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Abstract

Cryptoassets market is notoriously volatile and risky. In this context, market-neutral type strategies, such as pair-trading, may be relevant. In this article, we focus on the implementation of pair-trading strategies with a wide range of cryptoassets (209) over a period halved from 2021-08-01 to 2024-01-31. To carry out this study, we combine econometric and machine learning techniques to stand out from the existing literature. By using cointegration tests and error correction models, we identify a final sample of 229 pairs suitable for pair-trading strategies. Using a genetic algorithm and pair clustering, we test four strategies employing standard and optimized thresholds. The results highlight the existence of profitable cointegrating relationships and therefore short-term market inefficiencies in the cryptoassets market. Indeed, the best strategy identified in terms of risk-return couple, although it remains risky with a median maxdrawdown of 29%, delivers an average annual Sharpe ratio per pair of 1.53 over the backtesting period.

Keywords: Cryptoassets; Pair-trading; Cointegration; Error-correction models; Genetic algorithm; Bollinger bands; Short-term market inefficiencies

JEL Codes: C22, C61, G11, G12, G14

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1 Introduction

Since their emergence in 2008 with the creation of the Bitcoin blockchain, digital assets have enjoyed a spectacular rise in popularity. Indeed, at the beginning of 2024 in France[2] over 6.5 million people held cryptoassets, representing 12% of the population. By way of comparison, this percentage represents a 28% increase compared to 2023. At European level (Balva and Stachtchenko 2022), the figures are similar, with 10% of European households holding digital assets in May 2022.

This boom, bringing the overall valuation of this emerging asset class to $1,660 billion by January 31, 2024, is undoubtedly due to two factors.
On the one hand, the promise of digital assets, and first Bitcoin, to break away from the traditional financial system to create a peer-to-peer system has found its audience against a backdrop of economic crisis in 2008 and, more recently, health crisis in 2020.
On the other hand, the technological innovation of blockchain, which is the cornerstone of this new asset class, makes them particularly attractive. The growing interest in digital assets is driving a significant increase in transaction volumes, creating a dynamic market environment. This new demand opens new perspectives for traditional investment strategies. Due to their high volatility, these assets offer interesting arbitrage opportunities to enhance portfolio performance by adapting traditional or market-neutral investment strategies, such as pair-trading.

Pair-trading is a statistical arbitrage strategy. It takes advantage of the temporary divergence between the prices, also known as the "spread", of two assets linked over the long term. When such a divergence occurs, the overvalued asset is sold short and the undervalued asset is bought. Positions are closed when the divergence disappears. The profit on this strategy is the sum of the gains on the long and short positions. Since its inception in the 1980s, pair-trading has been a popular strategy for investment banks and

[2] ADAN, Web3 and Crypto in France and Europe: Continued Industry Adoption and Growth, 2024, https://www.adan.eu/publication/etude-2024-web3-et-crypto-en-france-et-en-europe/

hedge funds, as it allows them to avoid exposure to the market. In other words, profits are independent of market trends. This type of strategy has a twofold advantage in the context of a financial market.

(1) Market-neutral type strategies, which include pair trading, are known to adapt particularly well to turbulent market situations. In this sense, this category of financial strategies appears to be a good option for investing in asset markets deemed volatile, such as cryptoassets.

(2) The theory of market efficiency, developed by Eugène Fama (1970), asserts that asset prices adjust instantaneously to their fundamental values based on available information, making prices perfectly unpredictable. It is therefore impossible to predict returns higher than the average market return. However, in the context of a pair-trading strategy, this prediction is modified because: (i) it focuses not on the individual prices of an asset but on a linear combination of prices of two assets; (ii) it is not systematic at every period (day, hour...) but punctual when the deviation of the prices combination from its historical average is significant. This implies that if these arbitrage opportunities exist, they could illustrate short-term inefficiencies in digital asset markets.

While pair-trading is widespread on traditional financial markets, it is still under-exploited on cryptoasset market. Thus, our study aims to answer the following question: Are pair-trading strategies applicable and profitable in the digital asset market? If so, what implications do they imply for fundamental value dynamics and market efficiency?

To answer this question, our article focuses on pair-trading strategies within a cointegration framework. The notion of cointegration reflects the principle of a common stochastic trend between cryptoasset prices. It is conceivable that this common trend could be influenced by news affecting not only investor confidence (mistrust), but also the business models of the projects and companies developing these cryptoassets, considering them as both payment instruments and investment vehicles.

Furthermore, it's important to note that the investors profile in traditional markets differs significantly from that of cryptoasset investors. Traditional markets mainly attract institutional investors and well-informed individuals, whereas cryptoasset market includes a significant proportion of younger and sometimes less experienced retail investors[3]. If pair-trading strategies prove successful in the cryptoasset market, this would indicate a certain rationality in investment behavior and suggest that cryptoassets possess fundamental values recognized by investors due to a return mechanisms system for every deviation. This could demonstrate that, despite the volatility and specificities of this market, rational and profitable arbitrage opportunities exist. These arbitrage opportunities would be the revelation of temporary pockets of inefficiency in the market which, over the long term, display price spreads compatible with the fundamental value of assets.

Across a wide range of digital assets, we identify and optimize the entry and exit levels of positions in several strategies on the selected asset pairs. To be more precise, the technical elements of our approach are as follows:
Using Engle and Granger (1987) tests, we examine cointegration relationships between asset prices. Our sample consists of 209 cryptoassets listed on Binance exchange platform. To obtain an optimal strategy, we go through several steps: (i) we use all the information provided by error-correction models, enabling us, among other things, to identify the assets participating in the return to equilibrium of the long-term relationships of each pair. (ii) We compare two main strategies: standard deviation of long-term residuals and Bollinger bands. (iii) We test several strategy variants to identify the best in terms of risk/return couple. (iv) Finally, we optimize strategy parameters using a genetic algorithm to extract the full potential of pair-trading strategies in this market.
Our sample is divided in two periods. Pairs identification and strategy optimization period runs from 2021-08-01 to 2023-07-31, while the backtesting period runs from 2023-08-01 to 2024-01-31.

[3] https://www.benzinga.com/markets/cryptocurrency/23/02/30905456/from-retail-to-institutional-the-shift-in-crypto-investment https://www.binance.com/en/research/analysis/spot-etfs-in-crypto-markets/

Our results suggest the existence of cointegrating relationships between two assets on the cryptoasset market. Indeed, the various cointegration tests carried out agree on the presence of 1,541 cointegrated pairs between 163 assets. Although this figure is high, not all identified pairs are compatible with a pair-trading strategy. After applying several filters to select only the most relevant pairs, we isolate 229 pairs.
A comparison between the first two strategies identified, namely the long-term standard deviation strategy and the Bollinger bands, leads to the identification of changes in the volatility of the pairs' long-term relationships. Indeed, with the long-term standard deviation strategy, only 13% of pairs take at least one position over the backtest period. This can be explained by the fact that, for the majority of pairs, the residual of their cointegrating relationship does not reach the trigger thresholds, defined as a multiple of the standard deviation of this same residual over the pair identification period.
The optimization and variants tested on the more adaptable Bollinger Bands strategy finally yield an approach delivering a median Sharpe ratio on the 229 pairs of 1.70 for an average max drawdown on each pair of -34.41% over the backtesting period. The profits delivered by the strategies clearly suggest the existence of pockets of market inefficiency, associated with temporary anomalies in asset price dynamics.

The rest of this article is organized as follows.
Section 2 is devoted to literature reviews. Section 3 presents the empirical strategy of our paper, introducing the data sample used in this article and illustrating the principles of pairs selection through cointegration tests. We introduce an iterative methodology, incorporating error-correction models for each pair. At the end of this section, we illustrate how to test the different pair-trading approaches and the performance indicators obtained to evaluate and optimize them. The results of the different strategies and their variants applied to the backtesting phase are presented in section 4. Section 5 summarizes our main results, analyzing and discussing them in depth, particularly as regards their implications for cryptoasset market efficiency. Finally, Section 6 summarizes our study and suggests potential improvements for further research.

2 Literature Review

Within the literature, papers have already implemented pair-trading strategies on the cryptocurrency sector but, often, focusing on a limited number of assets. Figa-Talamanca, Focardi and Patacca (2021) focus in their study on four cryptocurrencies characterizing the market: Bitcoin, Ethereum, Litecoin and Monero. Singh et al (2023) focus on two cryptocurrencies (Ethereum and Bitcoin) to compare two trading strategies (double momentum and pair-trading). For their part, Leung and Nguyen (2019) construct cointegrated portfolios involving four cryptocurrencies: Bitcoin, Ethereum, Bitcoin Cash and Litecoin. Our study aims to break away from common apriori and beliefs by taking a large panel of digital assets in order to validate or invalidate a posteriori these beliefs.

The temporality of the data used in this type of study is also strategic and requires special consideration. While some articles study a specific temporality, others compare the results observed. For example, in their study Leung and Nguyen (2019) use the closing prices of selected cryptocurrencies on a daily basis. Similarly, Singh et al (2023) compare two strategies using daily data, and their results are conditional on this temporality. On the other hand, Fil and Kristoufek (2020) compare results over several timeframes. In their study, they compare two pairs selection methods for applying pair-trading strategies to 26 cryptocurrencies. They use frequencies of five minutes, one hour and one day. While gross returns are often better in a high-frequency setting, the introduction of external factors (i.e. transaction fees) has a significant impact on intraday performance compared to a daily setting. Similarly, Ko et al (2023) look at different temporalities in a high-frequency setting (one minute, five minutes and one hour) to compare several pairs selection methods. The observed results indicate that performance is significantly better at high frequency, suggesting that there is intraday mean-reverting behavior that would not be replicated at the daily level. Although raw performance appears better in an intraday setting, the inclusion of external factors such as transaction costs or market liquidity leads us, in this study, to focus on a daily setting.

Implementing a pair-trading strategy involves two steps. The first is to select pairs with specific characteristics that make them suitable for generating profits. The second step is to optimize the strategy with the identified pairs. The aim is to find entry and exit thresholds which generate the best return while controlling the investor's risk.

Pairs selection

Literature has developed a number of methods for selecting pairs when implementing a pair-trading strategy. The two main ones are distance and cointegration. Distance, the oldest, is a strategy that does not take economic factors into account, resulting in a lack of forecasting capacity. It consists in using the Euclidean quadratic distance on normalized price time series. The pairs with the smallest distance are selected to implement the strategy. The pioneers in the use of this method are Gatev et al (2006). Studying traditional markets, the authors found that this type of method generated profits when pair-trading strategies were implemented on the selected pairs.

Cointegration refers to the phenomenon whereby two assets show similar price trends over the long term. Vidyamurthy (2004) provided a comprehensive guide to implementing cointegration in a pair-trading strategy, taking into account risks, transaction costs and portfolio construction. Like distance, cointegration can present certain limitations, since it can be subject to structural breaks. Despite this, it remains a popular and widely used method for identifying pairs for pair-trading.

In the traditional market, Huck and Afawubo (2015) investigated whether the cointegration method provides better results than distance. Their study, based on a basket of S&P 500 stocks, suggests that, after controlling for risk, the distance method delivers only insignificant excess returns. In contrast, cointegration generates robust, high and stable returns over time. Similar studies on the cryptocurrency market have also already been carried out. Fil and Kristoufek (2020) compared these two methods. Their results suggest that the performance of the distance method increases significantly with higher frequency. Conversely, the cointegration method appears to perform much better in the daily setting, but does not scale as well with frequency, with performance deteriorating in the hourly setting. Lesa and Hochreiter (2023) also test these two methods on a basket of 20 cryptocurrencies with hourly and daily frequency. Results are similar to previous papers: in terms of temporality, intraday trading is more profitable in terms of gains with both methods when no external factors such as transaction fees or stop-loss are introduced. Cointegration method tends to outperform the distance method across the range of strategies and frequencies chosen.

Four other methods are illustrated in the literature. Correlation method calculates the correlation coefficient between two assets. This refers to the phenomenon whereby two assets show similar price trends over the short term. A high correlation indicates potentially profitable trading opportunities. Early work by Brooks et al (2001) examined the lead-lag relationship between the FTSE 100 index and the futures price index, calculating the correlation and using the results to create a trading strategy. Although lagged changes in futures prices can predict changes in spot prices, the strategy was unable to beat the benchmark due to transaction costs.

Stochastic differential residuals method on asset returns, developed by Do et al (2006), uses the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) to define the residual deviation function. This function, considering the relative valuation of the two values as equilibrium, represents the state of imbalance or mispricing. It is this function that captures any excess deviation from the spread value over the long term (which ultimately provides trading signals on the pair of two assets).

Recently, Stübinger and Bredthauer (2017) introduced the fluctuation behavior method. This involves identifying pairs with rapid mean reversion, measured by the number of times the pair's spread crosses back through zero, and high volatility, measured by the standard deviation of the spread. The pairs with the highest combined ranks are selected.

Finally, the Hurst exponent method, used for the first time for pair selection in the article by Ramos-Requena et al (2017), selects pairs with an exponent between 0 and 0.5, i.e. pairs with mean reversion or anti-persistent behavior.

All these methods were first implemented on traditional financial markets. Rad, Low and

Faff (2016) carried out a study of the performance of three different pair-trading strategies: distance, cointegration and copula methods, on the US stock market from 1962 to 2014. While they find that, in terms of continuity, copula methods are better able to adapt to financial crises, all three strategies deliver a positive average return. They perform better during volatile periods, but cointegration strategy is superior during turbulent market conditions. Nair (2021) uses three of the methods mentioned (distance, cointegration and correlation) with four cryptocurrencies (Bitcoin, Ethereum, Litecoin, Neocoin) across four samples. The study shows that there is long-term convergence in cryptocurrency prices: when two prices are correlated in one sample, there is a high probability that they will be correlated in the next. All strategies used in his study pay off (especially for pairs made up of large cryptocurrencies). Conversely, Ko et al (2023) compare the observed results of pair-trading strategies over the six methods listed above. In the end, the distance method brings better results in terms of return parameters for all frequencies. On the other hand, the cointegration method presents a lower risk for high frequencies.

Although distance sometimes provides superior returns, Krauss (2017) teaches us that cointegration method provides a more rigorous framework than distance due to the econometric identification of relationships between assets. Furthermore, Keilbar and Zhang (2021) show that cryptocurrencies are cointegrated with a rank of four, indicating a long-run equilibrium relationship that can be exploited to develop strategies. In this article, we therefore give preference to cointegration method for selecting pairs, especially as this method is better in turbulent markets.

Strategy optimization

Once the pairs have been selected using one of the methods described above, indicators need to be set up to trigger buy and sell orders for a pair. In a pair-trading strategy, a buy (sell) order is triggered when the spread between the two assets falls below (above) a certain threshold. Several tactics exist for setting up the different thresholds. Huang and

Martin (2019) compare three of them: a percentage method[4], one with a fixed standard deviation[5] and one reminiscent of Bollinger band strategies[6].

Once the strategies have been defined, their parameters need to be optimized. While Huang and Martin (2019) use two traditional optimization criteria, absolute profit and profit factor, there are now machine learning techniques whose aim is to optimize a pre-defined function: the genetic algorithm.

Developed by Holland (1992), genetic algorithm is an optimization technique inspired by evolutionary theory. It uses selection, crossover and mutation processes to find efficient solutions to complex problems. In recent years, it has been widely used in the field of finance to optimize investment strategies for stock market assets. The article by Huang et al (2015) uses Taiwan Stock Exchange shares to test the application of a genetic algorithm in the optimization of a pair-trading strategy. The algorithm optimizes the Bollinger bands used, the moving average and the weights of each asset within the strategy. With this method, they show that models based on genetic algorithms outperform significantly a benchmark and produce robust models. Chen et al (2022) use a genetic algorithm to incorporate more criteria in the implementation and optimization of pair-trading strategy on 44 stocks in the Taiwan 50 Index. The entire method, including pair selection, is encoded within the genetic algorithm. Finally, Sermpinis, Stasinakis and Zong (2021) compare three strategies: fixed thresholds defined as the benchmark strategy, a genetic algorithm to optimize the parameters of the Bollinger criteria, and a new structure for deep reinforcement learning. The study covers 35 commodities from 1980 to 2018. The results show insignificant returns for the first strategy, while the strategy with the genetic algorithm improves returns but increases the associated risk.

[4]It sets the minimum residual of the cointegration relationship at 0% and the maximum at 100%. It has six levels: sell-entry, sell-stop-loss, sell-take-profit, buy-entry, buy-stop-loss and buy-take-profit, each corresponding to a certain percentage that must be optimized.

[5]Similar to percentage, except that here it uses different multiples of the long-term standard deviation to replace percentage levels, with the mean of the cointegrating residuals being zero.

[6]The difference with the long-term standard deviation strategy is that here standard deviation levels are no longer fixed, but dynamically readjusted.

3 Modeling Strategy

Compared with the literature, our article presents several original features.

Firstly, our study uses a large number of digital assets to identify relevant pairs to trading strategies. This research is carried out without any preconceived ideas about potential relationships between assets.

Secondly, our study is based on a longer timeframe than those usually used in existing literature. As this market is still in full growth, with new cryptoassets appearing on a regular basis, studies already carried out were unable to exploit a time period as long as ours.

Another unique aspect of our research is the focus on studying the behavior of each individual asset within a pair. Thanks to the construction of simple error correction models (ECM) associated with the cointegration relationship between the prices of the two assets, we explain the mechanisms of return to equilibrium and identify whether each asset participates, or not, in the return to equilibrium. In this version of the article, we focus on pairs where the return to equilibrium is achieved by both assets. This question touches on the hypothesis of weak exogeneity of certain assets involved in cointegrating relationships, and also raises the question of leading or following cryptoassets in price evolution dynamics.

Finally, we use a genetic algorithm to optimize entry and exit thresholds in our strategies. This innovative approach combines econometrics with cointegration, error-correction models for pair selection and machine learning for strategy optimization.

3.1 Data

Data comes from the Binance exchange platform. We use the closing prices of 209 digital assets[7], retrieved daily from August 1, 2021 to January 31, 2024. The closing price is set at 23:59 GMT.

The price sample is divided in two periods, with a pair identification and optimization

[7] The list of all assets is available in Appendix A in appendix.

period from August 1, 2021 to July 31, 2023, followed by a backtesting and validation period from August 1, 2023 to January 31, 2024.

3.2 Pairs selection

To select relevant pairs to the implementation of pair-trading strategies, we adopt an iterative methodology described in Figure 1.

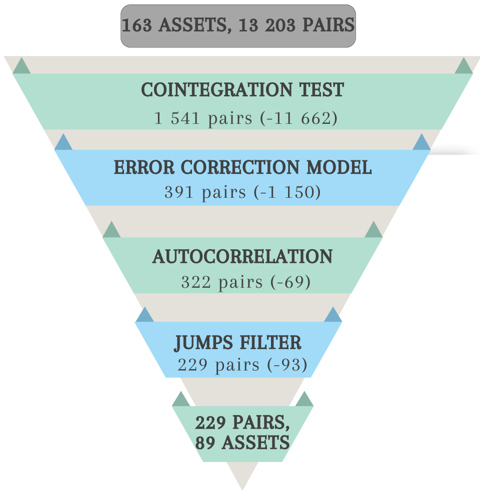


Figure 1: Iterative pair selection method.

3.2.1 Cointegration framework

In economics and finance, the majority of time series are non-stationary, giving rise to the spurious regression problems identified by Granger and Newbold (1974). A non-stationary time series exhibits trends, cycles, seasonal changes or other forms of structural variation. Aware of this phenomenon, Granger (1981) introduced the theory of cointegration. Two non-stationary series are cointegrated if there is a linear combination of the two that is stationary. From an economic point of view, the concept of cointegration is akin to a long-term relationship where it is possible to temporarily deviate from equilibrium, similar to short-term fluctuations.

To identify cointegrating relationships within our data sample, we first need to ensure that all series are integrated at the same order[8]. To this end, we perform four stationarity tests to ensure the robustness of our results. All the econometric tests carried out in this study are at the 1% threshold.

The first three stationarity tests have as null hypothesis the non-stationarity of the series tested. Augmented Dickey-Fuller (ADF) test provides a parametric correction to integrate heteroscedasticity and autocorrelation of residuals into the model. This correction directly modifies the model by incorporating lags:

$$\Delta X_t = \phi X_{t-1} + \sum_{j-1}^{p} w_j \Delta X_{t-j} + \epsilon_t \tag{1}$$

The test consists in testing H0 : $\phi = 0$ (i.e. presence of a unit root in the series).

Conversely, to incorporate heteroscedasticity and autocorrelation into the Dickey-Fuller (DF) model, Phillips-Perron (PP) introduces a non-parametric correction. He considers two measures to calculate the variance of the residuals in the DF model, one short-term (i.e. defined as the original model) and one long-term. The latter is used to calculate the test statistic.

Zivot and Andrews (1992) test has the particularity of taking into account structural breaks present in time series. It has two hypotheses: the null hypothesis suggests that the series analyzed has a unit root but no structural break, while the alternative hypothesis assumes that the series is stationary with a structural break at an unknown date. In addition to testing the stationarity of asset price series, it gives us an indication of the series' shape.

In contrast to the first three tests, Kwiatkowshi, Phillips, Schmidt and Shin (KPSS) test has as its null hypothesis the stationarity of the series. To this end, KPSS (1992)

[8] Series become stationary after being differentiated the same number of times.

proposes estimating the following model (for y_t= the series tested): $y_t = \mu_t + \beta_t + \epsilon_t$ where: $\mu_t = \mu_{t-1} + u_t$. The test statistic is then used to refute the null hypothesis (i.e. H0:$\sigma_u^2 = 0$ or H0:$\mu = constant$).

There are disparities between these four tests. ADF test reveals 41 stationary assets, while PP test reveals 11. Zivot and Andrew test, on the other hand, identifies 140 price series as stationary, with a structural break at an unknown date. Finally, KPSS test appears to be the most rigorous, since no series is deemed stationary. By crossing these different tests[9], we remove 46 assets from our sample[10].

We could have departed from the theory of cointegration by considering that two stationary assets can have a linear combination and thus play on investment strategies on the latter. However, for the sake of rigor and performance, we prefer to focus on the strict framework of cointegration. We have the assumption that a linear combination between two series that are already stationary would have a less violent mechanism for returning to equilibrium, making its residual similar to a white noise behavior.
To test cointegration between the remaining 163 assets, we use the Engle and Granger procedure. This involves regressing two series linearly against each other using ordinary least squares (OLS), and isolating the residuals from the regression:

$$P_{1,t} = \alpha + \beta P_{2,t} + \varepsilon_t \tag{2}$$

As the price series are left raw here, the constant, defined by α in the equation above, is of prime importance. It allows us to capture the difference in price scale between two assets and avoid bias in the analysis.
The stationarity of the regression residuals ($\hat{\varepsilon}_t$) is then assessed using Dickey-Fuller tests adapted with the tables of Phillips and Ouliaris (1990). Of the 13,203 possible pairs, the Engle and Granger test reveals 1,686 cointegrated pairs at the 1

[9] We assume that series are indeed stationary if at least two of the four tests show them to be stationary.
[10] The assets removed from the analysis are available in Appendix B in the appendix.

To put the results into perspective, we compare them with the less restrictive Johansen (1988)[11] procedure, which yields 3,773 pairs. By comparing these two procedures and after verification, we retain 1,541 pairs for the rest of our analysis.

3.2.2 Construction of an error correction model

Granger's (1987) representation theorem has shown that each cointegrated series can be represented by an error-correction model (ECM)[12]. By setting up an ECM for each asset in the cointegrated pair, short and long-term dynamics can be analyzed jointly, in order to reproduce the dynamics of adjustment towards long-term equilibrium. The two ECMs used for each cointegrated pair are as follows:

$$\Delta P_{1,t} = \alpha_1 - \lambda_1(P_{1,t-1} - \hat{\alpha} - \hat{\beta} P_{2,t-1}) + \varepsilon_{1,t} \tag{3}$$

$$\Delta P_{2,t} = \alpha_2 + \lambda_2(P_{1,t-1} - \hat{\alpha} - \hat{\beta} P_{2,t-1}) + \varepsilon_{2,t} \tag{4}$$

These models describe the variation of each series around its long-term trend. The choice of a simple model, i.e. with only one constant and one restoring force towards long-term equilibrium, is linked to the purpose of our modeling: the aim is to explain the mechanisms that govern a pair as it returns to equilibrium, and not to try to predict the short-term dynamics of assets[13].

Parameters λ_1 and λ_2 give an indication of the speed of each pair's adjustment towards its equilibrium level. If λ_1 is significant and negative for the first ECM, the first asset in the pair is participating in the return to long-term equilibrium of the cointegrating relationship linking the pair. Conversely, if λ_2 is significant and positive for the second

[11] Johansen's procedure is based on maximum likelihood estimation of a VECM.

[12] Granger's representation theorem also shows that the reciprocal of this relationship is true: if the series can be generated by an error-correction model, then they are cointegrated.

[13] Huang and Martin (2019) have shown in this regard the limited usefulness of a richer error-correction model, of the ECM-GARCH type, to better anticipate the pair's behavior in the vicinity of extreme points and therefore to optimize the implementation of the initialization moments of buy or sell strategies on pairs.

ECM, then the pair's second asset is participating in the return to equilibrium. If the adjustment parameter, λ, is not significant for an asset, this indicates that it is not participating in the return-to-equilibrium mechanism: its evolution is independent of the value of the residuals in the long-term equation, it satisfies the weak exogeneity criterion. In other words, this phenomenon means that the other asset in the pair, whose parameter is significant, ensures the existence of the cointegration relationship on its own, thanks to its "follower" price dynamics. The asset meeting the weak exogeneity criterion can be described as the pair's "leading" asset.

In order to analyze the dynamics of adjustment towards long-term equilibrium, we build an ECM for each asset of the 1,541 pairs selected. The observed results provide insights into the cryptoasset market in general. For the majority of pairs studied, 1,127 pairs, only one of the two assets participates in the return to equilibrium. Within these pairs, there are market leaders who cause other assets to oscillate around their trend. It is then possible to predict the short-term behavior of a pair's "follower" asset in relation to the behavior of the "leader" asset.

For 391 pairs, both assets participate in the return to equilibrium. In our study, it is these pairs that will interest us, as they are more conducive to the implementation of a pair-trading strategy. In fact, during a temporary deviation from long-term equilibrium, in theory, the price movements of these two assets will allow their cointegrating relationship to return to equilibrium; in other words, positions taken as part of a pair-trading strategy will be more likely to result in gains with this configuration[14].

Finally, for 23 pairs, neither of the two assets participates in the return to equilibrium. This result, although not very intuitive at first glance, invites us to look for hidden variables that contribute to the return mechanism of these pairs, such as staking performance or the influence of other assets. If this research leads to the involvement of other cryptoasset prices, pair-trading strategies with more than two assets should be investigated,

[14]The intensity of the restoring forces appears quite low for the majority of pairs, with a median of significant restoring forces at 0.08. It would be interesting to compare this intensity with the speed of return to equilibrium for each pair (calculated using an ARFIMA model, for example).

in particular looking for multiple cointegration relationships with Johansen's procedure. However, to date, no study suggests that multivariate cointegration is more interesting to trade than bivariate cointegration, especially as it would be difficult to find a common multiple and manage positions.

3.2.3 Evaluation of the long-term relationship residuals autocorrelation

To build pair-trading strategies, residuals of the cointegrating relationship, used to issue signals for opening and closing positions, must be exploitable. If the residuals are close to white noise, implementing a strategy around them is difficult because of the way they look[15].

In our study, we want the residuals to be autocorrelated in order to avoid trades that are too short and ultimately unprofitable. The typical behavior of the residuals is cyclical, so that they oscillate slowly around their mean (i.e. 0). To test and select only these pairs, we analyze the autocorrelation of the residuals by estimating AR(p) models. An AR(p) model with a relevant threshold could reflect a gradual adjustment of the residuals towards their central value.

An AR(p) model is built for the residuals of all 391 pairs. The parameter p of each model is chosen by maximizing the AIC criterion. To compare and remove pairs for which the residuals of their relationship do not behave in a way conducive to the desired strategies, we isolate the RMSE criterion of each AR(p) model[16]. Pairs whose RMSE is not good enough (i.e. above average) are removed from our study, 322 pairs are retained.

[15] i.e. residuals revolve around the average very quickly, making it impossible to be profitable and take viable positions over several days.

[16] The RMSE criterion is chosen here to compare the models, despite its non-standardization, because the models concern the residuals of the cointegrating relationships. Due to the presence of the constant in the linear relationship between the two assets, these residuals are of the same order of magnitude across all pairs.

3.2.4 Jumps filter

By observing the residual series graphically, the presence of outliers, due to the non-normality of residuals[17], is noticed. These peaks can be interpreted as sudden breaks in the cointegration relationship between two assets. They appear, for the most part, during turbulence periods on the cryptoasset market (i.e. in 2021, see Figure 2).

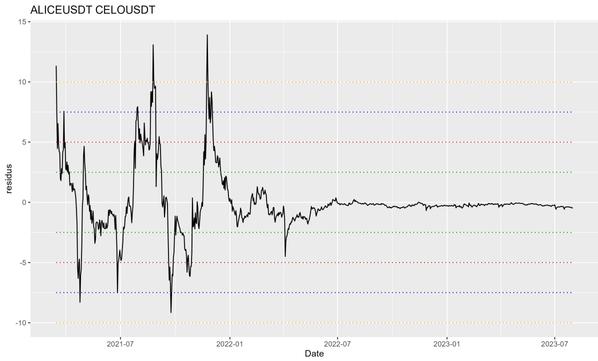


Figure 2: Presence of outliers in a series of residuals from a relationship.

We hypothesize that if a cointegrating relationship has experienced certain breaks in the past, it is likely to experience turbulence in the future. This type of relationship is dangerous in the context of a pair-trading strategy, since with the introduction of a stop-loss, an outlier can lead to heavy losses for the investor and high volatility. To avoid these relationships in our final sample, we apply a filter to all pairs. For each pair, we calculate the standard deviation of the residual series. If the series exceeds its standard deviation more than five times, the pair is removed from our study. In this way, 93 pairs are excluded.

Our final sample consists of 229 pairs[18]. It is interesting to note that 74 assets present after the stationarity tests are not found in the selected pairs[19] (see Figure 3). (i) Either because assets are not cointegrated with others, in which case it would be relevant to

[17] The Shapiro-Wilk test on the series of pairwise residuals showed that none of them was normal.
[18] All these pairs, and the assets that make them up, are available in Appendix C in the appendix.
[19] The 229 pairs in the final sample are made up of 89 unique assets. These assets are present in Appendix D in the appendix.

analyze them as safe havens. (ii) Or because the cointegrated pairs in which these assets are present did not pass the various filters applied, due to their volatility or their position as market "leader" or "follower".

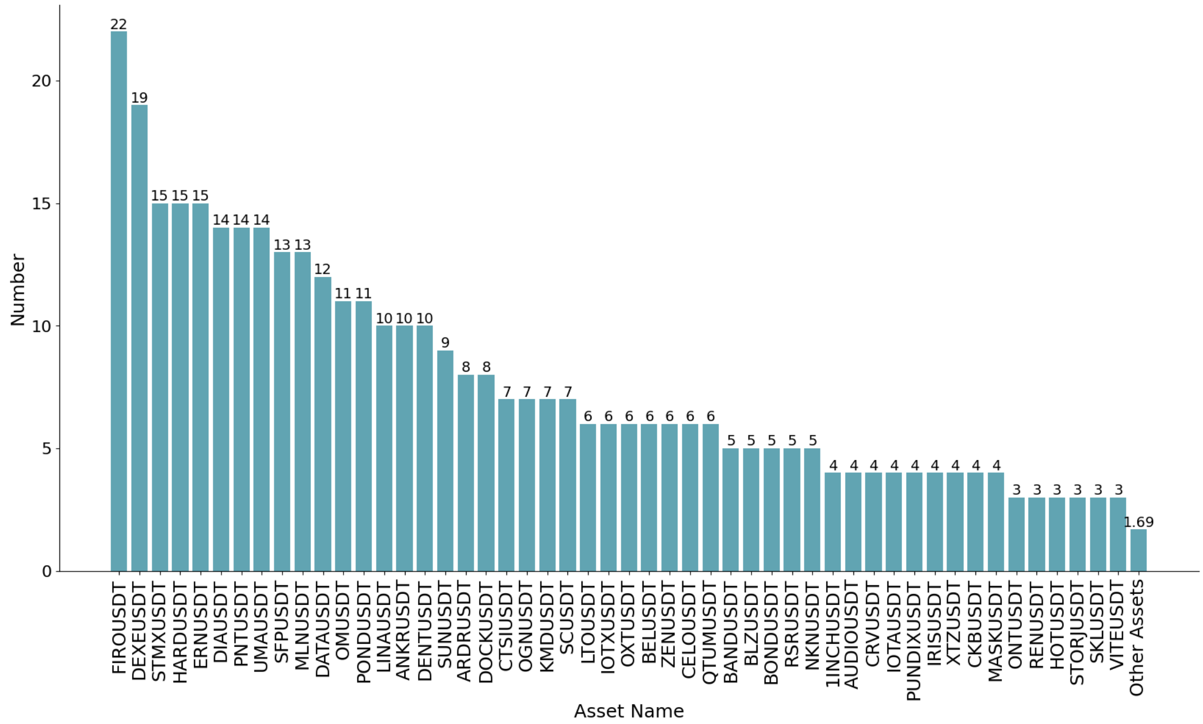


Figure 3: Plot of assets involved in selected cointegrated pairs.

On average, one asset is present in five selected pairs. Assets most cointegrated with the others are not the biggest/known ones: the lack of a priori knowledge of potential relationships at the start allows us to perceive relationships that would not correspond to market beliefs. The fact that the sector's dominant cryptoassets do not feature in the selected pairs is also explained by the choice to select only pairs where the assets complement each other. If we focus on the four largest cryptoassets in terms of capitalization (BTC, ETH, BNB and SOL): bitcoin and binance coin are not cointegrated with any selected asset. This lack of cointegration with the industry's other assets begs the question: do these two major cryptoassets have a safe-haven role towards the others?

As for ether, three assets are cointegrated with it (NULS, SFP and STPT). ECMs confirm our initial intuition: ether is a market-leading asset. This fact does not surprise us, since the three assets cointegrated with ether have a direct link with the Ethereum blockchain, as they exist as ERC-20 tokens.

In the final sample, solana appears in only one pair, SFP/SOL, while it is cointegrated with six assets (AR, ATA, COTI, EGLD, IOTX and SFP). Dedicated ECMs show that for four pairs (ATA, COTI, EGLD and IOTX) only one of the two assets present participates in the return to equilibrium. Although these four cryptoactives have no direct fundamental links with solana, the latter's importance in the industry can lead assets to oscillate around its trend, declaring it a "leader". The AR/SOL pair is excluded from the final sample, as its relationship is close to white noise behavior.

Finally, the asset most present in pairs is Firo, followed by Dexe. These two cryptoassets have different areas of focus. Firo, formerly known as Zcoin, is a cryptocurrency focused on privacy and security. It operates on a decentralized network with masternodes and a Proof of Work algorithm. In contrast, Dexe is the native token of the eponymous decentralized cryptoasset trading platform. It is primarily used for fees, platform governance and rewards.

3.3 Strategy construction

In a pair-trading strategy, a signal (buy or sell) on the pair is sent when the spread, or more precisely the residual of the relationship, between the two assets deviates from its mean. When this happens, inverse positions are opened on the two assets making up the pair. To take these two positions simultaneously, we exploit leverage within an investment. When a signal occurs on a pair, the entire portfolio is invested in the long position. A formula is then applied to find out how much the investor needs to short the other asset using leverage to play the return to the central value (0) of the linear price combination[20].

The use of leverage in a pair-trading strategy is feasible and often beneficial for two rea-

[20] This assumption takes into account unlimited collateral, as the long position is used as collateral to issue a short position on the other asset in the pair.

sons: (i) Leverage amplifies potential returns without significantly increasing net risk, as positions are designed to be market-neutral. (ii) Arbitraging market inefficiencies sometimes requires significant investment to make small price differences profitable. However, as pair-trading is a risky and potentially volatile strategy, a leverage limit of 2 has been introduced to moderate our exposure to risk[21].

3.3.1 Conditions to test and optimize strategies

In pair-trading strategies tested, three thresholds are set: a trigger threshold, at which a signal is sent to open a position (i.e. when the relationship between the two assets deviates from its equilibrium); a take-profit threshold which closes open positions with a gain (i.e. when the relationship between the two assets returns to its equilibrium); and a stop-loss threshold which closes open positions with a loss (i.e. when the relationship between the two assets breaks down). The levels of these thresholds are defined as multiples of standard deviations of the cointegration residuals. To compare strategies, we set standard thresholds: trigger = 2; stop-loss = 3; take-profit = 0. These parameters are then optimized using a genetic algorithm.

To make the tests realistic, fees are charged for opening and closing positions. A fee of 0.1% is charged for entering and exiting a long position, and a fee of 0.5% for entering and exiting a short position. Apart from position taking, the portfolio is in the money market and provides a zero return.

Two periods are used to evaluate the strategies: the "test" period is the period for optimizing the strategies, running from August 01, 2021 to July 31, 2023; the "backtest" period is the period for verifying the suitability of the chosen strategies, running from August 01, 2023 to January 31, 2024. At the start of each period, each pair's portfolio is

[21] To find out more about the equations used when taking positions, please refer to Appendix E of the appendix.

made up of 100 USDT[22].

To analyze the performance of the strategies studied, twelve indicators are calculated: cumulative return, annualized average daily return, standard deviation of returns (i.e. annualized average daily volatility), annualized Sharpe ratio[23], max drawdown[24], return per trade, return per winning trade, loss per losing trade, number of trades, percentage of winning trades, percentage of stop-losses hit and average duration of a trade.

3.3.2 Genetic algorithm

A genetic algorithm is an optimization method based on the principles of natural selection and genetics. It consists of several phases (see Figure 4): the genesis phase randomly initializes a set of potential solutions (representing potential candidates for solving the problem). These potential candidates are evaluated according to their quality, or aptitude, to solve the given problem by maximizing a given criterion. The selection phase isolates the best-performing individuals (i.e. those optimizing the desired criterion) in order to reproduce and train a new generation. This is done via various reproductive techniques, such as crossing and mutation. Crossover involves combining the characteristics of parents to create offspring, while mutation introduces a small amount of random variation into individuals to maintain genetic diversity (so as not to identify only a local maximum). The new generation replaces the old one, and the steps described above are repeated with the new one. The algorithm stops when one of the termination conditions is reached, such as convergence towards an acceptable solution or exhaustion of the

[22] USDT, also known as Tether, is a stable cryptocurrency (or stablecoin) that is indexed to the US dollar. This means that each USDT is designed to maintain a value equal to 1 USD. Stablecoins like USDT are used to provide price stability in the cryptocurrency universe, which is generally highly volatile. USDT is widely used on cryptocurrency exchange platforms to facilitate transactions, as it allows investors to transfer value without being exposed to the wide price fluctuations of other cryptocurrencies.

[23] The Sharpe ratio is calculated as the ratio between the annualized average daily return and the annualized volatility of returns. It is used to assess whether the additional return obtained by an investment is worth the risk taken to obtain it.

[24] Max drawdown measures the maximum loss an investor will incur if he buys at the top of the portfolio and sells at the next trough. This measure enables investors to understand the level of potential risk associated with a strategy and to which they are exposed.

number of iterations allowed.

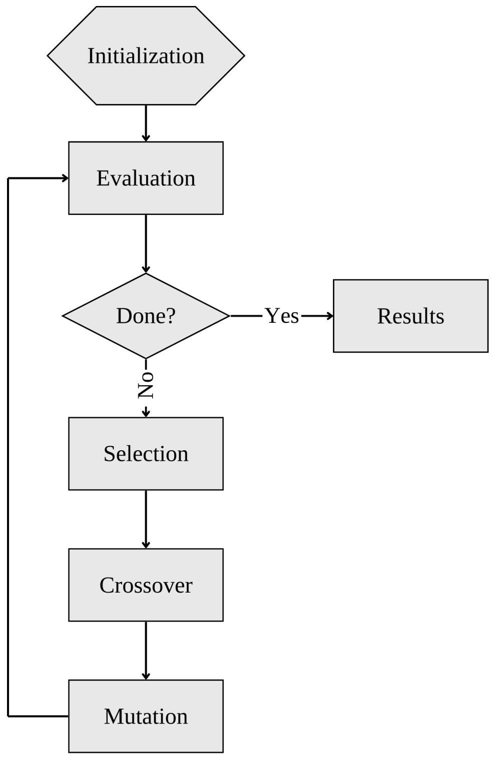


Figure 4: Genetic algorithm construction diagram.

The genetic algorithm has an initial population of ten potential candidates, is defined to be iterated ten times and to maximize the average Sharpe ratio of all pairs. It optimizes the parameters for triggering and closing strategy trades.
Known for its randomness, it is simulated several times to ensure the consistency of the results obtained.

4 Results

4.1 Standard tests

To begin our strategic analyses, we begin by comparing two pair-trading strategies widely used in the literature. Two variants are introduced at the end of this section to compensate for a specificity in the way stop-losses are taken into account in the original strategies.

4.1.1 Long-term standard deviation strategy

This strategy uses the long-term fixed standard deviation (SD) of the residual of the cointegration relationship. It includes six levels: sell-entry, sell-stop-loss, sell-take-profit, buy-entry, buy-stop-loss and buy-take-profit, each corresponding to a multiple of the fixed long-term SD (calculated over the entire test period). When the residual crosses the entry level, a corresponding transaction is opened. This transaction is finally closed when the residual reaches either the stop-loss level or the take-profit level.

For example (see Figure 5[25]), a position is opened (i.e. purchase of one asset and sale of the other) when the residual exceeds the long-term 2nd SD, indicated by the yellow lines on the chart. If the residual continues to rise and reaches the 3rd SD, visible with the red lines on the chart, then the position is stopped (stop-loss). Conversely, if the residual falls back towards the mean of the residual (green line), a profit is taken.

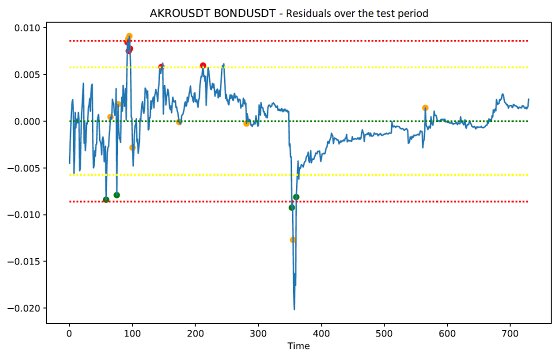


Figure 5: Residuals for the long-term standard deviation strategy on a pair.

Aggregate results for this strategy with standard thresholds are shown in Table I.

Over the selection period, only one pair has a negative return. With an average of 10 trades per pair over the 2-year period, the strategy with long-term standard deviations

[25]When the residual of the cointegrating relationship between the two assets rises above twice its long-term standard deviation, a short position on the pair is opened, i.e. short sale of the first asset offset by purchase of the second (red dot on the graph). Conversely, when the residual falls below minus twice its standard deviation, a long position is opened, i.e. purchase of the first asset offset by the short sale of the second (green dot on the chart). Finally, the position is exited, represented by the orange dots, either when the residual returns to its mean (take-profit), or when it exceeds three times its standard deviation (stop-loss).

Table I: Standard tests on the strategy with fixed long-term standard deviations.

	Test period				Backtest period*			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	-100	7322.07	368.23	206.83	-86.91	402.21	56.78	46.56
yield_day_%	-30.84	178.78	62.99	59.38	-100	381.33	64.72	81.85
vol_yield_%	14.86	145.35	51.39	48.60	19.95	130.70	68.41	60.88
sharpe_ratio_annual	-0.53	3.16	1.25	1.19	-1.99	3.62	1.17	1.66
maxdrawdown	10.10	100	38.54	35.26	2.31	88.58	28.44	26.32
avg_yield_trades_%	-12.69	52.68	16.14	14.42	-62.89	122.72	25.64	30.26
avg_yield_wintrades_%	11.40	81.91	33.75	31.50	8.97	157.10	55.96	51.23
avg_yield_losttrades_%	-100	-1.46	-15.54	-11.70	-62.89	-0.68	-24.67	-13.02
nbr_trades	3	23	10.48	10	1	9	2.17	2
winning_trades_%	14.28	100	63.57	62.5	0	100	67.94	91.67
stop_loss_%	12.5	85.71	43.68	44.44	0	100	30.30	0
avg_duration_trades	2.5	62.67	14.96	13.33	1	43	18.55	14.5

enables the investor to achieve an average cumulative return of 368.23%. The average duration of positions taken is 15 days. Despite this relatively short duration, the median return on each trade is 14.42%. This performance achieved in a very short time on a position taken can be explained by the volatility of the cryptoasset market, specifically in 2021. The Sharpe ratio ranges from -0.53 to 3.16 depending on the pair. In other words, the strategy here generates a positive and relatively high return compared to the risk taken.

Over the backtest period, the performance of this strategy is more nuanced. There are two groups of pairs:
The first group comprises pairs whose volatility in their relationship remains constant throughout the period studied. For these pairs, the thresholds defined via the long-term standard deviation are always reached during the backtest period, leading to regular trades on the pairs. The values given in Table 1 focus on these pairs. Out of our entire sample, this first group concerns 30 pairs (13%). For the majority, the strategy appears profitable, with an average cumulative return of 56.78% over 6 months. Only 6 pairs, or 20% of the sub-sample, ended in losses, with a minimum of -86.91%. The average percentage of winning trades over this period is positive at 67.94%. Risk indicators remain

relatively correct over this period, with an average volatility of 68.41% and an average max drawdown of -28.44%.

The second group concerns pairs with a change in volatility in their cointegrating relationship. No trades are taken over the period due to lower residual volatility in the backtest period than in the test period. Indeed, the test phase includes a period of high market volatility, which may have led to a greater amplitude in some of the cointegrating relationships identified. In the end, this group concerns the majority of pairs in our sample, since 199 pairs had no trade over the period, i.e. 87% of the pairs taken into consideration.

Taking these pairs into account in the calculation of indicators, the average return of this strategy over the backtest period falls to 7.44%.

4.1.2 Dynamic standard deviation strategy (Bollinger Bands)

The second strategy used and illustrated in the literature is Bollinger Bands (see Figure 6). Bollinger Bands are a tool invented by John Bollinger in the 1980s and a registered term since 2011. Derived from the concept of trading bands, they can be used to measure how "high" or "low" a price is in relation to past transactions.

Bollinger Bands are made up of an N-period moving average (MA), a band above K times an N-period standard deviation (SD) above the moving average (MA + K*SD) and a band below K times an N-period standard deviation below the moving average (MA - K*SD).

Standard deviation levels, unlike the long-term standard deviation strategy, are no longer fixed but re-estimated for the last period N. The most commonly used period N is 20 days. This standard configuration is recommended by John Bollinger (2002) and adopted by traders for its balance between sensitivity to price movements and reduction of market noise. However, this period can be adjusted according to trading objectives and asset type. Day, Cheng, Huang and Ni (2023) found that a 60-day period brings better results when implementing the Bollinger Bands strategy on Bitcoin. Furthermore, in the context of a pair-trading strategy, a 60-day duration is relevant to achieve a balance between responsiveness and signal stability, especially when dealing with strategies involving correlated assets. Consequently, in our study, this period is set at 60 days.

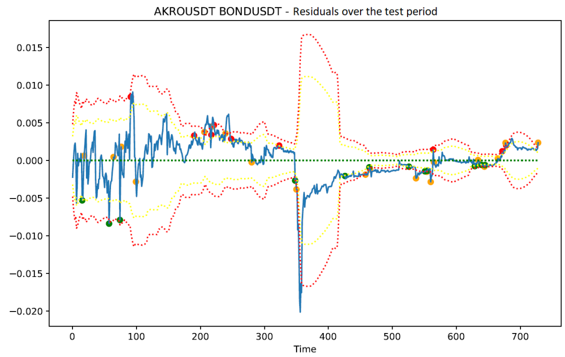


Figure 6: Example of Bollinger Bands residuals on a pair.

This strategy has the same six levels as before. Unlike the first strategy, stop-losses do not necessarily result in a loss. In fact, with daily stop-loss revaluation, a trade can hit a stop-loss and still end up a winner. This unintuitive result is linked to structural changes in the volatility amplitude of the pairs' cointegration residuals. Thus, the residual value at the start of the trade appears higher in absolute terms than its value when it hits the stop loss.

Bollinger Bands are interesting because they reason on a dynamic standard deviation and take into account potential changes in the volatility of the long-term relationship between two assets. In this way, they can solve the problem encountered with the first strategy tested. The implementation of this strategy with the standard thresholds is shown in Table II.

Over the test period, 29 pairs had a negative return. Nevertheless, this strategy outperformed its predecessor, with annualized daily returns of 456.21% versus 368.23% on average. The return per trade is lower than the first strategy, at 7.93% versus 16.14% on average, explained by the average winning trade rate, which is 20 percentage points lower, but offset by the higher number of trades (25 on average). Risk indicators are higher with average annualized daily volatility of 68.88% (vs. 51.39% previously), not

Table II: Standard tests on the Bollinger Bands strategy.

	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	-100	4714.27	456.21	231.76	-100	395.86	41.20	30.89
yield_day_%	-100	190.88	70.44	71.68	-100	302.53	49.60	61.59
vol_yield_%	33.49	164.19	68.88	66.76	26.82	361.03	73.02	62.06
sharpe_ratio_annual	-1.02	3.21	1.08	1.03	-2.98	4.60	0.92	0.94
maxdrawdown	12.10	100	54.45	53.08	4.24	100	33.93	27.78
avg_yield_trades_%	-12.23	21.09	7.93	7.93	-37.56	42.53	5.44	5.39
avg_yield_wintrades_%	14.37	54.09	26.97	26.40	0.92	84.28	21.49	18.31
avg_yield_losttrades_%	-54.72	-3.91	-10.78	-9.19	-100	-0.02	-10.91	-7.26
nbr_trades	9	41	24.52	24	2	22	7.62	7
winning_trades_%	19.35	84	49.31	50	0	100	51.79	50
stop_loss_%	18.18	87.5	58.80	59.09	0	100	50.10	50
avg_duration_trades	6.24	27.54	12.85	12.40	1	29.33	10.03	8.82

compensated for by the return, which worsens the Sharpe ratio to 1.08.

Over the backtest period, all combinations have at least two positions taken over the period. The average cumulative return is 41.20%, while 70 pairs (30%) end in losses. On average, 7 10-day trades are taken on each pair, resulting in a median gain of 5.44%. This result confirms our belief in the use of Bollinger Bands, as they enable us to adapt to structural changes in relationships.

4.1.3 Results summary

Equal threshold tests on the two types of strategy identified showed us that the long-term SD strategy is not suited to this type of market. Indeed, as the cryptoasset market is recent and turbulent, the change in volatility from one period to the next is not taken into account on a fixed SD strategy, resulting in a lack of arbitrage opportunity.

Moreover, in these two strategies, stop-loss does not seem to be taken into account in an optimal way, since a pair is eligible to open a trade as soon as the residual of its cointegration relationship lies between the stop-loss and the trigger threshold. This strategy specificity may lead to the stop-loss level being considered irrelevant. Indeed, if the pair is trading and the residual of its cointegration relationship touches the stop-loss level, the trade is closed. If, on the following day, the residual falls just below the stop-loss threshold, a new trade is initiated, and so on if, on the following day, the residual rises above the identified stop-loss. In short, this strategy specificity can gradually lead to heavy losses if a possible break in the cointegration relationship is not identified early enough (see Figure 7).

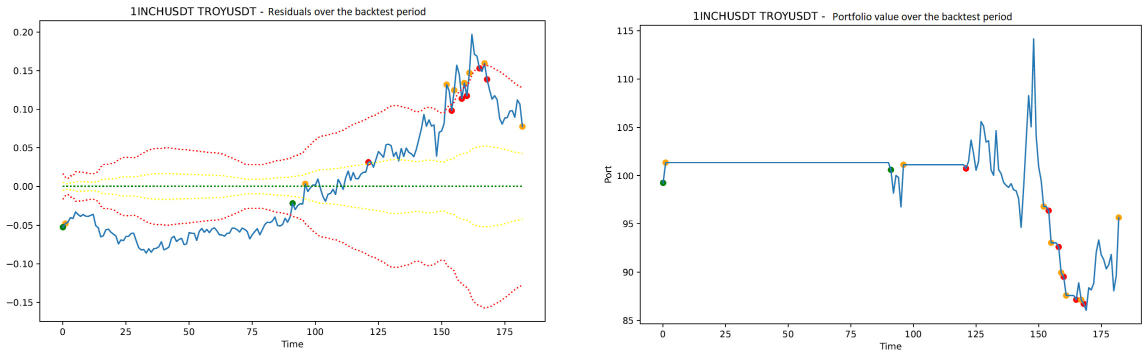


Figure 7: Example of the irrelevance of the identified stop-loss.

To mitigate the volatility induced by our strategy, two possible variants on the Bollinger Bands strategy are tested (the long-term standard deviation strategy not being relevant for this type of market).

4.1.4 Variant 1: Pair eligible for a trade if the residual is within a certain percentage of the trigger level

The first variant consists in making a pair eligible for a new trade (after hitting a stop-loss) when the residual of its cointegrating relationship lies between the trigger threshold and this same threshold increased by a certain percentage. In other words, with a percentage equal to 50%. If the pair's previous trade ends in stop-loss, a new trade is opened (in the same direction) only if his residual lies between the trigger threshold and a boundary situated 50% above this threshold (materialized by the yellow boundary in Figure 8). The results of this variant, applied to standard thresholds and a percentage set at 20%[26],

[26]i.e. 20% above the trip point in absolute value.

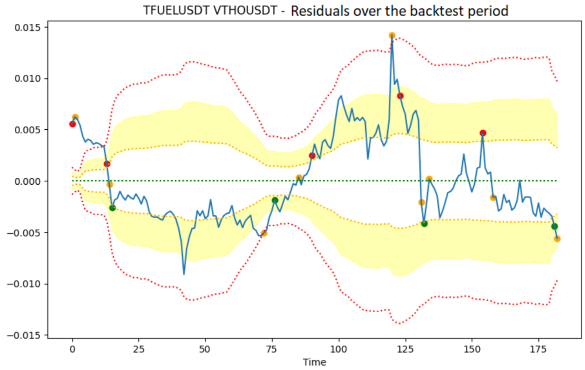


Figure 8: Cointegration residual applied to the first variant.

are shown in Table III.

Table III: Standard tests on the first variant.

	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	4708.05	437.07	213.86	−100	322.39	34.29	23.51
yield_day_%	−52.99	180.60	68.39	66.31	−100	276.16	39.50	49.42
vol_yield_%	32.86	163.99	65.46	64.11	17.72	361.03	67.10	54.64
sharpe_ratio_annual	−0.56	3.22	1.10	1.05	−3.10	4.47	0.78	0.86
maxdrawdown	10.74	100	51.70	50.41	4.24	100	31.38	26.07
avg_yield_trades_%	−12.95	28.68	9.42	9.38	−51.73	42.53	5.09	5.04
avg_yield_wintrades_%	10.34	52.54	26.39	25.55	0.41	130.54	21.05	16.80
avg_yield_losttrades_%	−77.40	−3.85	−13.60	−11.69	−100	−0.02	−11.23	−7.50
nbr_trades	7	29	18.49	19	2	13	6.09	6
winning_trades_%	25	86.96	57.48	57.89	0	100	52.37	50
stop_loss_%	10	80	51.22	50	0	100	49.71	50
avg_duration_trades	6.55	38.11	14.93	14.92	1	29.33	10.55	9.50

Over the test period, 36 pairs vs 29 for the Bollinger Bands strategy ended in losses. The return generated by this variant is on average lower than the original strategy, but the improvement in volatility, from 68.88% to 65.46%, brings the average Sharpe ratio higher to 1.10 vs 1.08. With the addition of a restriction on opening trades, the median number of positions taken over the period is lower at 19 vs 24, but they last longer. The percentage of winning trades has improved, with a difference of 10 percentage points, reinforcing the idea that it is relevant to observe a return in the relationship before initiating a new trade.

Over the backtesting period, results were less positive in terms of returns, with 74 pairs ending in losses. This mixed result is attributable to the Sharpe ratio, which averages "only" 0.78, even though risk indicators have improved.

4.1.5 Variant 2: Pair eligible for trade if residual has retouched take-profit

The second variant (see Figure 9) is more restrictive, requiring the residual of the pair's cointegration relationship to touch the take-profit level in order to be eligible for a new trade. In other words, when a trade ends in a loss because it has touched a stop-loss, the pair is once again eligible to open a trade as soon as the residual of its cointegration relationship has touched or crossed the take-profit threshold.

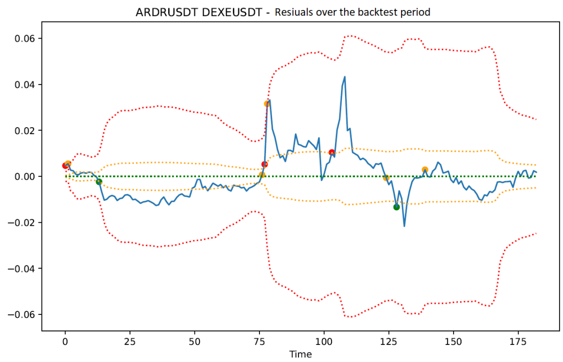


Figure 9: Cointegration residual applied to the second variant.

Table IV summarizes the results for the second variant.

The results of this more restrictive variant are not as good. Over the test period, 34 pairs ended in losses. The average Sharpe ratio is similar to previous strategies, despite lower average returns, and stands at 1.09. The improvement in the latter is due to the risk indicators, which are significantly better with this variant: annualized average daily volatility stands at 52.80% (versus 68.88% for the Bollinger Bands strategy and 65.46% for the first variant), median max drawdown is also improved at -38.78%. Due to the increased difficulty of making the pair eligible again for opening a position, the average number of trades recorded over the period is lower, with 11 positions opened. However, the percentage of winning positions is higher, giving an average return per position taken

Table IV: Standard tests on the second variant.

	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	8685.33	330.06	148.54	−100	239.25	14.95	6.66
yield_day_%	−73.56	211.61	56.73	53.03	−100	267.98	16.15	18.49
vol_yield_%	20.29	163.28	52.80	50.00	6.11	361.03	53.98	44.82
sharpe_ratio_annual	−1.03	3.35	1.09	1.11	−2.94	4.24	0.42	0.55
maxdrawdown	9.11	100	38.78	34.42	2.16	100	26.81	20.47
avg_yield_trades_%	−16.26	36.72	11.33	11.57	−59.86	46.65	0.99	2.51
avg_yield_wintrades_%	3.85	71.89	26.99	25.72	0.07	85.33	16.74	13.39
avg_yield_losttrades_%	−77.40	−1.56	−13.69	−11.07	−100	−0.02	−10.98	−7.24
nbr_trades	5	20	11.28	11	2	9	4.18	4
winning_trades_%	14.28	93.33	61.84	62.5	0	100	45.93	50
avg_duration_trades	4.43	31.18	13.32	12.50	1	37.5	9.96	8.75

of 11.33%.

Over the backtest period, 103 pairs (44.98% of the sample) lost money. The average cumulative return is 14.95% over six months. In contrast to the test period, the significant drop in returns is not offset by the improvement in risk indicators, leading to a deterioration in the Sharpe ratio to 0.42.

Finally, the introduction of both variants reduces the risk generated by the strategy. However, the introduction of overly restrictive rules leads, especially in the short term, to a deterioration in performance due to a lack of arbitrage opportunities, as illustrated by the backtest period of the second variant.

4.2 Strategy optimization

The genetic algorithm optimizes three thresholds: the trigger threshold, the stop-loss threshold and the take-profit threshold[27]. For the first variant, the algorithm also optimizes the percentage of eligibility to open a trade. It optimizes the parameters for all

[27] We optimize the thresholds symmetrically. The values optimized by the algorithm are positive values, corresponding to the thresholds for a sell order on the pair; the thresholds for a buy order are implicitly defined as the inverse of these values.

pairs at the same time, so that the end result is unique levels for all combinations[28].

The maximum parameter bound (i.e. the maximum stop-loss level the strategy can adopt) takes into account the characteristics of the cryptoasset market. Taking into account a relevant stop-loss level is necessary for the strategy to enable the induced risk to be reduced while not cutting positions too early[29]. The study by Białkowski (2020) thus helps to prove that introducing stop-losses into a strategy helps to reduce the strategy's risk and sometimes its return for want of sufficiently precise calibration. The more volatile digital asset market requires adjustments to methods known from traditional markets for calculating optimal stop-loss levels. This work, requiring further research on the subject, may lead to an optimal stop-loss calculation method. The article by Kaminski and Lo (2014) shows that under momentum-type return-generating processes or regime-switching models, the introduction of a stop-loss rule can be beneficial in terms of return while reducing the induced risk. Although these articles do not deal with the specific case of pair-trading strategies, the principle of introducing a stop-loss is the same. In the event of a breakdown in the cointegrating relationship between the two assets, the upstream introduction of a stop-loss makes it possible to limit losses by exiting the position "in time". Knowing that in Huang and Martin's (2019) paper, the stop-loss level for their CFD pair-trading strategy is four, we decide to position our maximum bound at five.
The defined bounds for the parameters are therefore [-1; 5]. The bounds for the percentage of trade eligibility in the first variant are [0; 100], with a constraint that the eligibility bound must not exceed the set stop-loss level. The optimization results are shown in Table V.
Optimizing thresholds using the genetic algorithm yields better results. The optimized thresholds for the Bollinger Bands strategy and the second variant are the same: trigger

[28] We optimized the thresholds pair by pair so as to have different thresholds for each pair. We concluded that this solution creates a lot of overlearning and little replicability for the future. In the interests of replicability, we therefore opted for a more stable solution.

[29] We optimized the parameters by [-1 ; 3], but found that this calibration led to too high an occurrence of stop-losses, and hence losses. The average percentage of stop-loss occurrences during the backtest period was 45.33%. In the end, we come back to the same problem as in the implementation of variants: calibrating between restrictions and risk management.

Table V: Parameter optimization results for the selected strategies.

	Bollinger Bands Strategy with Dynamic Standard Deviations 60 Days							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	21 082.90	1700.99	995.64	−100	511.21	87.58	71.37
yield_day_%	−100	3850.54	160.63	138.98	−100	1682.33	97.25	114.18
vol_yield_%	47.14	5259.28	128.31	83.96	26.19	1043.76	93.62	71.64
sharpe_ratio_annual	−0.69	4.10	1.59	1.61	−4.73	5.79	1.49	1.57
maxdrawdown	16.21	100	56.67	53.96	5.04	100	35.14	30.20
avg_yield_trades_%	−3.24	21.36	8.54	8.62	−65.95	28.80	5.15	5.05
avg_yield_wintrades_%	5.89	28.68	13.02	12.47	1.30	56.76	10.65	8.74
avg_yield_losttrades_%	−89.38	−0.13	−17.25	−13.15	−99.58	−0.10	−6.76	−3.85
nbr_trades	15	60	36.37	37	2	26	11.99	12
winning_trades_%	56.52	100	84.67	87.10	0	100	71.32	75
stop_loss_%	0	48.48	14.42	12.12	0	77.78	12.87	9.09
avg_duration_trades	3.44	21.86	9.42	9.06	2.24	23	7.56	6.55
	Variant 1 of the 60-day dynamic standard deviation strategy							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	10 405.65	1109.01	662.63	−100	520.73	83.96	72.67
yield_day_%	−20.58	280.40	117.86	122.96	−100	2893.72	112.92	121.59
vol_yield_%	38.65	248.79	85.61	79.20	26.95	2134.68	104.41	72.34
sharpe_ratio_annual	−0.27	3.40	1.49	1.49	−3.93	4.86	1.53	1.70
maxdrawdown	16.21	100	54.15	51.66	4.99	100	34.41	28.57
avg_yield_trades_%	−5.01	41.44	19.16	19.04	−46.84	73.25	14.37	13.10
avg_yield_wintrades_%	15.23	60.45	29.78	29.58	1.98	180.25	24.25	19.26
avg_yield_losttrades_%	−100	−1.42	−22.75	−17.30	−69.69	−0.02	−8.94	−4.77
nbr_trades	5	22	14.38	14	1	11	5.13	5
winning_trades_%	46.67	100	79.10	80	0	100	71.89	75
stop_loss_%	0	66.67	24.39	22.22	0	75	20.60	20
avg_duration_trades	9.44	54.38	26.10	25.33	1.33	69.50	18.18	16.75
	Variant 2 of the 60-day dynamic standard deviation strategy							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	21 082.90	1489.66	777.60	−100	400.14	77.14	62.20
yield_day_%	−100	3830.59	153.57	129.15	−100	2773.58	104.04	112.44
vol_yield_%	45.50	5259.28	123.10	76.89	26.26	2134.58	99.73	71.10
sharpe_ratio_annual	−0.67	4.10	1.60	1.61	−4.73	5.79	1.45	1.46
maxdrawdown	16.21	100	53.06	48.40	5.04	100	34.76	28.84
avg_yield_trades_%	0.37	18.73	8.50	8.52	−32.19	33.81	5.14	4.82
avg_yield_wintrades_%	5.75	25.45	12.13	11.69	0.41	63.70	10.37	8.58
avg_yield_losttrades_%	−89.38	−0.13	−17.99	−14.58	−66.65	−0.10	−6.61	−3.50
nbr_trades	15	60	33.92	34	2	26	11.17	11
winning_trades_%	54.90	100	87	89.19	0	100	71.18	75
stop_loss_%	0	65.31	13.22	8.57	0	66.67	14.08	11.11
avg_duration_trades	3.44	20.83	8.67	8.44	2	26	7.27	6.33

threshold = 1.25; stop-loss threshold = 5; take-profit threshold = 1.
For the first variant, they have more amplitude with: Trigger threshold = 2; stop-loss threshold = 5; take-profit threshold = 0; eligibility percentage = 93.
In all three cases, the optimized parameters are in line with the idea of a return to long-term equilibrium of the relationship between two assets after a short-term deviation. Although the Sharpe ratio takes into account a risk dimension in its denominator, the genetic algorithm, in seeking to maximize it, concludes that it is necessary to accept greater variations in performance and to increase the stop-loss threshold to maximize it.

As the results over the optimization period are over-learned (the genetic algorithm optimizes the thresholds using this period), we focus on interpreting the results over the backtest period. Optimizing strategy thresholds significantly improves results. Risk indicators are similar between the three strategies, with a median annualized volatility of 72% and an average max drawdown of 34%. The difference in Sharpe ratios lies in numerator, i.e. annualized daily returns. Figure 10 shows the dispersion of cumulative returns for the three optimizations.

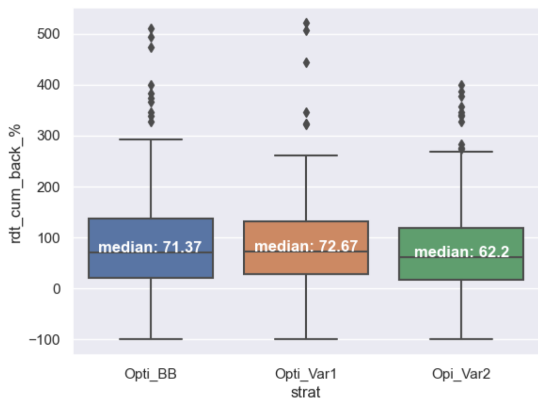


Figure 10: Boxplot comparing return dispersion between optimized strategies.

As for the Bollinger Bands strategy, 32 pairs ended in losses. The average cumulative return is good, at 87.58%, but the dispersion of pairs is greater, making this strategy more unpredictable. On average, 12 8-day trades are taken during the six months. Each winning trade yields an average return of 10.65%, while each losing trade generates a loss of 6.76%. The winning trade rate is very good, at 71%.

For the first variant, 36 pairs - four more than the basic strategy - end in loss, for an average cumulative return of 83.96%. However, this optimization offers a more centered dispersion of returns per pair, making it more interesting for portfolio construction. Thanks to the wider optimized thresholds, only 5 trades are taken over the period on average. Nevertheless, the difference between the gain generated by winning trades and the loss incurred by losing trades is more interesting here, since a winning trade generates gains three times greater than the losses of a losing trade, for the same percentage of winning trades (i.e. 71%).

Finally, for the optimization of the second variant, 38 pairs ended in losses, for a median cumulative return of 62.20

5 Discussion, robustness and limits

We would like to present some additional thoughts and results. These concern the optimization of pair-trading strategies refined by risk class, the analysis of pairs in loss situations, the implications of our results for the efficiency of cryptoasset markets and finally some limits about our results.

5.1 Risk classes

Implementations of pair-trading strategies in the cryptoasset market are performing well, despite the risks involved. In an attempt to reduce risk and understand where performance comes from, we classify pairs according to the volatility of their residuals. Using K-means, three clusters are identified (see Figure 11). The first cluster contains the majority of pairs, 198, with low volatility and stable relationships over time. The second cluster, containing 27 pairs, brings together those with a slightly volatile relationship over time. Finally, the third cluster, containing 4 pairs, contains pairs with highly turbulent long-term relationships.

Modeling and optimizing pair-trading strategies according to these three clusters has shown that these strategies work best for pairs with a perennial cointegrating relationship over time (i.e. low volatility). In view of these results, and from a portfolio construction perspective, it would be appropriate to adapt our sample of pairs and retain only those with a stable relationship[30].

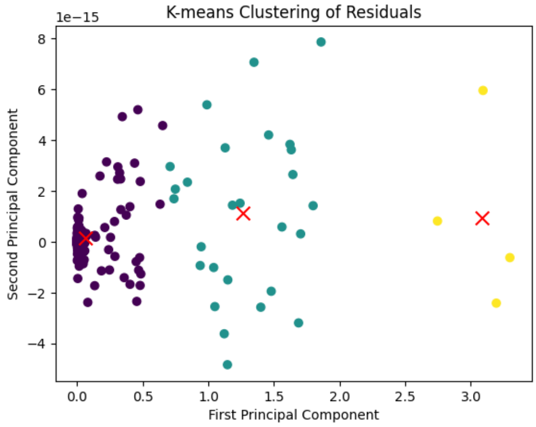


Figure 11: Pair clustering by volatility of cointegrating residuals.

Figure 12 shows the aggregate trajectories of the strategies tested. Optimizing the thresholds of the strategies significantly increases the results, since the performance of the Bollinger Bands strategy doubles that of the tests carried out with standard thresholds. In terms of returns, the differentiated optimization according to pair classification yielded a performance of 120% in 6 months. This result supports our belief that classifying pairs via common characteristics, such as the volatility of their long-term relationship, enhances and captures all the alpha present in the pairs.

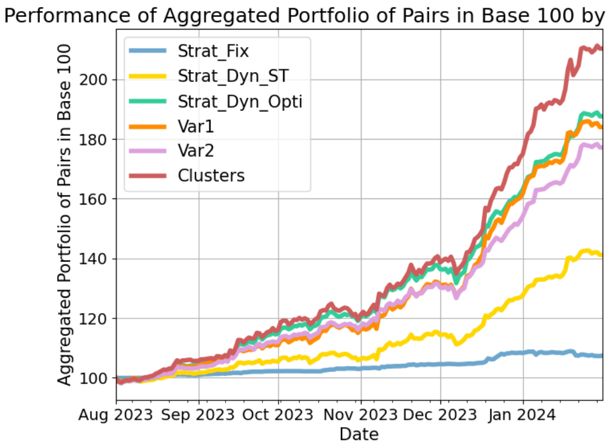
Although this classification and optimization maximize performance, the third class accentuates volatility in the strategy (with optimized thresholds which are more extensive than those of the other two classes), ultimately bringing more risk and degrading the average Sharpe ratio to 1.11 versus 1.49 for the classic optimized strategy.

Conversely, the second variant tested proves to be overly restrictive, limiting opportunities and resulting in lower performance. Despite a more linear dynamic (i.e. lower

[30]For more information on the construction of the classification and the results by cluster, please refer to Appendix F of the appendix.

volatility), the drop in performance results in a Sharpe ratio below that of the other strategies, at 1.45 on average.

Finally, the first optimized variant is one of the best proposals, combining risk management with performance, and achieves a Sharpe ratio of 1.53 on average.



Strategy	Mean Sharpe ratio
Strat_Fix	0.15
Strat_Dyn_ST	0.92
Strat_Dyn_Opti	1.49
Var1_Opti	1.53
Var2_Opti	1.45
Clusters_Opti	1.11

Figure 12: Aggregate performance of tested strategies over the backtest period.

5.2 Pairs analysis

Although the strategies work in aggregate, there are disparities between the pairs selected. Of all the strategies tested, 128 pairs out of the 229 end up in loss on at least one of the tests carried out. Four pairs[31] stand out as losing in all strategies, the particularity being that they all contain the same cryptoactive: OM (mantra). Mantra is the token of Mantra DAO, a decentralized platform on Ethereum that focuses on staking, lending and yield generation services. Its token, OM, is used for staking and governance.

Taking a closer look at the series of these five assets involved, cf Figure 13, by the end of 2023, the mantra had completely dropped its level, not taking with it the other assets usually cointegrated with it. This was due to governance decisions by the decentralized Mantra DAO protocol, which decided several times during January 2024 to significantly

[31] OM/STMX, OM/ZEN, OM/PNT and OM/REN

increase the staking yield assigned to the OM token[32]. As a result, more investors were attracted to the token and its potential return on staking, driving up its price.

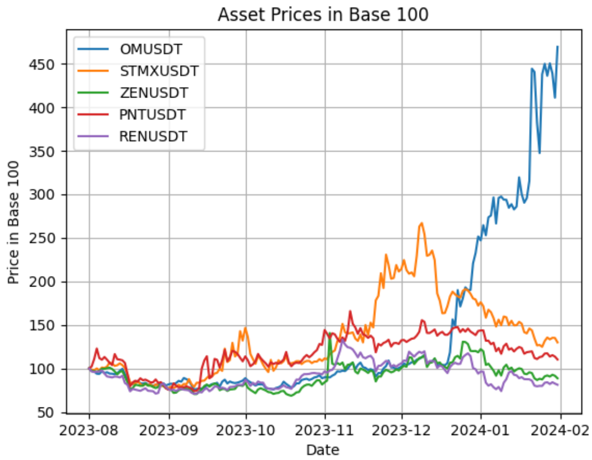


Figure 13: Price chart of five assets involved in loss-making pairs.

Finally, the inflating OM price led to breaks in these four known cointegrating relationships (see Appendix G in appendix). The break, coupled with a relatively high stop-loss level (at three or five multiples of standard deviation), led these pairs to incur heavy losses at the end of the backtesting period.

This result leads us to reconsider our approach: starting with no preconceived ideas for pairs selection is an interesting approach to avoid restricting potential choices. But, we need to identify the behavior and fundamentals of each asset in the pairs after this first step. Indeed, this type of break can be anticipated using the information available on the protocols. A change in asset fundamentals affects their cointegrating relationships, so it is important to take them into account in our strategies to avoid major losses.

5.3 Implications for market efficiency

Overall, our results reveal that, for a significant number of cryptoasset pairs, price forecasting - or more precisely, linear price combinations - becomes possible under particular

[32] https://x.com/MANTRA_Chain/status/1747921782361768391, https://x.com/MANTRA_Chain/status/1749325959889830373, https://x.com/MANTRA_Chain/status/1748337268014911558, https://x.com/mantra_chain/status/1750494405407236194

market conditions, notably when cointegrating relationships deviate too far from their central value. Not only are such forecasts possible, they also form the basis of systematic trading strategies that prove profitable according to the usual financial metrics used in this article.

This form of price predictability can be interpreted as evidence of temporary market inefficiencies, where prices deviate from a perceived fundamental level for the valuation differences between two cryptoassets, before gradually correcting the anomaly. It is specifically the weak form of market efficiency that is being challenged here, albeit in a temporary manner.

The high volatility of prices and price differentials seems legitimate for digital assets that do not distribute income (setting aside the role of stacking for certain assets). The valuation of these assets is therefore not anchored in revenue expectations, as is the case for conventional financial assets (dividends, coupons, etc.). It is essentially speculative, based on confidence in the current and future uses of cryptocurrencies as payment and investment instruments. This refers to the technical characteristics of the various cryptocurrencies as payment instruments, but also to the reliability of trading platforms. Confidence in the development of the cryptocurrency ecosystem also plays a role in valuations, probably as a common risk factor for most digital assets.

We can conjecture that the standard deviations of the cointegration relationships partly reflect uncertainty about the fundamental values of the various cryptocurrencies, and even more precisely about the differences in fundamental values between them. There are, of course, other factors that can influence the volatility of prices and price spreads. These could be identified through the prism of behavioral finance. These include the irrationality of certain investors, mimicry, market manipulation (notably through the dissemination of information on social networks), and the fragmentation of trading platforms.

Overall, pair-trading strategies such as those proposed in our research are likely to smooth out arbitrage opportunities and the associated pockets of inefficiency. However, they are unlikely to eliminate them completely, as there must still be incomprehensible uncertainty surrounding investors' perception of the fundamentals of cryptoasset prices and spreads. In other words, these strategies bolster investors' assessments of fundamental discrepancies between cryptoassets.

5.4 Limits

As previously noted with pairs involving the OM (mantra) asset, the primary limitation of our pair-trading strategies lies in potential breaks in the cointegration relationships between digital assets. Given the size of our test sample, it is not possible to conduct robust tests for cointegration relationship breaks. Practitioners interested in implementing this type of strategy should pay particular attention to the stability of cointegration relationships. Nevertheless, implementing stop-loss mechanisms remains an effective measure to guard against any atypical behavior of the pair out-of-sample and in trading conditions. A second limitation to mention concerns the liquidity of the assets involved in the pairs. This liquidity can be heterogeneous across assets and vary over time. Furthermore, it may be impacted by pair-trading strategies like those proposed in the article.
It should also be noted that not all the assets selected in our study are currently eligible for short selling. Finally, the brokerage fees used in the study are fixed for all pairs and may thus marginally differ from actual brokerage practices.

6 Conclusion

This article investigates optimal pair-trading strategies within the formal framework of cointegration.
The originality of our paper in relation to the existing literature lies in four points. First, our study is based on a very broad panel of digital assets. We make no assumptions about the potential relationships between assets. In total, we are working with 209 assets listed on the Binance centralized exchange since August 1, 2021. Secondly, our study is based on a longer timeframe than the existing literature on the subject. Indeed, as this market is still in its infancy, previous studies did not have a long time span at their

disposal. Another original aspect of our paper is the desire to understand the behavior of each asset within a pair. Thanks to the construction of a simple error-correction model, we are able to explain the mechanisms of return to equilibrium and to identify, or not, leaders within a pair. Finally, the choice of a genetic algorithm to optimize the entry and exit thresholds of our pair-trading strategies on cryptoasset market is innovative, since we are able to combine classical econometrics for pairs selection and machine learning for strategy construction.

In terms of pairs selection, some of our results show that, for certain pairs, neither asset participates in the return to equilibrium. This fact invites us to look for other variables which contribute to the mechanism of return. There are two possibilities. If the other variables concern the prices of other cryptoassets, then it would make sense to examine pair-trading strategies with pairs made up of more than two assets. It is also conceivable that the return mechanism of these pairs obeys asset-specific variables such as staking returns. In this case, it would be interesting to integrate these variables into the error-correction model, in order to quantify their contribution to the return mechanism in the event of a divergence in the long-term relationship.

In terms of strategies, our initial results suggest that the Bollinger Bands strategy is better suited to the structure of cointegrating residuals than the long-term standard deviation strategy. Indeed, by relying on historical standard deviations, the strategy fails to take into account possible changes in the volatility of residuals. This limitation translates into a significant number of missed opportunities in terms of trades taken, since of the 229 pairs selected, 199 have no trades during the backtest period. Conversely, the Bollinger Bands strategy adapted with dynamic 60-day standard deviations leads to trades on all pairs in the backtest phase. Over 6 months, the average return for our entire sample is 41.20%, with a median of 7 trades taken. Despite this good return, it should be noted that this strategy remains relatively risky, with a max drawdown ranging from 4.24% to 100%, but this is offset by an average annualized Sharpe ratio of 0.92, meaning that the strategy delivers a positive excess return in relation to the risk taken.

Parameter optimization using the genetic algorithm significantly improves the dynamic strategy, with an average annualized Sharpe ratio of 1.49 over the backtesting period. However, the classic Bollinger Bands strategy does not appear to be suited to the cryptoasset market due to its volatility, with the strategy's average volatility standing at 93.62% and a median max drawdown of -35.14%. To improve the latter, we implemented two variants, resulting in a pair-trading strategy delivering a median annualized Sharpe ratio of 1.70 in the backtest period. The first variant of the optimized strategy offers an interesting result, since it indicates the distance a pair's residual must travel after hitting a stop-loss in order to estimate that the trend is for the relationship to return to equilibrium. In this way, the investor only takes a position when the trend is confirmed by the relationship.

At the end of the article, we try to go a step further by implementing a K-means classification of our pairs according to the volatility of their relationships. The results obtained are particularly interesting, since they highlight that a pair-trading strategy works best on pairs with a stable relationship. These are the pairs that generate the highest alpha in terms of risk/return ratio. For the future, it would be worthwhile to pay particular attention to these pairs when constructing a portfolio involving several pairs at different scales.

Finally, our article shows that cointegration relationships exist in the cryptoasset market. These relationships can be exploited as part of a pair-trading strategy, and deliver good results in terms of risk/return ratios, even though volatility within these strategies remains relatively high compared to those implemented on traditional markets (see Appendix H). These results enable a comparison with the efficiency of the crypto-asset market. The existence of profitable pair-trading strategies confirms the existence of pockets of market inefficiency, characterized by short-term deviations of asset prices involved in the pairs from their equilibrium trajectory.

Future research will consist of cross-referencing all the results obtained on cointegration relationships, mechanisms for returning to equilibrium, the intensity of recall forces, and the performance of pair-trading strategies with the objective characteristics of cryptoassets: associated economic activities, outstanding amounts and liquidity of assets, the possibility and mechanism of short selling, the existence of stacking, etc.

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APPENDIX

Appendix A: Assets considered in the article

Table VI: List of digital assets used in our study

Symbol	Name	Sector
1INCHUSDT	1inch	Decentralized Exchanges
AAVEUSDT	Aave	Lending
ACMUSDT	AC Milan Fan Token	nan
ADAUSDT	Cardano	Smart Contract Platforms
AKROUSDT	Akropolis	Lending
ALGOUSDT	Algorand	Smart Contract Platforms
ALICEUSDT	My Neighbor Alice	Gaming
ALPHAUSDT	Alpha Finance Lab	Asset Management
ANKRUSDT	Ankr	Shared Compute
ANTUSDT	Aragon	Misc
ARDRUSDT	Ardor	Smart Contract Platforms
ARPAUSDT	ARPA Network	nan
ARUSDT	Arweave	File Storage
ASRUSDT	AS Roma Fan Token	nan
ATAUSDT	Automata	nan
ATMUSDT	Atlético de Madrid Fan Token	nan
ATOMUSDT	Cosmos	Smart Contract Platforms

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
AUDIOUSDT	Audius	Content Creation and Distribution
AVAUSDT	Travala.com	Payment Platforms
AVAXUSDT	Avalanche	Smart Contract Platforms
AXSUSDT	Axie Infinity	Gaming
BADGERUSDT	Badger DAO	Decentralized Exchanges
BAKEUSDT	BakeryToken	nan
BALUSDT	Balancer	Decentralized Exchanges
BANDUSDT	BAND	Data Management
BARUSDT	FC Barcelona Fan Token BAR	nan
BATUSDT	Basic Attention Token	Advertising
BCHUSDT	Bitcoin Cash	Currencies
BELUSDT	Bella Protocol	Asset Management
BLZUSDT	Bluzelle	File Storage
BNBDOWNUSDT	BNBDOWN	nan
BNBUPUSDT	BNBUP	nan
BNBUSDT	BNB	Smart Contract Platforms
BNTUSDT	Bancor	Decentralized Exchanges
BONDUSDT	BarnBridge	Derivatives
BTCDOWNUSDT	BTCDOWN	nan
BTCUPUSDT	BTCUP	nan
BTCUSDT	Bitcoin	Currencies
BURGERUSDT	BurgerCities	nan
C98USDT	Coin98	nan
CAKEUSDT	PancakeSwap	Decentralized Exchanges

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
CELOUSDT	Celo	Smart Contract Platforms
CELRUSDT	Celer Network	Scaling
CFXUSDT	Conflux Network	Smart Contract Platforms
CHRUSDT	Chromia	Application Development
CHZUSDT	Chiliz	Payment Platforms
CKBUSDT	CKB	Smart Contract Platforms
CLVUSDT	Clover Finance	Interoperability
COMPUSDT	Compound	Lending
COSUSDT	Contentos	nan
COTIUSDT	COTI	Application Development
CRVUSDT	Curve	Decentralized Exchanges
CTKUSDT	Shentu	nan
CTSIUSDT	Cartesi	Smart Contract Platforms
CTXCUSDT	Cortex	nan
DASHUSDT	Dash	Currencies
DATAUSDT	Streamr	Data Management
DCRUSDT	Decred	Currencies
DEGOUSDT	Dego Finance	nan
DENTUSDT	DENT	Data Management
DEXEUSDT	DeXe	nan
DGBUSDT	DigiByte	Currencies
DIAUSDT	DIA	Data Management
DOCKUSDT	DOCK	Data Management
DODOUSDT	DODO	Decentralized Exchanges
DOGEUSDT	Dogecoin	Currencies

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
DOTUSDT	Polkadot	Smart Contract Platforms
DREPUSDT	DREP	nan
DUSKUSDT	Dusk Network	Smart Contract Platforms
EGLDUSDT	MultiversX	Smart Contract Platforms
ENJUSDT	Enjin Coin	Gaming
EOSUSDT	EOS	Smart Contract Platforms
ERNUSDT	Ethernity Chain	Collectibles
ETCUSDT	Ethereum Classic	Smart Contract Platforms
ETHDOWNUSDT	ETHDOWN	nan
ETHUPUSDT	ETHUP	nan
ETHUSDT	Ethereum	Smart Contract Platforms
EURUSDT	Euro	nan
FETUSDT	Fetch.ai	Artificial Intelligence
FILUSDT	Filecoin	File Storage
FIOUSDT	FIO Protocol	Interoperability
FIROUSDT	Firo	Currencies
FISUSDT	Stafi	Derivatives
FLMUSDT	Flamingo	Decentralized Exchanges
FLOWUSDT	Flow	Smart Contract Platforms
FORTHUSDT	Ampleforth Governance Token	Currencies
FTMUSDT	Fantom	Smart Contract Platforms
FUNUSDT	FunToken	nan
GBPUSDT	Pound Sterling	nan
GRTUSDT	The Graph	Data Management
GTCUSDT	Gitcoin	Crowdfunding

Continued on next page

Table VI – *Continued from previous page*

Symbol	**Name**	**Sector**
HARDUSDT	Kava Lend	Lending
HBARUSDT	Hedera Hashgraph	Smart Contract Platforms
HIVEUSDT	Hive	Content Creation and Distribution
HOTUSDT	Holo	Decentralized Exchanges
ICPUSDT	Internet Computer	Smart Contract Platforms
ICXUSDT	ICON	Smart Contract Platforms
INJUSDT	Injective	Derivatives
IOSTUSDT	IOST	Smart Contract Platforms
IOTAUSDT	MIOTA	nan
IOTXUSDT	IoTeX	IoT
IRISUSDT	IRISnet	Interoperability
JSTUSDT	JUST	Decentralized Exchanges
JUVUSDT	Juventus Fan Token	nan
KAVAUSDT	Kava	Smart Contract Platforms
KLAYUSDT	Klaytn	Smart Contract Platforms
KMDUSDT	Komodo	Interoperability
KNCUSDT	KyberNetwork	Decentralized Exchanges
KSMUSDT	Kusama	Smart Contract Platforms
LINAUSDT	Linear	nan
LINKUSDT	ChainLink	Data Management
LITUSDT	Litentry	nan
LPTUSDT	Livepeer	Shared Compute
LRCUSDT	Loopring	Decentralized Exchanges
LSKUSDT	Lisk	Application Development

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
LTCUSDT	Litecoin	Currencies
LTOUSDT	LTO Network	Enterprise and BaaS
MANAUSDT	Decentraland	Virtual and Augmented Reality
MASKUSDT	Mask Network	Data Management
MATICUSDT	Polygon	Scaling
MBLUSDT	MovieBloc	nan
MDTUSDT	Measurable Data Token	Data Management
MDXUSDT	Mdex	nan
MKRUSDT	Maker	Lending
MLNUSDT	Enzyme	Asset Management
MTLUSDT	Metal	Payment Platforms
NEARUSDT	NEAR Protocol	Smart Contract Platforms
NEOUSDT	NEO	Smart Contract Platforms
NKNUSDT	NKN	IoT
NMRUSDT	Numeraire	Asset Management
NULSUSDT	Nuls	Enterprise and BaaS
OCEANUSDT	Ocean Protocol	Data Management
OGNUSDT	OriginToken	nan
OGUSDT	OG Fan Token	nan
OMGUSDT	OMG Network	Scaling
OMUSDT	MANTRA	Lending
ONEUSDT	Harmony	Smart Contract Platforms
ONGUSDT	Ontology Gas	Smart Contract Platforms
ONTUSDT	Ontology	Smart Contract Platforms

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
ORNUSDT	Orion Protocol	Decentralized Exchanges
OXTUSDT	Orchid	Data Management
PAXGUSDT	PAX Gold	nan
PERPUSDT	Perpetual Protocol	Derivatives
PHAUSDT	Phala.Network	nan
PNTUSDT	pNetwork	Decentralized Exchanges
POLSUSDT	Polkastarter	Crowdfunding
PONDUSDT	Marlin	Smart Contract Platforms
PSGUSDT	Paris Saint-Germain Fan Token	nan
PUNDIXUSDT	Pundi X	nan
QNTUSDT	Quant	Interoperability
QTUMUSDT	Qtum	Smart Contract Platforms
REEFUSDT	Reef	Asset Management
RENUSDT	Ren	Interoperability
RIFUSDT	RSK Infrastructure Framework	Application Development
RLCUSDT	iExecRLC	Shared Compute
ROSEUSDT	Oasis Network	Smart Contract Platforms
RSRUSDT	Reserve Rights	Asset Management
RUNEUSDT	THORChain	Decentralized Exchanges
RVNUSDT	Ravencoin	Currencies
SANDUSDT	The Sandbox	Gaming
SCUSDT	Siacoin	File Storage
SFPUSDT	SafePal	Wallet
SHIBUSDT	SHIBA INU	nan
SKLUSDT	SKALE Network	Scaling

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
SLPUSDT	Smooth Love Potion	Gaming
SNXUSDT	Synthetix Network Token	Derivatives
SOLUSDT	Solana	Smart Contract Platforms
STMXUSDT	StormX	Rewards
STORJUSDT	Storj	File Storage
STPTUSDT	Standard Tokenization Protocol	nan
STRAXUSDT	Stratis	nan
STXUSDT	Stacks	Smart Contract Platforms
SUNUSDT	SUN	nan
SUPERUSDT	SuperFarm	nan
SUSHIUSDT	Sushi	Decentralized Exchanges
SXPUSDT	Solar	Payment Platforms
TFUELUSDT	Theta Fuel	Content Creation and Distribution
THETAUSDT	Theta Token	Content Creation and Distribution
TKOUSDT	Tokocrypto	nan
TLMUSDT	Alien Worlds	nan
TRBUSDT	Tellor Tributes	Data Management
TROYUSDT	Troy	Asset Management
TRUUSDT	TrueFi	Scaling
TRXUSDT	TRON	Smart Contract Platforms
TWTUSDT	Trust Wallet Token	Payment Platforms
UMAUSDT	UMA	Derivatives
UNFIUSDT	Unifi Protocol DAO	Interoperability

Continued on next page

Table VI – *Continued from previous page*

Symbol	Name	Sector
UNIUSDT	Uniswap	Decentralized Exchanges
UTKUSDT	Utrust	Payment Platforms
VETUSDT	VeChain	Smart Contract Platforms
VITEUSDT	VITE	Smart Contract Platforms
VTHOUSDT	VeThor Token	Smart Contract Platforms
WANUSDT	Wanchain	Interoperability
WAVESUSDT	Waves	Smart Contract Platforms
WINGUSDT	Wing Token	Lending
WINUSDT	WINkLink	nan
WNXMUSDT	Wrapped NXM	Misc
WRXUSDT	WazirX	Centralized Exchanges
XEMUSDT	NEM	Smart Contract Platforms
XLMUSDT	Stellar Lumens	Currencies
XMRUSDT	Monero	Currencies
XRPUSDT	Ripple	Currencies
XTZUSDT	Tezos	Smart Contract Platforms
XVGUSDT	Verge	Currencies
XVSUSDT	Venus	Lending
YFIUSDT	yearn.finance	Asset Management
ZECUSDT	Zcash	Currencies
ZENUSDT	Horizen	Smart Contract Platforms
ZILUSDT	Zilliqa	Smart Contract Platforms
ZRXUSDT	0x	Decentralized Exchanges

Appendix B: Stationary assets

Table VII: List of assets excluded from the study following stationarity tests

Symbol	Name
AAVEUSDT	Aave
BADGERUSDT	Badger DAO
BNBDOWNUSDT	BNBDOWN
BURGERUSDT	BurgerCities
CLVUSDT	Clover Finance
COSUSDT	Contentos
CTXCUSDT	Cortex
DEGOUSDT	Dego Finance
DODOUSDT	DODO
EOSUSDT	EOS
FILUSDT	Filecoin
FISUSDT	Stafi
FORTHUSDT	Ampleforth Governance Token
ICPUSDT	Internet Computer
NEOUSDT	NEO
ORNUSDT	Orion Protocol
PSGUSDT	Paris Saint-Germain Fan Token
SLPUSDT	Smooth Love Potion
ATMUSDT	Atletico de Madrid Fan Token
BAKEUSDT	BakeryToken
BNTUSDT	Bancor
CAKEUSDT	PancakeSwap
COMPUSDT	Compound
CTKUSDT	Shentu

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Table VII – *Continued from previous page*

Symbol	**Name**
DCRUSDT	Decred
DGBUSDT	DigiByte
DREPUSDT	DREP
ETHDOWNUSDT	ETHDOWN
FIOUSDT	FIO Protocol
FLOWUSDT	Flow
GTCUSDT	Gitcoin
MDXUSDT	Mdex
OGUSDT	OG Fan Token
PHAUSDT	Phala.Network
RVNUSDT	Ravencoin
SUSHIUSDT	Sushi
SXPUSDT	Solar
UNFIUSDT	Unifi Protocol DAO
UTKUSDT	Utrust
WINUSDT	WINkLink
XVGUSDT	Verge
TRUUSDT	TrueFi
UNIUSDT	Uniswap
WINGUSDT	Wing Token
WRXUSDT	WazirX
XVSUSDT	Venus

Appendix C: Selected pairs

Table VIII: Selected pairs

Pair	**Pair**
1INCHUSDT BONDUSDT	1INCHUSDT BTCUPUSDT
1INCHUSDT FIROUSDT	1INCHUSDT TROYUSDT
AKROUSDT BONDUSDT	AKROUSDT MLNUSDT
ALGOUSDT ARUSDT	ALGOUSDT ATAUSDT
ALGOUSDT CELOUSDT	ALICEUSDT OMUSDT
ALICEUSDT PONDUSDT	ALPHAUSDT BONDUSDT
ALPHAUSDT ERNUSDT	ALPHAUSDT MLNUSDT
ANKRUSDT BLZUSDT	ANKRUSDT CKBUSDT
ANKRUSDT CTSIUSDT	ANKRUSDT DATAUSDT
ANKRUSDT DEXEUSDT	ANKRUSDT IOTXUSDT
ANKRUSDT LTOUSDT	ANKRUSDT PNTUSDT
ANKRUSDT SFPUSDT	ANKRUSDT UMAUSDT
ARDRUSDT ATAUSDT	ARDRUSDT DATAUSDT
ARDRUSDT DEXEUSDT	ARDRUSDT FIROUSDT
ARDRUSDT IRISUSDT	ARDRUSDT MLNUSDT
ARDRUSDT OXTUSDT	ARDRUSDT UMAUSDT
ARPAUSDT MASKUSDT	ATAUSDT SFPUSDT
AUDIOUSDT CTSIUSDT	AUDIOUSDT DATAUSDT
AUDIOUSDT HARDUSDT	AUDIOUSDT UMAUSDT
BANDUSDT BONDUSDT	BANDUSDT DIAUSDT
BANDUSDT DOCKUSDT	BANDUSDT ERNUSDT
BANDUSDT MLNUSDT	BATUSDT IOTXUSDT
BATUSDT SFPUSDT	BATUSDT STORJUSDT
BELUSDT BONDUSDT	BELUSDT DEXEUSDT
BELUSDT FIROUSDT	BELUSDT LINAUSDT

Continued on next page

Table VIII – *Continued from previous page*

Pair	**Pair**
BELUSDT MTLUSDT	BELUSDT SUNUSDT
BLZUSDT IOTXUSDT	BLZUSDT LTOUSDT
BLZUSDT MASKUSDT	BLZUSDT SFPUSDT
C98USDT OMUSDT	C98USDT STMXUSDT
C98USDT UMAUSDT	CELOUSDT IOTAUSDT
CELOUSDT MLNUSDT	CELOUSDT RENUSDT
CELOUSDT SFPUSDT	CELOUSDT XTZUSDT
CHRUSDT IOTXUSDT	CHRUSDT LTOUSDT
CKBUSDT CRVUSDT	CKBUSDT SFPUSDT
CKBUSDT SUPERUSDT	COTIUSDT OMGUSDT
CRVUSDT IOTXUSDT	CRVUSDT NULSUSDT
CRVUSDT SFPUSDT	CTSIUSDT ENJUSDT
CTSIUSDT MASKUSDT	CTSIUSDT POLSUSDT
CTSIUSDT SFPUSDT	CTSIUSDT SUPERUSDT
DATAUSDT DENTUSDT	DATAUSDT FIROUSDT
DATAUSDT HARDUSDT	DATAUSDT LINAUSDT
DATAUSDT MLNUSDT	DATAUSDT NKNUSDT
DATAUSDT PNTUSDT	DATAUSDT STMXUSDT
DATAUSDT UMAUSDT	DENTUSDT DEXEUSD
DENTUSDT ERNUSDT	DENTUSDT FIROUSDT
DENTUSDT HARDUSDT	DENTUSDT OGNUSDT
DENTUSDT OMUSDT	DENTUSDT PNTUSDT
DENTUSDT SKLUSDT	DENTUSDT STMXUSDT
DEXEUSDT FIROUSDT	DEXEUSDT IRISUSDT
DEXEUSDT LINAUSDT	DEXEUSDT LTOUSDT
DEXEUSDT MLNUSDT	DEXEUSDT NKNUSDT

Continued on next page

Table VIII – *Continued from previous page*

Pair	Pair
DEXEUSDT OMUSDT	DEXEUSDT OXTUSDT
DEXEUSDT PONDUSDT	DEXEUSDT STMXUSDT
DEXEUSDT STORJUSDT	DEXEUSDT SUNUSDT
DEXEUSDT UMAUSDT	DEXEUSDT VITEUSDT
DEXEUSDT WANUSDT	DIAUSDT DOCKUSDT
DIAUSDT ERNUSDT	DIAUSDT HARDUSDT
DIAUSDT HOTUSDT	DIAUSDT KMDUSD
DIAUSDT LINKUSDT	DIAUSDT MLNUSDT
DIAUSDT OGNUSDT	DIAUSDT PONDUSDT
DIAUSDT QTUMUSDT	DIAUSDT RSRUSDT
DIAUSDT SCUSDT	DIAUSDT THETAUSDT
DOCKUSDT ERNUSDT	DOCKUSDT KMDUSDT
DOCKUSDT MLNUSDT	DOCKUSDT PUNDIXUSDT
DOCKUSDT SCUSDT	DOCKUSDT SUNUSDT
DOGEUSDT PUNDIXUSDT	ERNUSDT FLMUSDT
ERNUSDT GRTUSDT	ERNUSDT HARDUSDT
ERNUSDT KMDUSDT	ERNUSDT LINAUSDT
ERNUSDT LITUSDT	ERNUSDT OGNUSDT
ERNUSDT ONTUSDT	ERNUSDT PNTUSDT
ERNUSDT RSRUSDT	FIROUSDT HARDUSDT
FIROUSDT LINAUSDT	FIROUSDT MLNUSDT
FIROUSDT MTLUSDT	FIROUSDT NKNUSDT
FIROUSDT ONGUSDT	FIROUSDT OXTUSDT
FIROUSDT PNTUSDT	FIROUSDT QTUMUSDT
FIROUSDT SCUSDT	FIROUSDT STMXUSDT
FIROUSDT SUNUSDT	FIROUSDT TROYUSDT

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Table VIII – *Continued from previous page*

Pair	**Pair**
FIROUSDT UMAUSDT	FIROUSDT VITEUSDT
FIROUSDT ZRXUSDT	GRTUSDT MLNUSDT
HARDUSDT KMDUSDT	HARDUSDT NKNUSDT
HARDUSDT OMUSDT	HARDUSDT PNTUSDT
HARDUSDT PONDUSDT	HARDUSDT STMXUSDT
HARDUSDT UMAUSDT	HARDUSDT WANUSDT
HARDUSDT ZENUSDT	HBARUSDT IOTAUSDT
HOTUSDT OGNUSDT	HOTUSDT SKLUSDT
ICXUSDT MLNUSDT	ICXUSDT PONDUSDT
IOTAUSDT PONDUSDT	IOTAUSDT XTZUSDT
IOTXUSDT LTOUSDT	IRISUSDT MLNUSDT
IRISUSDT SFPUSDT	KMDUSDT LINAUSDT
KMDUSDT QTUMUSDT	KMDUSDT WANUSDT
LINAUSDT PONDUSDT	LINAUSDT SCUSDT
LINAUSDT SUNUSDT	LINAUSDT WNXMUSDT
LTOUSDT MASKUSDT	NKNUSDT OXTUSDT
OCEANUSDT SFPUSDT	OGNUSDT QTUMUSDT
OGNUSDT SKLUSDT	OGNUSDT UMAUSDT
OMUSDT PNTUSDT	OMUSDT RENUSDT
OMUSDT STMXUSDT	OMUSDT SUNUSDT
OMUSDT UMAUSDT	OMUSDT ZENUSDT
ONGUSDT UMAUSDT	ONTUSDT PUNDIXUSDT
ONTUSDT THETAUSDT	OXTUSDT SFPUSDT
OXTUSDT VITEUSDT	PNTUSDT RSRUSDT
PNTUSDT SFPUSDT	PNTUSDT STMXUSDT
PNTUSDT SUNUSDT	PNTUSDT TLMUSDT

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Table VIII – *Continued from previous page*

Pair	Pair
PNTUSDT UMAUSDT	PNTUSDT ZENUSDT
POLSUSDT STORJUSDT	PONDUSDT RSRUSDT
PONDUSDT STMXUSDT	PONDUSDT SUNUSDT
PONDUSDT ZENUSDT	PUNDIXUSDT STRAXUSDT
QTUMUSDT SCUSDT	QTUMUSDT STMXUSDT
RENUSDT XTZUSDT	RSRUSDT TLMUSDT
SCUSDT UMAUSDT	SCUSDT ZENUSDT
SFPUSDT SOLUSDT	SNXUSDT STRAXUSDT
STMXUSDT SUNUSDT	STMXUSDT UMAUSDT
STMXUSDT XTZUSDT	STMXUSDT ZENUSDT
STMXUSDT ZRXUSDT	STPTUSDT TROYUSDT
TFUELUSDT VTHOUSDT	

Appendix D: Assets present on the selected pairs

Table IX: List of assets involved in the selected pairs

Symbol	Name	Pairs
FIROUSDT	Firo	22
DEXEUSDT	DeXe	19
ERNUSDT	Ethernity Chain	15
HARDUSDT	Kava Lend	15
STMXUSDT	StormX	15
DIAUSDT	DIA	14

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Table IX – *Continued from previous page*

Symbol	Name	Pairs
PNTUSDT	pNetwork	14
UMAUSDT	UMA	14
SFPUSDT	SafePal	13
MLNUSDT	Enzyme	13
DATAUSDT	Streamr	12
OMUSDT	MANTRA	11
PONDUSDT	Marlin	11
ANKRUSDT	Ankr	10
DENTUSDT	DENT	10
LINAUSDT	Linear	10
SUNUSDT	SUN	9
ARDRUSDT	Ardor	8
DOCKUSDT	DOCK	8
CTSIUSDT	Cartesi	7
KMDUSDT	Komodo	7
OGNUSDT	OriginToken	7
SCUSDT	Siacoin	7
BELUSDT	Bella Protocol	6
CELOUSDT	Celo	6
IOTXUSDT	IoTeX	6
LTOUSDT	LTO Network	6
OXTUSDT	Orchid	6
QTUMUSDT	Qtum	6
ZENUSDT	Horizen	6
BANDUSDT	BAND	5

Continued on next page

Table IX – *Continued from previous page*

Symbol	**Name**	**Pairs**
BLZUSDT	Bluzelle	5
NKNUSDT	NKN	5
RSRUSDT	Reserve Rights	5
BONDUSDT	BarnBridge	5
1INCHUSDT	1inch	4
AUDIOUSDT	Audius	4
CKBUSDT	CKB	4
CRVUSDT	Curve	4
IOTAUSDT	MIOTA	4
IRISUSDT	IRISnet	4
PUNDIXUSDT	Pundi X	4
MASKUSDT	Mask Network	4
XTZUSDT	Tezos	4
ALGOUSDT	Algorand	3
ALPHAUSDT	Alpha Finance Lab	3
ATAUSDT	Automata	3
BATUSDT	Basic Attention Token	3
C98USDT	Coin98	3
HOTUSDT	Holo	3
ONTUSDT	Ontology	3
RENUSDT	Ren	3
TROYUSDT	Troy	3
STORJUSDT	Storj	3
SKLUSDT	SKALE Network	3
VITEUSDT	VITE	3

Continued on next page

Table IX – *Continued from previous page*

Symbol	Name	Pairs
WANUSDT	Wanchain	3
AKROUSDT	Akropolis	2
ALICEUSDT	My Neighbor Alice	2
CHRUSDT	Chromia	2
GRTUSDT	The Graph	2
ICXUSDT	ICON	2
ONGUSDT	Ontology Gas	2
POLSUSDT	Polkastarter	2
MTLUSDT	Metal	2
SUPERUSDT	SuperFarm	2
THETAUSDT	Theta Token	2
ZRXUSDT	0x	2
TLMUSDT	Alien Worlds	2
STRAXUSDT	Stratis	2
ARPAUSDT	ARPA Network	1
COTIUSDT	COTI	1
DOGEUSDT	Dogecoin	1
HBARUSDT	Hedera Hashgraph	1
OCEANUSDT	Ocean Protocol	1
SNXUSDT	Synthetix Network Token	1
STPTUSDT	Standard Tokenization Protocol	1
TFUELUSDT	Theta Fuel	1
BTCUPUSDT	BTCUP	1
ARUSDT	Arweave	1
OMGUSDT	OMG Network	1

Continued on next page

Table IX – *Continued from previous page*

Symbol	Name	Pairs
NULSUSDT	Nuls	1
ENJUSDT	Enjin Coin	1
LINKUSDT	ChainLink	1
FLMUSDT	Flamingo	1
LITUSDT	Litentry	1
WNXMUSDT	Wrapped NXM	1
SOLUSDT	Solana	1
VTHOUSDT	VeThor Token	1

Appendix E: Calculating positions for trades

When a pair is signaled long or short, two opposite positions are taken. To respect the market-neutral aspect, these positions must take into account the cointegration coefficient, defined as in the cointegration relationship. In addition, to take the short position on one of the two assets in the pair, we use leverage, in the same way as the SRD in traditional finance. To limit our exposure and risk, as the cointegration coefficients between the assets can be high, a leverage limit of two is introduced.
To take all these constraints into account, we use a system of equations described below.

- Calculation of asset positions

Note that the equations are reversed depending on the direction of the signal transmitted.

For a long signal on the pair, i.e. a buy on the first asset and sell on the second, we can reason about the valuation of an elementary position (with a single security held as an asset in the position):

$$V_t^p = P_{1,t} - \beta P_{2,t} \tag{5}$$

The purchase of a security from the first asset (i.e. the asset side of the position's balance sheet) is offset by the short sale of securities from the second asset (i.e. the liability side of the position's balance sheet). Here we find the coefficient of the second asset on the linear regression of the first, β, which is defined as the cointegration coefficient of our pair.

By generalizing the equation to n securities purchased on the first asset:

$$V_t^p = nP_{1,t} - n\beta P_{2,t} \tag{6}$$

$n\beta$ is the number of securities sold short on the second asset in order to maintain the strategy's market neutrality.

Taking again the example of a position equal to 100 currency units, according to our strategy, these 100 units are positioned on the long position of the pair (i.e. the purchase of securities of the first asset), the number of securities purchased is then:

$$n = \frac{100}{P_{1,t}} \tag{7}$$

In turn, the number of shares in the second asset to be sold short is:

$$n\beta = \frac{100}{P_{1,t}}\beta \tag{8}$$

Bringing the amount of the short position at the start of the trade to:

$$\frac{100}{P_{1,t}}\beta * P_{2,t} \tag{9}$$

For a short signal on the pair, i.e. a short sale on the first asset and a purchase of the second, the method for calculating the position amounts is similar. The direction in which the equations are written is simply reversed, with n denoting the number of shares of the first asset to be sold short.

Thus, the valuation of the position generalized to n securities put on the short-sale position of the first asset, on the Liabilities side, is:

$$V_t^p = -nP_{1,t} + n\beta P_{2,t} \tag{10}$$

The amount of the portfolio (i.e. 100 currency units in our example) is allocated to the long position of the trade, here on the second asset of the pair:

$$100 = n\beta P_{2,t} \tag{11}$$

The number of shares in the first asset to be sold short is therefore:

$$n = \frac{100}{\beta P_{2,t}} \tag{12}$$

This brings the amount of the short position at the start of the trade to:

$$\frac{100}{\beta P_{2,t}} * P_{1,t} \tag{13}$$

- Introduction of leverage limit

Pair-trading remains a risky and potentially volatile strategy, even more so in the cryptoasset market. To moderate and manage our risk exposure, we have included a leverage limit on our short selling.

To implement these limits, we assume that when there is a signal on a pair, the sum of the two positions must not exceed twice the portfolio valuation (i.e. leverage of 2):

$$\max(long_t + short_t) = 2 * Ptf_t \tag{14}$$

So, when we receive a signal to take a position on a pair, we proceed in two steps. First,

we calculate the theoretical positions to be allocated to each asset according to the equations above.
Secondly, we check that the sum of the two positions does not exceed twice the amount in the portfolio at that moment. If this is the case, the calculated positions are implemented. If, on the other hand, the positions exceed the calculated amount, we use another set of equations to calculate a new amount to put on the long position, so that the proportion between the two positions and the leverage limit are respected.

As with the calculation of positions, the direction in which the equations are written depends on the direction of the signal sent. Thus, when there is a long signal on the pair (i.e. buy the first asset and sell short the second), the amount to be sold short is:

$$short_t = \frac{long_t}{P_{1,t}} * \beta * P_{2,t} \tag{15}$$

By introducing this measure into the leverage limit equation:

$$long_t + \frac{long_t}{P_{1,t}} * \beta * P_{2,t} = 2 * Ptf_t \tag{16}$$

$$long_t * (1 + \beta * \frac{1}{P_{1_t}} * P_{2,t}) = 2 * Ptf_t \tag{17}$$

By isolating the value of the long position, we can finally recalculate it, which will be less than the value of the portfolio (i.e. there is still some uninvested cash in our portfolio):

$$long_t = \frac{2 * Ptf_t}{1 + \beta * \frac{1}{P_{1_t}} * P_{2,t}} \tag{18}$$

The new amount of the short position is also calculated by repeating the first formula with the revised amount of the long position.

In the event of a short signal on the pair, the principle is the same except that the short-sale amount on the first asset is different, modifying the equations:

$$long_t + \frac{long_t}{P_{2,t} * \beta} * P_{1,t} = 2 * Ptf_t \tag{19}$$

By grouping the amount of the long position on one side, we obtain its new value:

$$long_t = \frac{2 * Ptf_t}{1 + \frac{1}{P_{2,t} * \beta} * P_{1,t}} \tag{20}$$

In the same way as for a long signal, the amount of the short position is revised according to the new calculated long position.

Appendix F: Classification of the pairs

From the graphical analyses we have carried out, we have noticed that the residuals of the cointegrating relationships of the selected pairs do not all have the same volatility amplitude. Based on this postulate, we want to test whether a certain type of volatility amplitude is preferable when implementing pair-trading strategies or not. To do this, we want to classify pairs according to the volatility of their residuals.
By classifying pairs into several categories, it might be possible to determine more suitable and efficient optimization parameters for each category.

To cluster pairs according to the volatility of their residuals, we use k-means. K-means is often considered one of the best clustering algorithms due to its simplicity, efficiency and ability to handle large datasets. K-means is used to group individuals with similar characteristics (i.e. clusters) through the analysis of two defined components of the dataset. This unsupervised learning algorithm segments individuals into "K" groups by minimizing the Euclidean distance between a given individual and the center of a cluster. K-means has certain limitations, the main one being the determination of the optimal position of the centroids of the initial clusters during the first iteration. These limitations have been addressed by implementing new approaches to reduce the number of iterations and the execution time, as in the paper by Zubair et al (2022) or Liu, Du and Ma (2024). Despite its limitations, k-means continues to be used in many fields, such as e-commerce with the recent paper by Prabhas et al (2023), medicine with the paper by Kakushadze and Yu (2017) or finance with the paper, for example, by Dang et al (2022). In fact, it enables individuals to be clustered, without apriori, by determining common patterns and without being programmed to predict a value from an analysis.

Clustering places a function under the principle of exclusive membership. In other words, the same data cannot be found in two different clusters. We use two methods to determine the optimum number of clusters according to the mean of the residuals and the variance of the residuals in each pair. Correctly determining the number of clusters ensures that the data is divided efficiently and correctly. An appropriate value for this number "K" helps to maintain a good balance between compressibility and precision.

The first is the elbow method. It is based on the fact that the sum of intra-cluster variance can be reduced by increasing the number of clusters. The higher the number of clusters, the more refined groups can be extracted from the analysis of data objects that are more similar to each other. We use the turning point of the sum-of-variances curve to select the right number of clusters. This method applied to our data is shown in Figure 14.

The second method used is the silhouette score. This method evaluates the quality of the clusters created by the clustering algorithms. Ranging from [-1,1], the silhouette score is sometimes used to find the optimal value for the number of clusters "K". To do this, we consider the value of "K" with the silhouette score closest to 1. The silhouette method applied to our pairs is shown in Figure 15.

Unanimously, both methods obtain the optimal value of three clusters ("K" = 3).

We therefore parameterize the K-means to make three clusters, and the result is shown in Figure 16.

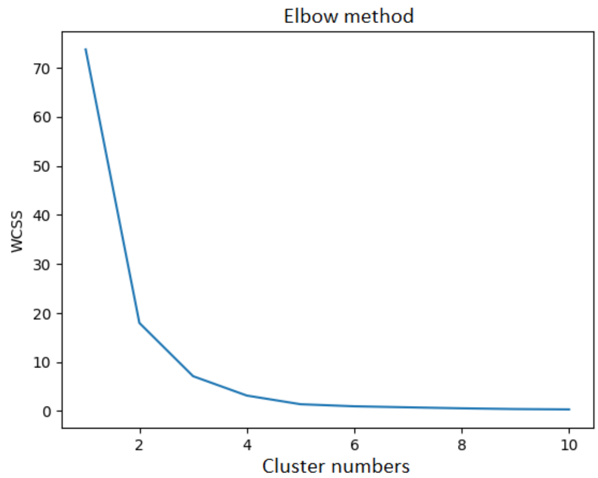

Figure 14: Elbow method applied to the residuals of our 229 pairs.

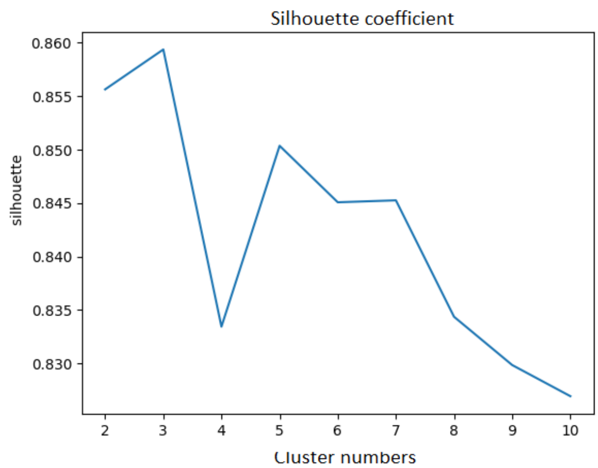

Figure 15: Silhouette coefficient applied to the residuals of our 229 pairs.

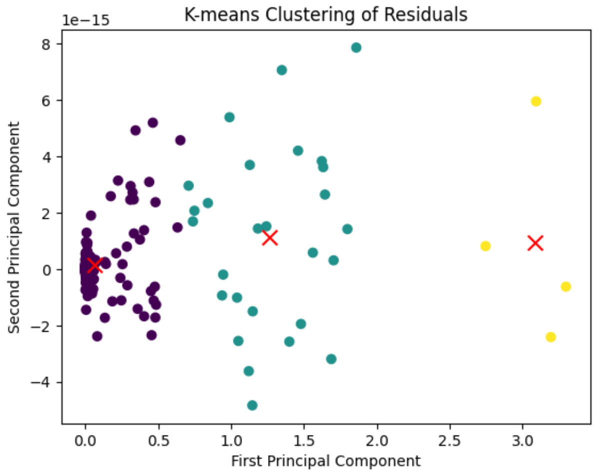

Figure 16: K-Means applied to the residuals of our 229 pairs.

Three clusters can be distinguished according to the variance of the pairs' cointegrating residuals.

The first and largest cluster groups 198 pairs (86.46% of the sample). The characteristic feature of this cluster is the low volatility (variance less than 0.5) of the cointegrating residuals of each pair.

The second cluster, made up of 27 pairs, has the characteristic of grouping together pairs with average residual variance, between 0.5 and 2.

Finally, the last cluster groups together 4 pairs with a high variance of cointegrating residuals (between 2.5 and 3.5). These four pairs can be seen here as outliers.

The identification of these clusters leads us to separate the pairs and test the Bollinger Bands strategy on each group. To do this, we take the Bollinger Bands strategy and test it with the predefined thresholds[33], before optimizing them via the genetic algorithm for each cluster (see following tables).

The standard tests, presented in the first part of the table, give interesting results. At equal thresholds, pairs with low residual volatility perform best. Indeed, we can see that

[33] Trigger point = 2; Stop-loss = 3 and Take-profit = 0.

Table X: Standard tests with cluster.

	Cluster 1							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	4714.27	435.94	235.17	−100	395.86	43.77	32.92
yield_day_%	−100	180.62	70.86	72.20	−100	302.53	53.06	64.91
vol_yield_%	33.49	164.19	68.13	65.77	26.83	361.03	73.55	62.39
sharpe_ratio_annual	−1.02	3.21	1.10	1.10	−2.99	4.60	0.98	1.15
maxdrawdown	12.10	100	53.72	51.90	4.24	100	32.98	26.50
avg_yield_trades_%	−12.23	21.09	7.94	7.97	−37.56	42.53	5.52	5.51
avg_yield_wintrades_%	14.37	48.75	26.73	26.14	0.92	84.28	21.16	17.89
avg_yield_losttrades_%	−54.72	−3.91	−10.50	−9.02	−100	−0.83	−10.95	−7.16
nbr_trades	9	41	24.53	24	2	22	7.60	7
winning_trades_%	19.35	84	49.34	50	0	100	52.54	50
stop_loss_%	18.18	87.50	58.49	58.72	0	100	48.99	50
avg_duration_trades	6.24	27.54	12.66	12.34	1	29.33	9.97	9
	Cluster 2							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−91.46	3885.72	644.63	232.60	−67.98	188.01	25.94	26.08
yield_day_%	−72.03	190.88	67.57	60.01	−100	250.94	29.28	34.58
vol_yield_%	58.45	102.01	74.84	73.73	34.99	107.28	67.57	57.97
sharpe_ratio_annual	−0.74	2.62	0.95	0.85	−1.83	4.14	0.51	0.45
maxdrawdown	23.68	96.16	60.01	62.08	5.41	73.54	40.05	41.21
avg_yield_trades_%	−4.17	20.23	8.03	7.61	−14.35	22.13	5.21	4.32
avg_yield_wintrades_%	18.31	54.09	28.55	27.34	6.28	80.13	23.79	21.32
avg_yield_losttrades_%	−33.52	−4.85	−13.00	−11.05	−47.31	−0.02	−10.88	−8.21
nbr_trades	11	33	24.74	25	4	12	7.52	8
winning_trades_%	26.67	73.68	50.05	50	0	88.89	48.33	50
stop_loss_%	33.33	81.48	60.01	60.61	11.11	83.33	56.02	60
avg_duration_trades	8.97	27.36	14.03	12.71	3.11	24.60	10.75	8.78
	Cluster 3							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	37.27	431.38	187.73	141.15	−69.21	90.77	16.97	23.16
yield_day_%	30.76	111.78	68.81	66.35	−100	160.15	15.77	18.99
vol_yield_%	54.28	75.20	65.78	66.82	52.78	136.20	83.96	73.42
sharpe_ratio_annual	0.57	1.49	1.01	0.99	−0.99	1.94	0.39	0.30
maxdrawdown	43.49	62.05	53.46	54.16	16.18	74.46	39.59	33.85
avg_yield_trades_%	2.99	10.56	6.62	6.46	−5.96	11.75	3.11	3.33
avg_yield_wintrades_%	21.87	34.18	28.13	28.23	13.57	32.16	22.58	22.29
avg_yield_losttrades_%	−13.25	−6.94	−10.14	−10.19	−17.10	−3.56	−8.75	−7.16
nbr_trades	16	30	22.50	22	7	10	9.25	10
winning_trades_%	33.33	56.52	42.93	40.92	30	42.86	38.21	40
stop_loss_%	52.17	76.19	66.05	67.92	60	71.43	65.36	65
avg_duration_trades	8.27	18.71	13.99	14.50	4.90	13.71	8.23	7.15

Table XI: Optimization with cluster.

	Cluster 1							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	50 258.82	2922.53	1449.10	−100	725.98	117.01	81.21
yield_day_%	−100	431.10	124.03	136.85	−100	2114.82	80.33	117.64
vol_yield_%	58.13	377.42	105.64	94.26	40.99	1593.79	137.08	88.70
sharpe_ratio_annual	−3.86	3.06	1.34	1.38	−5.38	5.33	1.10	1.29
maxdrawdown	19.39	100	60.65	60.25	7.74	100	45.07	37.27
avg_yield_trades_%	0.93	34.59	15.11	15.00	−57.03	49.66	10.25	9.35
avg_yield_wintrades_%	6.82	49.19	22.84	21.21	1.30	84.74	20.17	16.09
avg_yield_losttrades_%	−100	−1.31	−20.90	−14.64	−100	−0.30	−10.80	−5.26
nbr_trades	5	51	24.80	24	1	22	8.20	8
winning_trades_%	37.50	100	81.12	82.61	0	100	69.10	71.43
stop_loss_%	0	68.75	20.30	17.39	0	81.82	18.32	14.29
avg_duration_trades	5.20	44	23.17	22.66	5.75	55	19.14	17.56
	Cluster 2							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	−100	2297.73	716.65	611.60	−60.33	248.95	66.08	53.80
yield_day_%	−38.41	178.66	95.14	102.24	−100	236.23	82.15	83.82
vol_yield_%	57.51	141.76	78.46	73.99	30.97	125.25	70.40	64.95
sharpe_ratio_annual	−0.27	2.88	1.33	1.40	−1.21	3.80	1.21	1.20
maxdrawdown	16.76	100	53.74	53.07	3.36	71.45	31.08	30.33
avg_yield_trades_%	−0.90	19.32	10.07	10.49	−10.43	41.17	9.13	7.64
avg_yield_wintrades_%	12.83	41.68	22.99	22.06	6.06	56.53	17.37	15.01
avg_yield_losttrades_%	−73.14	−4.13	−18.69	−14.02	−27.42	−0.08	−5.64	−4.55
nbr_trades	12	35	23.19	22	3	12	7.07	6
winning_trades_%	46.67	90.91	67.14	63.33	25	100	64.89	63.64
stop_loss_%	13.64	66.67	38.21	39.13	0	66.67	28.69	25
avg_duration_trades	6.05	17.81	11.06	11.31	3.27	21.17	9.28	8.60
	Cluster 3							
	Test period				Backtest period			
	Min	Max	Mean	Median	Min	Max	Mean	Median
yield_cumul_%	372.48	5686.43	2934.08	2838.69	−5.93	196.52	72.83	50.37
yield_day_%	94.84	226.87	160.29	159.72	−12.43	211.25	103.94	108.48
vol_yield_%	87.81	123.97	104.96	104.03	81.24	156.81	114.54	110.06
sharpe_ratio_annual	1.01	1.83	1.49	1.56	−0.15	1.85	0.83	0.82
maxdrawdown	50.76	63.48	56.66	56.21	35.67	75.57	54.22	52.81
avg_yield_trades_%	10.47	29.66	21.28	22.49	2.11	55.70	19.03	9.16
avg_yield_wintrades_%	20.06	41.22	31.37	32.09	13.11	308.72	89.80	18.68
avg_yield_losttrades_%	−15.71	−7.59	−9.98	−8.30	−69.69	−6.32	−24.95	−11.89
nbr_trades	17	18	17.25	17	5	9	7.50	8
winning_trades_%	58.82	94.12	74.02	71.57	20	88.89	54.47	62.50
stop_loss_%	11.76	55.56	35.95	38.24	11.11	25	17.15	16.25
avg_duration_trades	27.41	38.35	35.33	35.78	13.75	33.80	21.50	19.22

the first and largest cluster delivers an average cumulative return of 43.77% over the backtest period. This is more than double the yield of the last cluster, at 16.97%.
Over the test period, 29 pairs lost out, with the majority (24) in the first cluster, easily explained as this is also the majority cluster, and a minority (5) in the second cluster. Over the backtest period, we have more disparities: for the first cluster, 60 pairs, i.e. 30.30% of the cluster, end up in loss with a minimum return leading to the loss of all capital. This ratio is higher for the second cluster, with 9 pairs, or 33.33% of the group, ending in loss with a minimum return of -67.98%. Finally, the last cluster, made up of volatile pairs, includes one pair, or 25% of the group, with a negative return at the end of the backtest period.

The last cluster, made up of the four most volatile pairs, has an average Sharpe ratio over the backtest period of 0.39 (versus 0.98 for the first and 0.51 for the second). This result can be explained by two factors. On the one hand, the performance delivered by these four pairs is far less impressive than the other two clusters, with an average performance of 16.97% over 6 months and an average annualized performance of 15.77%. This performance is directly linked to the volatility of these pairs' residuals. Indeed, given the construction of the pair-trading strategy, a turbulent cointegrating relationship between two assets, characterized by its residual, leads to more frequent stop-loss hits (i.e. more frequent peaks/outliers on these types of series) and, in turn, fewer winning positions. This phenomenon is verified here, since the last cluster has an average stop-loss percentage of 65.36% during the backtesting period, i.e. 10 and 15 percentage points higher than the other two clusters. The same observation applies to the percentage of winning trades, with a median percentage of 40% for the last cluster versus 52.54% for the first and 48.33% for the second. These findings ultimately impact the average return per trade, which stands at 3.11% versus 5.52% and 5.21%, resulting in a lower final return despite the greater number of positions taken on this cluster. On the other hand, the instability in the cointegration relationship is ultimately reflected in the portfolio of these pairs when the strategy is implemented. The median annualized volatility of returns in this cluster is 15 percentage points higher than in the other two clusters, even though the most volatile pair, i.e. with the highest annualized volatility of returns, is not in this cluster but in the first.

We optimize the pair thresholds using the genetic algorithm per cluster to confirm or not the observed phenomenon (see second part of the table). The results for the first cluster are broadly in line with previous tests. The optimized parameters are: Trigger point = 0.86; Stop-loss = 5; Take-profit = -0.17. Over the backtesting period, while 40 pairs ended in losses, the cluster still managed to generate a cumulative average return of 117.01%. According to the Sharpe ratio, the first cluster is not the best of the three this time, as its annualized volatility appears higher than the other two clusters, with an average annualized volatility per pair of 137.08% versus 70.40% and 114.54%.
The second cluster, despite having a lower average cumulative return, manages to achieve a more attractive annualized daily return, with an average of 82.15%. This, combined with lower volatility, resulted in an average Sharpe ratio of 1.21 over the backtesting period, versus 1.10 for the first cluster and 0.83 for the last. Four pairs end up in loss at the end of the 6-month period, with a minimum of -60.33%. The parameters optimized by the genetic algorithm for the latter are: Trigger point = 2; Stop-loss = 3.76; Take-profit =0.79.
Finally, the initial results obtained from the simulation of the strategy with standard thresholds are confirmed here. The last cluster, with optimized parameters of 1 for the trigger level, 5 for the stop-loss and -0.61 for the take-profit, appears to be the least efficient in terms of risk/return ratio. Indeed, despite a good delivered return (even higher than the second cluster), the risk indicators of the pairs making up this last cluster bring the average Sharpe ratio to 0.83 for an annualized volatility of 114.54% and an average max drawdown of -54.22% (versus -45.07% for the first and -31.08% for the second cluster).

In short, the results with optimized thresholds bring the same conclusions as before.

The pair-trading strategy works best on pairs with a perennial cointegrating relationship over time (i.e. low volatility), i.e. the first or second cluster. In view of these results, it would be appropriate to adapt our sample of pairs and retain only those with a stable relationship.

Appendix G: Residuals of losing pairs

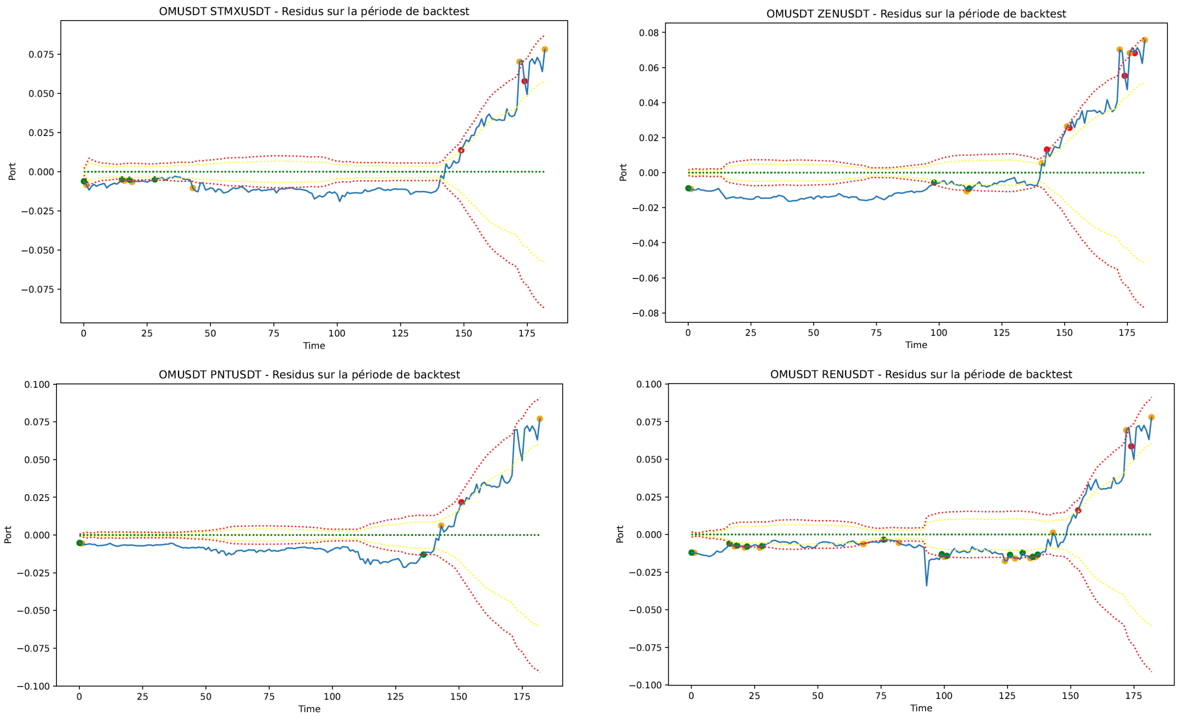

Figure 17: Residuals of pairs consistently in loss over the backtest period.

Appendix H: Pairs example

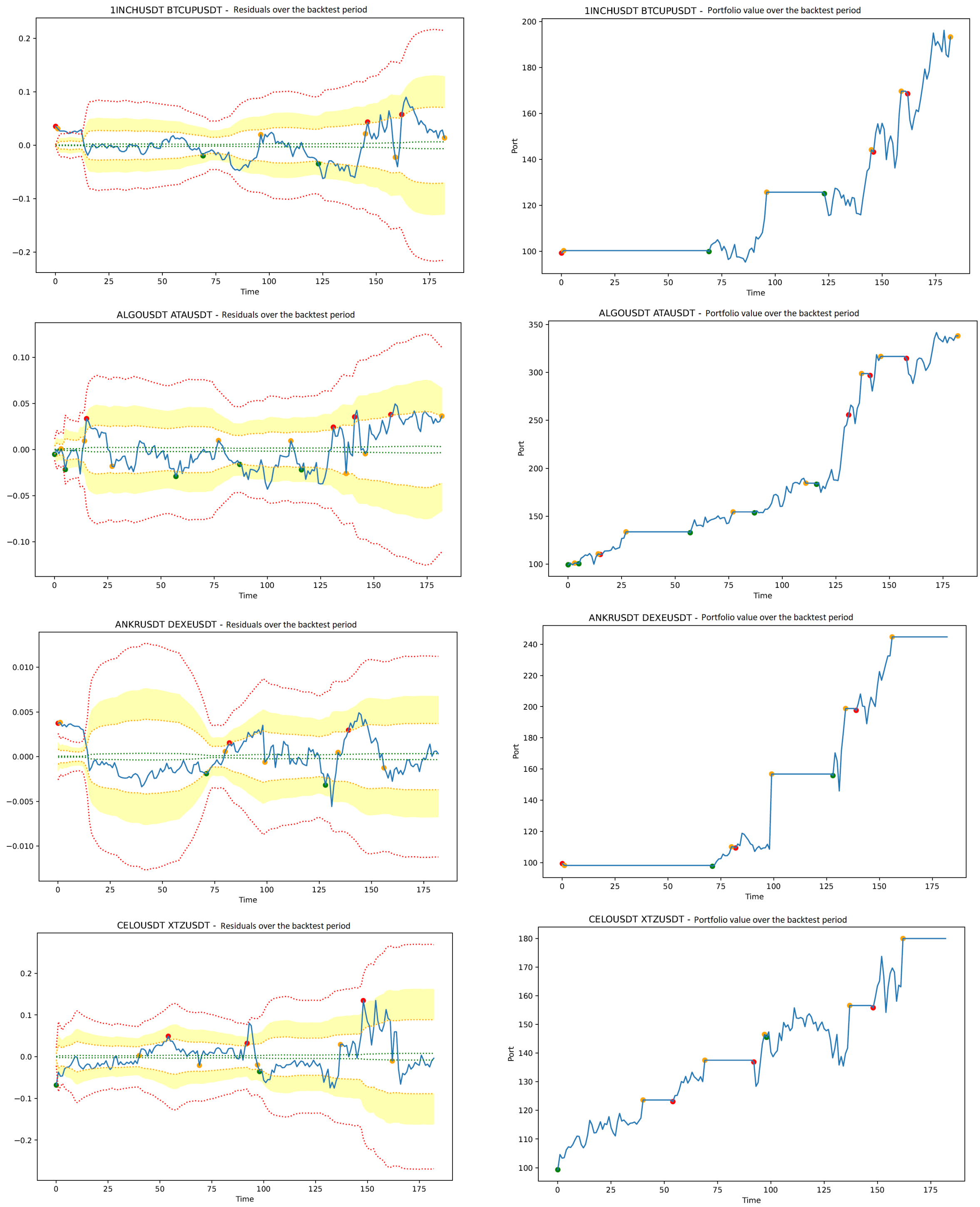

Figure 18: Example of pairs identified in our article.