Cryptocurrency Pair Trading

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Abstract

Pair trading is a strategy which relies on betting on the relative mispricing of the spread between two securities which share a long-term relationship. These strategies have shown to perform well with equities, however not much research has been conducted in the field of cryptocurrencies, even though this asset class has shown characteristics suggesting suitability for pair trading. The Distance Methods and Cointegration Method are applied to a set of cryptocurrencies at formation and trading periods of daily and hourly data. It is shown that the frequency of the selection period does not influence the pairs selected. Cointegration-selected pairs generally outperforms Distance-selected pairs. When trading frequency is analysed, intraday trading is more profitable, but not when using a stop-loss. Cointegration overperforms Distance, as the cost of the latter selection are increased by the higher number of trades.

1 Introduction

Pair trading is a statistical arbitrage strategy which involves betting on the spread between two securities. As defined by Ehrman (2006), pair trading means opening offsetting positions in securities which have been historically or statistically related, but whose price relationship is temporally deviating.

The pair trading process relies on the concept of mean-reversion, hence on the belief that anomalies in the difference in prices of the selected assets will revert to their mean value. As the difference between the securities' prices widens, the overpriced asset is shorted while the overpriced one is contemporaneously bought. When the spread narrows again to an equilibrium value, the positions are closed. Even though market inefficiency exist at some level, arbitrage activity is mostly done on assumed pricing flaws. The activity of opening and closing to offset positions is the key of the market neutrality of the strategy, since long-short strategies are meant to be independent from the market. Hence, these strategies are said to have a low beta (low positive correlation) to the market.

Pair trading strategies and their profitability have been widely studied for equities. For example, Rad *et al.* (2016) , Dunis *et al.* (2015), Dunis *et al.* (2006), Perlin (2009) , Huck (2010), Gatev *et al.* (1999), Caldeira & Moura (2013), Jurek & Yang (2007), Chang *et al.* (2021) , Figuerola-Ferretti *et al.* (2018) find that pair trading, as being a market neutral strategy, profits regardless of market conditions, with high positive Excess Returns, Sharpe Ratios and Information Ratio. However, there is scarce literature which compares the efficiency of several pairs selection methods (Blázquez *et al.* (2018)) and the performance of trading strategies when using different pair formation methods (Blázquez *et al.* (2018), Zhi *et al.* (2017), Huck & Afawubo (2015) , Rad *et al.* (2016) and Jurek & Yang (2007)).

Some comparative studies inspecting different data sampling frequency exist, even though pairs trading perform generally well with intraday data (Stübinger & Endres (2018),Liu *et al.* (2017), Dunis *et al.* (2010)). In particular, the latter paper finds that the traded portfolio produces Information Ratios of over 3 for a high frequency sampling interval and 1.3 for a daily sampling frequency, indicating a better performance for intraday trading.

So far, not much research has been conducted on pair trading profitability when applied to cryptocurrencies, which is the first motivation for choosing the topic of this research. Nair (2021), Tadi & Kortchemski (2021), and Osifo & Bhattacharyya (2020) report positive excess returns and high return on investment, while Fil & Kristoufek (2020) shows that under some conditions the technique can perform well with cryptoassets and in particular as the sampling frequency increases, with the Cointegration Method being more robust than the Distance Method.

Furthermore many trading strategies have been successfully ported from equities to cryptoassets. For example, Grobys *et al.* (2020) shows that applying a simple moving average rule on the eleven most traded coins produces annual excess returns of 8.76% after controlling for the average market return and that markets do not exhibit efficiency in its weak form. Corbet *et al.* (2019) tries different moving average trading rules and finds that, overall, they provide significantly high returns. Adding to this, Hudson & Urquhart (2021) employ almost 15.000 technical trading rules from five classes of technical trading rules, finding significant predictability and profitability once applied to different coins and that they give higher risk-adjusted returns than a buy-and-hold strategy.

Cryptos seems to reveal a high profitability potential in a pair trading strategy, since they exhibit characteristics which have been sources of profitability in other markets, see also the papers in Osterrieder & Barletta (2019) They are in fact, inefficient, have a problematic liquidity structure, are subject to bull and bear markets, are volatile (Woebbeking, 2021) and experience bubbles. The Efficient Market Hypothesis (EMH) (Fama, 1970) states that a market is efficient if the prices of the constituent assets fully reflect all available information. This means that for efficient assets, the information is instantly reflected in prices and returns are unpredictable, i.e. follow a random walk. By examining risk and returns of pair trading with daily data between 1962 and 2002, Gatev *et al.* (2006) it can be shown that annualized excess returns of 11% are not a result of simple mean reversion or momentum returns, as explained by Jegadeesh (1990) and Lehmann (1990), but rather an evidence of profitable arbitrage opportunities coming from mispricing. Al-Yahyaee *et al.* (2018) shows that the efficiency of the Bitcoin market compared to gold, stocks, and FX is low. Grobys *et al.* (2020) suggests that cryptocurrency markets does not exhibit market efficiency in its weak form. Zhang *et al.* (2018) identifies bull and bear market phenomena over the past years for the most important cryptocurrencies and shows the market is inefficient during bear periods. There is moreover evidence that markets may become less information efficient when decreasing the frequency of sampling as shown by Aslan & Sensoy (2020). Additionally, Sensoy (2019) finds that the higher the frequency of returns, the lower the informational efficiency is. Other studies such as Mensi *et al.* (2019b), Mensi *et al.* (2019a) ,Hu *et al.* (2019), Köchling *et al.* (2019), Charfeddine *et al.* (2020) provide evidence against efficiency in cryptocurrency markets. Hence, the majority of the literature would lean towards cryptocurrency inefficiency. Nevertheless, other studies show the market for cryptos can be efficient in some time intervals. Le Tran & Leirvik (2020) observes that the level of market efficiency in the five largest cryptos is largely time varying, especially before 2017, becoming more efficient over time in the period 2017-2019. Other findings are that efficiency increases over time, e.g. Le Tran & Leirvik (2020),Aslan & Sensoy (2020) and Al-Yahyaee *et al.* (2020). Additionally, Fry & Cheah (2016), Kristoufek (2018), and Corbet *et al.* (2018) identify the existence of bubbles in cryptocurrency markets.

The existing literature states that pair trading profits from high volatility periods. Huck & Afawubo (2015) shows that using the components of S&P 500 Index, that this strategy is more profitable when volatility is large. The reason for this stems from the fact that volatility allows for more profit opportunities due to the spread moving further away from the equilibrium value, especially when the Cointegration method is taken into account. Rad *et al.* (2016) and Van der Have *et al.* (2017) find that pair trading strategies perform better during periods of significant volatility, hence they profit from price fluctuations from the mean level and mispricing.

It has been proven that coins experience high price volatility. Baek & Elbeck (2015) and Fry & Cheah (2016) find that Bitcoin price variance is internally (buyer and seller) driven, meaning that the market is not influenced by the fundamentals economic factors, and is highly speculative and volatile. Sapuric & Kokkinaki (2014) discovers the annualized volatility is significantly greater than the one of normal currencies. However, when the transaction volume is taken into account, the volatility stabilizes. Positive connection between volatility and return predictability is found by Leirvik (2022) and Le Tran & Leirvik (2020). Charfeddine *et al.* (2020) finds that there is a long range dependence and hence persistence in the volatility of returns of cryptosassets.

The strategy also proves to deliver positive excess returns for stocks when there are crisis and illiquid periods (Bowen & Hutchinson, 2016). Engelberg *et al.* (2009) provides further evidence that long term profits are larger among illiquid stocks and the level of liquidity has a persistent effect on returns. In fact, pairs from the most illiquid tercile of the portfolio outperform those from the most liquid tercile by 70 to 80 basis points per month when the pair is held for 10 days, and 20 to 50 basis points per month when the position is instead kept open for six months. Cryptocurrencies, as predicted, are overall illiquid assets. As defined by Manahov (2021), liquidity for a certain crypto is the ease of which a coin can be converted into cash or other coins easily. Liquidity in cryptocurrency markets has been an issue since the birth of these assets, and not all virtual currency has the capacity to attract investors. Coin liquidity largely depends on which exchange the asset is traded (Marshall *et al.*, 2019; Włosik *et al.*, 2019). Moreover, many researches shows that liquidity is a key factor for price efficiency, as coin inefficiency is experienced when the liquidity is lower (Corbet *et al.*, 2019; Wei, 2018; Al-Yahyaee *et al.*, 2020). Nevertheless Leirvik (2022) and Scharnowski (2021) find that there is a trend towards an increase in liquidity in cryptocurrencies, however only the most popular cryptos have been inspected in the study.

An additional characteristic of cryptocurrencies is that they are generally highly cross-correlated. Katsiampa *et al.* (2019) finds volatility spillover effects in leading cryptocurrencies, Antonakakis *et al.* (2019) and Fry & Cheah (2016) discover that cryptos are correlated and their price are affected by volatility spillovers and experience market co-movement which intensifies when there is high market uncertainty. Wei (2018), Gkillas *et al.* (2018), Wątorek *et al.* (2021) show high cross-correlation and non-independence between cryptocurrencies. Nevertheless, contrasting to what could be expected, there is mixed evidence sustaining that correlation may be relevant to obtain excess returns (Krauss, 2017). However, Bui & Ślepaczuk (2021) finds that Correlation, used as a pair selection method for a portfolio of 103 stocks listed in the NASDAQ 100 index gives superior performance than the Cointegration Method.

A further reason to inspect the performance of pair trading on cryptos is that high frequency pair trading has been empirically proven to be profitable for diverse asset classes. The literature is scarce since obtaining high frequency data is usually problematic because it is generally proprietary and expensive to be obtained or not available at all. Dunis *et al.* (2010) uses Eurostoxx 50 equities data and compares the performance of daily and several intraday frequencies, finding that the high frequency strategies overperform daily ones. Positive performance is also reported in Liu *et al.* (2017). In the field of cryptos, the availability of free high-frequency data allows for an easy download of historical prices from cryptocurrency exchanges such as Binance and Coinbase. Fil & Kristoufek (2020) provides an optimistic view on the performance, as the study reports the encouraging performance of intraday pair trading when applied to cryptos, with the Distance Method showing higher returns with a higher frequency of data sampling. Stübinger & Schneider (2019) describes outperformance once distinct portfolios of stocks and coins using high frequency data are traded. The scarce literature on high frequency crypto pair trading provides an additional argument toward the assumption that virtual asset could represent a profitable target of pair trading strategies.

One contribution of this paper is to analyze the asset class of cryptocurrencies for pair trading. The second contribution is the application and comparison of various selection methods to different sampling frequencies (daily and hourly) to select the pairs and subsequently trade them at the same frequencies. These two contributions can be summarized in the following research questions: How does a pair selected with a specific method perform when traded? Does the frequency of data for the formation period impact the performance? Does trading with high frequency data improve the performance?

This paper has a twofold purpose, as it is can be relevant for both academic and industrial purpose. In fact, it primarily adds contribution to the scientific literature towards the understanding of pair trading in the field of cryptocurrencies, how pairs formed through specific selection methods and with different frequencies perform once pair trading strategies are applied. On the other side, from an industrial point of view, this paper can be interesting for hedge funds, trading firms and investment banks which are contemplating the application of pair trading to cryptos, either with daily or high frequency data, and want to assess the performance of such a strategy on this particular asset class.

This paper is organized as follows. Section 2 discusses the methodology used for this research, Section 3 discusses the results, while Section 4 concludes the paper and suggests possible extensions.

2 Methodology

This section discusses the methodology of this paper. Every pair trading strategy consists of two steps, selection and trading. This section aims at introducing the major pair selection methods applied in literature, and describes the main pair trading strategies afterwards. Most of the pair trading strategies start by dividing the sample of historical prices into a formation period and a trading period. The formation period aims at finding the assets which best satisfies the requirements of the selection methods among $\frac{n\times(n-1)}{2}$ possible combinations of pairs. Krauss (2017) provides a comprehensive overview of the most popular pair trading approaches. Using the latter paper as the starting point, this paper uses two selection methods: the Distance Approach and the Cointegration approach. The methods are applied to the in-sample or formation period at two different data frequencies - daily and hourly. The purpose of this procedure is to understand whether different price granularity does impact pairs choice for each selection method.

Trading is executed on the out-of-sample by testing pairs at the two different frequencies reported above. Pair trading strategies usually involve setting an upper and a lower threshold. If it is touched from below or above respectively, an order execution is triggered and a short or long position is opened. Four strategies are tested for each method: a fixed threshold, a dynamic threshold, a trailing stop-loss with fixed threshold, and a buy and hold. The latter has comparison purpose only.

Section 2.1 presents the data retrieval and preparation process, Section 2.2 describes the Distance Method (Gatev *et al.*, 1999). Section 2.3 introduces the Cointegration Method (Vidyamurthy, 2004). Each of these Sections include the strategies developed for that method. Section 2.4 explains the strategies developed for comparison purposes in the form of buy and hold long-short portfolios of two securities as selected.

Due to the substantial computational requirement, several programming languages are used. Data from Cryptocurrency Exchanges APIs is retrieved using Python, R is used for computations, while Microsoft Excel is employed for certain data management purposes.

2.1 Data

Twenty pairs are selected following Leung & Nguyen (2019) and Chang *et al.* (2021). The requirement for inclusion of these coins is to be in the top 20 currencies measured by market cap and the requirement to be continuously traded since 2018. Cryptocurrencies' prices are always quoted as currency pairs, meaning they are expressed in terms of a base currency where popular coins such as BTC or ETH, besides fiat currencies serve as base.

The choice of which market index to use for benchmarking is not straightforward, since cryptocurrencies are still a rather new asset and an official representative of this asset universe has not yet been developed, see also Häusler & Xia (2022). Additionally, index providers are known not to share data, especially at intraday granularity. Fortunately, there is a particular class of cryptos built as market indexes which can be used for this scope. The fact that these coins are usually not traded on the biggest crypto exchanges makes data fetching only slightly more difficult than for usual currencies. For this research, historical prices of the Cryptoindex.com 100 (CIX100) are employed, a value weighted AI-Based index computed every second and monthly rebalanced such that only the top 100 coins per market cap are included. Bitcoin (BTC) is also included in the performance evaluation process for comparison purposes.

Market capitalization has been retrieved from CoinMarketCap. Coin prices quoted on BTC are retrieved from Binance. For performance comparison purposes, BTC-USD is downloaded from Gemini (high-frequency) and from Bitstamp (daily). CIX100 historical prices are retrieved from Twelvedata API. The data used spans the interval from 1^{st} January 2018 to 31^{th} December 2021 at daily and hourly frequency.

The total sample has been split into in-sample (formation period) and out-of-sample (trading period) with a ratio of 2 : 1 (as done by Gatev *et al.* (2006), Liew & Wu (2013), Ospino *et al.* (2020), and Fil & Kristoufek (2020)) as shown in Tab. 1. NaN values were omitted from the data following the logic that they signal that trading did not happen in that specific day or hour.

Observations	1 day	1 hour
Formation	974	23,268
Trading	487	11,634
Total	1,461	34,902

Table 1: Division of the total sample to show the available observations at each frequency in the chosen interval from 1^{st} January 2018 to 31^{th} December 2021.

2.2 The Distance Method

2.2.1 Selection Method

The Distance Method was introduced by Gatev *et al.* (1999) and then revised in Gatev *et al.* (2006), whose renewed study take over all liquid U.S. CRSP stocks from 1962 to 2002. It is one of the most used methods by traders for actual trading, as investigated by Gatev *et al.* (2006) using interviews. First, the sample is split into a formation and a trading period. The pairs are selected by minimizing the sum of squared distances between the normalized prices of the assets, namely $P_{i,t}$ and $P_{j,t}$ for asset i and j. In other words, it aims at finding the pair of normalized price processes with the minimum Euclidean squared distance (SSD) for the time series of the spread $S_t^{i,j}$:

$$SSD_{P_i,Pj} = \sum_{t=1}^{T}(P_{i,t} - P_{j,t})^2$$

The method finds a matching stock i for every stock j. As explained by Do *et al.* (2006) and Krauss (2017) the main advantage of this method is that it is model-free, meaning easily applicable and computationally faster than other methods as well as applicable to any asset, and hence not subject to misspecifications and misestimations. Moreover, it is equivalent to compute the correlation among the assets.

Even though its implementation is easy, the SSD metric has some disadvantages. This is intuitive by looking at the formula for SSD rearranged to depend on the spread sample variance $s^2_{p_i-p_j}$ where p_i, p_j are realizations of the normalized price processes $P_i = (P_{i,t})_{t\in T}, P_j = (P_{j,t})_{t\in T}$:

$$s^2_{p_i-p_j} = \frac{1}{T}\sum_{t=1}^{T}(p_{i,t} - p_{j,t})^2 - \left(\frac{1}{T}\sum_{t=1}^{T}(p_{i,t} - Pp_{j,t})\right)^2 \tag{1}$$

Rearranging one obtains:

$$SSD_{p_i,pj} = \frac{1}{T}\sum_{t=1}^{T}(p_{i,t} - p_{j,t})^2 = s^2_{p_i-p_j} + \left(\frac{1}{T}\sum_{t=1}^{T}(p_{i,t} - p_{j,t})\right)^2 \tag{2}$$

It can be easily seen that the perfect pair, namely the one with the minimum SSD of zero, has a spread of zero and hence produces no profit. Generally, a pair with a low SSD value will also experience low spread variance and hence limited profit potential. An additional problem with this approach is that no guarantee of a long lasting relationship is given. Gatev *et al.* (2006) does not perform any additional test on the mean-reversion of the selected pairs. Given this, it is not surprising that Do & Faff (2010) shows that many of the same pairs identified by Distance Method do not actually converge.

In the framework of high frequency trading with cryptocurrencies, Fil & Kristoufek (2020) show that at hourly and 5-minute trading frequency, the Distance Method provides monthly returns respectively of 3.10% and 11.61%, higher than for the others pair trading strategies and selection methods used. Rad *et al.* (2016) show that the Distance Method was able to give higher significant results than the other inspected approaches. Given the approach's robustness and its reported profitability, additional to the low computational requirement and its wide employment in the industry, the Distance Approach is selected to be one of the methods applied in this research.

2.2.2 Trading Strategy: Fixed Threshold

The spread, and hence the difference between prices $p_{i,t}, p_{j,t}$ for asset i, j at time t is defined as shown in Eq. 3.

$$S_t = p_{i,t} - p_{j,t} \tag{3}$$

When the residuals diverge from the equilibrium, opposite positions of one unit of coin i and one unit of coin j are opened, obtaining an equally weighted long-short portfolio. The standardized residual spread, namely the z-score, is computed as shown in Eq. 4, i.e.

$$z_t = \frac{S_t - \mu_S}{\sigma_S}, \tag{4}$$

and traded allowing to work with a dimensionless measure. Conceptually, the the z-score measures the distance of the spread to its long-term mean in units of long-term standard deviation.

Following the literature, the choice of the fixed threshold is of $2 \cdot \sigma_z$. The logic behind why this threshold is used holds on the assumption that security prices are log-normally distributed, and hence log-prices are normally distributed. It follows that, given the shape of the normal distribution, 95% of the data points lies within two standard deviations from the mean. From a statistical point of view, whatever data point lies outside a range of an absolute value of 2 standard deviations is considered far from the mean, therefore an outlier. Above this threshold, there is not much guarantee mean reversion will happen and chances of potentially unlimited losses are growing as the spread diverges further and increases in terms of dollar value. Of course, the shape of the distribution of log-prices can be far from normal and 2 standard deviations may not be ideal, triggering non-optimal execution or even none at all. Nevertheless, it has generally provided a good performance in literature and will therefore be adopted in this research.

The basic trading rule consists of opening a short position when the z-score hits the threshold. This strategy benefits from the relative mispricing of the assets in terms of each other's value. In fact, when the -2 standard deviation threshold is hit from above, then the portfolio value is below its long-run value so that the spread is bought, which means buying coin i and selling coin j at the same moment. Conversely, if the z-score touches the 2 standard deviation threshold from above, the spread is overpriced and shorted by selling coin i and buying coin j. The position in the portfolio of coins i and j is closed when the z-score approaches the mean value of 0, which means closing simultaneously the positions in coin i and j. This trading strategy is depicted in Fig. 1.

2.2.3 Trading Strategy: Dynamic Threshold

This trading strategy - depicted in Fig. 2 - employs a dynamic threshold based on conditional volatility and mean computed on a rolling basis as shown by Ospino *et al.* (2020) and Figuerola-Ferretti *et al.* (2017). In these papers, the trading period consists of several years and hence in both of them a one year rolling window is applied. However, in this paper a 6-months window is used. This choice stems from to the fact that cryptos are a rather new asset class with few years of historical prices, from which follows a relatively small employed trading interval. The thresholds are:

$$u(\mu_t, \sigma_t) = \mu_t + \gamma\sigma_t \tag{5}$$

$$d(\mu_t, \sigma_t) = \mu_t - \gamma\sigma_t, \tag{6}$$

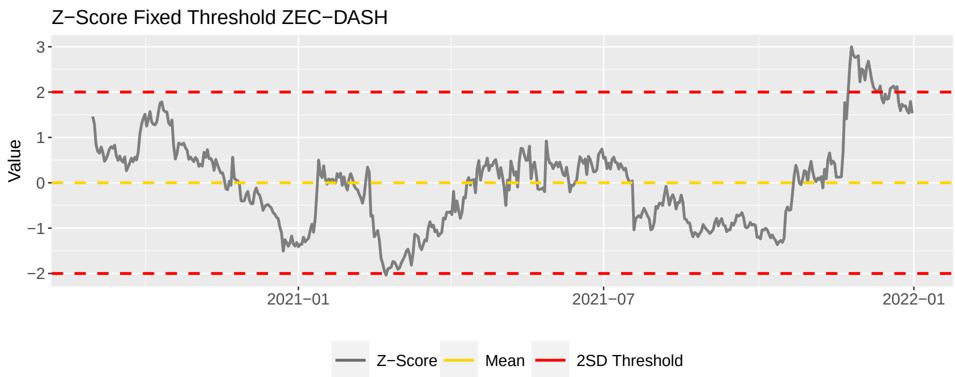

Figure 1: Fixed threshold for the pair ZEC-DASH: the grey line shows the normalized spread (z-score), the red lines are the upper and lower fixed thresholds. The yellow line is the mean of the in-sample process.

where $u(\mu_t, \sigma_t)$ and $d(\mu_t, \sigma_t)$ are the upper and lower dynamic thresholds respectively, μ_t and σ_t are the mean spread and the standard deviation of the spread, while the threshold multiplier γ is set to be 2 in the same logic of the fixed threshold strategy spread is computed as in Equation 3.

This method aims at capturing the time-variation in the spread, which theoretically speaking should be high in the case of cryptos due to their volatile nature. By using dynamically adjusted metrics, the spread is more closely followed by the threshold, which hopefully leads to better and more frequent trades. The trading strategy is homologous to the fixed threshold one.

2.2.4 Trading Strategy: Trailing Stop Loss

The z-score is computed similar to the Fixed Threshold method, but a trailing stop-loss is implemented as shown by Leung & Nguyen (2019). A trailing stop-loss is a trigger which closely follows the price and exits the trade when a loss is approaching given a predefined change in the price. The trigger is tracking the portfolio value at every time point, allowing the trader to close the position immediately when a sudden loss happens. For pair trading, the trade is closed whenever the current spread price is deviating from the previous one by a chosen percentage depending on the current position of the spread, i.e. when a long position in the spread is taken, hence we are below the lower threshold, the position is closed when the spread value decreases since it could be an indicator of excessive deviation from equilibrium. The opposite happens when we are in a short position in the spread, i.e. the spread is above the upper threshold. In this case the position is closed when the spread value increases too much from the previous time-point for the same reason of above.

Despite the fact that a trailing stop-loss could be a profit-saving mechanism, on the other hand it may happen that trades are executed too early without allowing the spread to deviate more before reverting. This constitutes an opportunity cost of not capturing an higher profit from mean reversion. This could also trigger sub-optimal trades that increase transaction costs. A trailing stop-loss of 5% is used as in Leung & Nguyen (2019).

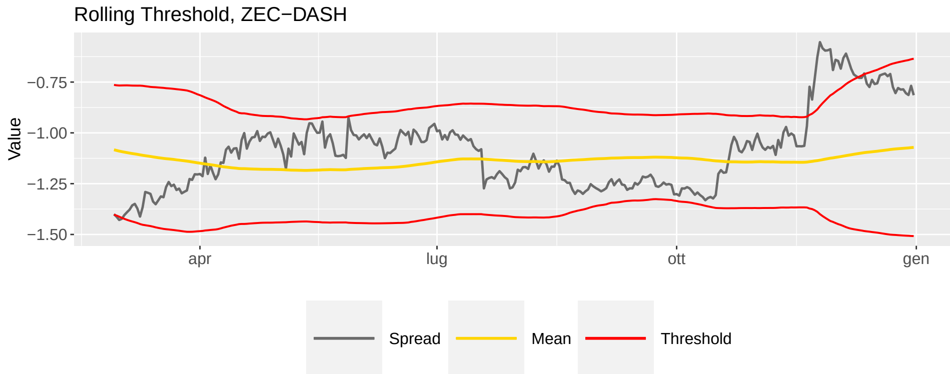

Figure 2: Dynamic threshold for the pair ZEC-DASH: The grey line represents the spread, the red lines the upper and lower dynamic thresholds computed on a rolling window of 6-months, the yellow is the rolling mean. The distance between the thresholds increases with high spread volatility and gets closer to the mean when the deviation to the difference of the prices is low.

2.3 The Cointegration Method

2.3.1 Selection Method

Vidyamurthy (2004) describes a parametrized selection method which consists of identifying the pairs which are cointegrated. Cointegration (Engle & Granger, 1987) is a statistical property of non-stationary time series or $I(1)$, whose linear combination is stationary or $I(0)$. Conceptually speaking, this means the linear combination of the times series exhibits a long-run correlation relationship characterized by mean-reversion: the time-series processes can diverge from their long-run mean, however eventually one or both of them will adjust to return to the equilibrium level.

Define $p_{i,t} = \log(P_{i,t})$ as the natural logarithm of the price P_i of security i at time t. Then the linear relationship between two securities i, j is written as an OLS regression: $p_{i,t} = \alpha + \beta p_{j,t} + \epsilon_t$.

The two-step Cointegration test of Engle & Granger (1987) is checking for stationarity and the pairs with the lowest p-value or, alternatively, the most negative DF test statistic from ADF test (stronger evidence for rejecting the null hypothesis of unit root) are chosen.

The Cointegration test has also some limitations. For instance, it is a single-equation test, which means only a regression of two series can be tested at once. Hence, it computationally intense to test for a whole asset universe and in case that there is a relationship among more than two variables, this test fails to recognize it. A second problem stemming from the two-step procedure is that errors in the first estimation are carried into the second estimation. The estimated residual series requires new tables of critical values for standard unit root tests. Moreover, Cointegration may also lead to spurious relationships between variables.

Vidyamurthy (2004) does not provide empirical results of the Cointegration. Nevertheless, there is a vast literature using this method to select pairs to be traded. Futhermore, see Keilbar & Zhang (2021) for a Cointegration analysis in the crypto space. Caldeira & Moura (2013) applies the Cointegration to 50 of the most liquid stocks of IBovespa, a Brazilian Stock index, finding statistically significant excess returns after transaction costs of 16%. Huck & Afawubo (2015) show that Cointegration-selected pairs traded were profitable and generated returns of 5%. Fil &

Kristoufek (2020) shows that cointegrated pairs achieve a good and robust performance. Leung & Nguyen (2019) report that the Engle-Granger approach for Cointegration leads to a portfolio with good properties of mean-reversion, being able to execute several trades.

On the other hand, Rad *et al.* (2016) finds that monthly excess returns prior transaction costs are similar between SSD and Cointegration. Cointegration is an appreciated method in literature since it is backed by a theoretical foundation explicitly aiming at discovering mean-reversion in the long run, avoids spurious relationships, and is able to better capture information from prices.

2.3.2 Trading Strategy: Fixed Threshold

Define the residual spread from a linear regression of the non-stationary log-prices $p_{i,t}, p_{j,t}$ for asset i, j at time t, i.e.

$$\epsilon_t = p_{i,t} - \beta p_{j,t}, \tag{7}$$

where ϵ_t is a stationary process. The coins are cointegrated and β denotes the relationship between their log-prices. When the residuals diverge from the equilibrium, opposite positions of one unit of coin i and β units of coin j are opened. The standardized residual spread, namely the z-score, is computed as for the Distance Method, but now using the residual spread:

$$z_t = \frac{\epsilon_t - \mu_\epsilon}{\sigma_\epsilon} \tag{8}$$

Following this, a similar trading strategy as the Fixed Threshold strategy of the Distance Method is employed for the Cointegration Method.

2.3.3 Trading Strategy: Dynamic Threshold

The dynamic strategy for the Cointegration Method resembles the previous Dynamic Threshold closely. The difference is given by the traded metrics. While the spread comes from am equally weighted long-short strategy in two paired coins previously, now the residual spread ϵ_t as of Equation 3 is used for the computation of the 6-months rolling window of the dynamic thresholds.

2.3.4 Trading Strategy: Trailing Stop Loss

The z-score is computed from the residual spread ϵ_t of Equation 7 but a trailing stop-loss trigger is implemented as in the case of the Trailing Stop-loss strategy of the Distance Method.

2.4 Buy and Hold

For comparison purposes, an additional strategy is implemented involving a buy and hold long-short portfolio of the pairs selected by both Distance Method and Cointegration. The strategy returns for the pair i, j are computed as follow: $r_t = r_{i,t} - r_{j,t}$, where $r_{i,t}$ and $r_{j,t}$ are the log-returns at time t of coins i, j chosen with a specific selection method and formation period frequency. The aim is to inspect whether passively keeping a portfolio of the same pairs selected and traded would be more profitable than actually implement pair trading. The trading frequencies are daily and hourly.

2.5 Performance Evaluation

After applying the selection method on all the possible pairs, the trade is executed. For this research, log-returns are computed from the traded log-prices and collected together with the number of transactions and the trading signals in order to examine the performance of each strategy. In the case of the Distance returns are computed in the following way:

$$r_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right), \tag{9}$$

while for the Cointegration method we have

$$r_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \beta \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right), \tag{10}$$

where

$$r_{n,t} = \ln(1 + R_{n,t}) = \ln\left(\frac{P_{n,t}}{P_{n,t-1}}\right) \quad \text{for} \quad n = i, j$$

is the log-return of asset n and $R_{n,t}$ is the simple return of asset n. Afterwards, returns are converted into simple returns:

$$R_{n,t} = e^{r_{n,t}} - 1 \quad for \quad n = i, j,$$

and the performance evaluation metrics are computed. Moreover, as previously mentioned, transaction costs are also included in the analysis in order to provide a more realistic simulation of trading with pair trading in the market of cryptocurrencies. Costs are computed from log returns as of Caldeira & Moura (2013) and in a similar manner for the Distance method

$$r_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) + 2\ln\left(\frac{1-C}{1+C}\right),$$

and for the Cointegration method

$$r_t = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - \beta \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) + 2\ln\left(\frac{1-C}{1+C}\right),$$

where C is the transaction cost of buying and selling asset i and j, assuming buy/sell costs are equal for both coins when traded on the same exchange. The intuition of adding the term of $2 \cdot \ln\left(\frac{1-C}{1+C}\right)$ can be explained as follows: suppose the coin i is bought for price $P_{i,t-1}$ at time $t-1$ and then subsequently sold at time t for price $P_{i,t}$. The real price at which you buy it is $P_{i,t-1}(1+C)$ and the profit from selling it, after accounting for the transaction costs C, is $P_{i,t}(1-C)$. Therefore, the net return is

$$r_{i,t} = \ln\left(\frac{P_{i,t}(1-C)}{P_{i,t-1}(1+C)}\right) = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) + \ln\left(\frac{1-C}{1+C}\right)$$

Assuming the Distance Method is used by trading two coins i, j, the log-return r_t for the long-short portfolio is

$$r_t = r_{i,t} - r_{j,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) - ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) + 2ln\left(\frac{1-C}{1+C}\right).$$

Following the principle of prudence, the highest Binance fee for instant buy/sell of 50 bp is utilized. The following common metrics are computed: Annualised Returns (including and excluding costs, Maximum and Minimum Returns, Kurtosis and Skeweness, Annualised Volatility (including and excluding Costs), Maximum Drawdown (including and excluding Costs), Calmar Ratio and Information Ratio following the paper of Dunis *et al.* (2015).

3 Results

This sections discusses the results obtained using the methodology described in Section 2 above.

3.1 Selected Pairs

The correlation among the coins' returns have been computed. As previously mentioned in the introduction of this research, it is expected to find high cross-correlation among the securities. If this hypothesis holds true, a linear relationship between coins is already a good signal that there are cryptos which move together in the long run. Despite previous empirical studies, most of the linear relationships in the correlation plot of Fig. 3 seem to be indeed positive, however generally of weak to moderate magnitude. Only a small percentage of 4.2% of the pairs have a correlation bigger than 0.5.

The 20 selected cryptos are then paired based on the Distance and Cointegration. The frequency of the in-sample on which the method is applied does not affect the selection. In case of Distance the same three pairs are selected at each formation period frequency, in the same order. Cointegration selects the same pairs in different orders for daily and hourly in-sample frequency. Dunis *et al.* (2010) comes to a similar conclusion, i.e. pairs cointegrated in any time interval higher than daily tend to be cointegrated across all the frequencies.

3.2 Method Performance

After the selection methods have been applied on data of different frequency and the relevant pairs are identified, the selected pairs are traded at daily and hourly granularity. This is done in order to first understand how a selected pair performs when traded. An additional aim of this section is to assess whether the frequency of the selection period impacts the performance and whether high frequency trading does improve the performance. First we observe how different pairs selected by each method perform once traded with the three different strategies. Tab. 2 reports a summary of performance evaluation for each strategy for key metrics.

Both Distance and Cointegration perform better than the buy-and-hold long/short portfolios in terms of average annualized returns pre-cost, but underperform them in case a stop-loss is introduced when accounting for costs due to the high fees of crypto exchanges.

The Cointegration method outperforms the Distance method in terms of annualized returns for the fixed threshold and stop-loss strategies, with average annualized returns of 104.78% and 41.74% gained over both daily and hourly trading. Nevertheless due to higher returns volatility it is also penalized in the risk-adjusted information ratio ex-ante and ex-post cost when no stop-loss is introduced.

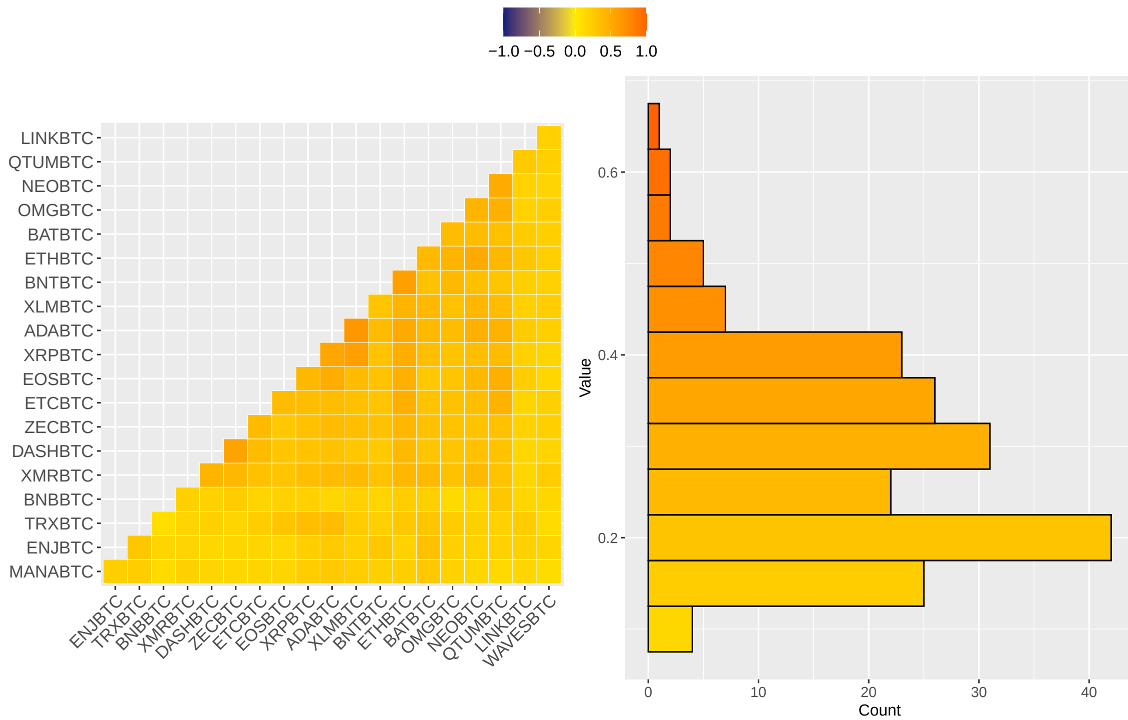

Figure 3: In-sample correlation plot and histogram with the distribution of the values of the correlations among pairs.

	Fixed Th. Dist.	Fixed Th. Coint.	Rolling Th.Dist.	Rolling. Th. Coint.	Stop Loss Dist.	Stop Loss Coint.	Buy Hold Dist.	Buy Hold Coint.	BTC	CIX100
N. Trades	4.00	3.33	4.33	5.17	161.00	90.33	-	-	-	-
Ann. Ret.	76.48	104.78	78.54	63.12	18.67	41.74	5.51	65.56	131.24	250.69
Ann. Ret. (TC)	70.40	99.60	68.11	50.58	-220.91	-92.27	-	-	-	-
Max. Ret.	12.26	18.17	13.54	20.21	9.98	13.37	33.66	45.97	22.43	192.93
Min. Ret.	-8.78	-17.36	-7.31	-18.76	-7.67	-9.97	-25.13	-23.83	-12.67	-36.46
Ann. Vol.	39.76	62.40	43.26	88.27	21.28	36.54	86.49	98.02	75.44	292.72
Skew.	2.04	0.47	1.84	1.50	2.13	2.26	1.49	2.33	0.26	7.07
Kurt.	68.14	60.44	44.75	45.07	241.52	96.64	17.80	28.74	5.74	80.61
Max. DD	0.21	0.34	0.27	0.48	0.14	0.24	0.65	0.63	0.54	0.89
Inf. Ratio	2.07	1.57	1.99	1.22	0.78	1.16	0.086	0.56	1.74	0.85
Inf. Ratio (TC)	1.92	1.50	1.76	1.06	-5.85	-1.75	-	-	-	-
Calmar Ratio	3.72	3.10	3.37	2.43	1.18	2.78	0.12	1.07	2.45	2.83
Calmar Ratio (TC)	3.28	2.92	2.86	2.11	-2.28	-0.32	-	-	-	-

Table 2: Average Metrics grouped by Strategy and Selection method. The long/short strategies for the pairs as well as CIX100 and BTC buy-and-hold strategies are reported for comparison purposes.

The Distance method pair performance is penalized by transaction costs in all cases but with the rolling threshold due to an higher number of executions, especially when traded with a stop-loss. When risk metrics are not taken into account, CIX100 and BTC are outperforming pair trading strategies. This is not surprising, as the out-of-sample includes the time interval from September 2020 to end of December 2021. These two years have seen cryptocurrencies growing at fast pace, with the total market cap growing by 187.5% and some cryptos making five-digits returns.*

Almost always, pair trading decreases return volatility compared to buy-and-hold strategies of long/short portfolios of the same pairs and of BTC and CIX100. A fixed threshold generally leads to a lower number of transactions and hence less costs which means higher risk-adjusted returns (Information Ratio and Calmar Ratio). Due to relatively low volatility of fixed threshold returns, risk adjusted measures are higher than those of CIX100 and BTC. These coins gain the highest returns but also have consistent price deviations.

The rolling threshold is more profitable with the Distance method, with average pre-cost annualized returns of 78.54% and Information Ratio of 1.99, which benefits from lower price variation. Stop-loss causes lower annualized returns and risk adjusted returns compared to other strategies, probably due to early and sub-optimal trade execution. The spread could have been in fact prevented to widen at a level which is needed to generate gains. Nevertheless, it is not surprising that parameters adopted from other authors are failing to perform and a grid-search for the best trailing stop-loss percentage would probably benefit the trades. Moreover, due to the vast number of trades, ex-post cost metrics are highly negatively impacted, with extremely low Annualized Returns, Calmar Ratios and Information Ratios. Fig. 4 explains what is described above and visualizes the damage incurred due to high exchange fees. However, when the measures are distinguished by trading frequency as reported in Tab. 2, the losses are more a phenomenon of high frequency. This is not surprising due to the large number of deviations in coin prices happening when monitoring at tighter time intervals. Kurtosis is also large in magnitude, indicating fat tails in annualized returns. Unsurprisingly, Maximum Drawdown is reduced by setting a stop-loss.

3.3 Performance of in-sample frequency

Subsequently, the evaluation metrics for pairs for both methods have been averaged grouping by frequency of the formation period and strategy. This procedure aims at testing whether the granularity of the in-sample on which the selection method is applied does impact the performance.

In Tab. 3, one can see that the frequency of the formation period does not impact performance significantly. In fact, both methods always selected the same pairs.

The box-plots show identical return distributions at all frequencies ex-ante and ex-post costs. Cointegration is performing better than Distance when trading the pairs selected at every in-sample frequency, even when accounting for transaction costs. Moreover, the Distance method is more severely hit by fees when trading with a stop-loss, due to the massive number of executions.

3.4 Performance of Trading Frequency

This section aims at showing the effect of different trading frequencies on the performance of selected pairs. The trading frequency impacts the number of executions and consequently, due to the harmful effect of transaction costs, i.e. the after-costs metrics are highly impacted. In literature,

*Source: Conte, Niccolo. 2021. "This is how the top cryptocurrencies performed in 2021", World Economic Forum.

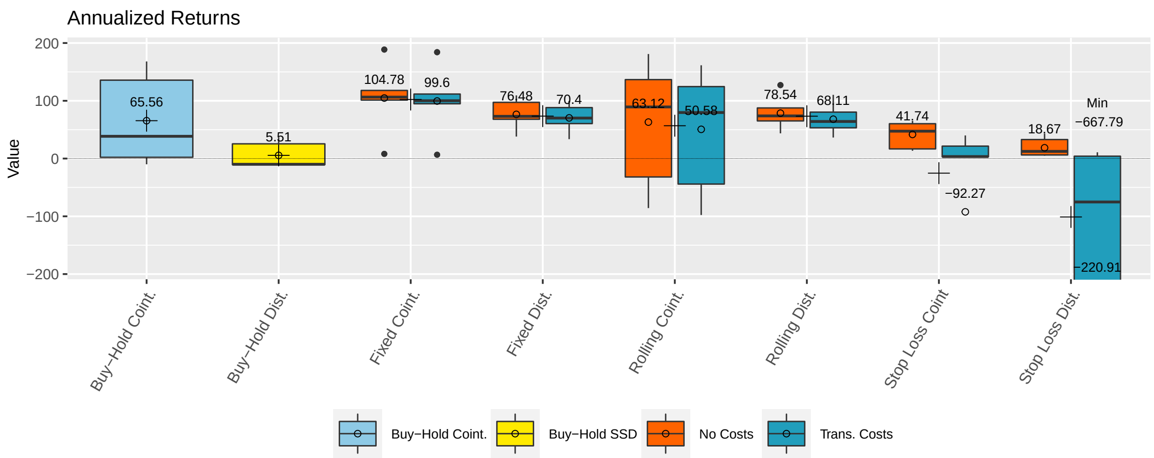

Figure 4: Annualized Return distributions (with and without transaction costs) grouped by method and strategy for each method. The first two boxes indicate the buy-and-hold long/short strategies.

	Fixed Th. Dist.		Fixed Th. Coint.		Rolling Th. Dist.		Fixed Th. Coint.		Stop Loss Dist.		Stop Loss Coint.		Buy&	Buy &	BTC	CIX100
	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Hold Dist.	Hold Coint.		
N. Trades	4.00	4.00	3.33	3.33	4.33	4.33	5.17	5.17	161.00	161.00	90.33	90.33	-	-	-	-
Ann. Ret.	76.48	76.48	104.78	104.77	78.54	78.54	63.12	63.10	18.67	18.67	41.74	41.74	5.51	65.56	131.24	250.69
Ann. Ret.(TC)	70.40	70.40	99.61	99.59	68.11	68.11	50.59	50.57	-220.91	-220.91	-92.27	-92.27	-	-	-	.
Max. Ret.	12.26	12.26	18.18	18.17	13.54	13.54	20.21	20.20	9.98	9.98	13.37	13.37	33.66	45.97	22.43	192.93
Min. Ret.	-8.78	-8.78	-17.37	-17.36	-7.31	-7.31	-18.76	-18.76	-7.67	-7.67	-9.97	-9.97	-25.13	-23.83	-12.67	-36.46
Ann. Vol.	39.76	39.76	62.40	62.39	43.26	43.26	88.28	88.27	21.28	21.28	36.54	36.53	86.49	98.02	75.44	292.72
Skew.	2.04	2.04	0.47	0.47	1.84	1.84	1.50	1.49	2.13	2.13	2.26	2.26	1.49	2.33	0.26	7.07
Kurt.	68.14	68.14	60.43	60.45	44.75	44.75	45.10	45.04	241.52	241.52	96.63	96.65	17.80	28.74	5.74	80.61
Max. DD	0.21	0.21	0.34	0.34	0.27	0.27	0.48	0.48	0.14	0.14	0.24	0.24	0.65	0.63	0.54	0.89
Inf. Ratio	2.07	2.07	1.57	1.57	1.99	1.99	1.22	1.22	0.78	0.78	1.16	1.16	0.086	0.56	1.74	0.85
Inf. Ratio (TC)	1.92	1.92	1.50	1.50	1.76	1.76	1.06	1.06	-5.85	-5.85	-1.75	-1.75	-	-	-	-
Calmar Ratio	3.72	3.72	3.10	3.10	3.37	3.37	2.43	2.42	1.18	1.18	2.78	2.78	0.12	1.07	2.45	2.83
Calmar Ratio (TC)	3.28	3.28	2.92	2.92	2.86	2.86	2.11	2.11	-2.28	-2.28	-0.32	-0.32	-	-	-	-

Table 3: Average annualized metrics of both pairs selected with Cointegration and Distance method for each strategy, grouped by frequency of the formation period on which the selection method is applied.

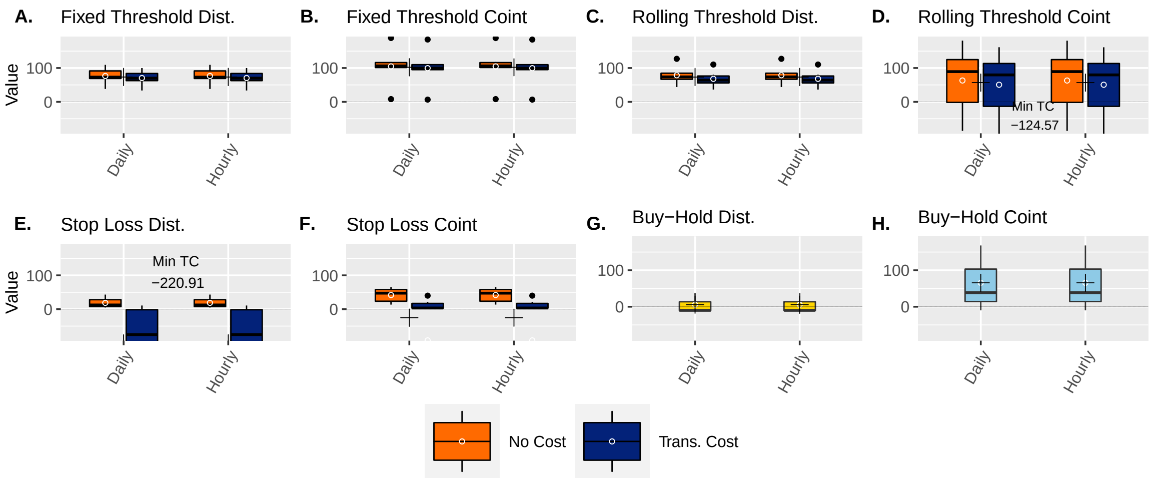

Figure 5: Distribution of the Annualized Return over the same in-sample frequency on which the selection method has been applied.

	Fixed Th. Dist.		Fixed Th. Coint.		Rolling Th. Dist.		Fixed Th. Coint.		Stop Loss Dist.		Stop Loss Coint.		Buy& Hold Dist.	Buy & Hold Coint.	BTC	CIX100
	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly	Daily	Hourly				
N. Trades	3.67	4.33	3.00	3.67	3.67	5.00	4.67	5.67	14.33	307.67	16.33	164.33	-	-	-	-
Ann. Ret.	73.77	79.19	73.29	136.26	69.11	87.97	64.70	61.53	19.80	17.54	39.21	44.28	5.51	65.56	131.24	250.69
Ann. Ret.(TC)	68.15	72.66	68.56	130.63	60.23	76.00	53.33	47.83	-1.35	-440.47	15.57	-200.11	-	-	-	-
Max. Ret.	12.74	11.78	17.00	19.35	15.12	11.97	25.05	15.36	11.44	8.52	16.51	10.23	33.66	45.97	22.43	192.93
Min. Ret.	-11.07	-6.50	-23.57	-11.15	-8.13	-6.49	-26.95	-10.56	-9.20	-6.14	-11.85	-8.09	-25.13	-23.83	-12.67	-36.46
Ann. Vol.	37.45	42.07	51.17	73.63	35.55	50.96	83.66	92.89	20.84	21.72	33.45	39.63	86.49	98.02	75.44	292.72
Skew.	1.49	2.60	-1.08	2.01	2.12	1.56	1.09	1.90	1.20	3.06	2.95	1.57	1.49	2.33	0.26	7.07
Kurt.	20.34	115.93	45.28	75.60	28.86	60.64	21.79	68.36	74.88	408.17	59.30	133.98	17.80	28.74	5.74	80.61
Max. DD	0.17	0.26	0.32	0.36	0.19	0.34	0.44	0.52	0.12	0.17	0.14	0.34	0.65	0.63	0.54	0.89
Inf. Ratio	2.07	2.07	1.30	1.84	2.07	1.91	1.24	1.20	0.80	0.76	1.16	1.17	0.086	0.56	1.74	0.85
Inf. Ratio (TC)	1.92	1.92	1.23	1.76	1.85	1.66	1.09	1.03	-0.41	-11.29	0.46	-3.96	-	-	-	-
Calmar Ratio	4.28	3.16	2.39	3.80	3.94	2.80	2.56	2.29	1.37	0.98	4.13	1.43	0.12	1.07	2.45	2.83
Calmar Ratio (TC)	3.70	2.87	2.20	3.63	3.32	2.39	2.24	1.97	-0.09	-4.47	1.26	-1.91	-	-	-	-

Table 4: Average annualized metrics of the six pairs selected and traded by both Cointegration and Distance methods grouped by the frequency of the trading period.

the profitability of high frequency trading is well-known. Fil & Kristoufek (2020) and Dunis *et al.* (2010) both report higher profits when trading intraday prices. In this paper, high-frequency is not always generating the highest returns and risk-adjusted metrics, as it happens that daily strategies outperform hourly ones.

The returns gained from intraday trading are higher before and after costs in the case of fixed threshold and rolling threshold for Distance. The opposite happens in the case of a stop-loss, which shows gains of 17.54% for hourly compared to the daily trades of 19.80%. Cointegrated pairs traded at hourly frequency outperform daily trading only in the case of the fixed threshold. Especially when introducing a stop-loss, a high number of trades is executed, resulting in highly negative values when fees are included.

Once again pair trading is decreasing performance volatility, obtaining on average an higher Information ratio than in the case of CIX100 and of the buy-and-hold long/short strategy. This is not the always the case comparing with BTC. Not surprisingly, since return variation is higher when trading with intraday out-of-sample, Information Ratio is affected negatively. Calmar Ratio is also hit by higher Drawdowns in the high-frequency case. For both risk-adjusted measures, intraday

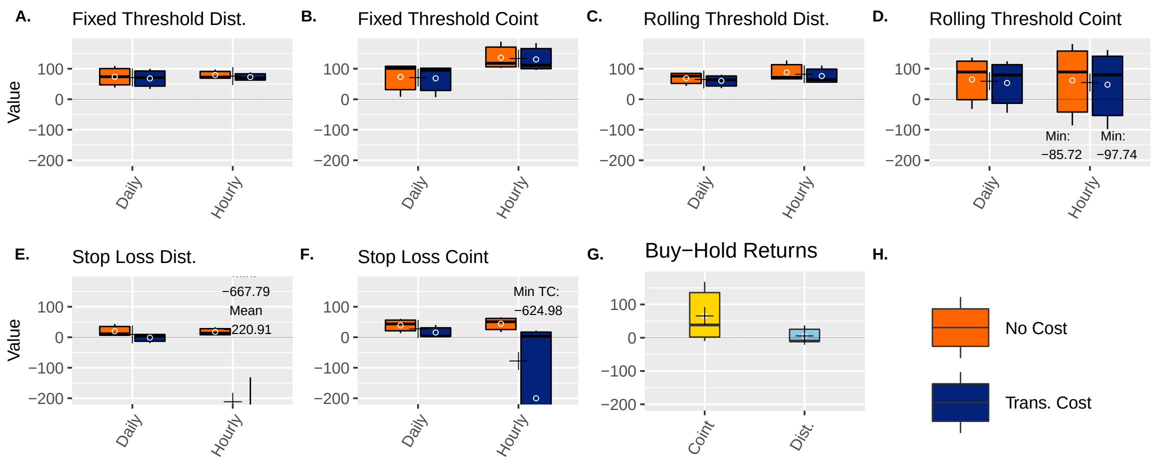

Figure 6: Distribution of the Annualized Returns over the same trading frequency on which the specified selection method has been applied.

trading is penalized by costs. Due to smaller drawdowns of the strategies compared to BTC and CIX100, Calmar Ratios are generally higher than the two coins' ratios before costs for fixed and dynamic threshold strategies, but hardly hit after costs.

4 Conclusion

The main purpose of this paper is to show how the combination of pair selection methods and trading strategies perform on cryptos. It is done by inspecting whether the frequency of the selection period does impact the performance by choosing different pairs and by analysing the performance of different trading frequencies by showing the performance of daily versus hourly strategies.

As shown in Subsection 3.1, both Distance and Cointegration methods are applied to the in-sample at daily and hourly frequency. Distance and Correlation systematically select the same pairs when the selection method is applied to daily and hourly formation period. The top three pairs for each selection criteria are retained for trading as in Do *et al.* (2006).

Secondly, the spread is computed from each pair and then traded with three different strategies: a fixed threshold, a dynamic threshold as of Figuerola-Ferretti *et al.* (2017) and Ospino *et al.* (2020) as well as a fixed threshold approach but additionally includes a trailing stop-loss of 5% (Leung & Nguyen, 2019).

The frequency of the formation period is not relevant. In fact, both methods always select the same pairs. Cointegration usually outperforms Distance, while Distance is hurt by transaction costs due to the numerous executions. Both methods are performing better than the buy-and-hold long/short strategies, but achieve less returns than CIX100 and BTC. The two coins are gaining extraordinary returns of 250.69% and 131.34% respectively, mainly due to an increase in crypto prices recorded between 2020 and 2021.

The evaluation of the trading frequency is discussed in Section 3.4. It can be shown that high-frequency trading does not generate the highest returns and risk-adjusted metrics. For fixed and rolling thresholds, Distance intraday trading outperforms daily trading, however the situation is overturned when a stop-loss is introduced. Cointegration hourly trading gains better returns than daily trading only when applying a fixed threshold. Not surprisingly, a higher number of trades increases transaction costs.

Further research in this field include testing different thresholds and trailing stop-losses as done by Leung & Nguyen (2019) and Fil & Kristoufek (2020), since the choice of the 2-standard deviation multiplier for the threshold was deducted from the literature's use. Moreover, the research could be extended to include the whole cryptocurrency universe instead of only 20 coins. Furthermore, the performance comparison can be extended to other approaches than Distance and Cointegration, such as the Copula Method (Liew & Wu (2013)), Time Series Methods (Elliott *et al.*, 2005), (Bundi & Wildi, 2019) and Machine Learning (Huck (2009),Huck (2010), Van der Have *et al.* (2017), Ospino *et al.* (2020)). In particular, employing Machine Learning has already demonstrated to gain interesting results with digital coins as in Fil & Kristoufek (2020).

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