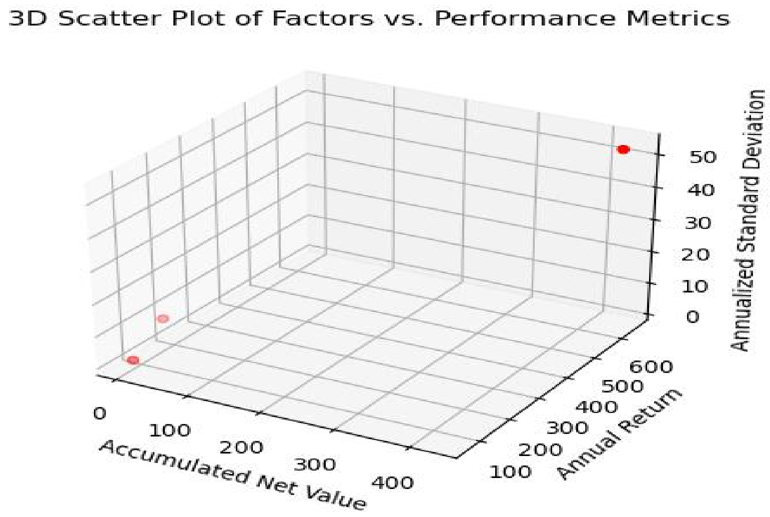

FIGURE 6: 3D Scatter For The TOP 3 Two Factor Model of Annual Return

From the result, it is evident that the Portfolio 4 has shown exceptional performance in terms of cumulative net value and annual return, reaching values as high as 429.6% and 654.90%, respectively. However, this comes with a relatively high annualised standard deviation of 52.440.

The Portfolio 5 has also demonstrated a high annual return of 141.24%, but with a relatively lower annualised standard deviation of 10.67484.

The Portfolio 6 excels in terms of annualised standard deviation at 1.74%, but its annual return is relatively lower at 66.71%. Regarding the risk-return trade-off for these combinations, the third combination has the highest Sharpe ratio at 2.6573%, indicating that it maintains a higher return while assuming lower risk. The first combination's Sharpe ratio is 0.1344%, suggesting that its return is average relative to its risk.

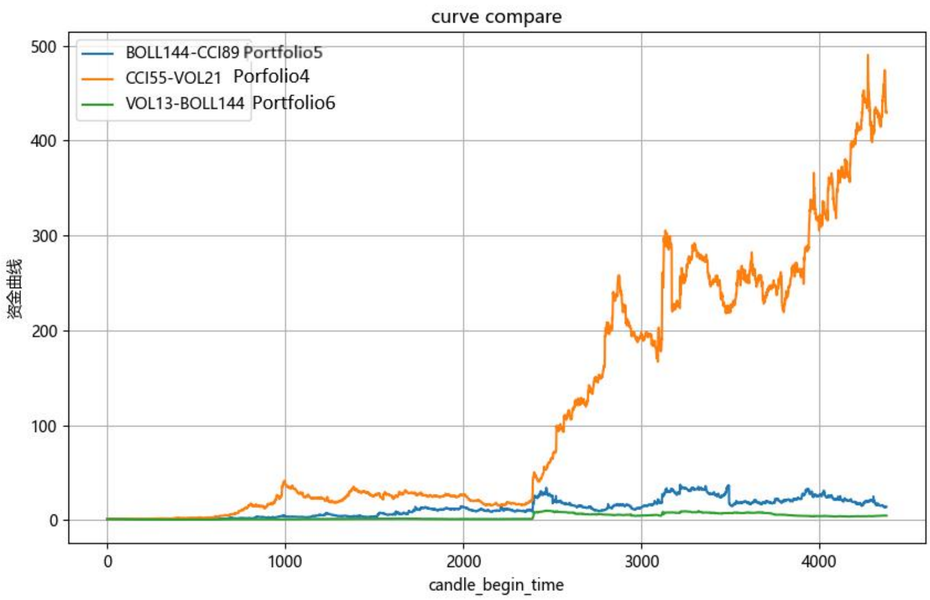

FIGURE 7: Return Curve For The TOP 3 Two Factor Model of Annual Return

Portfolio 4 exhibits a gradually increasing growth trend. Its maximum draw-down primarily occurred from May 27, 2021, to March 24, 2022. The overall annualised return-to-draw-down ratio for Model One is 10.24. During the period of the maximum draw-down in *Portfolio 4*, the price of Bitcoin, which is an Index of the cryptocurrency market, also experienced a drop-down from \$64,829 to \$29,413, with a decline of over 54% from April 14, 2021, to July 20, 2021 (See Figure 7). It then exhibited a sideways downward trend. The CCI and Volume indicators are typically used to identify trending markets. Price fluctuations are relatively small in sideways markets, and no clear directional trend exists. In such cases, CCI and Volume indicators may generate false signals or be less valuable.

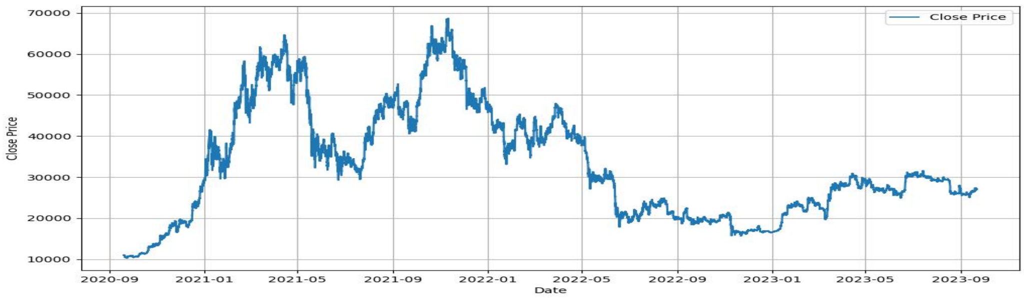

FIGURE 8: Close Price of Bitcoin from 2020-09-20 to 2023-09-20

Compared to *Portfolio 4*, *Portfolio 5* and *Portfolio 6* experience oscillation periods, with both models having their maximum draw-downs concentrated within 2-3 months. These periods are from May 25, 2021, to October 27, 2021, and from October 6, 2020, to December 27, 2020. The former maximum draw-down period largely coincides with a sharp Bitcoin price decline. This may be because CCI and Boll_Count indicators may not provide sufficient warnings or signals during market sentiment-induced large price and volume fluctuations.

4.4 Three-Factor Portfolio Performance

Three-Factors are used to build the model. Portfolios are constructed by summarising the coins in long-short positions in each offset over the time horizon from 20-SEP-2021 to 20-SEP-2023. Through the hyperparameter tuning using Grid search by Python, 144 sets of hyperparameter groups were obtained.

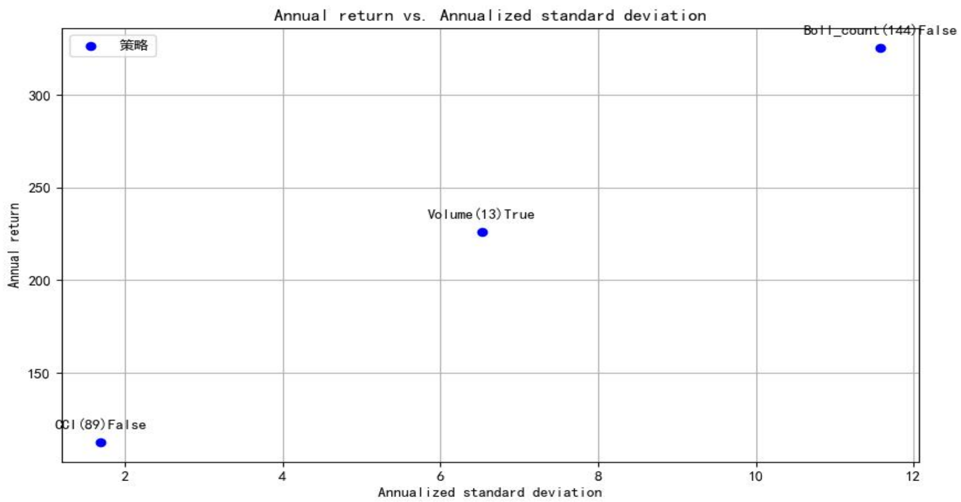

FIGURE 9: Scatter For The TOP 3 Three-Factor Model of Annual Return

Portfolio 7 exhibits the highest cumulative net value and annualised return, which are 76.98 and 25.39%, respectively. Its maximum draw-down is 54.72%, resulting in an annual return-to-draw-down ratio 5.95. From the annualised standard deviation and Sharpe ratio perspectives, this combination indicates relatively lower returns relative to the risk taken.

On the other hand, *Portfolio 9* has a lower annualised standard deviation of 1.69% and a higher Sharpe ratio of 2.6506%. However, its annualised return is relatively lower. This combination is more suitable for investors who prioritise risk control.

Furthermore, *Portfolio 8* exhibits higher annualised returns and a favourable Sharpe ratio while maintaining a relatively lower annualised standard deviation. It demonstrates strong performance with relatively manageable risk, making it suitable for investors seeking a balanced approach.

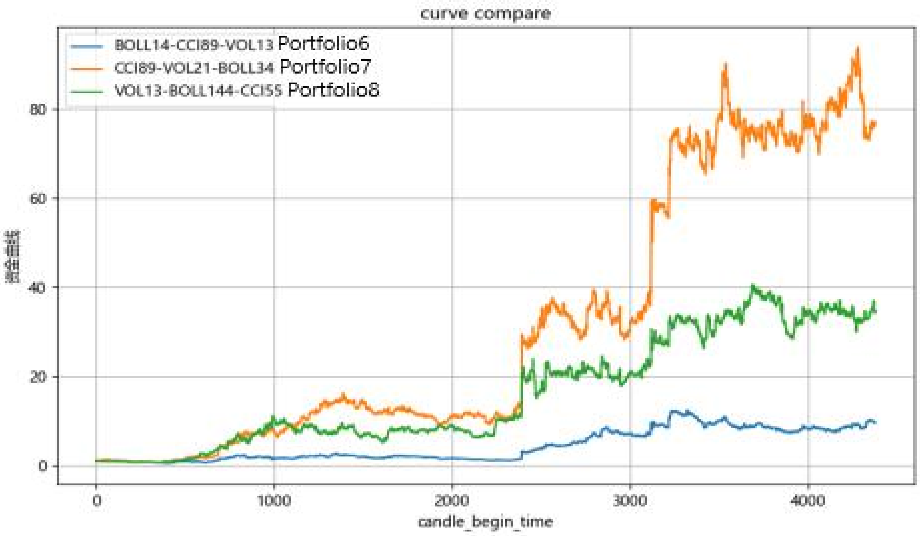

FIGURE 10: Return Curve For The TOP 3 Three-Factor Model of Annual Return

FIGURE 9 shows that over time, the capital return of the three-factor model is smoother compared to the two-factor and single-factor models, and all three models show an upward trend. The draw-down periods for all three models are relatively short, and the draw-down ratios are all kept around 50%. This result indicates that under different market conditions, the three-factor strategy can more effectively manage risk reduce the volatility brought about by a Single-Factor, and the combination of the three-factor strategy can better adapt to changing market conditions.

4.5 Benchmark Portfolio Analysis—Bitcoin

Numerous studies have explored the concept of portfolio diversification, often utilizing Bitcoin as the sole benchmark (Borri, 2019; Brauneis & Mestel, 2019). This research also takes buy and hold Bitcoin as the benchmark Portfolio from 2020-09-20 to 2023-09-30.

		Accu, Net Value	Annual return	Stand.Dev.	Sharp Ratio	Max draw-down
Index	The market portfolio of Bitcoin	248.121	7.8%	0.0171	25.11%	-77.19%

TABLE 4: Benchmark Portfolio Analysis

The calculation shows that the Accumulate Net Value reached 248.121, and the annual return is 7.8%. The standard deviation of the holding Portfolio is 0.0171, and the sharp ratio is 25.11%, which is a high value, indicating a good performance that the return obtained per unit of risk is relatively high. The Max draw-down is 77%, from April 14, 2021—and the whole retracement period started from 2021 OCT to 2022 SEP.

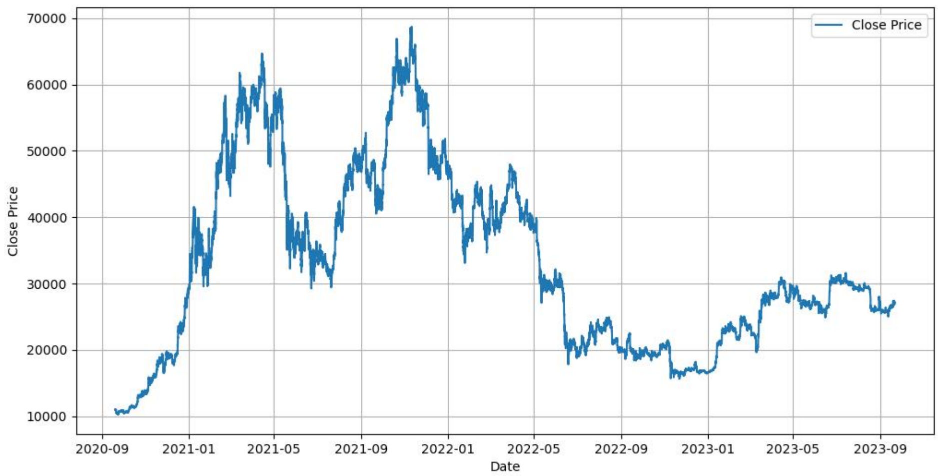

FIGURE 8:Close Price of Bitcoin from 2020-09-20 to 2023-09-20

4.6 Comparison and Discussion

This study explores the impact of different indicator factor models on the performance of portfolios under the same trading strategy within the same time frame.

		Accu. Net Value	Annual Return	Stand. Dev.	Sharp Ratio	Max draw-down	Information Ratio	Alpha	Beta
Index	The market portfolio of Bitcoin	248.121	7.8%	0.0171	25.11%	-77.19%			
Risk-free			4.72%						
Single-Factor Model	*Boll_Count* (144)	44.61	254.77%	48.43	-0.073%	-86.51%	-1.985%	0.0014	-0.0004
	'Volume (21)	1.62	17.44%	0.83	-5.70%	-75.45%	-2.005%	0.0010	0.00086
	'CCI (34)	8.26	0.82%	8.44	-0.54%	-92.03%	-2.058%	0.00020	-0.0001
Two factor Model	CCI(5) 'Volume (21)	429.6	654.90%	52.44	0.13%	-63.97%	-1.968%	0.00163	-4.1703
	Boll_Count (144) CCI(89)	14.03	141.24%	10.67	-0.41%	-72.40%	-1.997%	0.00122	-0.00015
	Boll_Count (144) '*Volume (13)*	4.63	66.71%	1.74	2.66%	-67.92%	-2.033%	0.00064	-0.00037
Three Factor Model	*Boll_Count* (144) CCI(89) *Volume (13)*	76.98	325.39%	11.57	0.23%	-54.72%	-1.976%	0.00119	-0.00017
	Boll_Count (34) CCI(89) 'Volume (21)	34.67	226.06%	6.53	0.58%	-54.60%	-1.982%	0.00108	-0.00038
	Boll_Count (144) '*Volume (13)* CCI (55)	9.59	112.50%	1.69	2.65%	-65.92%	-2.025%	0.00073	-0.00011

TABLE 5: Summarized Data For All Models Studied in This Research

First, this research analyses the results moved from a single-factor model that only uses *'Boll_count'* to the two-factor combinations model of *'Boll_Count with CCI'* and *'Boll_Count with Volume'*. With the move, the values of Accumulated Net Value, Annual Return, Standard Deviation, and Maximum Draw-down all decrease. Commonly, combining two different strategic factors can reduce the risk associated with a Single-Factor, enhance the Portfolio's robustness, and diversify risks under specific market conditions. However, the Portfolio 5 did not improve the model's performance, as the Sharp ratio dropped significantly from -0.073% to -0.41%, indicating unfavourable risk/return ratio. Correlation analysis suggests that *'Boll_Count'* has a fragile relationship with *'CCI'*, indicating that combining unrelated factors may increase risk and reduce annual returns in a model. In contrast, although the annual returns and accumulated net value were reduced in *Portfolio 6*, it effectively reduces portfolio volatility and risk exposure. Moreover, correlation analysis finds a strong positive correlation between *'Boll_count'* and *'Volume'*, indicating that combining positively correlated factors can optimise risk exposure, even though it may reduce annual returns.

Next, this research analyses the transition from a single-factor model that only includes *'CCI'* to the two-factor combined model of *'Boll_count with CCI'* and *'Volume with CCI'*. Moving from a single-factor to two-factor combinations, the values of Accumulated Net Value, Annual Return, Standard Deviation, and Sharp Ratio all increase while the Maximum Draw-down ratio decreases. This result suggests that combining weakly correlated or uncorrelated factors may increase annual returns while reducing portfolio risk.

Moving from two-factor model to three-factor combined model, the most representative ones are Portfolio 6 to Portfolio 7 and Portfolio 9. With the new factor included, Accumulated Net Value and Annual Return increase while Maximum Draw-down decreases. However, the addition of 'CCI' with different parameters has a significant impact on risk control and annual return. For example, adding 'CCI(89)' increases both annual returns and risk, decreasing the Sharp ratio, indicating that the investment performance did not meet expectations or that the risk increased. On the other hand, adding 'CCI (55)' maintains the risk level while increasing annual returns.

Finally, this research analysed the benchmark Portfolio of Bitcoin by applying the Buy-Hold strategy. Compared to other single-factor or multiple-factor models, the single-factor Portfolio 3 is the only model whose annual return does not surpass the benchmark buy-hold strategy. This result is because the CCI Single-Factor is very timely responsive, and there are situations or market conditions in which the CCI may not work as effectively or may produce less reliable signals. For example, the CCI can produce numerous false signals in a sideways or range-bound market with no clear trend. The markets with low liquidity, infrequent trading, as well as the sharp and sudden Price gaps and whipsaw Conditions will leads to the failure of the CCI indicator. Also, using the CCI in isolation without considering other indicators or market analysis can be a mistake. This because markets evolve over time, and what works well in one period may not work as effectively in another. The CCI's parameters may need adjustment to adapt to changing market conditions.

Besides, the annual return of *Portfolio 2* needs to be better performed. The reasons why a Single-Factor of Volume does not work can be found in the explanation of Babiak and Dickerson (2022). They highlighted that strategies based on historical trading volume are inherently vulnerable to systemic risk sources and shared factors.. For example, when the market index shows gains on the previous day, This results in a simple strategy that entails taking long positions in low-beta assets and short positions in high-beta assets, thereby introducing a substantial exposure to overall market risk..

Besides, this study also finds that combining factors does not reduce risks and volatility because all model standard deviations are more significant than the benchmark portfolio while the Shape Ratios are smaller. Maximum draw-down is minimised by adding more factors. This phenomenon can be explained by Koutmos (2019), that an elevated volatility regime is linked to increased average returns. However, it is important to highlight that during periods of high volatility, returns may not reliably offset the increased levels of volatility, making investors more vulnerable to tail risks compared to low volatility periods.

5. CONCLUSION AND LIMITATIONS

This research proposed two research questions. For the first question, *"1. Does a multiple-factor portfolio generate better annual returns while minimising the risks than single factor portfolio under the same trading strategy?"*, this research found that combining additional factors into the model has enormous possibilities to increase annual returns. However, it does not help reducing portfolios' volatility and risk exposure. Combining positively correlated factors can optimise risk exposure, even though it may reduce annual returns. Moreover, combining weakly correlated or uncorrelated factors may increase annual returns while reducing portfolio risk.

For the second question, *"2-Does a single or multiple-factor portfolio by using a Long-short strategy generate abnormal returns while minimising the risks than a Buy-Hold strategy?"* Most single or multiple-factor portfolios that use a Long-short strategy have higher annual returns than its benchmarks. However, it has exceptions. Further, combining factors does not lead to reducing risks and volatility below the benchmark portfolio despite multiple-factor decreasing the volatility generally. Moreover, returns may only sometimes compensate investors for the heightened levels of volatility.

Overall, the analysis suggests that the impact of additional factors on portfolio performance and risk can vary significantly depending on the specific factors and their correlations, emphasising the importance of careful factor selection and combination in portfolio optimisation.

There are several limitations of this work.Firstly, a limitation of this study lies in the choice of factors. The study focused on CCI, volume, and Boll_count, all of which are positively correlated. This approach may not capture the full spectrum of potential factors influencing cryptocurrency returns. Future research can address this limitation by including factors that exhibit negative correlations, providing a more comprehensive view of the market dynamics.

Secondly, the study's use of artificially set hyperparameters, such as 3, 5, 8, 13, 21, 34, 55, 89, and 144, for computational efficiency through Grid search is another limitation. While these settings expedited the analysis, the best combination may not have been fully explored. Future work can employ methods like Randomized Grid search to comprehensively evaluate hyperparameters and identify the most optimal settings, thereby enhancing the robustness of the study.

The study's results were found to be sensitive to configuration settings, indicating a limitation in terms of stability and consistency. Researchers should consider this while interpreting the findings. To address this limitation, future research could implement more robust and stable configuration settings that produce less volatile results.

Lastly, the performance evaluation in this study relied on specific indicators such as Accumulated Net Value, annual return, standard deviation, Sharpe ratio, and others. While these are valuable metrics, future research can broaden the scope of performance evaluation by incorporating additional indicators, risk measures, and statistical tests to gain a more comprehensive understanding of the strategies' effectiveness.

In summary, this study provides a solid foundation for cryptocurrency trading strategies, but there is room for improvement and expansion. Addressing these limitations and exploring the suggested areas for future research can enhance the depth and breadth of knowledge in this field.

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7. APPENDIX

TABLE 6: SINGLE-FACTOR MODEL PEFORMANCE

		Accu. Net Value	Annual Return	Stand. Dev.	Sharp Ratio	Max draw-down	Information Ratio	Alpha	Beta
Single-Factor Model	*Boll_Count* (144)	44.61	254.77%	48.43	-0.073%	-86.51%	-1.985%	0.0014	-0.0004
	'Volume (21)	1.62	17.44%	0.83	-5.70%	-75.45%	-2.005%	0.0010	0.00086
	'CCI (34)	8.26	0.82%	8.44	-0.54%	-92.03%	-2.058%	0.00020	-0.0001

TABLE 7: TWO-FACTOR MODEL PEFORMANCE

		Accu. Net Value	Annual Return	Stand. Dev.	Sharp Ratio	Max draw-down	Information Ratio	Alpha	Beta
Two factor Model	CCI(5) 'Volume (21)	429.6	654.90%	52.44	0.13%	-63.97%	-1.968%	0.00163	-4.1703
	Boll_Count (144) CCI(89)	14.03	141.24%	10.67	-0.41%	-72.40%	-1.997%	0.00122	-0.00015
	Boll_Count (144) '*Volume (13)*	4.63	66.71%	1.74	2.66%	-67.92%	-2.033%	0.00064	-0.00037

TABLE 8: THREE-FACTOR MODEL PEFORMANCE

		Accu. Net	Annual Return	Stand. Dev.	Sharp Ratio	Max draw-do	Informa tion	Alpha	Beta

		Value				wn	Ratio		
Three Factor Model	*Boll_Count* (144) CCI(89) *Volume (13)*	76.98	325.39%	11.57	0.23%	-54.72%	-1.976%	0.00119	-0.00017
	Boll_Count (34) CCI(89) 'Volume (21)	34.67	226.06%	6.53	0.58%	-54.60%	-1.982%	0.00108	-0.00038
	Boll_Count (144) '*Volume (13)* CCI (55)	9.59	112.50%	1.69	2.65%	-65.92%	-2.025%	0.00073	-0.00011

Data and Python code for this study can be accessed from:

https://phdisegutl-my.sharepoint.com/:f:/g/personal/zhaowenyan_aln_iseg_ulisboa_pt/EgGcwVwbbh9JuKjXXESjD-MBRk3feWObbmxmRKZrrztLUw?e=U1NHxU

TABLE 9: ALL TRADED CRYPTOCURRENCIES IN BINANCE PLATFORM

symbol	Annual Return	symbol	Annual Return	symbol	Annual Return
1000BTTC-USDT	-3. 30%	APE-USDT	-51. 80%	BLUR-USDT	-34. 77%
1000FLOKI-USDT	-23. 92%	API3-USDT	-44. 98%	BLZ-USDT	30. 36%
1000LUNC-USDT	-46. 60%	APT-USDT	-18. 88%	BNB-USDT	99. 58%
1000PEPE-USDT	-30. 58%	AR-USDT	-54. 82%	BNT-USDT	-5. 96%
1000SHIB-USDT	-27. 25%	ARB-USDT	-10. 17%	BNX-USDT	-86. 35%
1000XEC-USDT	-50. 24%	ARKM-USDT	-6. 48%	BTC-USDT	34. 64%
1INCH-USDT	-33. 82%	ARPA-USDT	-33. 88%	BTCDOM-USDT	20. 86%
AAVE-USDT	21. 91%	ASTR-USDT	-21. 49%	BTCST-USDT	-3. 13%
ACH-USDT	-26. 31%	ATA-USDT	-61. 06%	BTS-USDT	-34. 26%
ADA-USDT	40. 44%	ATOM-USDT	14. 29%	BTT-USDT	-33. 42%
AGIX-USDT	-21. 92%	AUDIO-USDT	-62. 40%	BZRX-USDT	-9. 31%
AGLD-USDT	-3. 28%	AVAX-USDT	28. 90%	C98-USDT	-69. 90%
AKRO-USDT	-41. 72%	AXS-USDT	111. 57%	CELO-USDT	-56. 98%
ALGO-USDT	-34. 62%	BAKE-USDT	-61. 82%	CELR-USDT	-48. 19%
ALICE-USDT	-62. 85%	BAL-USDT	-43. 84%	CFX-USDT	-21. 07%
ALPHA-USDT	-30. 14%	BAND-USDT	-46. 66%	CHR-USDT	-39. 49%
AMB-USDT	-14. 45%	BAT-USDT	-10. 56%	CHZ-USDT	43. 58%
ANC-USDT	-74. 44%	BCH-USDT	-2. 56%	CKB-USDT	-15. 69%
ANKR-USDT	13. 84%	BEL-USDT	-21. 78%	COCOS-USDT	-12. 61%
ANT-USDT	-28. 16%	BLUEBIRD-USDT	-16. 54%	COMBO-USDT	-24. 79%

symbol	Annual Return	symbol	Annual Return	symbol	Annual Return
COMP-USDT	-36.17%	HFT-USDT	-18.48%	MTL-USDT	-41.50%
COTI-USDT	-51.63%	HIGH-USDT	-23.95%	NEAR-USDT	10.59%
CRV-USDT	-33.43%	HNT-USDT	-1.18%	NEO-USDT	-32.53%
CTK-USDT	-27.99%	HOOK-USDT	-34.60%	NKN-USDT	-53.31%
CTSI-USDT	-44.20%	HOT-USDT	-65.83%	NMR-USDT	-2.50%
CVC-USDT	-3.43%	ICP-USDT	-78.17%	NU-USDT	-21.98%
CVX-USDT	-17.18%	ICX-USDT	-28.77%	OCEAN-USDT	-15.01%
CYBER-USDT	11.39%	ID-USDT	-24.26%	OGN-USDT	-63.63%
DAR-USDT	-58.56%	IDEX-USDT	-23.67%	OMG-USDT	-47.05%
DASH-USDT	-28.87%	IMX-USDT	-39.02%	ONE-USDT	-61.36%
DEFI-USDT	-9.64%	INJ-USDT	65.91%	ONT-USDT	-39.75%
DENT-USDT	-60.59%	IOST-USDT	3.79%	OP-USDT	3.79%
DGB-USDT	-60.97%	IOTA-USDT	-18.34%	OXT-USDT	0.17%
DODO-USDT	-69.19%	IOTX-USDT	-46.66%	PENDLE-USDT	-2.22%
DODOX-USDT	-6.08%	JASMY-USDT	-48.13%	PEOPLE-USDT	-58.71%
DOGE-USDT	181.42%	JOE-USDT	-27.47%	PERP-USDT	-5.04%
DOT-USDT	-5.80%	KAVA-USDT	-36.82%	PHB-USDT	-27.93%
DOTECO-USDT	27.50%	KEEP-USDT	34.85%	QNT-USDT	-19.38%
DUSK-USDT	-42.83%	KEY-USDT	-6.57%	QTUM-USDT	-5.76%
DYDX-USDT	-42.00%	KLAY-USDT	-58.53%	RAD-USDT	-16.29%
EDU-USDT	-29.50%	KNC-USDT	-17.46%	RAY-USDT	-67.77%
EGLD-USDT	29.23%	KSM-USDT	-14.01%	RDNT-USDT	-10.48%
ENJ-USDT	15.57%	LDO-USDT	-1.22%	REEF-USDT	-65.14%
ENS-USDT	-45.36%	LEND-USDT	-5.97%	REN-USDT	-46.97%
EOS-USDT	-40.27%	LEVER-USDT	-8.45%	RLC-USDT	-0.83%
ETC-USDT	44.04%	LINA-USDT	-57.13%	RNDR-USDT	-7.11%
ETH-USDT	61.91%	LINK-USDT	-11.94%	ROSE-USDT	-53.94%
FET-USDT	-6.53%	LIT-USDT	-59.45%	RSR-USDT	-50.03%
FIL-USDT	-50.71%	LPT-USDT	-55.20%	RUNE-USDT	57.22%
FLM-USDT	-40.30%	LQTY-USDT	-38.62%	RVN-USDT	-53.50%
FLOW-USDT	-59.64%	LRC-USDT	1.47%	SAND-USDT	51.25%
FOOTBALL-USDT	-31.57%	LTC-USDT	11.04%	SC-USDT	-51.58%
FTM-USDT	69.91%	LUNA-USDT	-82.59%	SEI-USDT	-5.53%
FTT-USDT	-66.72%	LUNA2-USDT	-54.34%	SFP-USDT	-29.45%
FXS-USDT	-22.02%	MAGIC-USDT	-31.88%	SKL-USDT	-43.83%
GAL-USDT	-45.93%	MANA-USDT	-33.11%	SNX-USDT	-20.67%
GALA-USDT	-48.70%	MASK-USDT	-39.96%	SOL-USDT	87.46%
GMT-USDT	-41.02%	MATIC-USDT	213.58%	SPELL-USDT	-24.77%
GMX-USDT	-22.34%	MAV-USDT	-16.94%	SRM-USDT	-47.76%

symbol	Annual Return	symbol	Annual Return	symbol	Annual Return
GRT-USDT	-44.76%	MDT-USDT	-6.51%	SSV-USDT	-27.00%
GTC-USDT	-56.37%	MINA-USDT	-29.06%	STG-USDT	-18.56%
HBAR-USDT	-45.82%	MKR-USDT	36.38%	STMX-USDT	-48.54%
STORJ-USDT	-1.41%	STX-USDT	-10.90%	SUI-USDT	-29.85%
SUSHI-USDT	-29.77%	SXP-USDT	-43.58%	T-USDT	-25.56%
THETA-USDT	1.91%	TLM-USDT	-58.65%	TOMO-USDT	21.18%
TRB-USDT	7.77%	TRU-USDT	-28.37%	TRX-USDT	45.05%
UMA-USDT	-15.54%	UNFI-USDT	-27.28%	UNI-USDT	3.48%
USDC-USDT	0.08%	VET-USDT	4.63%	WAVES-USDT	-15.18%
WLD-USDT	-14.11%	WOO-USDT	-29.56%	XEM-USDT	-67.47%
XLM-USDT	14.62%	XMR-USDT	15.69%	XRP-USDT	27.35%
XTZ-USDT	-33.73%	XVG-USDT	-24.82%	XVS-USDT	-16.13%
YFI-USDT	-43.94%	YFII-USDT	-21.84%	YGG-USDT	-16.43%
ZEC-USDT	-23.56%	ZEN-USDT	-14.85%	ZIL-USDT	-1.18%
ZRX-USDT	-25.40%				