Pair Trading Strategy with ANN Technique in Cryptocurrency Market

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Abstract

This study examines the profit and risk obtained from pair trading strategy, by takes advantaging of the mean-reversion property of two assets with long-term relationship, in the cryptocurrency market. First of all, we use the cointegration and the Hurst exponent tests for selecting the ten pairs of asset and the Artificial Neural Network (ANN) is used to forecast the spread and trading signal of ten pairs. The results show that the pair trading strategy could yield a positive profit for all cryptocurrency pairs and has a lower investment risk compared to single asset trading. Specifically, the ANN with sigmoid activation function could provide higher cumulative profit with lower value of risk on the average when compared to the traditional ARIMA model.

KEYWORDS: Artificial Neural Network; Cumulative profit; Cryptocurrency; Forecasting; Pair Trading Strategy

1 INTRODUCTION

Pair trading is an investment strategy that invests in a pair of assets with correlated prices. The returns of the strategy rely on the mean-reversion property, which suggests that the spread between the prices of the paired assets can be volatile, but it will eventually return to the mean level. With the mean-reversion property, when the prices of the two assets diverge, a short position should be opened for the asset with the higher price and a long position should be made for another asset with the lower price. When the prices of two assets converge back to the mean (i.e. the mean-reversion is observed), then both the short and long positions should be closed for both assets. For two assets that have a long-run relationship with mean-reversion property, a positive return can be made from such pair trading strategy (Chen et al., 2014). The pair trading strategy emerged in the 1980s at Morgan Stanley (Broel-Plater & Nisar, 2010) and has become very popular for hedging and profiting in markets regardless of market direction (Liang et al., 2021; Zhang, 2021).

To perform the pair trading strategy, most studies focus on assets with similar characteristics and, thus, the prices are highly positively correlated, such as gold and silver (Desai et al., 2012), gold and mining securities (Gutierrez & Tse, 2007), securities in the same industry (Gatev et al., 2006; Chen et al., 2019; Huck & Afawubo, 2015; Zhang, 2021; Nobrega & De Oliveira, 2013; Nobrega & De Oliveira, 2014) or ETFs that invest in same-market indexes (Van der Have et al., 2017).

The pair trading strategy is conducted in three steps, which are to (1) select pairs of assets based on the correlation or long-term relationship of their prices, (2) develop forecasting models for the spread between each pair of cryptocurrency prices and, and (3) design and test trading strategies based on the spread forecasting models. For the pair selection process, there are several pair selection techniques. Gatev et al. (2006) used daily securities data from the center for research in security prices (CRSP) and used the distance method to select trading pairs and found the pair trading strategy that can make excess return up to 11% from portfolio of pairs. In addition, Huck & Afawubo (2015) used the cointegration method for pair selection of securities in the S&P500 and found that the cointegration method is more effective and it delivers excess return 1.38% per month up to 5% per month and reducing significantly nonconvergence risk than the distance method. And Ramos-Requena et al. (2017) used the new method for pair selection based on the Hurst exponent and compared to classical methods (Distance method and correlation method), in this paper show that the Hurst exponent is better than classical methods when the portfolio has ten or more pairs. In addition to the cointegration, Zhang (2021) also used the Hurst exponent test in the pair selection process to ensure the mean-reversion property, which is essential for the pair trading strategy.

In terms of spread forecasting, previous literatures also applied several forecasting methods. The traditional pair trading strategy uses the ARIMA as a forecasting method. However, later studies have found that applying machine learning methods can improve the returns. Specifically, Dunis et al. (2015) applied the artificial neural network (ANN) to predict the spreads between corn futures and ethanol futures and found that the method can improve the returns of pair trading strategy. In addition, Van Der Have (2017) applied the Feedforward Neural Network (FNN) and the Recurrent Neural Network (RNN) to predict the spreads between ETFs on the NYSE Arca and found that the RNN can generate return from pair trading strategy around 11% and the FNN can generate return around 3% and these two prediction method can improve the return of pair trading strategy. For the trading strategy, the trading signals to open and close positions are estimated from the price spreads of each paired assets.

Later studies have applied the pair trading strategy to the cryptocurrency market. Cui & Chen (n.d.) examined the pair trading strategy with Bitcoin (BTC) and Litecoin (LTC) and found that the pair trading strategy for both daily and intraday trading leads to positive returns. Fil & Kristoufek (2020) studied pair trading strategy among 26 cryptocurrencies and also found positive returns in daily trading from pairs that selected by cointegration method and negative returns from than distance method. In addition, Nair (2021) studied pair trading between Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC) and Neocoin (NEO) found that there is a high potential for the pair trading strategies in the cryptocurrency market and can overcome a buy-hold strategy. With the limited studies on pair trading strategy in the cryptocurrency market, this study re-examines the strategy with more recent pair trading methodologies. Specifically, this study applies the cointegration and the Hurst exponent tests for the pair selection process and the Artificial Neural Network (ANN) for the spread forecasting process to conduct the pair trading strategy on 10 cryptocurrencies with the highest market capitalization.

2 METHODOLOGY

A pair trading strategy is conducted in three steps, which are to (1) select pairs of assets based on the long-run relationship of their prices, (2) develop forecasting models for the spread between each pair of cryptocurrency prices and, and (3) design and test trading strategies based on the spread prediction models. This study conducts the pair trading strategy using the Artificial Neural Network (ANN) with detailed methods as follows.

2.1 Pair selection

This study applies the two-step Engle-Granger cointegration test and Hurst exponent methods to select pairs of cryptocurrencies with long-run relationship.

2.1.1 The cointegration test

For the two-step Engle-Granger cointegration test, the first step is to estimate the spread of the prices of each pair of cryptocurrencies i and j (S_t^{ij}) using the following linear regression.

$$S_t^{ij} = P_{it} - \beta P_{jt} \tag{1}$$

where P_{it} and P_{jt} are the prices of each cryptocurrency pair. The second step is to test for the stationary of the spread using the Augmented-Dickey-Fuller test. Any cryptocurrency pairs that are cointegrated are considered to have a long-run relationship.

2.1.2 The Hurst exponent method

For each cointegrated pair, the Hurst exponent method is used to test the mean-reversion property. Specifically, the Hurst exponent (H) is defined as follows.

$$E[\frac{R(n)}{S(n)}] = Cn^H \tag{2}$$

where $R(n)$ is range of cumulative spread of each pair deviate from the mean.
$S(n)$ is the estimated standard deviation of spread of each pair.
$R(n)/S(n)$ is the rescaled range.
C is constant.
n is number of observations.
H is the Hurst exponent

Any cryptocurrency pairs with the Hurst exponent (H) of 0.5 or lower are said to have the mean-reversion property (Brooks, 1995; Ramos-Requena et al., 2017; Zhang ,2021) and are selected for the pair trading strategy in this study.

2.2 Spread forecast

The spread forecasting models for each pair of cryptocurrencies that are cointegrated and present the mean-reversion property are constructed using two methods including (1) the standard ARIMA model and (2) the ANN technique with four different activation functions of hidden layers including linear, tanh, sigmoid, and exponential functions.

2.2.1 ARIMA

$$\phi(L)(1-L)^d S_t^{ij} = \theta(L)\varepsilon_t \tag{3}$$

where S_t^{ij} is the spread of the prices of each pair of cryptocurrencies i and j
$\phi(L)$ is the autoregressive polynomial.
$(1-L)^d$ is the integrated term, d is the difference order.
$\theta(L)$ is the moving average polynomial.
L is lag operator.
ε_t is error term.

2.2.2 ANN

$$\hat{S}_t^{ij} = f_{ANN}(\sum_{k=1}^{K} w_k S_{t-1}^{ij}) \tag{4}$$

where $\hat{S}_t^{ij}$ is the spread of the price of each pair of cryptocurrencies i and j at time t
S_{t-1}^{ij} is the spread of the price of each pair of cryptocurrencies i and j at time $t-1$.
w is weight

2.3 Trading strategy

For the trading strategy, we compute the Z-score of the predicted spread $Z_t(\hat{S}_t^{ij}) = \frac{\hat{S}_t^{ij}-\mu}{\sigma \hat{S}_t^{ij}}$ where μ and σ are the mean and standard deviation of the predicted spread over time. The decision to open a trade position is contingent to the lower and upper thresholds set at 0.2 and 0.8 quantiles (which are the Z-scores of -0.8 and 0.8 (Zhang, 2021). Specifically, when the Z-score is -0.8 or lower, we long cryptocurrency i and short cryptocurrency j. When the Z-score is 0.8 or higher, we short cryptocurrency i and long cryptocurrency j. With the spread defined in Eq. (1), the ratio of short and long positions of cryptocurrencies i and j is 1 share of cryptocurrency j to β share of cryptocurrency j. The position is closed when the prices converge, and Z-score is zero (Zhang, 2021). The performance of the trading strategy is reported in term of the cumulative profit and loss (Cumulative PnL) and the value-at-risk (VaR) at 95% confidence interval.

3 DATA

The data used in this study are the daily prices of 10 cryptocurrencies from 1 January 2019 to 23 May 2022 retrieved from investing.com. The cryptocurrencies selected are those created before 1 January 2019 and had the highest market capitalization in May 2022 (Web-1). The list of 10 cryptocurrencies and the descriptive statistics of their prices are shown in Table 1.

Table 1: *Descriptive Statistics of Cryptocurrency Prices (USD)*

Cryptocurrency	Mean	S.D.	Min	Max	Skewness	Kurtosis
DOGE	0.026	0.087	0.002	0.687	4.855	27.497
ETH	529.113	720.394	104.550	4167.780	2.545	9.452
USDT	1.001	0.004	0.986	1.029	0.930	13.596
BTC	15658.260	15465.950	3397.700	63540.900	1.837	4.981
XRP	0.359	0.270	0.136	1.836	3.323	14.350
USDC	0.999	0.010	0.852	1.070	-4.141	67.457
BNB	64.239	128.587	5.470	676.560	3.177	12.380
ADA	0.227	0.403	0.023	2.300	2.545	8.532
TRX	0.030	0.026	0.008	0.164	3.113	12.631
DAI	1.003	0.015	0.918	1.079	-0.943	7.473

4 RESULTS

4.1 Pair selection results

From all possible pairs of the 10 cryptocurrencies, the results of the two-step Engle-Granger cointegration test show that 65 pairs are cointegrated indicating that their prices have long-term relationships. Among the 65 pairs, the Hurst exponent test shows that 32 pairs have the mean-reversion property. The list of the 65 cointegrated pairs is shown in Table 2 and the list of the 32 pairs that also have the mean-reversion property is shown in Table 3.

Table 2: *Cointegration Test*

Pairs	Cointegration test	Pairs	Cointegration test	Pairs	Cointegration test
DOGEETH	-0.042***	BTCADA	-0.015*	BNBTRX	-0.072***
	(0.011)		(0.007)		(0.013)
DOGEBTC	-0.017*	BTCTRX	-0.011*	ADADOGE	-0.027**
	(0.008)		(0.005)		(0.008)
DOGEXRP	-0.069***	XRPDOGE	-0.070***	ADAETH	-0.044***
	(0.014)		(0.013)		(0.010)
DOGEBNB	-0.057***	XRPETH	-0.034***	ADAXRP	-0.018**
	(0.013)		(0.009)		(0.007)
DOGEADA	-0.036***	XRPBTC	-0.020**	ADABNB	-0.026**
	(0.010)		(0.007)		(0.009)
DOGETRX	-0.035**	XRPBNB	-0.058***	ADATRX	-0.018*
	(0.011)		(0.012)		(0.008)
ETHDOGE	-0.034***	XRPADA	-0.028***	TRXDOGE	-0.034**
	(0.010)		(0.008)		(0.010)
ETHXRP	-0.024**	XRPTRX	-0.080***	TRXETH	-0.027***
	(0.007)		(0.013)		(0.008)
ETHBNB	-0.015*	XRPDAI	-0.013*	TRXBTC	-0.016*
	(0.007)		(0.006)		(0.006)
ETHADA	-0.044***	USDCDOGE	-0.476***	TRXXRP	-0.076***
	(0.010)		(0.035)		(0.012)

Table 2: *Cointegration Test*

Pairs	Cointegration test	Pairs	Cointegration test	Pairs	Cointegration test
ETHTRX	-0.021** (0.007)	USDCETH	-0.476*** (0.035)	TRXBNB	-0.076*** (0.014)
USDTDOGE	-0.126*** (0.019)	USDCUSDT	-0.520*** (0.036)	TRXADA	-0.025** (0.008)
USDTETH	-0.127*** (0.019)	USDCBTC	-0.476*** (0.035)	DAIDOGE	-0.106*** (0.017)
USDTBTC	-0.127*** (0.019)	USDCXRP	-0.476*** (0.035)	DAIETH	-0.106*** (0.017)
USDTXRP	-0.127*** (0.019)	USDCBNB	-0.476*** (0.035)	DAIUSDT	-0.119*** (0.018)
USDTUSDC	-0.152*** (0.020)	USDCADA	-0.476*** (0.035)	DAIBTC	-0.106*** (0.017)
USDTBNB	-0.127*** (0.019)	USDCTRX	-0.476*** (0.035)	DAIXRP	-0.109*** (0.017)
USDTADA	-0.127*** (0.019)	USDCDAI	-0.485*** (0.035)	DAIUSDC	-0.111*** (0.018)
USDTTRX	-0.128*** (0.019)	BNBDOGE	-0.050*** (0.012)	DAIBNB	-0.106*** (0.017)
USDTDAI	-0.139*** (0.020)	BNBETH	-0.0174* (0.007)	DAIADA	-0.106*** (0.017)
BTCDOGE	-0.010* (0.005)	BNBXRP	-0.050*** (0.011)	DAITRX	-0.108*** (0.017)
BTCXRP	-0.011* (0.005)	BNBADA	-0.029** (0.009)		

Table 3: *Hurst Exponent Test*

Pair	Hurst exponent	Pair	Hurst exponent	Pair	Hurst exponent
DAIUSDT	0.426	USDCTRX	0.440	USDTETH	0.446
USDTUSDC	0.434	USDCDOGE	0.440	USDTXRP	0.446
USDTDAI	0.435	USDCXRP	0.440	USDTDOGE	0.446
DAIXRP	0.439	USDCDAI	0.440	USDTBNB	0.446
DAIUSDC	0.439	DAIADA	0.441	USDTBTC	0.446
DAITRX	0.440	DAIDOGE	0.442	BNBXRP	0.456
USDCUSDT	0.440	DAIBNB	0.442	BNBTRX	0.461
USDCBTC	0.440	DAIETH	0.442	TRXBNB	0.465
USDCETH	0.440	DAIBTC	0.443	XRPBNB	0.470
USDCBNB	0.440	USDTTRX	0.446	ETHDOGE	0.484
USDCADA	0.440	USDTADA	0.446		

From the Hurst exponent results, stable coins including USDT, DAI, and USDC are most likely to have long-term relationships and mean-reversion property compared to other cryptocurrencies. Besides the stable coin pairs, it can be observed that pairs with a stable coin and a non-stable coin have a lower Hurst exponent coefficient compared to pairs with two non-stable coins. This implies that non-stable coins fluctuate in different patterns and less likely to present mean reversion.

4.2 Trading results

Table 4: *Cumulative PnL for No-reinvestment and Reinvestment*

Pair	ARIMA		ANN-linear		ANN-tanh		ANN-sigmoid		ANN-exp	
	No-reinv	Re-inv	No-reinv	Re-inv	No-reinv	Re-inv	No-reinv	Re-inv	No-reinv	Re-inv
XRPBNB	353.87	721.95	337.69	620.04	353.87	721.95	353.87	721.95	353.87	721.95
BNBXRP	305.28	530.18	306.90	538.93	306.90	538.93	306.90	538.93	305.28	530.18
TRXBNB	256.50	327.33	272.04	389.24	277.19	405.98	261.62	344.46	277.19	405.98
USDCUSDT	241.08	304.79	209.88	223.23	243.69	334.91	246.31	343.53	190.15	183.97
ETHDOGE	245.69	-381.94	202.25	-266.09	94.38	94.38	239.68	-355.78	247.82	-391.71
BNBTRX	223.70	270.88	232.73	297.11	228.10	283.36	228.10	283.36	223.70	270.88
USDCDOGE	134.45	134.63	140.96	143.77	140.96	143.77	150.81	159.71	139.99	142.36
USDCXRP	134.08	134.12	140.04	142.45	150.31	158.91	150.31	158.91	140.00	142.36
USDCETH	131.94	131.28	140.00	142.37	155.87	168.23	150.30	158.91	140.04	142.46
USDCBNB	142.33	145.75	139.98	142.36	153.17	163.81	149.51	157.67	139.98	142.36
USDCADA	131.94	131.28	140.96	143.78	138.52	140.30	148.78	156.51	139.99	142.36
USDCTRX	131.94	131.27	140.96	143.77	139.99	142.36	140.96	143.77	139.99	142.36
USDCBTC	143.60	147.62	139.99	142.37	139.00	140.98	139.99	142.37	139.00	140.98
DAIXRP	119.97	119.67	132.53	135.58	132.10	135.00	132.53	135.58	132.53	135.58
USDCDAI	139.27	142.06	131.29	131.27	131.29	131.27	131.29	131.27	132.77	133.25
DAITRX	117.39	116.69	127.20	128.60	127.20	128.60	126.98	128.32	127.20	128.60
DAIADA	119.12	118.72	123.79	124.07	123.79	124.07	123.79	124.07	123.57	123.80
DAIBNB	123.12	123.39	123.00	123.10	123.00	123.10	123.00	123.10	123.00	123.10
DAIDOGE	119.13	118.74	123.77	124.04	123.77	124.04	122.99	123.08	123.77	124.04
DAIETH	116.48	115.25	121.28	120.99	120.83	120.45	121.28	120.99	121.28	120.99
DAIBTC	118.91	118.14	119.66	119.03	119.66	119.03	119.66	119.03	120.06	119.60
DAIUSDC	121.89	122.44	118.84	118.73	118.84	118.73	118.84	118.73	118.84	118.73
DAIUSDT	109.84	109.89	115.84	116.64	115.84	116.64	115.84	116.64	115.84	116.64
USDTUSDC	107.31	107.38	108.13	108.28	108.13	108.28	108.13	108.28	108.13	108.28
USDTBNB	107.04	107.15	106.54	106.62	106.54	106.62	106.54	106.62	106.54	106.62
USDTTRX	108.13	108.33	106.33	106.41	106.33	106.41	106.33	106.41	106.33	106.41
USDTXRP	108.56	108.80	106.23	106.29	106.23	106.29	106.23	106.29	106.23	106.29
USDTDAI	107.63	107.79	105.80	105.86	105.80	105.86	105.80	105.86	105.80	105.86
USDTDOGE	105.76	105.78	105.65	105.67	105.65	105.67	105.65	105.67	105.65	105.67
USDTADA	107.02	107.13	105.47	105.48	105.47	105.48	105.47	105.48	105.47	105.48
USDTBTC	106.60	106.68	105.21	105.21	105.21	105.21	105.21	105.21	105.21	105.21
USDTETH	106.43	106.51	104.97	104.95	104.97	104.95	104.97	104.95	104.97	104.95
Average 32 pairs	**148.31**	**153.11**	**148.00**	**156.25**	**147.27**	**176.05**	**151.80**	**160.93**	**148.07**	**153.61**

Table 4 and 5 show the cumulative profit and loss (PnL) with reinvestment and no reinvestment and the value at risk (VaR) from the pair trading of 32 cryptocurrency pairs with long-term relationship and mean reversal property using the ARIMA model and the ANN models with different activation functions of hidden layers including linear, tanh, sigmoid, and exponential functions. The results show that the ANN model with the sigmoid activation functions of hidden layers gives the highest PnL and lowest VaR.

The three cryptocurrency pairs with the highest cumulative PnL in the case with no reinvestment are XRPBNB, BNBXRP and TRXBNB with the cumulative PnL from 1 January 2019 to 23 May 2022 (874 days) of 353.87%, 306.90% and 261.6%, respectively. For the PnL with reinvestment, the three highest pairs are the same as the no reinvestment case, which are XRPBNB, BNBXRP and TRXBNB with the cumulative PnL of 721.95%, 538.93% and 344.46%,

Table 5: *Value at risk*

Pair	ARIMA	ANN-linear	ANN-tanh	ANN-sigmoid	ANN-exp
XRPBNB	-4.494	-4.668	-4.494	-4.494	-4.494
BNBXRP	-4.982	-4.988	-4.988	-4.988	-4.982
TRXBNB	-4.557	-4.442	-4.488	-4.553	-4.488
USDCUSDT	-4.879	-4.881	-4.720	-4.557	-5.483
ETHDOGE	-4.648	-4.945	-5.624	-4.590	-4.676
BNBTRX	-4.332	-4.322	-4.318	-4.318	-4.332
USDCDOGE	-2.414	-1.833	-1.833	-1.946	-2.113
USDCXRP	-2.384	-1.826	-2.008	-2.008	-2.113
USDCETH	-2.413	-2.114	-1.740	-2.009	-2.239
USDCBNB	-1.783	-2.116	-1.739	-1.991	-2.116
USDCADA	-2.413	-1.833	-2.134	-1.925	-2.113
USDCTRX	-2.414	-1.833	-2.114	-1.833	-2.114
USDCBTC	-1.776	-2.113	-2.155	-2.113	-2.155
DAIXRP	-1.349	-1.200	-1.204	-1.200	-1.200
USDCDAI	-2.110	-1.827	-1.827	-1.827	-1.894
DAITRX	-1.678	-1.554	-1.554	-1.556	-1.554
DAIADA	-1.365	-1.439	-1.439	-1.439	-1.444
DAIBNB	-1.358	-1.483	-1.483	-1.483	-1.483
DAIDOGE	-1.377	-1.440	-1.440	-1.483	-1.440
DAIETH	-1.371	-1.376	-1.397	-1.376	-1.376
DAIBTC	-1.329	-1.333	-1.333	-1.333	-1.322
DAIUSDC	-1.329	-1.388	-1.388	-1.388	-1.388
DAIUSDT	-0.655	-0.631	-0.631	-0.631	-0.631
USDTUSDC	-0.442	-0.385	-0.385	-0.385	-0.385
USDTBNB	-0.351	-0.337	-0.337	-0.337	-0.337
USDTTRX	-0.340	-0.353	-0.353	-0.353	-0.353
USDTXRP	-0.336	-0.356	-0.356	-0.356	-0.356
USDTDAI	-0.347	-0.350	-0.350	-0.350	-0.350
USDTDOGE	-0.362	-0.338	-0.338	-0.338	-0.338
USDTADA	-0.350	-0.364	-0.364	-0.364	-0.364
USDTBTC	-0.365	-0.341	-0.341	-0.341	-0.341
USDTETH	-0.375	-0.364	-0.364	-0.364	-0.364
Average 32 pairs	**-1.896**	**-1.837**	**-1.851**	**-1.820**	**-1.886**

respectively.

For the investment risk, VaRs of the three pairs with the highest cumulative profit, XRPBNB, BNBXRP and TRXBNB, are -4.49%, -5.00% and -4.55%, respectively. This indicates a 5% chance that the daily returns of the pairs would be under -4.49%, -5.00% and -4.55% in the 874-day period.

From the PnL results, cryptocurrency pairs with no stablecoin tend to have higher returns than pairs with at least one stable coin except for the USDCUSDT pair. For pairs with one stable coin, the pairs with USDC yield higher PnL compared to pairs with DAI or USDT. The VaR have an opposite pattern from the PnL. Specifically, pairs with no stablecoin tend to have lower VaRs than pairs with at least one stable coin. This is without exception as the USDCUSDT pair also has lower VaR than non-stable coin pairs despite its high PnL.

To compare with single coin trading, this study also shows the cumulative PnL with reinvestment and no reinvestment calculated using the daily returns of each coin, as well as the VaR, as shown in Table 6. The cumulative PnL results for pair trading compared to single coin trading vary. There are cases that pair trading yields higher PnLs and also cases that single coin trading yields higher PnLs. The results show that pair trading yields lower VaR on the average for the non-stable coins reflecting that the risk from the pair trading strategy is lower than a single coin trading. As an example, consider the pair with the highest PnL, which is XRPBNB with the PnL of 353.87% with no reinvestment and 721.95% with reinvestment. If XRP and BNB are traded separately, the XRP would yield the cumulative PnL of 177.89% with no reinvestment and 35.25% with reinvestment and the BNB would yield 477.66% with no reinvestment and 807.59% with reinvestment. However, the VaR of the pair trading for XRPBNB is only -4.49%, while the VaR for XRP is -8.30% and the VaR for BNB is -7.60%.

Table 6: *Cumulative PnL for No-reinvestment and Reinvestment from single cryptocurrency*

Pair	PnL - No reinvestment	PnL - Reinvestment	Value at risk
DOGE	587.039	-11850.409	-8.203
ETH	371.148	392.454	-7.388
USDT	99.542	99.352	-0.259
BTC	320.868	413.118	-5.754
XRP	177.885	35.251	-8.295
USDC	98.934	93.043	-0.757
BNB	477.661	807.585	-7.595
ADA	444.407	583.995	-8.529
TRX	218.377	61.414	-8.751
DAI	102.084	99.498	-1.026

5 CONCLUSION

The results of this study show that the pair trading strategy, which takes advantage of the mean-reversion property of two assets with long-term relationship, yields positive profit for all cryptocurrency pairs in the time period used in this study and results in a lower investment risk compared to single asset trading. The pair trading using ANN with sigmoid activation function as the spread forecasting model gives higher cumulative PnLs and slightly lower VaRs on the average compared to the pair trading using ARIMA.

For the limitations of this study and future extensions, it should be noted that this study used in-sample prediction and did not take into account the transaction cost. The incorporation of the transaction cost should lower the PnL significantly, especially for the stable coin pairs, which have a strong mean-reversion property but smaller spreads. Moreover, for volatile assets such as cryptocurrency, stop loss strategy should also be introduced into the model.

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