Digital Assets Pair Trading

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Abstract

Pair Trading is a trading strategy that involves opening a long and short position for two assets that have a high degree of correlation. Multiple studies have been done on pair trading for equities and crypto-currencies which have given positive returns in the case of both. However, the field of NFTs (Non Fungible Tokens) has yet to be explored when it comes to Pair trading and that is what this paper will be focusing on. Quite a few NFT Collections have launched their own tokens with the idea of them being used in their ecosystem, thereby suggesting strong correlation between the collection and token and making them suitable candidates for pair-trading. The Distance Method is applied to a set of NFT-Token pairs at a formation and trading period of daily data. It is then compared to a benchmark strategy of simply buying and holding the portfolio to see if the additional risk factor of pair trading provides any major benefits while being compared to a conservative strategy.

1. Introduction

Pair trading at the crux of it is a statistical arbitrage strategy that involves opening up positions on two assets (that share strong correlation) that are trading at a price that is contradictory to their historical trading prices.

The process is built on the concept of mean-reversion. The basic principle behind mean reversion is that after an extreme price move, asset prices tend to return back to normal or average levels. Using this theory, we apply it to pair-trading: as the difference between the prices of two assets (spread) widens, the overpriced asset is shorted while the underpriced one is bought. When the spread narrows again to an equilibrium position (i.e. the mean), the positions are closed. As you would have guessed, this strategy is more profitable in a more volatile environment as high volatiltiy allows for more profit opportunities.

Many studies have been done on pair trading strategies for equities. For instance Caldeira & Moura (2013), Perlin (2009), Han et al. (2023) all suggest that pair trading equities net a high positive excess return. However, the number of studies decreases in quantity (comparitively) when we enter the world of blockchain. Some of the studies like Lesa & Hochreiter (2023) and Tadi & Witzany (2023) conclude that pair-trading cyrpto-curriecies can yield positive returns depending on factors such as folding period, correlation between coins etc. The number of studies is minimal as we go into a more niche market of NFTs which is one of the major driving factors for doing this research.

The crypto-currency market is a high risk high reward market. Factors such as liquidity issues, constant rugs and scams create a lot of risks which might scare away a passive investor, but the same investor might be lured in because of the high return opportunites the market provides (Leirvik (2022)). It is the only market in the world which provides investors to 10x, 100x and even 1000x their investments on a constant basis. All this just further cements the fact that this market is a highly volatile market which provides multiple opportunites to apply pair trading due to mispricing of assets.

1.1 Non Fungible Tokens

So what are NFTs and what differentiates them from crypto-curriencies? While the coins are simply an encrypted form of digital currency that rely on a certain blockchain technology, NFTs are one of a kind digital assets that are stored on blockchain and cannot be duplicated. They can represent anything from photos, music, videos etc. Both these assets don't rely on government or any financial institutions. We know that the price of a crypto-currency is dependent on many factors such as market beta, trading volume, attractiveness and volatility (Sovbetov (2018)), but what factors influence the price of an NFT? NFTs vary widely within a category and across different categories such as arts, music, sports, club memberships, games etc. Unlike cryptocurrencies, every NFT is distinct, and the value of an NFT may be more personal to a particular buyer rather than universal across all buyers. Essentially, it's the individual buyer's readiness to pay that primarily influences the peak price of an NFT. In addition, the value of NFTs isn't solely based on the artistic quality or their scarcity, though these aspects are important. Their worth largely stems from the substantial benefits they offer to owners in both real and virtual worlds, by design (Zhang (2023)). Another factor which is the previous sales of the related NFTs as it captures the risk and reward associated with marketing new NFTs (Nadini et al. (2021)). This does not mean that NFTs are not affect by the factors effecting prices of crypto-currencies. In the early days, one of the biggest factors driving the prices of NFTs was exclusivitey and hype. Even if the NFT provided no utility, their prices were going high. But post the NFT bubble burst, there wasn't herd investing happening (Özdemir & Kumar (2023)) more and only those NFTs were performing well that provided some real-world utilities - be it giving access to certain tools like custom trading algorithms or early seed investing opportunities in popular upcoming projects.

As NFTs started getting more and more popular, a lot of them started launching their own tokens. The idea behind most of the token launches was to create a use-case for them in the ecosystem the NFTs had built. For example, when the NFT collection Neo Tokyo launched their coin **BYTES**, the goal was to make bytes a hard value backed token for NT holders, by making it finite and making it the means of transaction for all apps, tools and systems inside of NT. So it is natural to see that if an NFT is doing well and providing good utility, its custom token would also be doing well as it is being traded/used on a constant basis (high market volume). However, if post the token launch, the NFT turns out to be a scam, the price of the token would go to zero as there is no longer a use-case. *Hence, it is safe to assume that an NFT Collection and its custom token share a strong correlation. If we add other factors of the cryptocurrency market such as high volatility, it gives investors a perfect opportunity to do pair-trading.* This is because at the end of the day, high volatiltiy means that the spread is moving further away from the equilibrium position (Rad et al. (2016)). And this is what the entire paper will be focusing on.

In a lot of these studies that have been mentioned above, there are quite a few methods that are used for making selections of pairs including but not limited to the Distance Method, the Cointegration Method (Leirvik (2022)), the Copula Method (Rad et al. (2016)) and then performing the trading strategy based on the selection method. For instance, in the case of the Distance Method, post selection, when we need to enter a position, we long one asset and short the other. In the case of Cointegration Method, we long one asset and short β units of the other asset. (β is calculated via the cointegration method)

Since the world of NFTs and their custom tokens is still relatively new, we cannot really filter out pairs so we do not need to focus on the selection methods used in previous studies because of lack of data. We shall be focusing on just 5 pairs. The NFT Collections I have chosen have a proven track record. Some factors that were looked into while making the selections were:

1. **Longetivity**: All these NFT Collections are more than two years old
2. **Utilities**: All these collections provide some kind of real-world utility in one way or the other
3. **Doxxed Creators**: If the creators are not doxxed, there are high chances that it is a scam
4. **Trading Volume**: These NFTs are being traded (bought and sold) regulalry.

2. Data and Methodology

The 5 pairs that I have selected are as follows:

Table 1: NFT Collections and Their Tokens

NFT	Coin
Bored Ape Yacht Club	$APE
Neo Tokyo	$BYTES
Impostors Genesis Aliens	$BLOOD
Goons of Balatroon	$GOB
Caveworld 3	$CAVE

2.1 Data

Out of all these pairs, all of them except Caveworld is based on the ethereum blockchain while Caveworld is built on Solana blockchain. The cryptocurrency related data was extracted from coinmarketcap.com and coingecko. For the NFT prices (for ethereum based ones), I used the public api provided by NFTPriceFloor. This API gave us the floor price for individual NFT collections. I could not find anything similar for the Solana based NFT so I manually scrapped its data using a parser. All the prices (both coins and collections) are in USD and the granularity is daily.

Since the data is not easily available as most of the sites only have data going back to an year at most for NFTs, the date-ranges for each pair are different. I am keeping the end date(2024-04-24) the same for all collections, but the starting date range is different for all pairs but that should not matter that much. The date ranges are as follows:

Table 2: NFT Collections and Their Start Date

NFT	Date
Bored Ape Yatch Club	2022-11-07
Neo Tokyo	2023-06-04
Impostors Genesis Aliens	2022-11-07
Goons of Balatroon	2022-11-07
Caveworld 3	2023-01-06

2.2 Methodology

This section of the paper discusses the methodology used. Most of the previous papers on pair-trading focus on two steps: selection and trading (Vidyamurthy (2004)) we are only going to focus on the trading part of it since we have already selected the pairs. We shall simply apply the trading strategy behind the selection method.

The data is divided into two parts: the formation period and the trading period. We apply the trading strategy on the trading period data. Unlike previous papers where formation period is usually 6 months (Figuerola-Ferretti et al. (2017)), we have taken a smaller formation period window because nfts are still a new asset class and there is not a large amount of historical data. Hence, the paper will mainly focus on 5 main formation period windows: 30, 45, 60, 75, 90 and 120 days and will then compare the results to see which formation period gives the best returns.

Pair trading involves setting an upper and lower threshold. If any of the two thresholds are touched/crossed an order is executed (based on what kind of method we are using). I am using two strategies for each method: fixed threshold and dynamic threshold. I am also implementing a buy and hold strategy and am going to use it as a benchmark strategy only.

2.2.1 Z-Score vs Spread

We will look at the perform pair-trading on two signals: the z-score and the spread. Both of them are used to identify trading opportunities but at the end of the day, they serve different purposes:

1. Z-Score: The Z-score provides a standardized way to identify extreme deviations. A high positive or negative Z-score indicates that the spread is significantly different from the mean, suggesting a potential mean-reversion opportunity. This method allows traders to quantify the deviation in terms of statistical significance.

2. Spread: Traders look at the spread to identify deviations from the historical norm. When the spread widens or narrows beyond a certain threshold, it may indicate a trading opportunity. For example, if the spread is wider than usual, a trader might short the outperforming asset and go long on the underperforming one, expecting the spread to revert to its mean.

So this brings us to the question when should one use spread and when should one use Z-score. When dealing with pairs where the historical spread range is well-known and relatively stable spread tends to be better and when comparing multiple pairs or when the spread's volatility is not constant, Z-score is preferred.

In this paper, we will use both of them, see which gives better returns and then use that for calculating the benchmark returns as well.

2.3 The Distance Method

We do not have to worry about the selection process since we have already decided on our pairs. We shall simply be focusing on the trading strategy execution part of this method. In the distance method, each time the threshold is breached, opposite positions of one unit of asset A and one unit of asset B is opened, thereby obtaining an equally weighted (in units) long-short portfolio.

2.3.1 Trading Strategy: Fixed Threshold

We are going to define the term **spread** which is the difference between the prices of NFT and its coin. The spread at time t can be defined as:

$$S_t = p_{n,t} - p_{c,t} \tag{1}$$

where $p_{n,t}$ is price of the NFT at time t and $p_{c,t}$ is the price of the coin at time t.

The standardized residual spread can then be defined as:

$$z_t = \frac{S_t - \mu_s}{\sigma_s} \tag{2}$$

where μ_s and σ_s are calculated using the formation period. Simultaneously, the upper and lower thresholds can be defined as:

$$T_u = \mu_z + 2 * \sigma_z \tag{3}$$

$$T_d = \mu_z - 2 * \sigma_z \tag{4}$$

The logic behind using $2 * \sigma_z$ as a threshold according to (Leirvik (2022)) is that security prices are log-normally distributed and hence the log-prices are normally distributed. So given the shape of a normal distribution, 95% of the data lies within two standard deviations from the mean and those lying outside two standard deviations can be considered an outlier. However, in order to do a more comprehensive analysis, we are going to use different values of threshhold to see if there is a performance difference. The different thresholds used will be: $0.5 * \sigma_z$, $1 * \sigma_z$, $1.5 * \sigma_z$, $2 * \sigma_z$, $2,5 * \sigma_z$

The basic trading rule for this strategy is that whenever the upper threshold is breached, we short one unit of the nft and long one unit of the coin. If the lower threshold is breached, we long one unit of the nft and short one unit of the coin. The following figures depict this strategy for different pairs:

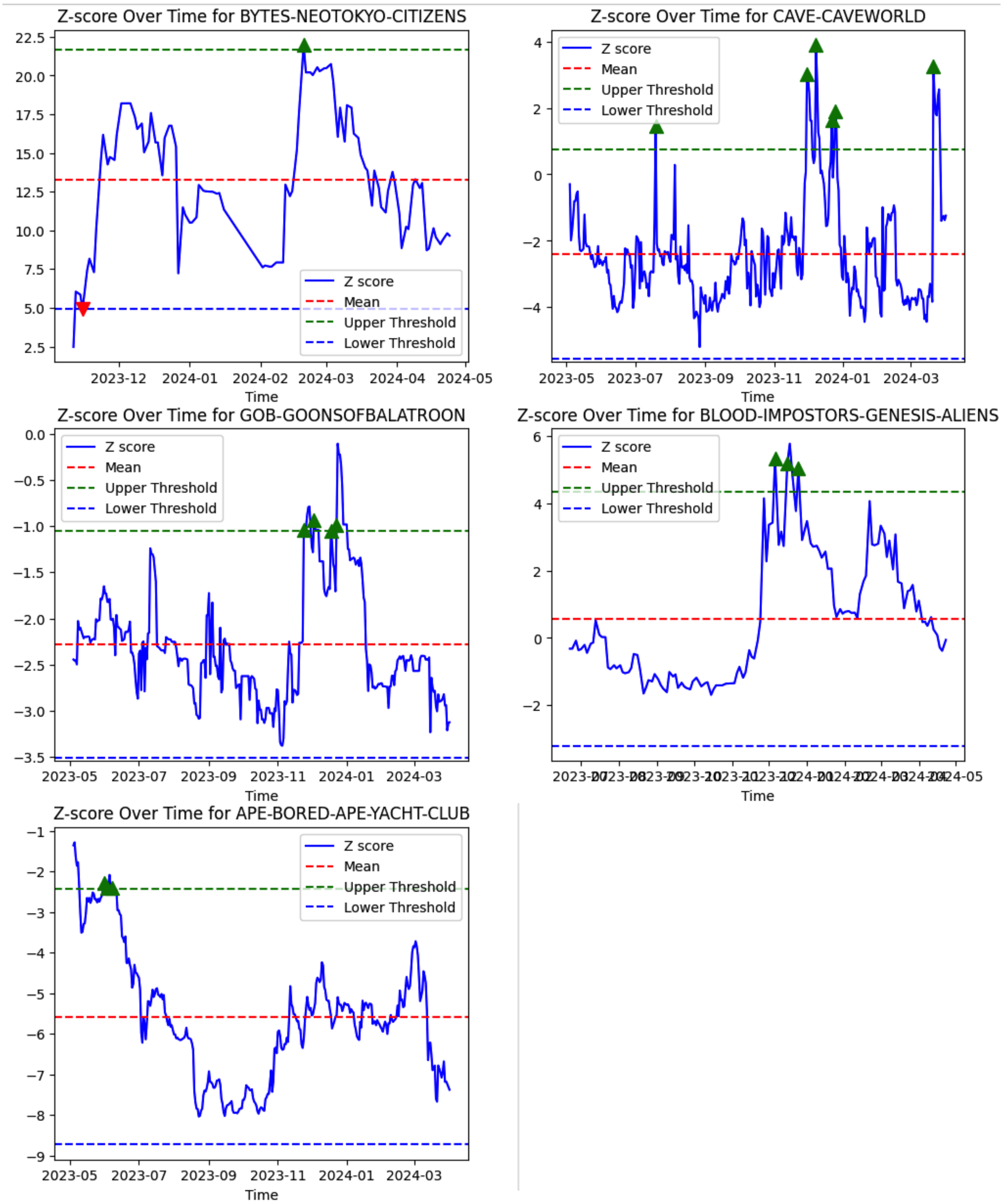

Figure 1: This shows all the times threshold has been breached and where we can open positions for different pairs.

2.3.2 Trading Strategy: Dynamic Threshold

This strategy uses a dynamic threshold based on the volatiltiy and mean computed on a rolling basis. As mentioned above, we will use different values of the formation period and compare results to see which formation period provides the best results. The equations for the thresholds are (when using spread):

$$T_u = \mu_t + 2 * \sigma_t \tag{5}$$

$$T_d = \mu_t - 2 * \sigma_t \tag{6}$$

This method is used to capture the time variation in the spread. The following figures depict this strategy for different pairs:

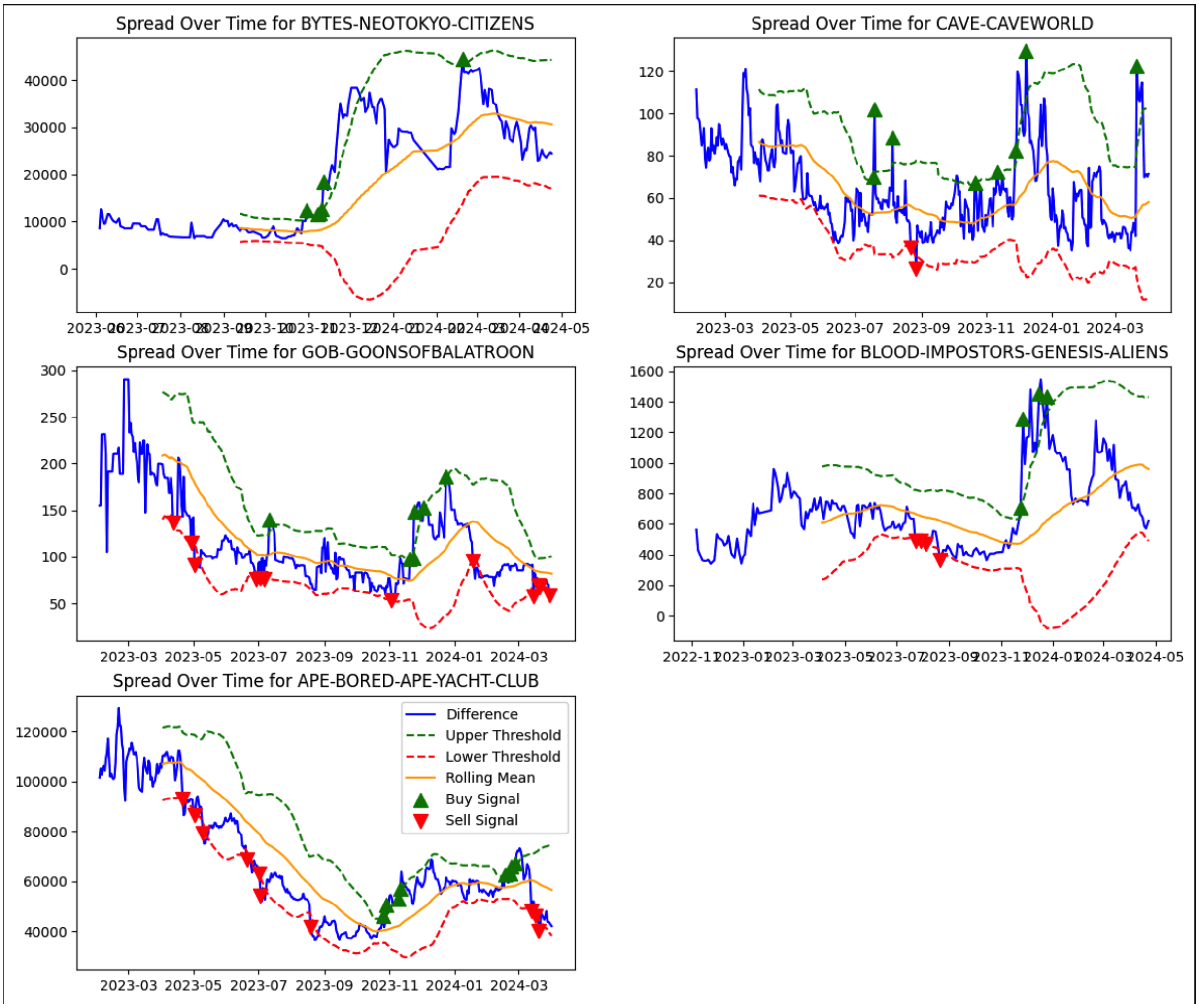

Figure 2: This shows all the times the dynamic threshold has been breached and where we can open positions for different pairs.

2.3.3 Buy and Hold

This is a benchmark strategy that will be used to compare the results of different strategies we have discussed above. The aim of this portfolio is to passively invest in a strategy and to see whether holding onto the positions would be more profitable than actually implementing pair trading. In this strategy, no positions will be closed when mean reversion takes place. Rather, we will simply calculate the paper profits at the end of the date range.

2.3.4 Stop Loss Method

This is another benchmark strategy that will be used to compare the results of different strategies we have discussed above. The aim of this portfolio is to minimize risk and exit positions whenever a the loss is greater than a defined threshold. The idea behind this strategy in a pair-trading strategy is when the spread of an open position crosses a certain threshold (either upper or lower), that particular open position is closed to reduce exposure. This threshold is pre-decided. The one major drawback of this strategy is even though it is a profit-saving strategy, it might close positions too early (before reverting) which means that the investor is denied capturing a higher profit from mean reversion.

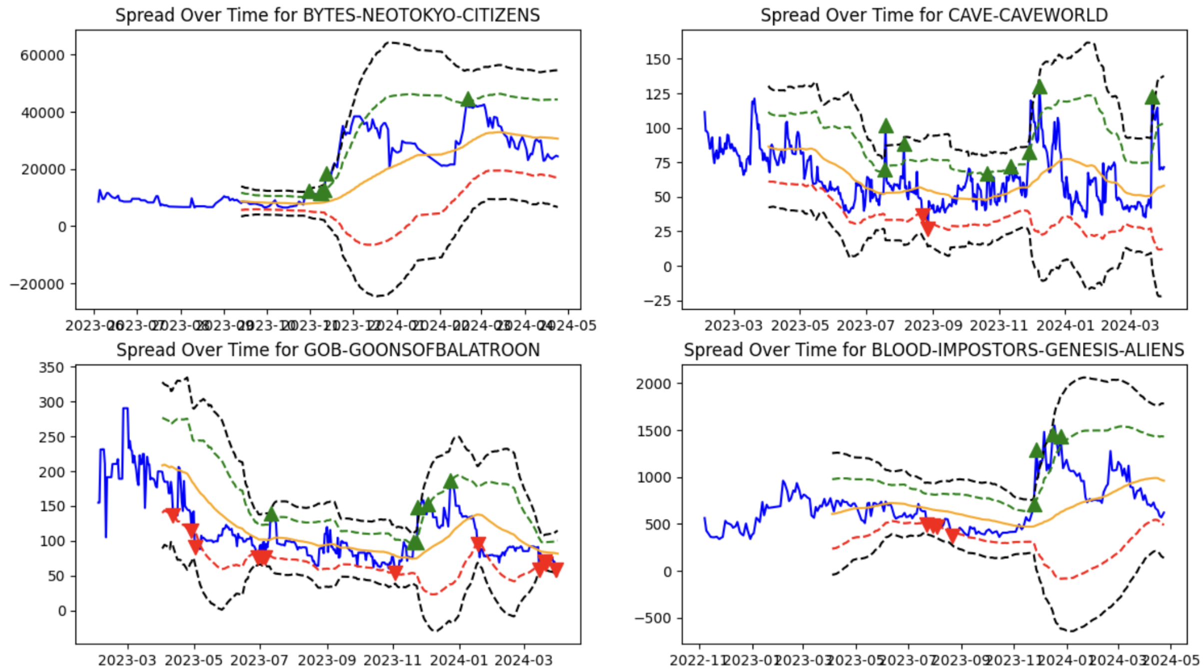

Figure 3: The Black dotted line shows the stop loss thresholds based on current spread

2.4 The Co-integration Method

Unfortunately we cannot implement the Co-integration Methodology for pair-trading NFTs and their native crypto-currencies and there are two main reasons for it. As we know, co-integration method involves calculating β (Rad et al. (2016)) and when a threshold is breached we long one unit of asset A and short β units of asset B. The value of β can be less than 1 which causes two main problems:

1. **Fractionalized NFTs**: Unlike other assets like stocks and crypto-currencies where we can buy fractional quantities as well, buying fractionalized units of an NFT is not that widely supported apart from one or two marketplaces at most.

2. **Multiple NFTs**: If $\beta > 1$ and is a whole number, that would mean buying multiple NFTs from the same collection. But the price of each NFT would not be same since buying one NFT first, would cause the floor price to change. It could be a huge

jump in price or a small jump in price. It all depends on the next minimum price of an NFT from the same collection that has been listed for sale.

Both these reasons make implementing pair-trading unrealistic and as a result, this paper shall not be focusing on that.

2.5 Transaction Costs

Cryptocurrencies are known for their high and volatile transaction fees. There are multiple reasons for it: busy network, poor scalability etc (Ko et al. (2022)). NFTs are no different. There are no fixed transaction fees associated with a sale. The fee varies depending on the time of the day and how busy the network is. This is especially the case for NFTs based on ethereum blockchain. As a result, the gas fee data for ethereum was scrapped from the internet and for each day the 25^{th} percentile, the 50^{th} percentile, the 75^{th} percentile and the mean of the gas fees was calculated. The net returns were calculated while taking each fee into account. The different return results were compared to see if the change in transaction fees cause a major difference in the returns or not. Example:

Table 3: ETH Gas Price

Date	Mean	50^{th}	75^{th}	25^{th}
...	...	...	...	...
2024-04-28	6.770833	6.5	8.00	5.000
2024-04-29	8.791667	9.0	11.00	7.000
2024-04-30	13.446809	9.0	16.00	7.000
...	...	...	...	...

Note: Fees are in USD

For the Solana blockchain, the fees are more or less constant so I did not have to do the same thing for the CaveWorld-$CAVE pair.

2.6 Evaluation Metrics

For this research, I have not used log returns as suggested in (Perlin (2009)). The reason for that is because if I use the formula:

$$r_t = ln(\frac{P_{i,t}}{P_{i,t-1}}) - ln(\frac{P_{j,t}}{P_{j,t-1}}) + 2ln(\frac{1-c}{1+c}) \tag{7}$$

we end up with a negative term inside the log function which leads to issues (Gas prices can be > 1). As a result, I am calculating the returns through simple profit and loss formula.

Let $p_{a,x}$ be the price of asset a which we are going to long at time x and let $p_{b,x}$ be the price of asset b which we are going to short. Let the gas price at time x be g_x

Let $p_{a,y}$ be the price of asset a when we close the position at time y and let $p_{b,y}$ be the price of asset b when we close the position at time y. Let the gas price at time x be g_y. So the return can be calculated as:

$$r_{xy} = \frac{(p_{b,y} - p_{b,x}) + (p_{b,x} - p_{a,y}) - 2(g_x + g_y)}{p_{b,x} + p_{a,x} + 2 * g_x} \tag{8}$$

3. Results

3.1 Z-score vs Spread

While comparing the returns for fixed-threshold and dynamic-threshold method for both z-score and spread, I found out that using spread gave better returns, which you can see from the table below:

Threshold	Rolling Period	Fix. (Spread)	Fix. (Z)	Dyn.(Spread)	Dyn. (Z)
0.5	30	0.197249	0.197249	-0.005330	-0.119372
	45	0.161964	0.161964	-0.065089	-0.063526
	60	0.157358	0.157358	-0.092108	-0.113532
	75	0.261583	0.261583	-0.086243	-0.401209
	90	0.248336	0.248336	-0.033959	-0.103978
	120	0.153499	0.153499	0.022446	-0.035363
1.0	30	0.496975	0.496975	0.022908	-0.096703
	45	0.485434	0.485434	-0.026605	-0.070859
	60	0.478682	0.478682	-0.095795	-0.104289
	75	0.451120	0.451120	-0.128730	-0.390741
	90	0.388285	0.388285	0.027257	-0.083928
	120	0.253309	0.253309	0.097580	-0.037487
1.5	30	0.136220	0.136220	-0.048280	-0.154195
	45	0.279597	0.279597	-0.113672	-0.150612
	60	0.412132	0.412132	-0.131520	-0.200622
	75	0.228818	0.228818	-0.024508	-0.474681
	90	0.290376	0.290376	-0.068151	0.129318
	120	0.259096	0.259096	0.100991	-0.005727
2.0	30	0.215912	0.215912	-0.004875	-0.245347
	45	0.228615	0.228615	-0.138166	-0.249640
	60	0.158209	0.158209	-0.226923	-0.274848
	75	0.234119	0.234119	-0.139163	-0.405102
	90	0.307087	0.307087	-0.069294	0.218052
	120	0.233463	0.233463	0.178896	-0.023601
2.5	30	0.214325	0.214325	-0.083461	-0.200143
	45	0.246087	0.246087	-0.056433	-0.244953
	60	0.246276	0.246276	-0.118625	-0.339339
	75	0.201528	0.201528	-0.051863	0.000172
	90	0.265735	0.265735	-0.043140	0.022811
	120	0.184610	0.184610	0.125622	0.009745

Table 4: Comparison of Different Thresholds and Rolling Periods

The returns were exactly the same for Spread and Z-score for the threshold which was very surprising. However, Dynamic Threshold method gave much better returns for Spread. Hence we will be using Spread results for comparision purposes with benchmark methods.

3.2 Number of Transactions

The number of transactions decrease as we increase the formation period. And the number of transactions in dynamic threshold strategy are much higher as compared to the number of trades in fixed threshold strategy.

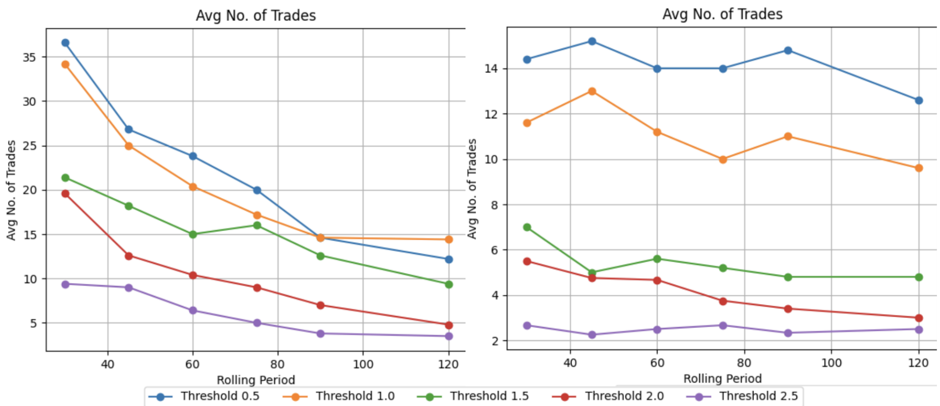

Figure 4: This shows the average number of trades. Dynamic on the left, Fixed on the right

3.3 Different Formation Periods

As the formation period increases, we see that the returns are decreasing as well. The returns decrease by nearly 50% as we move from 30 formation days to 120 formation days. Currently we are limited to just roughly a years worth of data, but it would be good to know in the future if we have more data points and we use 6 months as the formation period, will the returns continue to dip?

3.4 Different Thresholds

For all the different threshold values: 0.5, 1, 1.5, 2 and 2.5 it seems that the threshold value of 1 returns the best results by a large margin. While for others it seems that they somewhat have the same performance except when the formation day is 60 days. That is the only point where there is a big noticeable difference in the returns for different thresholds.

3.5 Different Transaction costs

Surprisingly, the different transaction costs do cause somewhat of a difference in returns. The model with Mean transaction fee performs the best while the model with the 25^{th}

percentile transaction cost performs the worst. While the 25^{th} percentile model yields a 0.43 return, the mean model yields a return of roughly 0.5 which is significant. This also tells us that the transaction costs are skewed and that there is no uniformity in the increase or decrease of gas prices. So in retrospect, we should implement pair-trading for nfts when the network is not busy.

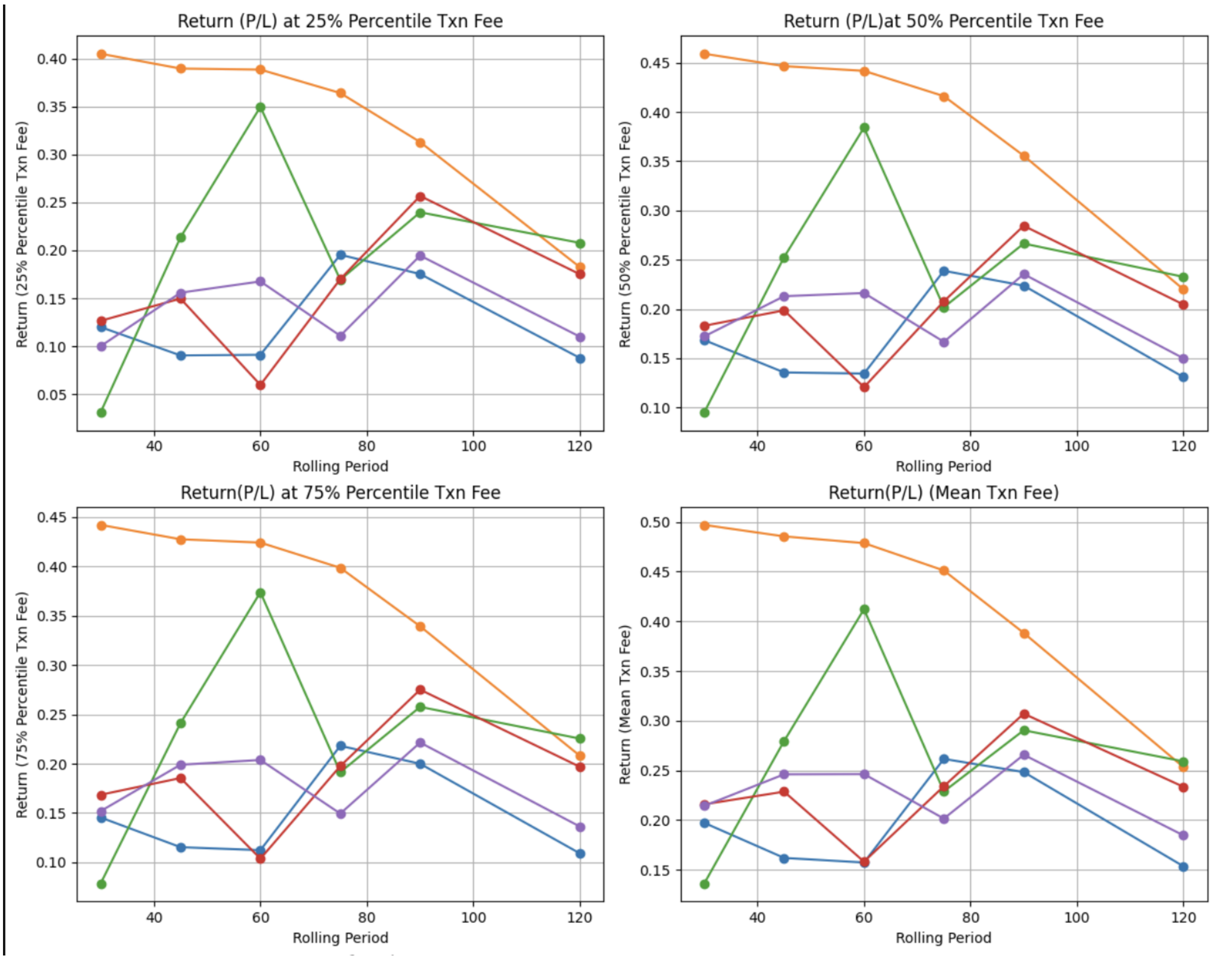

Figure 5: This shows the returns for different formation periods, thresholds and txn fees

3.6 Method Performance

3.6.1 Sharpe Ratio

The Sharpe ratio is a measure used to evaluate the risk-adjusted return of an investment or a trading strategy. It is calculated by subtracting the risk-free rate of return from the mean return of the investment and then dividing the result by the standard deviation of the investment's return. The formula for the Sharpe ratio is:

$$SharpeRatio = \frac{R_p - R_f}{\sigma_p} \tag{9}$$

A higher Sharpe ratio indicates that the investment has a better risk-adjusted return.

1. Sharpe Ratio < 1: The strategy has not been able to generate returns higher than

what could be earned on a risk-free investment. This is considered suboptimal.

2. Sharpe Ratio = 1: Indicates that the investment's return is exactly in line with the level of risk taken. This is considered a neutral performance.

3. Sharpe Ratio > 1: Indicates that the investment or strategy has provided a higher return per unit of risk. This is generally considered good.

4. Sharpe Ratio > 2: Indicates excellent risk-adjusted performance.

Table 5: **Sharpe Ratio for Strategies for different thresholds and formation periods.**

Threshold	Formation Period	Fixed Sharpe Ratio	Dynamic Sharpe Ratio	Stop-Loss Sharpe Ratio	Buy-Hold Sharpe Ratio
0.5	30	0.160468	-0.260634	-0.456640	-0.258195
	45	0.175004	-0.350597	-0.395710	-0.328551
	60	0.125762	-0.395596	-0.448712	-0.285553
	75	0.310093	-0.277421	-0.368469	-0.350945
	90	0.231856	-0.193895	-0.329443	-0.294435
	120	0.108188	-0.048203	-0.208081	-0.124280
1.0	30	0.630812	-0.240288	-0.402276	-0.229675
	45	0.594689	-0.290282	-0.327290	-0.242358
	60	0.528250	-0.388690	-0.449356	-0.233803
	75	0.570848	-0.283662	-0.369454	-0.403942
	90	0.373734	-0.144278	-0.224294	-0.331868
	120	0.373248	-0.078036	-0.196581	-0.254192
1.5	30	0.443533	-0.270628	-0.390180	-0.179335
	45	0.576434	-0.521091	-0.612610	-0.485041
	60	0.324544	-0.500308	-0.544502	-0.466552
	75	0.280560	-0.318803	-0.359375	-0.343405
	90	0.355635	-0.295453	-0.392486	-0.236040
	120	0.405666	-0.184408	-0.313814	-0.219754
2.0	30	0.583218	-0.292503	-0.433396	-0.388771
	45	0.477367	-0.593429	-0.687426	-0.499224
	60	0.462870	-0.602958	-0.719937	-0.457978
	75	0.612420	-0.483476	-0.587480	-0.321952
	90	0.496656	-0.309549	-0.404753	-0.204386
	120	0.492821	0.119936	-0.165720	0.086533
2.5	30	0.554760	-0.350048	-0.574714	-0.176285
	45	0.488780	-0.307818	-0.463842	-0.219555
	60	0.091754	-0.402975	-0.511505	-0.252401
	75	0.487974	-0.221670	-0.463092	-0.034947
	90	1.548581	-0.062091	-0.354127	0.161602
	120	1.171096	0.307118	-0.514546	0.548301

The Fixed-Threshold strategy has the best sharpe ratio (1.548581) while the benchmark strategies and the dynamic threshold strategy have negative sharpe ratios indicating poor performance. Infact, the Stop-Loss strategy has the worst Sharpe Ratios amongst all four strategies.

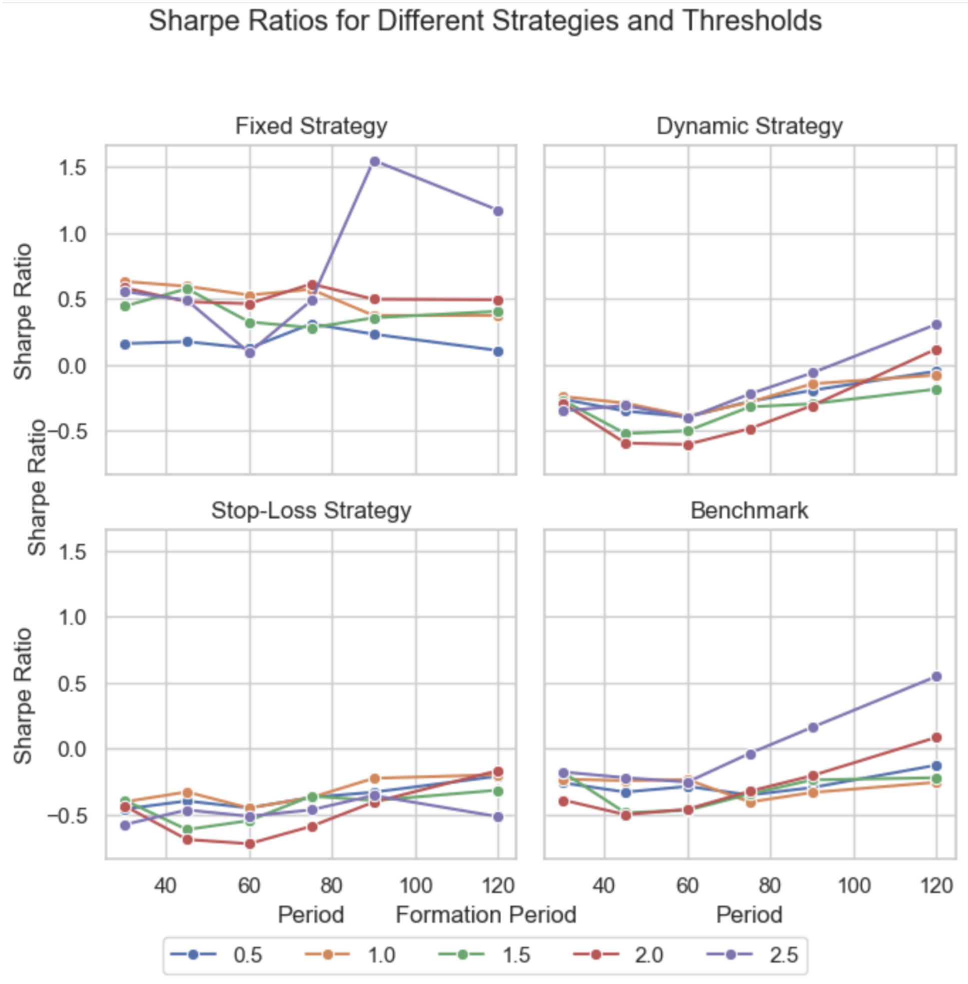

Figure 6: Sharpe Ratio for Strategies for different thresholds and formation periods

3.6.2 Returns

Let us now look at the performance of the three main strategies: fixed threshold, dynamic threshold and buy-hold strategies. We will compare the results for different thresholds and frequencies. We will use the Mean Transaction fee model since that was the best performing model.

It turns out that that fixed-threshold strategy performs the best among the three with a 48% return as compared to 17.8% return for the dynamic threshold strategy. The increase in the number of trades in the case of the dynamic threshold strategy would have also led to increase in transaction costs that would have affected the returns. The Buy-Hold strategy yields a 19.8% return which is even better than the dynamic threshold strategy.

An interesting thing to note here is that for the dynamic-threshold strategy, there wasn't any best threshold value as different values of threshold were giving better returns for different formation periods.

Let us now touch base on the Stop-Loss Model. As I had stated earlier, that even though this method prevents extreme losses from happening, it also makes the investor lose out on profit opportunites. This model turns out to be the worst performing model, which brings up the question: Is being conservative a drawback in a volatile market?

Table 6: **Returns for Strategies for different thresholds and formation periods.**

	Formation	Fixed		Dynamic		Buy & Hold	
Threshold	Period	Avg Trades	Return	Avg Trades	Return	Avg Trades	Return
0.5	30	14.400000	0.197249	36.6	-0.005330	-	-0.055000
	45	15.200000	0.161964	26.8	-0.065089	-	-0.115635
	60	14.000000	0.157358	23.8	-0.092108	-	-0.063300
	75	14.000000	0.261583	20.0	-0.086243	-	-0.088615
	90	14.800000	0.248336	14.6	-0.033959	-	-0.029465
	120	12.600000	0.153499	12.2	0.022446	-	0.022775
1	30	11.600000	0.496975	34.2	0.022908	-	-0.005877
	45	13.000000	0.485434	25.0	-0.026605	-	-0.035723
	60	11.200000	0.478682	20.4	-0.095795	-	0.043406
	75	10.000000	0.451120	17.2	-0.128730	-	-0.089561
	90	11.000000	0.388285	14.6	0.027257	-	0.019689
	120	9.600000	0.253309	14.4	0.097580	-	0.061095
1.5	30	7.000000	0.136220	21.4	-0.048280	-	-0.008495
	45	5.000000	0.279597	18.2	-0.113672	-	-0.178699
	60	5.600000	0.412132	15.0	-0.131520	-	-0.069294
	75	5.200000	0.228818	16.0	-0.024508	-	-0.023398
	90	4.800000	0.290376	12.6	-0.068151	-	-0.007825
	120	4.800000	0.259096	9.4	0.100991	-	0.098599
2	30	5.500000	0.215912	19.6	-0.004875	-	-0.069144
	45	4.750000	0.228615	12.6	-0.138166	-	-0.136522
	60	4.666667	0.158209	10.4	-0.226923	-	-0.135160
	75	3.750000	0.234119	9.0	-0.139163	-	-0.171608
	90	3.400000	0.307087	7.0	-0.069294	-	-0.012397
	120	3.000000	0.233463	4.8	0.178896	-	0.181493
2.5	30	2.666667	0.214325	9.4	-0.083461	-	-0.004250
	45	2.250000	0.246087	9.0	-0.056433	-	-0.045547
	60	2.500000	0.246276	6.4	-0.118625	-	-0.049219
	75	2.666667	0.201528	5.0	-0.051863	-	-0.007094
	90	2.333333	0.265735	3.8	-0.043140	-	0.061010
	120	2.500000	0.184610	3.5	0.125622	-	0.198008

4. Future Opportunities

The world of NFTs is an esoteric market, there is much more to discover:

1. Right now, we are simply working with 5 pairs. We can collect data for more pairs and even perform selection methods used in Distance Method (in other papers) etc

to choose the best pairs. Right now, the lack of data could be causing underfitting.

2. We have just been in a way backtesting data. What we can do next is create a trading bot that actually implements this strategy in realtime. This would also require us to generate signals and metrics. We can then tune the strategy based on the results we are getting

3. We can use Machine Learning to find the optimal hyper-parameters that give us the best results (that is, the most profits)

5. Conclusion

The main aim of this paper was to check the feasibility of pair-trading NFTs and cryptocurrencies. I chose 5 NFT-cryptocurrency pairs with high market cap. I analyzed different transaction fees, formation periods and threshold values on fourdifferent strategies: Fixed-Threshold, Dynamic-Threshol, Stop-Loss and Buy and Hold.

Using Spread gives better results as compared to z-score while performing pair-trading. Out of the four strategies, Fixed-Threshold had the best results followed by Buy-Hold and then Dynamic-Threshold strategy. Stop Loss strategy had the worst performance. The returns of the dynamic-threshold and stop-loss strategies were diminished because of higher number of transactions which adds up the transaction fees.

Another interesting thing which I found was that transaction fees do affect the returns a lot with a difference of 13%. So trading during off-hours when the network is less busy is definitely more profitable.

Overall, a return of roughly 49% is very profitable which tells us that pair-trading NFTs is definitely feasible.

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