Semi Risk-free Arbitrages with Cryptocurrency

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Abstract: Much research is done on cryptocurrency time-series and cross-section price prediction due to the sharp rise of cryptocurrency prices. However, arbitrage can provide minimum risk opportunities that are very beneficial for portfolio optimization, based on paper and theory. So we summarized the popular arbitrage methods on the stock market and cryptocurrency. More importantly, we tested the potency of some traditional stock market arbitrage techniques through cryptocurrency data backtesting and live trading. This paper examines some common and unique arbitrage opportunities in cryptocurrency exchanges that are not widely mentioned in academic journals. Though backtesting with trading fees and live trading, we analyzed the validity of the following arbitrage methods: Exchange futures contract funding rate arbitrage, Exchange futures contract intertemporal arbitrage, and asset price deviation arbitrage. The asset price deviation arbitrage here includes the triangular arbitrage, the pairs trading, and the order book spread prediction arbitrage.

1. Introduction

1.1. Background

Cryptocurrency has enjoyed a spectacular rise in adoption and market cap over the last decade since Satoshi Nakamoto released the Bitcoin whitepaper in 2008 [1]. Especially, the market cap rose from 1 trillion dollars to an all-time high of 3 trillion dollars in 2021 [2], and a wide range of financial institutions and public traded companies started to hold cryptocurrency assets, such as bitcoins [3]. Much research is done on cryptocurrency time-series and cross-section price prediction, but not enough effort has been put into cryptocurrency arbitrage. Cryptocurrency arbitraging space may have become more crowded; traders have to use higher frequency data with special trading fees to stay profitable. Moreover, special trading fees usually involve a lengthy negotiation process with exchanges or a considerable amount of existing trading volumes, which stops much research. Plus, due to its minimum risk feature, profitable arbitrage strategies are usually protected as trade secrets and avoided being published. We first go over some related research on the review of the quantitative analysis done in the cryptocurrency space, especially some arbitrage analysis. Then we go over some theories and practices of arbitraging done in the traditional financial market, such as stocks. The main body shows how we apply those theories specifically to the cryptocurrency market and the results we get. We discuss the importance of our findings and what needs to be done in the future.

Corbet et al. provide a systematic review of the empirical literature based on the major topics associated with the cryptocurrency market since 2009 [4]. They mention that cryptocurrencies have been accused of pricing bubbles due to the trilemma of regulatory oversight, the potential for illicit use through anonymity within a young under-developed exchange system, and infrastructure breaches influenced by the growth of cyber criminality, each of which affects the perception of cryptocurrencies as a legitimate asset class and store of value. Especially, they listed nine gaps in the cryptocurrency field that need to be investigated more, shown in table 1.

Table.1. Gaps in the literature

Number	Gap
1	Expand datasets and number of cryptocurrencies studied
2	Study the legal, economic and regulatory issues of cryptocurrencies
3	Asymmetrical information issues
4	Theoretical development
5	Alternative potential benefits and uses of blockchain
6	Evaluate the benefits of cryptocurrencies separately, and not as one large asset class
7	Evaluate cryptocurrencies based on their use, rather than just their financial performance
8	Address the environmental challenges of cryptocurrencies
9	Evaluate the benefits of cryptocurrencies as an asset class part of a diversified portfolio
10	Ongoing study of cryptocurrencies since their behaviour is continually changing

Bariviera et al. build on the summary by Corbet et al. After machine learning bibliometric analysis and detailed literature review of all previous economic research, it lists the lack of research in the following area for quantitative cryptocurrency analysis: high-frequency data, environmental impact, mining protocols influence on price, ico, national regulations, and more diversity of cryptocurrency [5]. They also filled the lack of mentioning cryptocurrency arbitrage methods in Corbet et al. by mentioning the Markarov and Schoar paper.

Markarov and Schoar investigate arbitrage opportunities between frequent exchanges in cryptocurrency markets. These price differences are substantially more considerable across nations than within countries, illustrating the necessity of capital constraints for arbitrage capital movement. Countries' price differentials co-move and open up during bitcoin appreciation. Countries with more significant bitcoin premia see more arbitrage discrepancies when bitcoin appreciates. Finally, they split each exchange's signed volume into two parts. The common component accounts for 80% of bitcoin returns. The idiosyncratic components explain exchange arbitrage spreads [6].

Not enough research has been done regarding arbitraging in the cryptocurrency space. Next, let us review some research on theories and practices of arbitraging that have been done in the traditional financial market, such as stocks.

Yang investigates how to optimize some traditional arbitrage methods in the financial market. Their method could be applied to the crypto field [7]. According to them, StatArb is a short-term spread trading method that profits on the spreads of two fully diversified portfolios. The cointegration approach and canonical correlation analysis are two traditional statistical arbitrage methods for mean reversion. It is critical for theoretical and practical reasons to understand how to broaden the range of the portfolio spread and create substantial opportunities. The ideal weight for the spread combination is determined by minimizing the Box and Pierce mixed test statistics under a variance restriction. It establishes a theoretical foundation for trading in statistical arbitrage strategy trading for stock selection and risk management.

1.2. Other related research

Liu et al. find that three variables capture cross-sectional expected cryptocurrency returns: market, size, and momentum [8]. They construct cryptocurrency equivalents of a long list of price and market-related factors in the stock market. Nine cryptocurrency factors combine to form large and statistically significant excess returns. The cryptocurrency's three-factor model accounts for all of these strategies. The results show that standard asset pricing tools can meaningfully analyze the cross-section of cryptocurrencies. We show that, like other asset classes (e.g., Asness et al., 2013), size and momentum play a role in capturing cryptocurrency returns. Moreover, a simple three-factor model based on market data works well in pricing cryptocurrency strategies, creating a set of stylized facts on cryptocurrencies that can be used to evaluate and develop theoretical models.

Liu et al. build on their previous paper: Common risk factors in cryptocurrency and expand their research to more factors, such as network, production, and investor attention factors [9]. They show that factors specific to cryptocurrency markets drive and predict returns. Cryptocurrency returns are susceptible to network but not production factors. They build network factors to proxy for user adoption of cryptocurrencies and production factors to proxy for production costs. Not only that, but proxies for investor attention strongly predict future cryptocurrency returns.

Brauneis et al. use the Markowitz mean-variance framework to assess cryptocurrency portfolio risk-return benefits [10]. They compare the risk and return of different mean-variance portfolio strategies to single cryptocurrency investments and two benchmarks, the naively diversified portfolio and the CRIX. Ex-sample analysis shows that combining cryptocurrencies increases the number of 'low-risk' cryptocurrency investment opportunities. The 1/N-portfolio outperforms single cryptocurrencies and over 75% of mean-variance optimal portfolios in terms of Sharpe ratio and returns.

Cong et al. create a dynamic cryptocurrency/token pricing model that allows users to transact on digital platforms [11]. Equilibrium token prices are determined by aggregating transactional demand rather than discounted cash flows as traditional valuation models. Endogenous platform adoption follows an S-curve, starting slowly, becoming volatile, and finally tapering off. Tokens lower platform transaction costs by allowing users to profit from platform growth. Concurrent feedback between user adoption and token price speeds up adoption while reducing user base volatility. They study cryptocurrency pricing based on network factors and the supply and demand framework. They also study the evolution of user adoption of cryptocurrency, token's benefits to platforms, and the feedback loop between price and adoption.

Feng et al. use statistical methods to assess the common factor structure of two markets and identify possible common factors [12]. The comprehensive dataset covering cryptocurrencies and the US equity universe shows no common pervasive factors governing returns before 2019 but one common factor post-2020. Thus, equity factors can help explain common variations in returns across equities and cryptocurrencies. In addition, the pattern is consistent across US equity market classifications, return specifications, and statistical methods. This pattern also holds on the global equity markets. Their findings point to common factors driving returns on both markets. Specifically, equity factors help explain recent cross-sectional cryptocurrency returns.

Li et al. investigate the MAX effect in the cryptocurrency market. The MAX effect thrives in the cryptocurrency market due to its lottery-like features (i.e., large positive skewness) [13]. Unlike other markets, we show that crypto-currencies with higher maximum daily returns tend to have higher returns in the future. THE MAGNITUDE OF the MAX momentum effect varies with market conditions, investor sentiment, and cryptocurrency undervaluation. Other MAX measures and sample selection criteria do not affect this effect.

Flori uses a Bayesian framework to show how Bitcoin can be used to build diversified investment strategies [14]. They propose to relate portfolio construction to the role of news in generating investors' subjective beliefs, which are computed based on recent market reactions to similar announcement events. To test this approach, the analysis uses a highly volatile Bitcoin market period from mid-2017 to mid-2018. The results show that Bitcoin can help diversified portfolios perform risk-adjusted and that investors' subjective beliefs can help interpret fundamental drivers of crypto-currency market behavior. This approach may also encourage the development of more sophisticated strategies based on the interaction of news and investor sentiment on the Bitcoin market.

Assuming state (regime) dynamics, Koki et al. investigate the use of multi-state hidden Markov models for predicting and explaining Bitcoin, Ether, and Ripple returns. Several financial, economic, and cryptocurrency-specific predictors are also examined [15]. The non-homogeneous hidden Markov (NHHM) model with four states provides the greatest one-step-ahead forecasting performance for all three series. Predictive density outperforms the single regime, random walk model because they capture alternating phases with varied return characteristics. The four-state NHHM model distinguishes between bull, bear, and calm regimes for Bitcoin and profit and risk magnitudes for Ether and Ripple. It also discovers predictors with various linear and non-linear effects on bitcoin returns. These insights are helpful for portfolio management and policy execution.

2. Concepts and methods

2.1. Exchange futures contract funding rate arbitrage

In order to improve the liquidity for the perpetual futures market, decrease the bid-ask spread, and make sure it regularly settles, especially for the newly added trading pairs, cryptocurrency exchanges require a mechanism to ensure that futures prices and index prices regularly converge [16]. The funding rate provides this mechanism by periodically paying long or short traders based on the price difference between perpetual contract markets and spot markets. For example, Binance exchange settles this fee transfer every 8 hours so that traders longing for a popular long asset compensate the short seller regularly, and traders shorting in a famous short asset compensate the long seller regularly. Essentially, the exchanges do the arbitrage between sport and perpetual market for traders to let them focus on trading. To profit from this mechanism, we look at the historical funding rate, and trend for the perpetual future enable cryptos list. There are more than 100 cryptos on this list up to 2022. Moreover, traders tend long cryptos due to the continued rise. In other words, holding crypto is a long-term winning strategy, so investors tend to hold and long bitcoin in the long term.

Moreover, a risk-free profitable strategy in the long term is to short bitcoin in the perpetual market and long bitcoin in the spot market with an equal amount to earn the funding rate without the minimal influence of bitcoin price fluctuation. This is risk-free arbitrage in the long term without considering exchange and cryptocurrency market risks.

2.2. Exchange futures contract intertemporal arbitrage

As we mentioned, that perpetual futures market has the funding rate as a mechanism to make sure it settles regularly. There is also arbitrage opportunities for future contracts with different settlement date. Cross-maturity future arbitrage is a low-risk intertemporal arbitrage method that profits from the price difference between perpetual futures and futures of the same asset.

Suppose the perpetual contract is A and the futures is B. Due to exchange restrictions, the futures B described is a quarterly contract. Their current prices corresponding to P_a and P_b are respectively , and the two prices should regress to the same at the quarterly contract maturity date. At some date before the maturity date, if $P_a > P_b$, short A and long B, and vice versa.

This is also risk-free arbitrage in the fixed term since you are guaranteed with the profit due to different spread prices of future contract dates, without considering exchange risk and cryptocurrency market risk.

2.3. Asset price deviation arbitrage

2.3.1. The triangular arbitrage

The triangular strategy is a risk-free arbitrage method that uses three assets to hedge risks and profit from the spread. Assuming thang with the position m/4, A/B pair is long with the position mt the three trading pairs are A/USDT, B/USDT, and A/B, respectively, and the corresponding current prices are, respectively, there are two situations with profit potential.

$$\frac{P_a}{P_b} > P_{ab} \tag{1}$$

$$\frac{P_a}{P_b} < P_{ab} \tag{2}$$

In Equation (1), the A/USDT pair is short with position m/2, B/USDT pair is lo/4, and the value of long and short positions are kept the same; and vice versa.

2.3.2. The pairs trading

The spread strategy is a low-risk pairs trading arbitrage method that uses two assets to hedge risks and profit from the spread.

AlphaGo is provided human knowledge (Human Knowledge) and rules (Rules), so researchers can use it to train a large strategy tree to complete the search and help make decisions. AlphaGo Zero removes the human knowledge requirement. After providing rules to AI, it can learn its strategy through self-playing. AlphaZero, on the other hand, can be trained with completely zero information. It includes using reinforcement learning algorithms that generalize better and can learn different games such as Go, Chess, and Shogi. MuZero is an upgraded version of the previous stage; without human knowledge and rules, it can play different games by analyzing the environment and unknown conditions (Unknown Dynamics). This policy model consists of Representation_model, Dynamics_Model, and Prediction_Model [17].

The Representation_model maps a set of observations to the hidden state s of the neural network; the dynamic Dynamics_Model maps the state s_t to the next state s_(t + 1) according to the action a_(t + 1), while estimating the reward r_t in this process, so that the model can continue to expand forward; the Prediction_Model estimates the policy p_t and the value v_t based on the state s_t.

Suppose the two asset pairs are A/USDT and B/USDT, respectively, and the corresponding current prices are, respectively. Use MuZero to perform reinforcement learning on the order books of A/USDT and B/USDT to predict the price fluctuations in a future period. The price fluctuation V is defined as follows:

$$V = \frac{P_a}{P_b} \tag{3}$$

The future price fluctuation is defined as V'

$$\frac{P_a}{P_b} > V' \tag{4}$$

$$\frac{P_a}{P_b} < V' \tag{5}$$

In Equation (4), AUSDT is short with position m/2, and BUSDT is long with position m/2 to keep the same long and short; vice versa.

2.3.3. The order book spread prediction arbitrage

Prices are hard to predict, and it is hard to understand every market detail in the long term. However, traces of short-term market data make it much more predictable. The order book forecast strategy is a low-risk arbitrage method that analyzes and predicts the spot market data and futures contract data of a specific asset to obtain the short-term change trend and then obtain the price difference between the futures and the spot.

Assuming that a currency is A, its futures are A1, and its spot is A2, use LTSM to predict the order books of A1 and A2 to obtain price fluctuations in the future. If A1's predicted return is less than A2's, then A1 is short, and A2 is long.

3. Results and discussion

3.1. Exchange futures contract funding rate arbitrage

Here we lists some details regarding the prices and amounts of the trading pair and the earnings from each fund distribution. Binance distributes the perpetual future fund every eight hours, as mentioned previously. Here are some additional details regarding the manual arbitrage trial process:

Opening time: 2021-7-28 14:56

Ending time: 2021-8-2

contract: BTC perpetual future contact with 20x leverage

Open a position with funds:
Spot (unlevered): 39.51 usdt
Contract*20: 1.98 usdt each = 39.6 usdt in total
Taker fee (during the period):
Spot: 0.00009568 BNB = 0.028704 usdt
Contract: 0.01579974 usdt
Estimated taker fee (during the period):
Spot: 0.00009568 BNB = 0.028704 usdt
Contract: 0.01579974 usdt
5 day earnings: 0.05185547 usdt

Under the premise that the spot does not use leverage, the real annualized rate of return: 0.05185547/5/(39.51+1.98+0.028704*2+0.01579974*2) * 365 = 9.1%

Figure 1 shows the three-month return of this strategy with zero trades since the setup, according to Binance's calculation. The cumulative profit and loss for our bitcoin funding rate arbitrage for the past three months is the brown curve, which looks very smooth. The unrealized PNL is 0.57, with an ROE of 29.07%

3.2. Exchange futures contract intertemporal arbitrage

Figure 2 shows the yield curve of Bitcoin intertemporal arbitrage. Among them, RET-A is the profit curve of the BTCUSDT perpetual contract, and RET-B is the profit curve of the quarterly delivery contract. RET is the sum of RET-A and RET-B. The transaction fee is 4/10000 for each entering and exiting of a position. The annualized rate of return is 250%, and the maximum drawdown is 13%.

3.3. Asset price deviation arbitrage

3.3.1. The triangular arbitrage

Figure 3 shows the yield curve of the triangular arbitrage strategy. Among them, RET-A is the profit curve of BTCUSDT, RET-B is the profit curve of ETHUSDT, and RET-AB is the profit curve of BTC ETH. RET is the sum of RET-A, RET-B, and RET-AB. The handling fee is 4/10000 of each entering and exiting of a position. The annualized rate of return is 350%, and the maximum drawdown is 7%.

3.3.2. The pairs trading

Figure 4 shows the yield curve of the pairs trading spread strategy. Among them, RET-A is the profit curve of BTCUSDT, and RET-B is the profit curve of ETHUSDT. RET is the sum of RET-A and RET-B. The transaction fee is 4/10,000 of each entering and exiting a position. The annualized rate of return is 205%, and the maximum drawdown is 8%.

3.3.3. The order book spread prediction arbitrage

Figure 5 shows the yield curve of the market forecast strategy. Among them, RET-A is the profit curve of the BTC/USDT spot, and RET-B is the profit curve of BTCUSDT futures. RET is the sum of RET-A and RET-B. The transaction fee is 4/10,000 for each entering and exiting a position. The annualized rate of return is 1005%, and the maximum drawdown is 28%. This method produces much smoother return curves for A and B than the previous two methods, resulting in a much higher shape ratio.

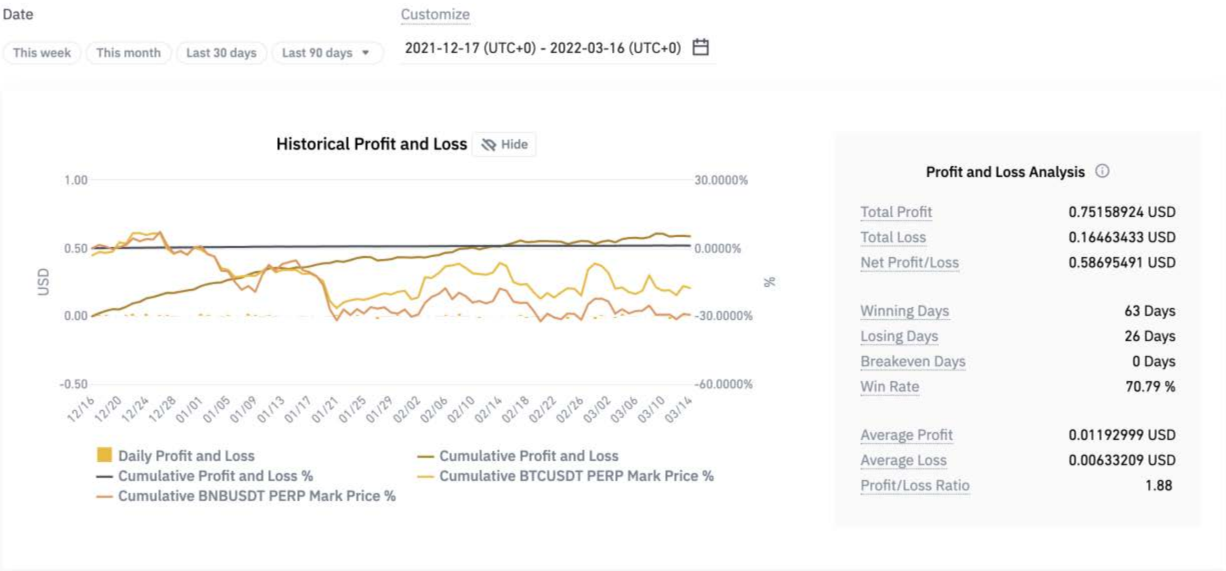

Figure 1. Portfolio curve analysis by Binance

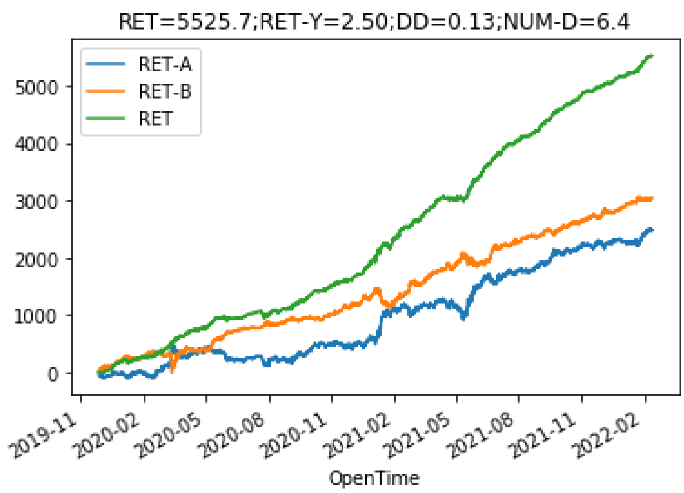

Figure 2. Yield curve of Bitcoin intertemporal arbitrage

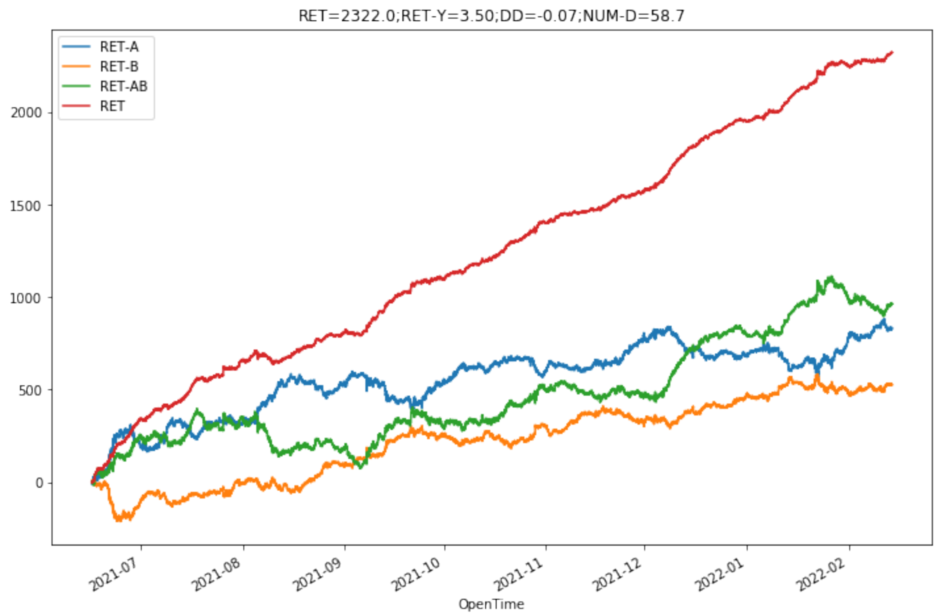

Figure 3. Yield curve of the trianglular arbitrage strategy

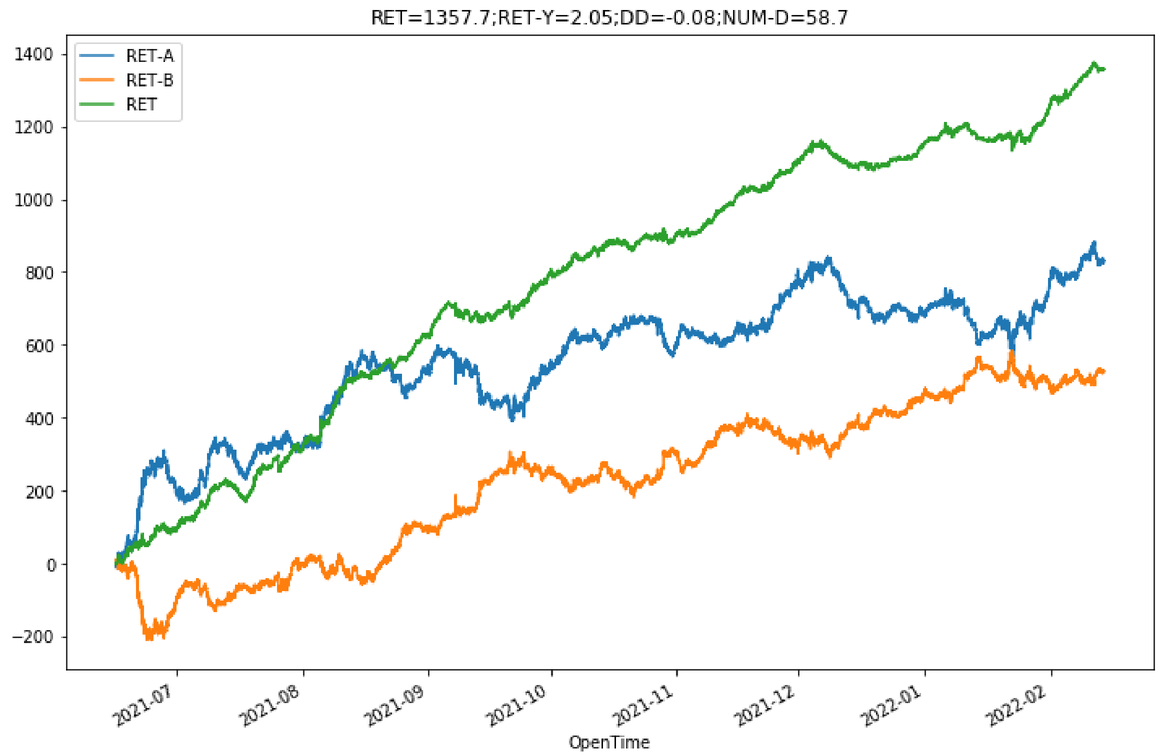

Figure 4. Yield curve of the pairs trading spread strategy

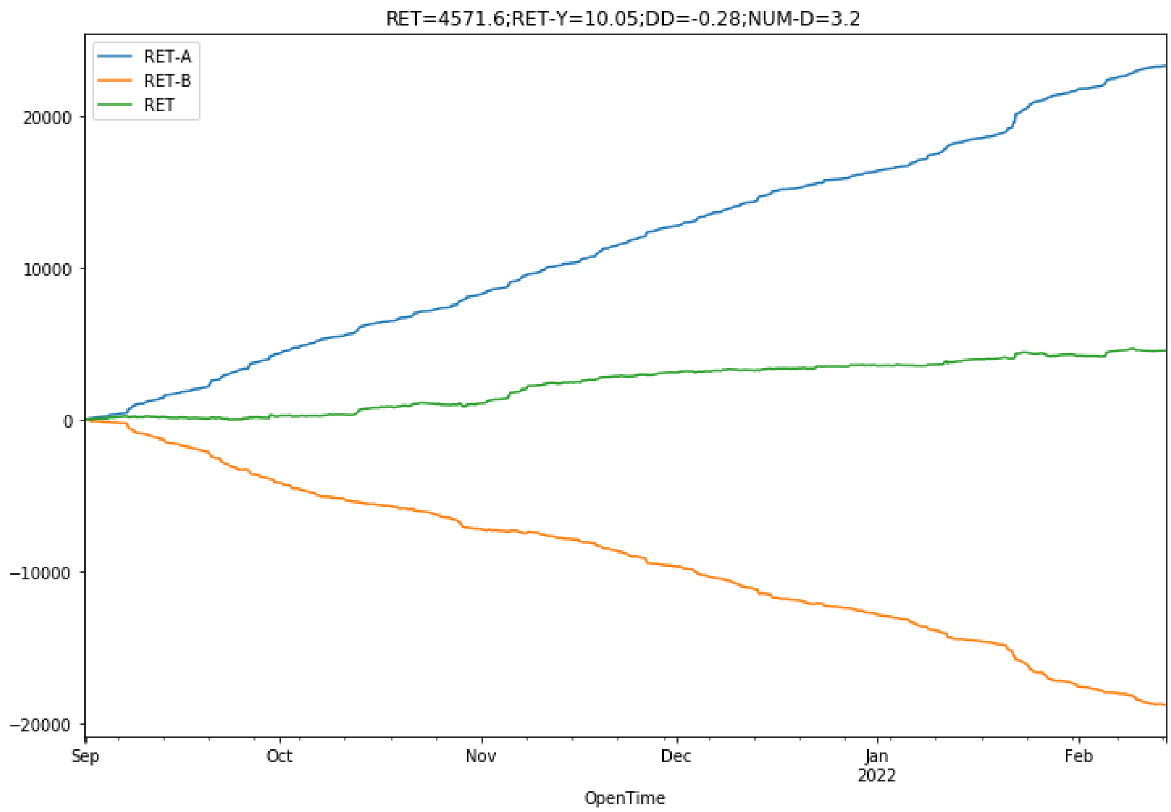

Figure 5. Yield curve of the market forecast strategy

4. Further discussion

There are some details regarding applying the funding rate arbitrage strategy in the Binance exchange:

1. Open a position using the taker method to open a position, which can ensure that the spot and the contract are opened at the same time at the closest price, thereby minimizing the hedging risk, but it will increase the handling fee cost when opening a position

2. The funding rate will be continuously adjusted based on the market, and the use of a short-term rate may have a specific error in the calculation of the annualized income

3. Without leverage, the cost of borrowing interest can be saved, but the utilization rate of funds is meager, which significantly reduces the arbitrage income

4. The cost of handling fees will be increased when the position is adjusted according to the capital rate situation, thereby reducing the income. The position adjustment should be adjusted according to the actual situation.

When used in live trading, the three asset price deviation arbitrage methods have limited returns. The reason is that centralized exchange such as Binance would require VIP status or profit commission when they detected use were doing this type of low-risk arbitrage. As a result, the real return could be halved. However, it is still a great return.

It is shown that these semi-risk free arbitrage can provide a great return with minimal risk. Their addition to the portfolio can significantly increase the Sharpe ratio of the overall portfolio as they provide a much greater return than leading stable coins in the crypto market. For example, the usual usdt annual interest rate for Binance exchange is only 10 percent, which is a lot compared to the usual banking interest rate, but its return is low compared to these arbitrages. By mixing these strategies into portfolios, we could achieve a higher Sharpe ratio than simply holding cryptos.

To overcome the control of the centralized exchange, traders could use decentralized exchanges when they become more mature. Decentral exchange is not adequate for frequent trading due to low liquidity, high trading fee, and high slippage. However, these conditions make the simple arbitrage on the price difference between centralized and decentralized exchange potentially very profitable, which could be explored in future research. The emergence of new blockchain technologies, such as flash loans, allows traders to take advantage of opportunities for virtual assets. Flash loans allow users to borrow money without collateral as long as the transactions are completed in a single transaction block. This allows arbitragers to use minimal interest cost to gain a leverage multiple when purchasing popular NFT tokens and sell them immediately in the same block to earn a profit.

5. Conclusion

Many pieces of research are done on cryptocurrency time-series and cross-section price prediction. This paper examines some common and unique arbitrage opportunities in cryptocurrency exchanges that are not widely mentioned in academic journals. It is shown that these semi-risk free arbitrage can provide a great return with minimal risk, despite constraints of actual market conditions and exchanges conditions that make them perform worse in live trading than backtesting. By mixing these strategies into portfolios, we could achieve a higher Sharpe ratio than simply holding cryptos.

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