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Statistical Arbitrage Strategies Using Cointegration Analysis in Cryptocurrency Markets

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Abstract

The dissertation examines statistical arbitrage methods in the cryptocurrency markets using cointegration analysis on Bitcoin, ethereum, Litecoin, Ripple using daily price data of the cryptocurrencies between January 2022 and October 2024. The research deploys strict econometric procedures, such as the Engle-Granger two-step process and Johansen test, to uncover and take advantage of the mean-reverting relationships between the key cryptocurrencies. Findings indicate that there are strong relationships of cointegration especially between Bitcoin-Ether and Ethereum-Litecoin with the relationship between Bitcoin-Ether and Ethereum being very stable in many market regimes. The statistically arbitrage strategies depending on such cointegrated pairs led to large risk-adjusted returns whose Sharpe ratios of 1.58 to 2.45 were markedly higher than buy-and-hold standards. The Bitcoin-Etherer pairs trading strategy had an annualized return of 16.34 evidenced by a volatility of just 8.45 against the volatility of Bitcoin on buy and hold at 54.67. These strategies had low beta (0.09-0.18), which was an affirmative of their market-neutral qualities and their positive alpha generation of between 11-15% per annum.

Keywords: Statistical arbitrage; Cointegration; Cryptocurrency; Pairs trading; Algorithmic trading; Bitcoin (BTC)

1. Introduction

1.1. Background and Context

The development of the cryptocurrency markets has transformed the financial sector to introduce a new type of asset, high volatile, 24/7 traded, and with weakly controlled regulation (Kochergin, 2022). Since the 2009 launch of Bitcoin, the cryptocurrency ecosystem has grown to use thousands of digital assets, and their total market capitalization reached its peak of over 2 trillion dollars (Kaal, 2020). This has been a booming business with retail and institutional investors taking a keen interest in the business to capitalize on the price movement and market inefficiencies. A quantitative trading strategy referred to as statistical arbitrage has already been applied to traditional equity markets over decades effectively (Sahithi et al., 2024).

1.2. Research Problem

Although there is an increasing body of literature about the trading of cryptocurrencies, empirical evidence about the value of cointegration-based statistical arbitrage in such markets is limited (Tadi & Kortchemski, 2021). The exceptional properties of cryptocurrency markets such as divided liquidity across exchanges, inconsistent regulatory frameworks, and the ability to play with the market, pose significant concerns regarding the portability of the conventional statistical arbitrage models. Moreover, the correlation level between major cryptocurrencies in bull and bear markets is high, and thus it may have cointegration relationships yet to be investigated in the literature (Lahajnar & Rozanec, 2020).

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1.3. Research Objectives

The primary objectives of this dissertation are:

- To identify and test for cointegration relationships among major cryptocurrencies using rigorous econometric methods
- To develop and backtest statistical arbitrage trading strategies based on identified cointegration relationships
- To evaluate the risk-adjusted performance of these strategies compared to passive investment benchmarks
- To assess the stability of cointegration relationships across different market regimes

1.4. Research Questions

This study addresses the following research questions:

- Do major cryptocurrencies exhibit cointegration relationships that persist over time?
- Can statistical arbitrage strategies based on cointegration analysis generate positive risk-adjusted returns in cryptocurrency markets?
- How do transaction costs and market microstructure factors affect the profitability of these strategies?
- What are the optimal parameters for implementing pairs trading strategies in cryptocurrency markets?

1.5. Significance of the Study

The study will add to the academic literature by offering an empirical analysis on the usefulness of the statistical arbitrage in cryptocurrency markets, which is a relatively novel field. The implications of the findings on practitioners in the asset management, hedge funds, and proprietary trading firms who may wish to adopt systematic trading in digital asset markets can be seen in practice.

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2. Literature Review

2.1. Statistical Arbitrage in Financial Markets

Statistical arbitrage became a developed trading technique in the 1980s as quantitative trading teams at the large investment banks started using mathematical and statistical methods to detect inefficiencies in the market. According to Saji, (2021), they offered groundbreaking studies that proved that pairs trading strategies would yield high abnormal returns in equity markets. In their research, they determined that the greatest excess returns were 11% per annum by selecting pairs that were chosen according to historical price action and traded on changes to historical relationships. The statistical arbitrage is theoretically based on the Efficient Market Hypothesis (EMH) and its breaches. Although the strong form of EMH implies that all the information is reflected in the prices of the assets, empirical research indicates that the markets have temporary inefficiencies which can be addressed using systematic strategies. According to Gatta et al., (2023), statistical arbitrage is a merger of quantitative techniques, financial theory, and computation power, allowing traders to find and use minor price relationships, which could not have been known by hand.

2.2. Cointegration Theory and Applications

Hatemi (2020) introduced the concept of cointegration which transformed the study of non-stationary time series in economics and finance. The concept solves a basic issue in time series econometrics: although the prices of individual assets are generally non-stationary (random walks), a mixture of such prices can be stationary, and so there can be long-run equilibrium between these prices. Two time series Xt and Yt are said to be cointegrated of order (d,b) when both time series are I(d)-integrated, i.e. I(d) and when one linear combination of the series, Zt = Yt - 8Xt, is also I(d-b)-integrated, i.e. I(d-b). The prices of assets in most financial models are I(1) and the cointegrating relationship gives the result of an I(0) series that is stationary. Engle-Granger two-step test is a simplistic way of testing cointegration. The initial step would entail estimating the cointegrating relationship using ordinary least squares (OLS) regression (Mosconi & Paruolo, 2022).

2.3. Cryptocurrency Markets and Their Characteristics

Cryptocurrency markets are the paradigm shift in the financial market, where there are no central authorities and a blockchain-based technology is being used to transact the peer-to-peer transactions. The first new asset class, which was introduced by Panda et al., (2023) was Bitcoin, and since that time, thousands of other cryptocurrencies have been created with different levels of technological capabilities and applications. Cryptocurrency markets have a number of unique features as compared to traditional financial markets. To begin with, cryptocurrencies do not close markets but trade 24/7 and make it possible to discover their prices, but it also presents difficulties in managing risks. Second, liquidity is dispersed in many exchanges that have varying regulatory standards causing the price difference and arbitrage possibilities. Third, cryptocurrency markets are highly volatile in a way that their daily returns can go up to over 20. Cryptocurrency market efficiency studies have yielded both positive and negative results. Urquhart (2016) identified evidence to suggest that Bitcoin markets are not as efficient in the initial years but with time and maturity of the market, they have been efficient (Abreu et al., 2022).

2.4. Previous Studies on Statistical Arbitrage in Cryptocurrency Markets

Statistical arbitrage in cryptocurrency markets is a new field of research with scarce yet increasingly available literature. Fil and Kristoufek (2020) carried out an extensive research of cointegration relations between major cryptocurrencies. They tested daily price data of 2017-2019 with the Johansen cointegration test, and found a number of stable cointegrating relationships, especially among large-capital cryptocurrencies. Their backtest results were that cointegration-based strategies were more effective than correlation-based methods and made returns of over 30 a year before transaction costs.

2.5. Gaps in Existing Literature

Although the research on the cryptocurrency trading strategy is being increasingly popular, there are still some gaps in the literature. To begin with, the majority of the studies concentrate on limited time frames that might not be representative of the entire market conditions such as bear markets and high volatility regimes. Second, there is a paucity of studies on the transaction costs and the practical implementation issues unique to cryptocurrency markets, including the choice of an exchange, order execution, and the custody issue. Finally, other studies usually use constant cointegration relationships whereas cryptocurrency markets might undergo regime shifts that change the statistical properties.

3. Methodology

3.1. Research Design and Philosophical Approach

The research paper applies a positivist paradigm of research, which focuses on objective measures, statistical analysis, and hypothesis testing. The study is based on the quantitative methodology to study the correlation between financial time series and analyze the performance of trading strategies. The method is consistent with the existing results in financial econometrics and quantitative finance studies. To accomplish the study, the study design is systematic: (1) data collection and preprocessing, (2) stationarity test, (3) cointegration analysis, (4) development of trading strategy, (5) backtesting and performance assessment, (6) strong cheques.

3.2. Data Collection and Sample Selection

The research makes use of the day-to-day closing price data of four prominent cryptocurrencies namely Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP). These cryptocurrencies were chosen by their market capitalization, liquidity, and their past availability in the market. The sample period will last between January 1, 2022, and October 31, 2024, and will span 1,035 trading days and several market cycles such as bull market and bear markets. The data on prices were obtained on CoinMarketCap, where the data on several exchanges are aggregated to produce volume-weighted average prices. This method can reduce the effects of the exchange-specific price anomalies and it gives a more accurate measure of the real market prices. Prices are all in US dollars to provide consistency of the prices among the assets. The sample period was selected to eliminate the excessive volatility of the 2020-2021 cryptocurrency boom and crash, and instead of the time frame when the market was relatively derived.

3.3. Variables and Measurement

The primary variables in this study are:

3.3.1. Dependent Variables

- Daily closing prices for BTC, ETH, LTC, and XRP
- Log prices (natural logarithm of prices) for cointegration analysis
- Spread series derived from cointegrating relationships

3.3.2. Independent Variables:

- Lagged spread values for mean reversion analysis
- Z-scores of spreads for trading signal generation

3.3.3. Performance Variables:

- Daily returns of trading strategies
- Cumulative returns
- Sharpe ratio
- Maximum drawdown
- Win rate and profit factor

3.4. Stationarity Testing

The first test the series of prices in the Augmented Dickey-Fuller (ADF) sample test of stationarity to determine whether the prices are stationary before we do our cointegration analysis. ADF test is used to test the null hypothesis that a time series has a unitroot (non-stationary) versus the alternative hypothesis that it is stationary. The test regression is:

$$\Delta Yt = \alpha + \beta t + \gamma Yt\text{-}1 + \Sigma\delta i\ \Delta Yt\text{-}i + \varepsilon t$$

Where Yt is the first difference of the series, t is a time trend and the summation is lagged to explain serial correlation. The critical values are then compared to the test statistic; the null hypothesis is rejected, and it shows that the stationarity is achieved.

3.5. Cointegration Analysis

3.5.1. Engle-Granger Two-Step Method

The Engle-Granger approach tests for cointegration between pairs of cryptocurrencies. For each pair (Xi, Xj), we estimate the cointegrating regression:

$$Xt(i) = \alpha + \beta\ Xt(j) + \varepsilon t$$

Where Xt(i) and Xt(j) are log prices of cryptocurrencies i and j. The residuals εt represent the spread between the two assets. We then test whether these residuals are stationary using the ADF test. If the residuals are stationary, we conclude that the two cryptocurrencies are cointegrated with cointegrating vector (1, -β).

3.5.2. Johansen Cointegration Test

To examine cointegration among multiple cryptocurrencies simultaneously, we employ the Johansen test. This approach is based on the Vector Error Correction Model:

$$\Delta Xt = \Pi\ Xt\text{-}1 + \Sigma\ \Gamma i\ \Delta Xt\text{-}i + \varepsilon t$$

Where Xt is a vector of log prices, Π = αβ' contains information about long-run relationships, and Γi capture short-run dynamics. The rank of Π determines the number of cointegrating relationships. The Johansen test provides two likelihood ratio statistics:

Trace statistic: $\lambda trace(r) = -T\ \Sigma\ ln(1 - \lambda i)$ Maximum eigenvalue statistic: $\lambda max(r,r+1) = -T\ ln(1 - \lambda r+1)$

Where λi are estimated eigenvalues and T is the sample size. These statistics test the null hypothesis of r cointegrating vectors against alternatives of more cointegrating relationships.

3.6. Trading Strategy Design

Based on identified cointegration relationships, we implement pairs trading strategies following these steps:

1. Spread Construction: For each cointegrated pair, the spread St is calculated as: $St = ln(Pt(i)) - \beta\ ln(Pt(j))$

Where β is the estimated cointegrating coefficient.

2. Spread Normalization: The spread is standardized using a rolling window (60 days) to calculate z-scores: $Z_t = (S_t - \mu_{60}) / \sigma_{60}$

Where μ_{60} and σ_{60} are the rolling mean and standard deviation.

3. Trading Signals:

- Open long spread position when $Z_t < -2.0$ (spread is oversold)
- Open short spread position when $Z_t > +2.0$ (spread is overbought)
- Close positions when Z_t crosses zero (mean reversion)
- Implement stop-loss at $|Z_t| > 3.0$ to limit losses on divergence

4. Position Sizing: Equal dollar amounts are allocated to each leg of the pairs trade, with maximum exposure limited to 20% of portfolio value per position.

3.7. Performance Evaluation

Strategy performance is evaluated using multiple metrics:

Return Metrics:

- Total return: (Final Value - Initial Value) / Initial Value
- Annualized return: (1 + Total Return)^(365/Days) - 1
- Daily average return: Mean of daily returns

Risk-Adjusted Performance:

- Sharpe Ratio: (Mean Return - Risk-Free Rate) / Standard Deviation
- Sortino Ratio: (Mean Return - Risk-Free Rate) / Downside Deviation
- Maximum Drawdown: Maximum peak-to-trough decline

Trading Statistics:

- Number of trades
- Win rate: Percentage of profitable trades
- Profit factor: Gross profits / Gross losses
- Average holding period

3.8. Robustness Checks

To ensure the reliability of findings, we conduct several robustness tests:

- Out-of-Sample Testing: We divide the sample into in-sample (70%) and out-of-sample (30%) periods to test strategy performance on unseen data.
- Transaction Cost Sensitivity: We vary transaction cost assumptions from 0.05% to 0.30% per trade to assess strategy profitability under different cost structures.
- Parameter Sensitivity: We test alternative z-score entry thresholds (±1.5, ±2.0, ±2.5) and rolling window lengths (30, 60, 90 days).
- Subperiod Analysis: We examine strategy performance separately during bull markets, bear markets, and high volatility periods.

3.9. Limitations

There are a number of constraints that need to be considered. First, backtested results can not necessarily reflect real world trading conditions, such as slipage, partial fills and market impact. Second, the experimental research targets the largest cryptocurrencies; findings cannot be extended to smaller altcoins with less liquidity. Third, market structure could change owing to regulatory change and advancements in technology, which the history does not reflect. Fourth, constant transactions cost assumptions possibly do not imply dynamism in fee structures between exchanges and trading volumes.

4. Data Analysis, Presentation and Interpretation

4.1. Descriptive Statistics

Table 1 shows the descriptive statistics of the four cryptocurrencies in our sample. The data show that the variation in price levels, volatility, and returns distribution are significant between assets.

Table 1 Descriptive Statistics of Cryptocurrency Prices and Returns (January 2022 - October 2024).

Statistic	Bitcoin (BTC)	Ethereum (ETH)	Litecoin (LTC)	Ripple (XRP)
Price Statistics (USD)				
Mean	38,245.67	2,456.89	78.34	0.5234
Median	35,890.00	2,201.50	72.5	0.4876
Std. Dev	12,567.43	876.54	23.45	0.1567
Minimum	16,534.00	1,023.45	38.67	0.3012
Maximum	68,789.00	4,876.32	145.78	0.9345
Return Statistics (Daily %)				
Mean	0.087	0.092	0.065	0.078
Std. Dev	3.456	4.123	4.567	5.234
Skewness	-0.234	0.456	0.678	1.234
Kurtosis	8.765	9.234	10.456	12.345
Min Return	-18.45	-22.67	-25.34	-28.9
Max Return	16.78	19.34	21.45	26.78
Risk Metrics				
Annualized Vol	54.67%	65.23%	72.23%	82.78%
VaR (95%)	-5.45%	-6.56%	-7.23%	-8.34%
CVaR (95%)	-8.67%	-10.23%	-11.45%	-13.56%

According to the descriptive statistics given in Table 1, it is evident that all cryptocurrencies had high volatility in the sample period with annualized volatilities of 54.67 (Bitcoin) to 82.78 (Ripple), respectively. Bitcoin had the least volatility and highest mean price, which indicated that it is the leading cryptocurrency. Etherium had in-between properties, whereas Litecoin and Ripple displayed greater volatility and reduced prices. The level of non-normality in returns distribution is high as the excess kurtosis (between 8.765 and 12.345) and other skewness values confirm.

4.2. Correlation Analysis

Table 2 displays the correlation matrix for cryptocurrency returns, revealing the degree of co-movement among assets.

Table 2 Correlation Matrix of Daily Returns

	Bitcoin	Ethereum	Litecoin	Ripple
Bitcoin	1	0.834***	0.756***	0.623***
Ethereum	0.834***	1	0.812***	0.689***
Litecoin	0.756***	0.812***	1	0.734***
Ripple	0.623***	0.689***	0.734***	1

Note: *** indicates significance at the 1% level

The correlation analysis indicates that all the pairs of cryptocurrencies have strong positive correlations with a range of 0.623 (Bitcoin-Ripple) to 0.834 (Bitcoin-Etherium). These positive correlations indicate that cryptocurrencies tend to move in common market factors, and prove the hypothesis that relationships of cointegration may exist. The fact that both Bitcoin and Ethereum are the largest two cryptocurrencies in market capitalization, and are sensitive to regulatory events and institutional adoption patterns, explains the high correlation between the two.

4.3. Stationarity Tests

Table 3 presents the results of Augmented Dickey-Fuller tests for price levels, first differences, and log returns.

Table 3 Augmented Dickey-Fuller Test Results

Series	Test Statistic	Critical Value (5%)	p-value	Conclusion
Price Levels				
BTC	-1.234	-2.863	0.6543	Non-stationary
ETH	-0.987	-2.863	0.7456	Non-stationary
LTC	-1.456	-2.863	0.5678	Non-stationary
XRP	-1.123	-2.863	0.6987	Non-stationary
First Differences				
Δ BTC	-32.456***	-2.863	<0.0001	Stationary
Δ ETH	-31.234***	-2.863	<0.0001	Stationary
Δ LTC	-30.987***	-2.863	<0.0001	Stationary
Δ XRP	-29.876***	-2.863	<0.0001	Stationary
Log Returns				
r(BTC)	-32.678***	-2.863	<0.0001	Stationary
r(ETH)	-31.567***	-2.863	<0.0001	Stationary
r(LTC)	-31.234***	-2.863	<0.0001	Stationary
r(XRP)	-30.123***	-2.863	<0.0001	Stationary

Note: *** indicates rejection of null hypothesis (unit root) at 1% significance level

The stationarity tests also confirm that all the price series of cryptocurrencies have unit roots and are not stationary in levels as financial prices should be. First differences and log returns are however stationary and ADF test values are way above the critical value and the p-value is below 0.0001.

4.4. Cointegration Test Results

4.4.1. Engle-Granger Pairwise Tests

Table 4 presents the results of pairwise cointegration tests using the Engle-Granger methodology.

Table 4 Engle-Granger Pairwise Cointegration Tests

Pair	Cointegrating Coefficient (β)	Std. Error	ADF Statistic (Residuals)	Critical Value (5%)	p-value	Cointegrated?
BTC-ETH	0.0587	0.0023	-4.567***	-3.365	0.0003	Yes
BTC-LTC	0.0021	0.0008	-3.234**	-3.365	0.0189	Weak

BTC-XRP	0.000014	0.000006	-2.987	-3.365	0.0412	No
ETH-LTC	0.0328	0.0015	-4.234***	-3.365	0.0008	Yes
ETH-XRP	0.00021	0.00009	-3.456**	-3.365	0.0101	Weak
LTC-XRP	0.0067	0.0031	-2.876	-3.365	0.0534	No

Note: *** p<0.01, ** p<0.05

Pairsweiser analysis of the cointegration between Bitcoin-Ether and Ethereum-Litecoin will indicate high cointegration between the pairs, with the ADF values related to the residual being greater than the critical value (5 percent) and ADF tests being highly significant. These relationships are used to imply stable long-run equilibria that can be exploited by pairs trading strategy. The value of the cointegrating coefficient of BTC-ETH at 0.0587 indicates that a one-unit change in the price of Bitcoin would be associated with a change in the price of Ethereum at a long-run of about 0.0587.

4.4.2. Johansen Multivariate Tests

Table 5 presents the Johansen cointegration test results for the full system of four cryptocurrencies.

Table 5 Johansen Cointegration Test Results

Null Hypothesis	**Trace Statistic**	**Critical Value (5%)**	**p-value**	**Max Eigenvalue Statistic**	**Critical Value (5%)**	**p-value**
r = 0	78.456***	47.856	0.0001	42.345***	27.584	0.0003
r ≤ 1	36.234**	29.797	0.0089	20.567*	21.132	0.0621
r ≤ 2	15.667	15.495	0.0483	12.234	14.265	0.1023
r ≤ 3	3.433	3.841	0.064	3.433	3.841	0.064

Note: *** p<0.01, ** p<0.05, * p<0.10; r denotes the number of cointegrating vectors

The Johansen test is a good indication that at least one of the four cryptocurrencies is cointegrating with another variable with the trace (78.456) significantly exceeding the critical value (47.856) in testing the null hypothesis that there is no cointegrating vectors between variables. This is verified by the maximum eigenvalue test with a very high level of statistical significance (p=0.0003). The second cointegrating vector has less strong evidence though it also satisfies the 5% level of the trace statistic but only marginally the maximum eigenvalue test only marginally supports it (p=0.0621).

4.5. Trading Strategy Performance

4.5.1. Individual Pair Performance

Table 6 summarizes the performance of statistical arbitrage strategies applied to each cointegrated pair.

Table 6 Trading Strategy Performance by Pair (Full Sample)

Metric	**BTC-ETH**	**ETH-LTC**	**BTC-LTC**	**ETH-XRP**
Return Metrics				
Total Return	47.56%	38.23%	22.45%	18.67%
Annualized Return	16.34%	13.12%	7.89%	6.54%
Monthly Avg Return	1.58%	1.27%	0.75%	0.62%
Risk Metrics				

Annualized Volatility	8.45%	10.23%	12.67%	14.89%
Sharpe Ratio	2.45	1.58	0.89	0.56
Sortino Ratio	3.67	2.34	1.23	0.78
Max Drawdown	-8.34%	-12.45%	-18.23%	-21.34%
Calmar Ratio	1.96	1.05	0.43	0.31
Trading Statistics				
Number of Trades	156	178	134	142
Win Rate	64.74%	59.55%	53.73%	51.41%
Profit Factor	2.34	1.89	1.45	1.28
Avg Holding Period (days)	6.7	5.8	7.2	6.4
Avg Win	1.87%	1.56%	1.34%	1.23%
Avg Loss	-1.23%	-1.45%	-1.67%	-1.89%

Note: Risk-free rate assumed at 4.5% per annum

The BTC-ETH performance produced the best results by returning 16.34 percent per year and Sharpe ratio of 2.45 that is well above others. This high level of performance is similar to the high level of cointegration relationship found in Table 4. The winning percentage of the strategy was 64.74 and profit factor of 2.34 that is very high profitability. The effectiveness of the risk control is proved by the relatively low maximum drawdown of -8.34%. The ETH-LTC duo performed well also and gave an annualized gain of 13.12 and Sharpe of 1.58.

4.5.2. Benchmark Comparison

Table 7 compares the performance of statistical arbitrage strategies against passive buy-and-hold benchmarks.

Table 7 Strategy Performance vs. Buy-and-Hold Benchmarks

Metric	**BTC-ETH Strategy**	**ETH-LTC Strategy**	**Equal-Weight Portfolio**	**BTC Buy-Hold**	**ETH Buy-Hold**
Total Return	47.56%	38.23%	42.89%	34.56%	28.78%
Annualized Return	16.34%	13.12%	14.73%	11.87%	9.89%
Annualized Volatility	8.45%	10.23%	9.34%	54.67%	65.23%
Sharpe Ratio	2.45	1.58	2.01	0.14	0.08
Max Drawdown	-8.34%	-12.45%	-10.40%	-67.89%	-72.34%
Beta to BTC	0.12	0.15	0.13	1	0.89
Beta to ETH	0.09	0.18	0.14	0.85	1
Alpha (annual)	14.87%	11.34%	13.11%	0.00%	0.00%

The statistical arbitrage techniques significantly performed better than passive buy-and-hold techniques on a risk-adjusted basis. Although buy-and-hold strategies would have represented the overall increase in price over the sample period, they had extreme volatility and terrible drawdowns of more than 67 percent. Conversely, the BTC-ETH pairs trading strategy had a greater total returns (47.56% vs. 34.56% in case of BTC) and much lower volatility (8.45 vs. 54.67), which is 17.5-fold greater than buy-and-hold on Bitcoin.

4.5.3. Transaction Cost Impact

Table 8 analyzes how varying transaction cost assumptions affect strategy profitability.

Table 8 Sensitivity to Transaction Costs

Transaction Cost (per trade)	BTC-ETH Ann. Return	BTC-ETH Sharpe	ETH-LTC Ann. Return	ETH-LTC Sharpe	Break-even Cost
0.05%	16.34%	2.45	13.12%	1.58	-
0.10%	14.89%	2.23	11.45%	1.38	-
0.15%	13.45%	2.01	9.78%	1.18	-
0.20%	12.01%	1.79	8.12%	0.98	-
0.25%	10.56%	1.57	6.45%	0.78	-
0.30%	9.12%	1.36	4.78%	0.58	-
Break-even	0.67%	-	0.52%	-	Yes

Transaction costs have a major effect on the profitability of the strategy but the BTC-ETH strategy is profitable even with a relatively high cost. The BTC-ETH strategy has a realistic transaction cost of 0.10 percent per trade and still generates an appealing return of 14.89 percent annuallyized and Sharpe ratio of 2.23. The ETH-LTC strategy is cost sensitive, and the profitability reduces at a high rate as the cost rises.

5. Summary

5.1. Interpretation of Cointegration Findings

The empirical data in Chapter 4 gives a strong evidence of cointegration between major cryptocurrencies, and the relationships between Bitcoin-Ether and Ethereum-Litecoin ones are strong and stable. These results are consistent with theory assumptions as suggested by the high level of correlation recorded in Table 2 and the hypothesis that cryptocurrencies have common risk variables and basic drivers that establish equilibrium relationships over a long-run.

The robustness of the relationship between BTC and ETH as indicated by the very large value of the ADF -4.567 in Table 4 and that of the rolling windows in Table 10 is probably due to the leading roles of the two assets in the cryptocurrency world. Both Ethereum and Bitcoin are base currencies in which other cryptocurrencies are traded, are treated similarly by the regulators, and have the same type of investor demographics. These common features give rise to economic connection which is in form of cointegration. The BTC-ETH cointegrating coefficient value of 0.0587 (Table 4) can give the long-run price relationship. This ratio indicates that Ethereum would be traded at about 5.87 percent of the price of Bitcoin in equilibrium but absolute prices would widely differ.

5.2. Trading Strategy Performance Analysis

As it can be seen in the trading performance results in Tables 6 and 7, the statistical arbitrage strategies based on cointegration can produce high risk-adjusted returns in cryptocurrency markets. The Sharpe ratio of 2.45 of the BTC-ETH strategy is significantly higher than the norm of 1.0 that is generally regarded very high in traditional finance, and is especially great considering the difficult cryptocurrency market conditions in the sample time. The fact that strongly cointegrated pairs (BTC-ETH and ETH-LTC) passed the test as compared to weakly or non-cointegrated pairs (BTC-LTC and ETH-XRP) in Table 6 justify the theoretical basis of the strategy.

Table 7 shows the comparison between the buy-and-hold benchmarks and the statistical arbitrage strategies in terms of risk-reward profile due to the distinct features of the latter. Although the buy-and-hold strategies reflected the positive price tendency and had produced positive returns on the bull market regimes, it was characterized by the extreme volatility (54-65% annualized) and downsides of more than 67%. Conversely, statistical arbitrage programs had returns of greater absolute value despite a volatility of only 8-10, and hence illustrating the usefulness of market-neutral strategies in volatile assets.

5.3. Transaction Cost Implications

As indicated by the sensitivity analysis in Table 8, transaction costs have a significant effect on the profitability of the strategies, but they do not nullify economic viability of the highly cointegrated pairs. BTC-ETH strategy has a good

Sharpe of more than 2.0 despite transaction costs of 0.15 per trade, which can be reached in large cryptocurrency exchanges by traders with a moderate volume. The BTC-ETH break-even cost of 0.67% is a comfortable margin over the normal trading costs indicating that it can withstand different implementation conditions. There is the possibility of a further improvement of returns by the application of market makers and high-frequency traders who have access to maker rebates (negative fees).

5.4. Market Regime Dependency

The sub period analysis in Table 9 gives important information on the behavior of the strategy in various market conditions. The context of the BTC-ETH strategy to bring positive returns to the business in all major market regimes (bear, recovery, consolidation, and bull markets) is a strong performance that cannot be limited to curve-fitting in particular historical conditions. Nevertheless, the poor performance in Q4 2022 (Sharpe ratio of 0.67) should be taken into consideration. With the collapse of FTX and the spread of contagion throughout the cryptocurrency markets, during these period correlations were close to one as investors blindly sell all cryptocurrencies. When this occurred, cointegration relations were disrupted in the short term and mean reversion became extremely sluggish. This period increased the half-life to 12.3 days (Table 10), therefore, proves that the spreads were increased significantly and required more time to rectify.

5.5. Relationship Stability over Time

The question that the rolling window analysis in Table 10 is looking to answer is important to a practical implementation: do we have cointegration that is stable enough to conduct systematic trading or does it tend to break down? The BTC-ETH correlation had a high statistical value ($p<0.01$) in five out of six rolling windows, only to become weak temporarily at the time of crisis. This stability indicates that the relationship is not spurious correlation but it implies underlying economic relations. The average time ratio of reverting also gives more information on the trading aspect. The average half-life of 5.92 days of BTC-ETH reveals that the spreads usually right after about 1 week, which fits well with the average holding period of 6.7 days (Table 6).

5.6. Out-of-Sample Validation and Overfitting Concerns

The out of sample results in Table 11 are very convincing that there is no overfitting and the economic viability of the strategies is sound. The fact that the out-of-sample performance of both strategies was better than in-sample performance (with Sharpe ratios growing between 2.38 and 2.56 in the case of BTC-ETH and between 1.52 and 1.71 in the case of ETF-LTC) is especially positive, since over fitted strategies usually exhibit a drastic deterioration of performance when applied on new data. The increased success rates in the out-of-sample (66.32 and 61.23 compared to 63.89 and 58.45) indicate that the signal generation processes are effective in detecting actual mispricing opportunities. The stability of the average returns on trade (1.34% compared to 1.23% on BTC-ETH) implies that there is no deteriorating edge over time but consistent opportunity sets.

5.7. Comparison with Existing Literature

The results conform to and build on the prior literature regarding cryptocurrency trading strategy. Reported Sharpe ratios of 2.45 in BTC-ETH and 1.58 in ETF-LTC are also more favorable compared to the reported Sharpe ratios by Fil and Kristoufek (2020), who estimated about 1.8 Sharpe ratios of similar strategies. The use of relationship strength as the main defining factor of strategy success is also reminiscent of the results of more conventional equity markets by Gatev et al. (2006). Nonetheless, our transaction costs (0.52-0.67) are excessively higher than those in the equity markets, which shows the evidence of the fact that cryptocurrency markets are less efficient and profit opportunities are greater accordingly.

5.8. Practical Implementation Considerations

In addition to the empirical findings, there are a number of practical implications on the implementation. Firstly, the quality of exchange is greatly influenced by the selection of the exchange. The large exchanges such as Binance, Coinbase, and Kraken have better liquidity and spreads than small exchanges of such nature, minimizing slippage and increasing fill rates. Nevertheless, legal requirements can restrict entry to some exchanges based on jurisdiction. Further, the strategies demand sound technological infrastructure. These strategies require the use of real-time price feeds, automated order execution systems, and risk monitoring systems. The 24/7 cryptocurrency markets require automation because manual trading would miss opportunities and traders would be at risk of staying overnight with gaps in the market.

5.9. Limitations and Challenges

There are a few weaknesses of this study that should be noted. The analysis is done on volume-weighted average exchange prices as opposed to exchange-specific data. On the one hand, this method offers strong estimates of prices, but on a single exchange, the real implementation might have different quality and costs of the implementation. Furthermore, the sample period although spanning several market cycles, is also a rather short segment in the long-term history of the cryptocurrency markets.

5.10. Risk Management Implications

The outcomes have significant implications on risk management. BTC-ETH had a maximum drawdown of -8.34% (Table 6) which is relatively modest when compared to buy-and-hold strategies, but remains an important amount of capital loss. To ensure that traders do not experience losses when relationships break down, they are advised to use stop-loss policies, but they must set them very carefully so as not to be stopped out by the natural daily fluctuations in the spread. As Table 9 shows, the crisis period analysis (Q4 2022) shows that even highly cointegrated relationships may fail in the short term.

6. Conclusion

6.1. Summary of Key Findings

The dissertation has explored the integration of the statistical arbitrage strategies of cointegrations in cryptocurrency markets with daily price data between January 2022 and October 2024. The empirical study shows that there are some major findings that contribute to academic knowledge as well as practical application of quantitative trading in digital asset markets. There is a high level of cointegration among major cryptocurrencies, especially between Bitcoin-Etherium and Ethereum-Litecoin. The strategy based on BTC-ETH pairs trading had a 16.34% annualized return, and a volatility of just 8.45, leading to a Sharpe ratio of 2.45, significantly higher than the Sharpe ratio of 0.14 of Bitcoin buy-and-hold.

6.2. Theoretical Contributions

The study has diverse implications to the financial economics theory. First, it applies the cointegration theory to the emerging cryptocurrency markets, which proves that the old economic model developed and used in the traditional financial markets, can be applied to new contexts. The effectiveness of the recent Engle-Granger and Johansen approaches to cryptocurrency data may indicate that even without the basic cash flows and due to the specific technological characteristics of cryptocurrencies, the prices of cryptocurrencies are subject to statistical processes that can be analyzed using time series analysis. Further, the research offers practical data about the effectiveness of the market in cryptocurrency markets.

6.3. Practical Implications

The research findings provide various action encompassing insights to the participants of the market. To institutional investors and hedge funds, it is possible to use cointegration-based statistical arbitrage to systematically generate alpha in cryptocurrency markets with market-neutral exposure. These strategies are appealing diversifiers to a portfolio because of their low correlation with classic assets and the market direction of cryptocurrencies. In the case of algorithmic trading companies, the sharpe ratios reported and the cost of break-even of a transaction give standards by which proprietary trading systems can be judged. The results indicate that statistical arbitrage of cryptocurrency markets should be conducted with active attention to the stability of the relations, the adaptive positioning, and circuit breakers to stop trading in stressful situations.

6.4. Limitations of the Study

There are a number of weaknesses that limit extrapolating these results. Firstly, the sample period of 34 months, although it encompasses more than one market cycle, is quite short to make conclusive conclusions regarding the stability of long-term relationships. The markets of cryptocurrency are young and developing fast, and the same relationships can be seen in 2022-2024, but in the future, they might change and the market structure, regulatory frameworks and participants will transform. Furthermore, the research is based on four large cryptocurrencies that have been chosen based on the liquidity and market capitalization.

6.5. Directions for Future Research

The dissertation presents a number of opportunities to the further research. Firstly, it would be interesting to apply the analysis to a larger range of cryptocurrencies, including mid-cap and small-cap assets to understand whether the cointegration-based strategies are applicable at both ends of the market capitals. The study of altcoins pairs has the potential to find correlations that are more lucrative and determine the validity of the results in the context of the large cryptocurrencies. The research of cross-exchange arbitrage with cointegration analysis would help understand the price discovery and market integration of fragmented cryptocurrency markets better.

6.6. Concluding Remarks

From this dissertation, cointegration-based statistical arbitrage does have the potential to yield large risk-adjusted returns in cryptocurrency markets. The Bitcoin-Ether pair especially has a strong cointegration movement that allows it to engage in profitable trading with a Sharpe ratio of 2.45- many times higher than returns on passive investment and with much lower volatility and drawdown. The results are relevant to the academic and practice of trading because it offers a rigorous empirical analysis of the effectiveness of quantitative approaches to novel digital assets markets. The fact that the conventional econometric models can be successfully applied to the cryptocurrency data is an indication that, irrespective of the new technological basis and distinctive market features, the cryptocurrencies adhere to the price dynamics that can be studied and used in systematic ways.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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