The Turtule Trading Strategy for the Crypto-markets

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Abstract

Turtle trading strategy is a complete set of rules for trading. It was developed by Richard Dennis in the 1980s, and later was widely used in stock markets. In our report, we tried to utilize turtle trading strategy in the cryptocurrencies markets to check its effectiveness. However, we found out that the traditional rules for daily trading of bitcoin performed not very well. To improve the strategy, we used three methods including increasing risk tolerance, adding other filter CMI, and using Ethereum daily data. Finally, we provided some suggestions about further improvements.

Key words: Turtle trading strategy, Bitcoin, Etheruem, Cryptocurrency, CMI

1 Introduction

As the total market capitalization of cryptocurrencies reached over $2,000 billion that hit an all-time high in April 2021 [1], cryptocurrencies have definitely become an emerging asset class for global investment [2]. An increasing number of financial institutions including hedge funds [3] and investing banks [4] are evaluating the role of cryptocurrencies in their global portfolios to improve their annualized returns without significantly increasing volatility. The development of cryptocurrencies is also attracting investors and scholars to do much research. In this report, by studying turtle trading rules, we try to implement the strategy and evaluate its results for cryptocurrencies markets.

1.1 Related Research

Research on cryptocurrencies trading strategies can be categorized into three aspects. In the first aspect, many papers focus on technical analysis on trading strategies. [5] provides a view on the application of high frequency momentum tactics for cryptocurrencies trading. Some forecast cryptocurrencies prices by using machine learning technique such as support vector machines, random forests, or linear models [6][7]. Second, some research use sentiment analysis for cryptocurrencies market. [8] uses available social media data to predict cryptocurrencies movement. Some also explore the relationship between cryptocurrencies' performance and social media network [9]. In the last perspective, behavioral finance theory is applied. [10] exams herding and feedback trading behaviors contributing to price dynamics.

1.2 Characteristics of Cryptocurrencies

Actually, compared to traditional asset classes such as stocks and bonds, cryptocurrencies have very unique characteristics. First, cryptocurrencies have higher volatility [11]. For example, Bitcoin has experienced four crashes of greater than 80% and 16 crashed of more than 30% since 2011[4]. The volatility of 20% is common but at least three times that of S&P 500 and Nasdaq Composite [4] (See Figure 1). Second, cryptocurrencies values are mainly based on market sentiment [12]. They do not have underlying real assets at present, so it is difficult to determine the intrinsic value by fundaments. Third, cryptocurrencies appear to have low correlations relative to other traditional asset classes [4][13] (See Figure 2). These low correlations are thought to be an opportunity to help minimize idiosyncratic risks and reduce overall volatility, so as to gain higher risk-adjusted returns [13].

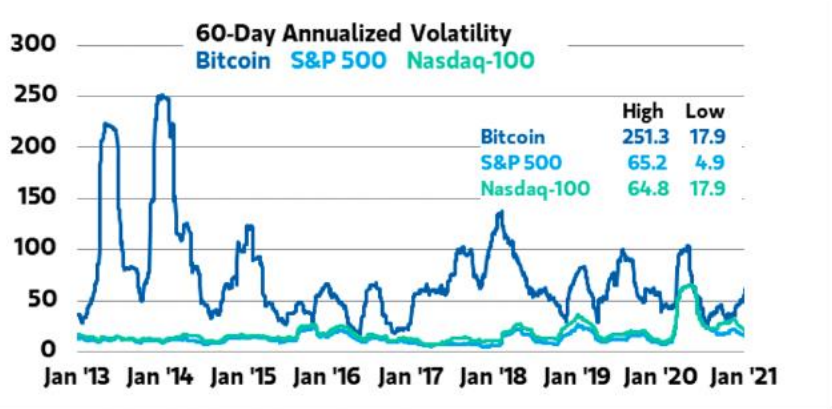

Figure 1. 60-Day Annualized Volatility of Bitcoin, S&P 500 and Nasdaq-100

Source: Morgan Stanley

High correlation: coefficient value lies between ± 0.50 and ± 1
Moderate correlation: coefficient value lies between ± 0.30 and ± 0.49
Low correlation: coefficient value lies below ± .29

	Bitcoin	S&P 500	Bonds	Gold	Oil	Emerging Market Currencies	Real Estate	TSLA	AAPL	BAC
Bitcoin										
S&P 500	0.26									
Bonds	-0.14	-0.62								
Gold	0.24	0.37	0.61							
Oil	0.19	0.59	-0.44	0.43						
Emerging Market Currencies	0.13	0.52	-0.36	0.37	0.53					
Real Estate	0.34	0.89	-0.49	0.26	0.48	0.45				
TSLA	0.15	0.51	-0.30	0.22	0.42	0.29	0.47			
AAPL	0.17	0.69	-0.29	-0.22	0.37	-0.22	0.57	0.40		
BAC	0.25	0.89	-0.61	-0.55	0.53	0.42	0.77	0.42	0.49	

Figure 2 Correlation among assets classes

Source: ARK Invest

1.3 Investment Philosophy

Due to these characteristics of cryptocurrencies, our investment philosophy is the technical analysis. The technical analysis is the study of market movement through charts and statistical analysis solely by past prices and volumes [14]. There are also three premises that technical analysis follows. First one is that market action discounts everything including supply and demand information. Second premise is that prices move in trends such as uptrend, downtrend and sideways. Last but significant one is believed that history repeats itself [15]. Our trading strategy is developed based on the investment philosophy, so we choose Turtle Trading system to trade cryptocurrencies.

1.4 Turtle Trading System

Turtle Trading system is a trend following strategy developed by Richard Dennis in the 1980s. Traders can take advantage of sustained momentum to look

for breakouts to the upside or downside for cryptocurrencies trading. The system requires every aspect that traders need to know, including position size, entries, stop losses, exits and tactics. Thus, Turtle Trading system is a continuous process for traders. There are three reasons for us to choose the turtle trading system. First, it fits our investment philosophy we talked about before. Second, it provides a complete set of rules for quantitative trading beginners to study and follow. Third, we also want to check the effectiveness of the turtle trading system used in cryptocurrencies markets.

2 Data processing

2.1 Data source and analysis

To examine the Turtle Trading strategy performance in Cryptocurrency we used TA-LIB (a library in Python) to calculate indicators and conduct back tests. We experimented on two assets, Bitcoin and Ethereum, over a 3-year period, from 17 August 2017 to 31 March 2021, those data gained from CCXT (a library in Python) which provides access to crypto-market data for analysis, storage and algorithmic trading. We set the initial capital of each test as $1,000,000. To compare the performance of Turtle Trading strategy, we used long-and-hold as a benchmark.

2.2 Data verify and integration

Raw data is collected from CCXT library, first, we ensure there is not null value and extreme value.

The chart flow of Turtle Trading strategy can be seen in Figure 3.

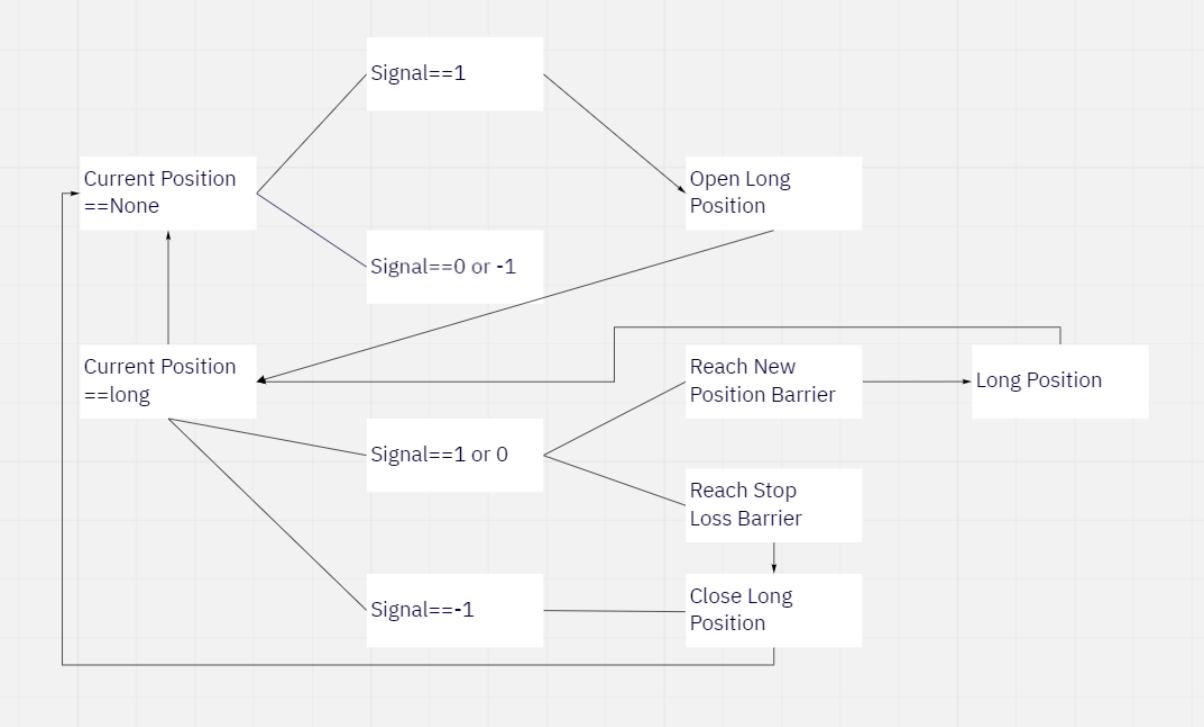

Figure 3. Chart flow of Turtle Trading strategy

3 Methodology

Turtle Trading strategy can be divided into two parts, momentum capture and position management.

3.1 Momentum Capture

Donchian Channel is used to detect the market volatility and trading signals. It is formed around the price series by the high and low price over a past period. The price reaches the 20-day high, buying signal triggers, in contrast, shorting signal triggers when price reaches the 20-day low. An example of Donchian Channel can be seen in Figure 4.

Figure 4. Donchian Channel of period 20.

3.2 Position management

The trading unit is defined as $N * \text{Account}$, $N$is the average of maximum of following three amplitudes:

a. the high and low of trading day
b. the high of trading day and the close of previous trading day
c. the low of trading day and the close of previous trading day

$n\,day\,N$ is defined as

$$N = (PreN[-n+1:] + TrueRange)/n$$

and the True Range is calculated as

$$TrueRange = Max[High - Low, abs(High - PreClose), abs(PreClose - Low)]$$

$Unit$ is calculated as

$$Unit = 1\% * Account/N$$

The meaning of $Unit$ is to control the volatility of asset, the volatility of total asset would not exceed x% if we buy x $Unit$ securities.

In order to simplify programming, N is replaced by n-day Average True Range(ATR).

$$ATR(n) = MA(TrueRange, n)$$

Once the price drops to Stop Loss Barrier, our position will be closed.

$$Stop\ Loss\ Barrier = Opening\ Price - x * ATR(n)$$

The price reaches the New Position Barrier, we open a new long position.

$$New\ Position\ Barrier = Closing\ Price + x * ATR(n)$$

After analysing the performance of traditional Turtle Trading strategy, we are aware that invalid breakout signals might cause wrong entry. In order to eliminate noise signals, we apply the Choppy Market Index(CMI) to further determine the momentum of the trend.

$$CMI(n) = Abs(Close - PreClose(n-1)) * 100/(Max(Close, n) - Min(Close, n))$$

4 Results

4.1 Original strategy backtesting

First of all, we used daily bitcoin data and hourly bitcoin data to test the efficiency of turtle trading strategy. The initial account amount is $1,000,000, the daily data is from 2017-08-18 to 2021-03-31, the hourly data is between 2017-08-18 13:00 and 2021-03-31 23:00, and we used the long-and-hold strategy as a benchmark. The backtesting results are as follows:

4.1.1 Bitcoin daily data

As we can see from the chart below, the red line represents the accumulated return of turtle trading strategy, and the black line represents the accumulated return of the benchmark. It is obvious that the turtle trading strategy did not perform as well as the benchmark in the bitcoin market, since the annualized return of turtle strategy is 40.43%, while for the benchmark, its return is 63.953%. In terms of risk, the max drawdown of turtle strategy is smaller than that of benchmark, with figures being 75.245% and 88.575% respectively. However, the sharpe ratio of benchmark (14.950) is larger than that of turtle strategy (6.46). Therefore, the original turtle trading strategy does not perform well in bitcoin market.

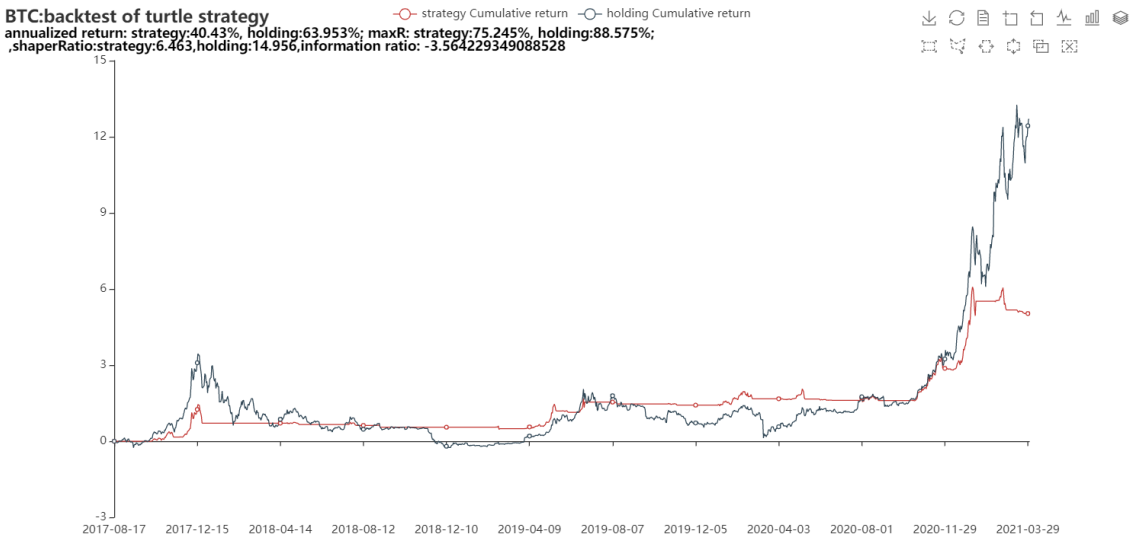

Figure 5. Backtesting result for Bitcoin daily data

4.1.2 Bitcoin hourly data

As for the hourly data, the performance of turtle trading strategy is even worse. As we can see, the accumulated return of turtle strategy is only 11.537%, while for the benchmark, the figure is 63.82%. In terms of risk, the max drawdown of turtle strategy is much smaller than that of benchmark. In this case, the max drawdown of turtle strategy is 42.897%, compared with 89.04% in benchmark. However, the sharpe ratio of the benchmark is still larger than that of turtle strategy.

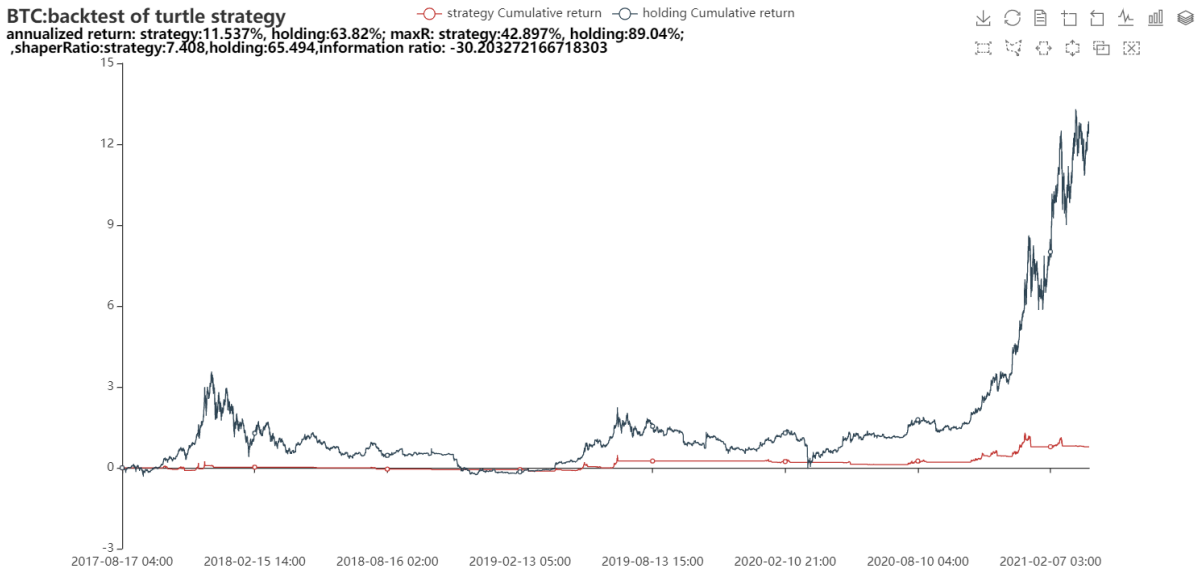

Figure 6. Backtesting result for Bitcoin hourly data

As for the unsatisfactory performance of turtle trading strategy on bitcoin data, there are several possible reasons. Firstly, since the volatility of

Bitcoin is larger than other financial products like stocks and futures, it is reasonable that we should increase our risk tolerance for Bitcoin. Secondly, not all the signals in turtle trading strategy are effective, we should take some ways to filter those wrong signals. In addition, Bitcoin price has a significant upward trend, which means we can already gain a lot of money by holding it passively, so active investment strategies like turtle trading strategy may not perform well in it.

4.2 Improved strategy backtesting

We tried three ways to improve our original trading strategy. The first one is increasing risk tolerance from 1% to 2%, 3%, 5%, 8% and 10%, the second one is adding the Choppy Market Index (CMI) to filter useless signals, the third one is doing the strategies on Ethereum market.

4.2.1 Increasing risk tolerance

As we can see from Table 1, after increasing risk tolerance, the annualized return increases. However, the max drawdown also increases. According to the sharpe ratio, the strategy with 2% risk tolerance has the largest sharpe ratio (6.67), so in this case, 2% risk tolerance is most suitable for turtle strategy.

Table 1. Backtesting results for strategies with different risk tolerance for Bitcoin

Risk tolerance	Annualized return	Max drawdown	Sharpe ratio
1%	40.40%	75.2%	6.46
2%	48.50%	82.7%	6.67
3%	51.3%	84.5%	6.61
5%	53.1%	86.1%	6.19
8%	56.1%	87.7%	5.67
10%	58.4%	88.6%	5.49

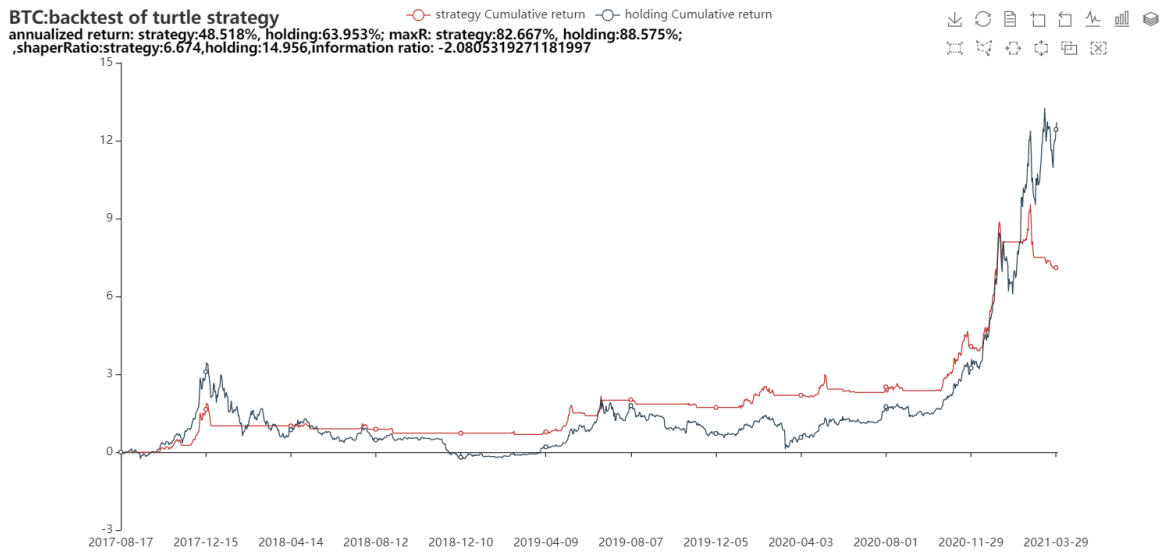

Figure 7. Backtesting result for strategy with 2% risk tolerance

4.2.2 Adding CMI (choppy marklet index)

After adding CMI, the number of tradings decreases from 80 to 68, at the same time, the annualized return increases from 40.40% to 43.495%, so the average profit of each trading rises from 62881 to 84712. This demonstrates that the CMI does filter some wrong trading signals.

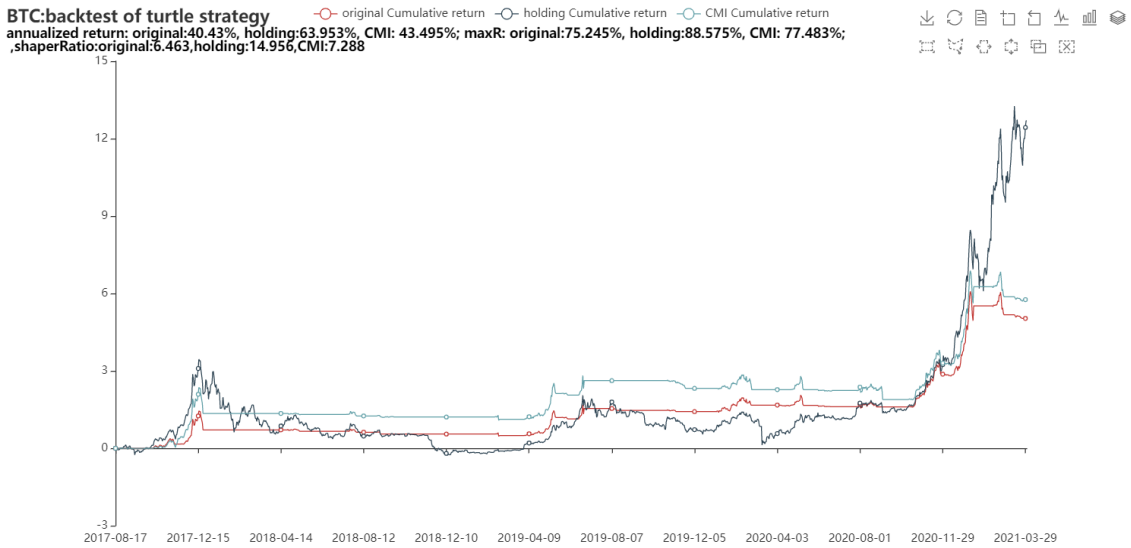

Figure 8. Backtesting result after adding CMI in Bitcoin

4.2.3 Ethereum daily data

In order to make the result more general, we also tried turtle strategy on Ethereum. As we can see from Figure 9, the performance of turtle strategy in Ethereum market is much better than that in Bitcoin. More specifically, the annualized return of turtle strategy is 39.865%, which is very close to the benchmark (41.828%).

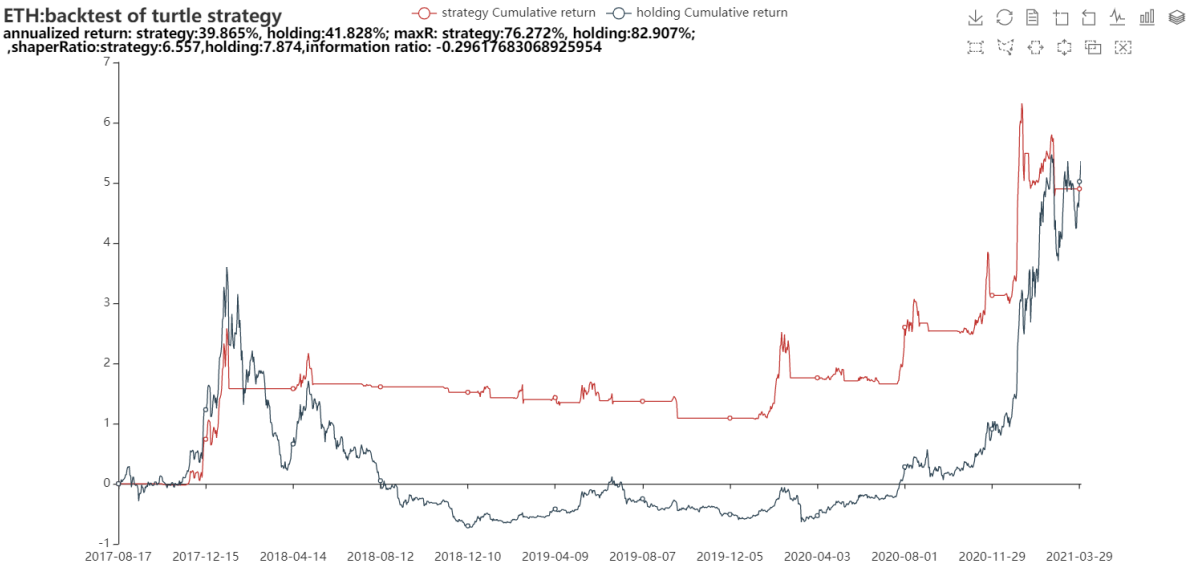

Figure 9. Backtesting result for Ethereum daily data

Since the CMI works in Bitcoin, we also added CMI in Ethereum. Although the annualized return dropped a little bit from 39.865% to 39,765% after adding CMI (Figure 10), the number of trading decreased from 88 to 73, and the ave rage profit of each trading increased from 55718 to 66863.

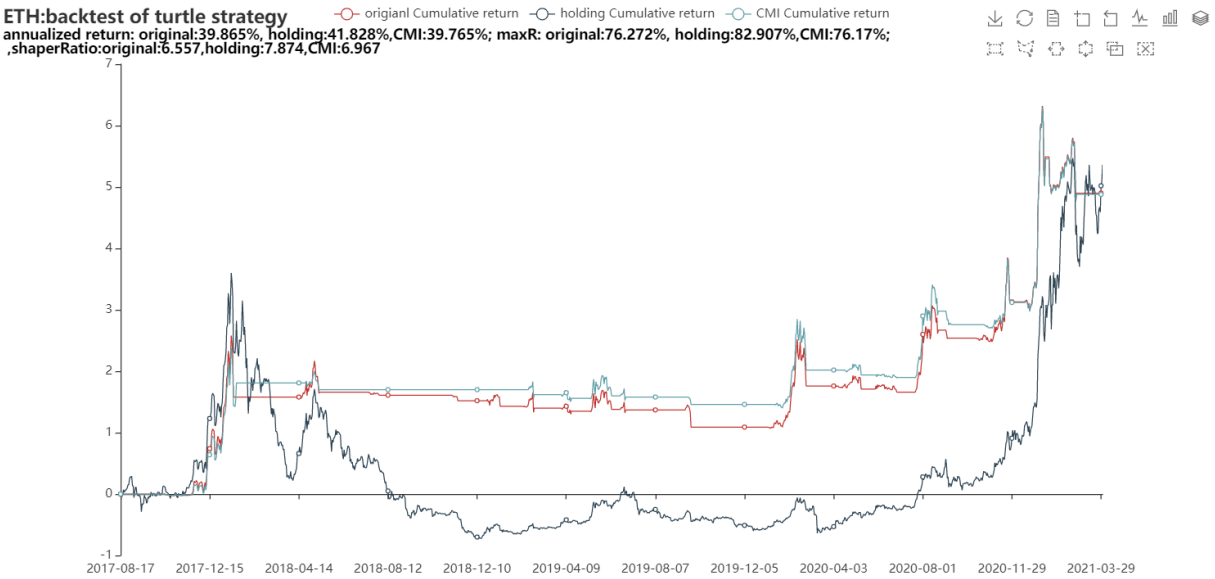

Figure 10. Backtesting result after adding CMI in Ethereum

In addition, we also test different risk tolerance rates in the Ethereum ma rket. As is shown in Table 2, with the increase of risk tolerance rate, th e annualized return rises from 39.86% to 58.34%. Although the max drawdown increases from 76.3% to 86.9%, the sharpe ratio changes from 6.557 to 7.38.

Therefore, increasing risk tolerance can improve the overall performance of turtle strategy in Ethereum market.

Table 2. Backtesting results for strategies with different risk tolerance for Ethereum

Risk tolerance	Annualized return	Max drawdown	Sharpe ratio
1%	39.86%	76.30%	6.557
2%	50.89%	75.47%	6.48
3%	58.34%	86.9%	7.38

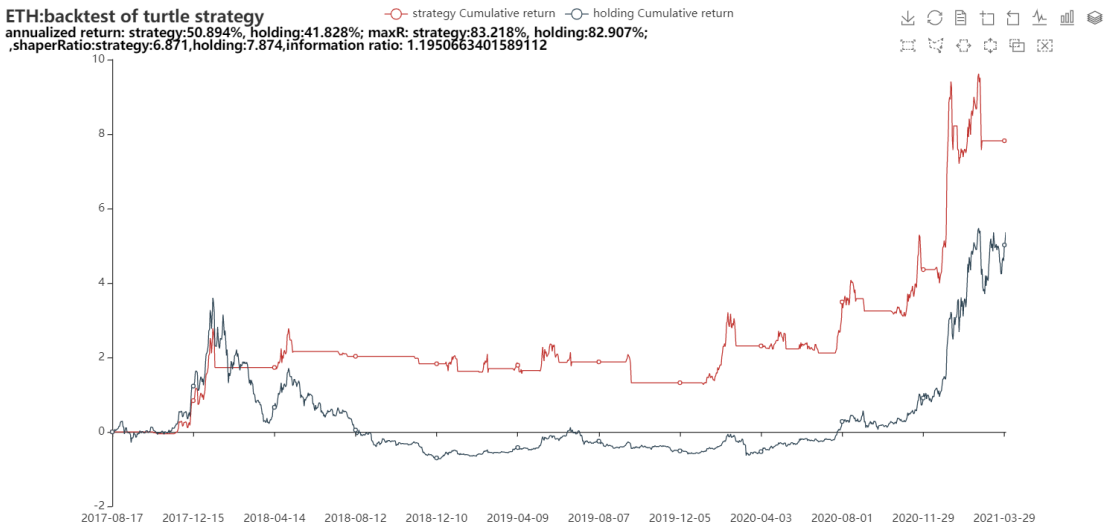

Figure 11. Backtesting result for strategy with 2% risk tolerance for Ethereum

5 Summary

5.1 Further improvement

Owing to the time limitation, we can only suggest the following improvements for the Turtle trading Strategy in Cryptocurrency market.

First, according to some research papers the maximum drawdown using turtle trading strategy in future markets can reach more than 40%. It is suggested to use some signals such as kaufman adaptive moving average to improve the enter and exit rules of turtle trading strategy.[16] Second, short selling by using turtle trading strategy is suggested to be added in order to increase the win ratio in the cryptocurrency market. According to some research on the stock markets, the time ratio of the trending market and the equilibrium market is 3:7.[17]That means if we only use turtle trading strategy in the uptrend market to gain the high profit but not with the downtrend marke

t, the win ratio and the return cannot be increased. Third, in our backtesting, we only consider the 20-day high/low as the enter rule but there should be another fair comparison by using the 55-day high/low for turtle trading strategy. Last but not least, adding more assets instead of cryptocurrencies using turtle trading strategy is one of the ways to increase the win ratio and the stability as well as lower the risk.

5.2 Conclusion

According to our analysis, the annualized return of Turtle Trading strategy in the cryptocurrency market can be improved by introducing the CMI or increasing the risk tolerance rate. Although it is a trend following strategy and our backtesting period of the cryptocurrency market is showing an uptrend, we can still see the maximum drawdown can reach to more than 80%. It is not recommended to use one strategy on one single asset but a multi-asset portfolio.

Reference

[1] CoinMarketCap, “Today’s Cryptocurrency Prices by Market Cap”. https://coinmarketcap.com

[2] Krückeberg, Sinan, and Scholz, Peter. “Cryptocurrencies as an Asset Class.” *Cryptofinance and Mechanisms of Exchange,* Springer International Publishing, Cham, 2020, pp. 1–28. https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_springer_books_10_1007_978_3_030_30738_7_1

[3] PWC, “2020 Crypto Hedge Fund Report”, 2019 March. [Online] Available: https://www.pwc.com/gx/en/financial-services/pdf/pwc-elwood-annual-crypto-hedge-fund-report-may-2020.pdf

[4] Lisa Shalett, Denny Galindo, “The Case for Cryptocurrency as an Investable Asset Class in a Diversified Portfolio”, Morgan Stanley, March 2021. https://advisor.morganstanley.com/scott.altemose/documents/field/s/sc/scott-a--altemose/Case%20for%20Cryptocurrency_MAR%2017%202021.pdf

[5] Chu, Jeffrey, et al. “High Frequency Momentum Trading with Cryptocurrencies.” Research in International Business and Finance, vol. 52, 2020, p. 101176. https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_crossref_primary_10_1016_j_ribaf_2019_101176

[6] Zhao, David, et al. “Cryptocurrency Price Prediction and Trading Strategies Using Support Vector Machines”, 2019. https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_arxiv_primary_1911_11819

[7] Sebastiao, Helder, and Godinho, Pedro. “Forecasting and Trading Cryptocurrencies with Machine Learning under Changing Market Conditions.” *Financial Innovation*, vol. 7, no. 1, 2021, pp. 1–30. https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_doaj_primary_oai_doaj_org_article_bbd6c530d1594679892e1433260987d7

[8] Valencia, Franco, et al. “Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning.” *Entropy (Basel, Switzerland)*, vol. 21, no. 6, 2019, p. 589.
https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_doaj_primary_oai_doaj_org_article_59a628e2025740f28123921b059b66af

[9] Park, Han Woo, and Lee, Youngjoo. “How are Twitter Activities Related to Top Cryptocurrencies’ Performance?”, *Društvena Istraživanja*, vol. 28, no. 3, 2019, pp. 435 – 460.
https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_webofscience_primary_000491132500004CitationCount

[10] King, Timothy, and Koutmos, Dimitrios. “Herding and Feedback Trading in Cryptocurrency Markets.” *Annals of Operations Research*, vol. 300, no. 1, 2021, pp. 1 – 18.
https://julac.hosted.exlibrisgroup.com/permalink/f/1h1uk14/TN_cdi_proquest_miscellaneous_2479040048

[11] Chris Burniske & Jack Tatar, *Cryptoassets: The Innovative Investor’s Guide to*
Bitcoin and Beyond, McGraw-Hill Education, 2018.

[12] Yuan Hu, Svetlozar T. Rache & Frank J. Fabozzi, "Modelling Crypto Asset
Price Dynamics, Optimal Crypto Portfolio, and Crypto Option Valuation,"
Papers 1908.05419, arXiv.org, 2009.
https://arxiv.org/pdf/1908.05419.pdf

[13] Yassine Elmandjra, “Bitcoin as An Investment”, ARK Invest, Sep 2020.
https://research.ark-invest.com/hubfs/1_Download_Files_ARK-Invest/White_Papers/ARKinvest_091729_Whitepaper_Bitcoin_II_An%20Investment.pdf?hsCtaTracking=71be7529-9a39-404e-97b3-04fd4ccf80ec%7C07365ce1-0ed3-4835-9c3c-ac33c030cd70

[14] Fontanills, George., and Tom Gentile. T*he Stock Market Course*, New York: Wiley, 2001.
https://julac.hosted.exlibrisgroup.com/permalink/f/1fusua3/CUHK_IZ519741056900003407

[15] John J. Murphy, Technical Analysis of the Financial Markets: *A Comprehensive Guide to Trading Methods and Applications.* New York: Penguin Group, Jan 1999.

[16] Chen,X.T & Li,C.S(2016). “Analysis of the Turtle Rule trading strategy improvement and its application”, *Northern Finance Journal*, DOI:10.16459/j.cnki.15-1370/f.2016.11.002

[17] Shen,R.G, (2018). “Discussion and Testing of Reverse Application of Turtle Trading System”, *Times Finance,* No.12 2018(Cumulatively NO.718)