COINTEGRATION TRADING STRATEGY APPLIED TO THE CRYPTO MARKET

1) Abstract :

This paper investigates the feasibility and performance of a systematic cointegration-based trading strategy applied to cryptocurrency markets. While digital assets are typically characterized by strong non-stationarity, structural regime shifts, and high transaction costs, we test whether certain pairs exhibit stable long-run equilibrium relationships that can be exploited for mean-reversion trading. Using high-quality Binance perpetual futures data, we construct a full empirical framework that includes data cleaning, rolling cointegration estimation, dynamic hedge-ratio computation, residual stationarity testing, and execution-aware backtesting.

We first test a broad universe of altcoin pairs and identify those that pass Engle–Granger cointegration criteria over recent windows. For each pair, we dynamically estimate the hedge ratio via rolling OLS, compute a stationary spread, and extract a Z-score to generate long/short signals. We incorporate realistic assumptions for execution—maker/taker fees, spread costs, and funding payments—to evaluate tradeable profitability rather than theoretical performance. Pairs are then ranked by Sharpe ratio, and the top 20 pairs are combined using a risk-parity allocation to construct a diversified, market-neutral portfolio.

Our results show that while many crypto pairs do not sustain a stable long-run equilibrium, a subset displays consistent mean-reversion properties with statistically significant ADF p-values, reasonable half-lives, and stable rolling hedge ratios. After accounting for realistic trading frictions, several pairs remain profitable, and the aggregated portfolio exhibits positive risk-adjusted returns with controlled drawdowns. However, performance is highly sensitive to regime changes, window selection, and fee structure, underscoring the importance of dynamic parameter estimation and continuous validation.

Overall, this study demonstrates that cointegration can offer exploitable inefficiencies in cryptocurrency markets but requires robust rolling estimation and strict execution-aware constraints to be viable in practice.

2) **Introduction :**

Quantitative trading in cryptocurrency markets has grown rapidly as digital assets mature into a structurally diverse and highly volatile asset class. Despite substantial improvements in liquidity and market efficiency over recent years, crypto markets continue to exhibit persistent mispricings, structural frictions, and strong behavioral components. These features create opportunities for mean-reversion strategies, which aim to exploit temporary deviations from an underlying equilibrium relationship between assets. Unlike trend-following approaches, mean-reversion strategies are built on the expectation that short-term dislocations eventually converge back to a stable long-term value, producing recurrent and theoretically predictable profit opportunities.

Among the different mean-reversion frameworks, cointegration has emerged as one of the most theoretically appealing. Cointegration describes a situation where two (or more) non-stationary price series move together in such a way that a linear combination of them is stationary—implying a long-run economic or structural relationship between the assets. When such a relationship exists, deviations from the equilibrium spread can be interpreted as *temporary distortions*, which should mean-revert over time. This makes cointegration-based strategies particularly compelling in cryptocurrency markets, where projects often share common fundamentals (e.g., same ecosystem, similar narratives, correlated liquidity cycles) but price dynamics can diverge sharply due to market noise, liquidity constraints, or speculative flows.

However, applying classical cointegration methods to crypto introduces several challenges. Unlike equities or traditional FX pairs—where relationships between assets can be fundamentally grounded in earnings, sector linkages, or macroeconomic co-movement—crypto assets often exhibit structural breaks, regime changes, and rapid changes in utility or market relevance. Liquidity conditions are uneven across exchanges, and high transaction fees, slippage, and funding rate payments can materially erode performance. Existing research on crypto mean-reversion tends to remain limited in scope, usually examining only a few major assets or relying on simplified assumptions that do not reflect real-world trading constraints. As a result, there is a significant gap between theoretical cointegration literature and practical, tradeable, execution-aware strategies in the crypto space.

This paper contributes to closing that gap through a comprehensive, data-driven approach to building and evaluating cointegration strategies for cryptocurrency pairs. We construct a full pipeline that includes robust data cleaning, synchronization of multi-asset time series, Engle–Granger and Johansen cointegration tests, hedge-ratio estimation, spread construction, mean-reversion analysis, and systematic backtesting. Unlike simpler approaches, our framework explicitly incorporates risk-based position sizing—notably risk parity and volatility-adjusted weights—to control for heterogeneous variances across assets. We extend the methodology to a broad universe of altcoin pairs and subsequently select the top 20 pairs ranked by Sharpe ratio, providing a diversified and statistically grounded multi-pair portfolio.

Crucially, our results account for realistic trading frictions, including maker/taker fees, slippage assumptions, and perpetual futures funding payments when relevant. This ensures that the conclusions reflect not merely theoretical profitability but actual implementability under live market conditions. By combining rigorous econometric methods with practical constraints, our study demonstrates both the potential and the limitations of cointegration strategies in modern crypto markets, offering a foundation for further refinements such as dynamic hedge ratios, regime-switching models, and volatility-aware entry signals.

3) Data Description :

Exchange : Binance Futures

Source of historical candle : https://fapi.binance.com/fapi/v1/klines

Data frequency : 4h

Lookback in time : 730 days

Number of coins initially considered : 70

Filtering criteria : Layer 1 primary tokens

At least 730 days of historical data

Final number of pairs tested : 2415 pairs

Final number of pairs selected for cointegration tests : 407

Removal of delisted assets

We use future datas for accuracy

4) Methodology :

Our methodology is simple and clear : the goal is to backtest cointegration trading strategy, by using quantitative framework to get the most precise model possible. Cointegration trading need clear methodology, cleaned data and accuracy.

To begin with, we need to evaluate cointegration between assets, by using specific method. The cointegration will be evaluate in a static manner, later, we will evaluate it dynamically.

Cointegration is evaluated thanks to Engle–Granger cointegration test between two price series. Here is how it works :

We suppose we have two assets P1 and P2, individually, their prices drift, trend, and behave like random walks, with a non-stationary behavior. But sometimes, there's a linear combination of them:

$$Spread = P1 - \beta \times P2$$

If this spread is stationary (no trend, finite variance, mean reversion), then the assets are cointegrated, it means that they move together in the long run, and deviations from equilibrium eventually correct.

Here is the Engle-Granger (EG) procedure we use :

$$P1 = \alpha + \beta \times P2 + \varepsilon_t$$

β = Hedge ratio

α = Intercept

The residual (spread) :

$$\epsilon_t = P1 - \alpha - \beta \times P2$$

We apply the Augmented Dickey-Fuller test on the residuals, to get the p-value :

If ADF p-value < threshold -> Cointegration is confirmed

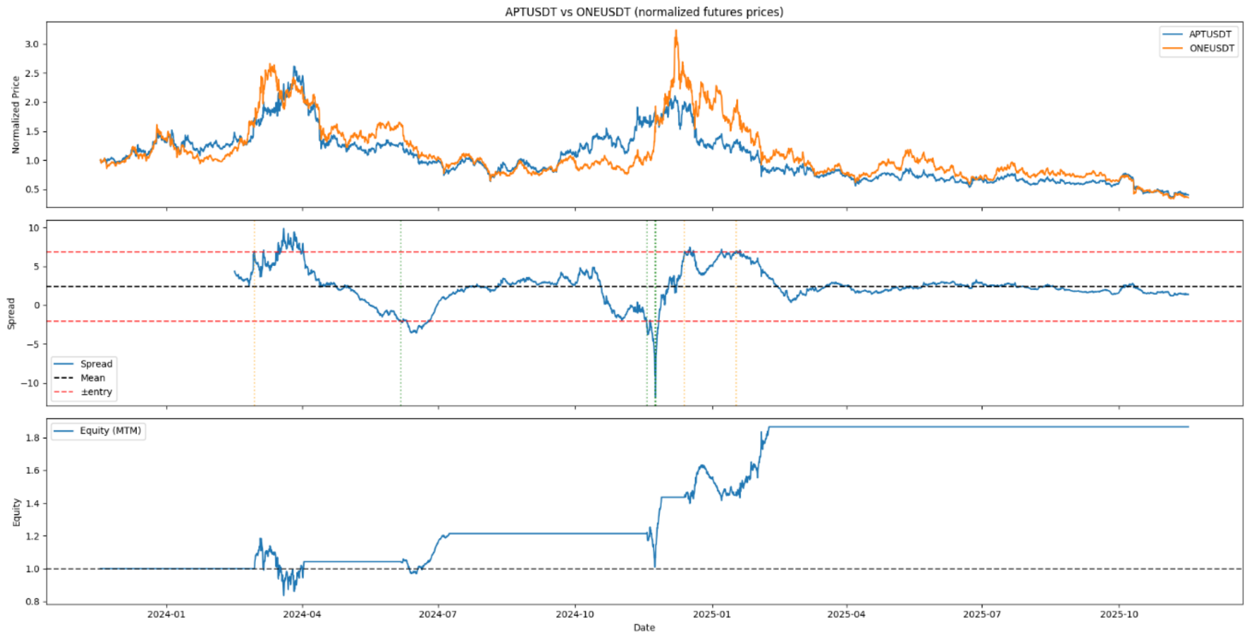
If ADF p-value > threshold -> No cointegration

We will use python statsmodels to find cointegrated pairs.

In our methodology, it's key to consider the beta dynamically. Beta is the hedge ratio, it tells you how much of asset B you need to hedge 1 unit of asset A in order to obtain a mean-reverting spread. But through time, quantity of the asset B to hedge one unit of the asset A varies, because prices move.

So if Hedge ratio is moving through time, and we have to take that into account in our model. We can compute p-value by changing beta through time. If we stay on a fix beta, the Alpha we get is "fake" because it doesn't represent reality for our backtest. Particularly, we will compute the rolling beta in a 90 days window.

After doing that, we can see the spread evolves through time. In this strategy, we'll trade the spread. The threshold is set up at 2. We also set an emergency setting that stop the trade is the spread goes to 4, it acts as a stop loss, because it means we aren't really cointegrated at this level. For a given pair, we have this kind of backtest :



We will then compute ratios and metrics to evaluate those trades.

After compounding Beta ratio and having cointegrated pairs, it's time to optimize.

If we look at all cointegrated pairs, we can notice that we have 407 pairs, so it's hard to trade on all those pairs. We can optimize our system by getting just one and only one metric : Sharpe Ratio. For our trade, Sharpe ratio can be defined with this formula :

$$Sharpe\ Ratio = \frac{\mu}{\sigma} \times \sqrt{Annualization}$$

Sharpe ratio evaluates risk reward opportunity of an investment. To make it efficient and practical, we will keep the best 20 cointegrated pairs, in terms of Sharpe Ratio (in our window analysis, 730 days).

We also add fees to our backtest model, we assume fees are fix at 4 bps, as taker fees. We have 4 taker fees per trade, so we have 16 bps per trade.

Risk management is also key in our model, especially managing token risk and volatility. Token risk can be associated with diversification risk.

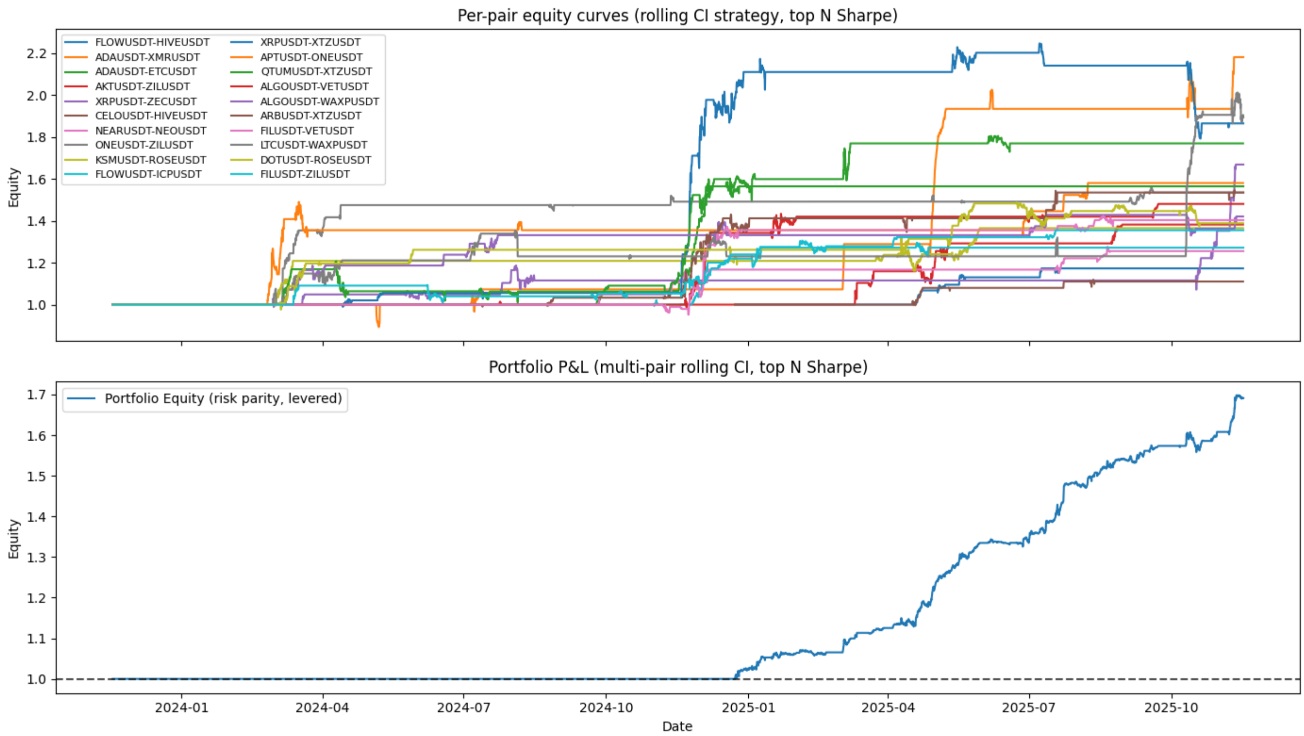
We have to keep pairs that are linked to different tokens, because if all pairs we keep are linked to a single token, and the token disappears, we would lose everything. Moreover, we have to be hedge against volatility spikes and weight our trades using risk parity, define like :

$$w_i = \frac{\sigma(w)^2}{(\sum w)_i N}$$

After this we can run our backtest and find results.

5) Results :

We can now analyse our backtest results and see if this strategy works. If we look at the P&L graph it shows a really positive return :



The performances start at the beginning of 2025 because we use a rolling beta with a 90 days window.

We use the top 20 Sharpe Ratio pairs, among more than 400 pairs :

FLOWUSDT-HIVEUSDT: Sharpe = 2.462

ADAUSDT-XMRUSDT: Sharpe = 2.390

ADAUSDT-ETCUSDT: Sharpe = 2.210

AKTUSDT-ZILUSDT: Sharpe = 2.199

XRPUSDT-ZECUSDT: Sharpe = 2.100

CELOUSDT-HIVEUSDT: Sharpe = 1.920

NEARUSDT-NEOUSDT: Sharpe = 1.900

ONEUSDT-ZILUSDT: Sharpe = 1.864

KSMUSDT-ROSEUSDT: Sharpe = 1.836

FLOWUSDT-ICPUSDT: Sharpe = 1.811

XRPUSDT-XTZUSDT: Sharpe = 1.721

APTUSDT-ONEUSDT: Sharpe = 1.661

QTUMUSDT-XTZUSDT: Sharpe = 1.633

ALGOUSDT-VETUSDT: Sharpe = 1.631

ALGOUSDT-WAXPUSDT: Sharpe = 1.615

ARBUSDT-XTZUSDT: Sharpe = 1.601

FILUSDT-VETUSDT: Sharpe = 1.566

LTCUSDT-WAXPUSDT: Sharpe = 1.549

DOTUSDT-ROSEUSDT: Sharpe = 1.543

FILUSDT-ZILUSDT: Sharpe = 1.536

Then, we can weight trades and pairs with risk parity :

FLOWUSDT-HIVEUSDT w = 0.0534

ADAUSDT-XMRUSDT w = 0.0189

ADAUSDT-ETCUSDT w = 0.0267

AKTUSDT-ZILUSDT w = 0.0243

XRPUSDT-ZECUSDT w = 0.0270

CELOUSDT-HIVEUSDT w = 0.0635

NEARUSDT-NEOUSDT w = 0.0827

ONEUSDT-ZILUSDT w = 0.1029

KSMUSDT-ROSEUSDT w = 0.0392

FLOWUSDT-ICPUSDT w = 0.0557

XRPUSDT-XTZUSDT w = 0.0307

APTUSDT-ONEUSDT w = 0.0531

QTUMUSDT-XTZUSDT w = 0.1367

ALGOUSDT-VETUSDT w = 0.0364

ALGOUSDT-WAXPUSDT w = 0.0486

ARBUSDT-XTZUSDT w = 0.0335

FILUSDT-VETUSDT w = 0.0681

LTCUSDT-WAXPUSDT w = 0.0142

DOTUSDT-ROSEUSDT w = 0.0297

FILUSDT-ZILUSDT w = 0.0549

Let's apply a 5 leverage on the strategy to get bigger return (it doesn't impact performance metrics, it increases risk and return)

Unlevered annual volatility	1.84%
Target annual volatility (risk parity)	20%
Applied leverage	5
Sharpe Ratio	4.259
Sortino Ratio	4.325
Calmar	9.807
Total return	69.14%
CAGR	30.05%
Max Drawdown	-3.06%
Final equity (performance)	1.691

Those performances take fees into account.

This strategy works and gives absolute return, but of course, execution is different from backtesting, make this strategy algorithmic can give absolute return and passive returns. A certain amount of money is needed to apply this strategy, it's also possible to vary the leverage and adjust our returns.

A Sharpe ratio at more than 4 is exceptional, max drawdown is low compared to returns (Calmar ratio).

7) Conclusion :

This study set out to evaluate whether cointegration-based mean-reversion strategies can be systematically exploited in cryptocurrency markets, using a robust execution-aware framework built on rolling hedge-ratio estimation, dynamic spread modeling, and realistic trading frictions. Our findings show that while stable long-run relationships are relatively rare across the broader crypto universe, a well-filtered subset of pairs demonstrates persistent statistical structure and economically tradeable convergence behavior.

From the initial pool of tested altcoin pairs, we selected the top 20 by Sharpe ratio. These pairs exhibit strong mean-reversion characteristics, with Sharpe ratios ranging from 1.53 to 2.46 at the individual-pair level. Rolling cointegration metrics—specifically dynamic β estimates, ADF p-values, and half-life stability—confirm that these pairs maintain consistent local equilibrium relationships, even across changing market regimes. The diversity of selected pairs (L1–L2 relationships, cross-ecosystem spreads, and structurally linked narrative-based pairs) enabled meaningful diversification when assembled into a portfolio.

Applying a risk-parity allocation provided balanced exposure across pairs before scaling the portfolio to a 20% annual volatility target. The resulting leverage factor of 5× remains modest relative to the smoothness of the underlying P&L stream, with the unlevered portfolio exhibiting only 1.84% annualized volatility. After scaling, the portfolio achieves a Sharpe ratio of **4.26**, a Sortino of **4.33**, and a Calmar ratio of **9.81**, with a CAGR of **30.05%**, total return of **69.1%**, and a very limited maximum drawdown of **–3.06%**. The smooth equity curve and robustness across more than 2200 trades indicate that performance is not attributable to a handful of outliers but emerges from a consistent, diversified set of convergence events.

These results show that cointegration remains a viable and exploitable inefficiency in cryptocurrency markets—but only under stringent methodological conditions: rolling estimation to capture time-varying relationships, strict filtering based on statistical significance and stability, and careful incorporation of trading costs, slippage, and funding. At the same time, the strategy's sensitivity to regime shifts and window parameters suggests that continuous monitoring and dynamic recalibration are necessary to maintain robustness in live trading.

Overall, this research demonstrates that properly engineered cointegration strategies can deliver strong, risk-adjusted returns in crypto, provided that the statistical foundations are continually validated and execution realities are fully integrated into the workflow. Future extensions may include regime-switching cointegration models, Kalman-filter hedge ratios, cross-sectional optimization beyond pairs, and the integration of macro- or order-book-based filters to further stabilize the performance across market cycles.