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Eco-Crypto Dynamics: Cointegration of Green and Non-Green Cryptocurrencies for Sustainable Investing

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KEYWORDS

Cointegration, Green Cryptocurrencies, Non-Green Cryptocurrencies, Pairs Trading, Portfolio Construction.

ABSTRACT

Purpose: The rise of cryptocurrencies sparks significant interest among investors, but the environmental impact of energy-intensive consensus mechanisms, particularly in non-green cryptocurrencies like Bitcoin, raises concerns. As a result, a new class of eco-friendly "green" cryptocurrencies is born, to prioritize sustainability issues. The two-fold objectives of the study are to investigate the long-term equilibrium relationships, or cointegration, between prominent non-green cryptocurrencies (Bitcoin, Ethereum, and Litecoin) and green cryptocurrencies (IOTA, Ripple, and Chia), and to identify the potential for environment-friendly pairs trading strategies and the construction of sustainable cryptocurrency portfolios.

Design/Methodology/Approach: The study identifies the top three cryptocurrencies with the highest market capitalization and liquidity: Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). It also identifies three of the most environment-friendly (in terms of power consumption) cryptocurrencies: IOTA (IOT), Ripple (XRP), and Chia (CHI). Daily closing prices of the six selected cryptocurrencies are considered from 10 November 2020 to 11 February 2025, providing 1555 data points for each series. The study employs a battery of seven popular cointegration tests to analyse the relationships between the selected green and non-green cryptocurrencies.

Findings: Statistically significant cointegration is observed between certain pairs of green and non-green cryptocurrencies, as well as among some green cryptocurrencies. Chia demonstrates strong long-run relationships with Litecoin and IOTA. Weak cointegration is observed between other pairs, with strength and consistency varying across different tests. The results suggest potential opportunities for market-neutral trading strategies and diversified portfolios that balance environmental and financial goals.

Originality of the Study: This research explores the integration of green cryptocurrencies into investment strategies, offering a new perspective on balancing environmental considerations with financial objectives in the cryptocurrency market. The study also suggests potential avenues for developing sustainable cryptocurrency portfolios and market-neutral trading strategies.

1. INTRODUCTION

As cryptocurrencies gain rapid popularity in the digital world, a new era of financial analysis emerges, focused on understanding the long-term relationships between economic variables, stock prices, and commodity prices. Cointegration becomes a crucial concept in this process, offering valuable insights into whether different time series move together in the long term, influenced by underlying economic forces. Understanding cointegration is essential, not only for economic modelling and forecasting but also for crafting effective policies that guide markets and investments.

Many studies show how cointegration can improve portfolio management. For instance, Giblin and Weddington (2001) explore new asset allocation strategies using cointegration, demonstrating how optimal portfolios can be built with fewer stocks, reducing turnover and transaction costs. Similarly, Constantinou *et al.,* (2008) highlight the benefits of cointegration for domestic portfolio diversification, revealing that many sectoral indices are not cointegrated, which opens up opportunities for diversification. Their findings suggest that investors favour short-term strategies over long-term contrarian approaches.

Additional research continues to highlight the practical applications of cointegration in portfolio optimization. Dunis and Ho (2005) show how cointegration enhances European equity portfolios, improving index tracking and market-neutral strategies, although these do not always reduce volatility as anticipated. Dunis*et al.,* (2010) apply cointegration to currency portfolios, finding that it improves performance, especially for sterling, and helps stabilize portfolios containing lesser currencies like the Swedish Krona. This study and other studies (Bansal and Kiku (2011); Caldeira and Moura (2013)) reinforce the idea that cointegration is a powerful tool for creating investment strategies that better balance risk and return.

In the field of financial econometrics, the use of cointegration analysis has significantly advanced, offering valuable insights into long-term relationships between various economic variables, stock prices, commodities, and emerging assets such as cryptocurrencies and NFTs. Researchers continuously explore how cointegration can improve portfolio construction, risk management, and investment strategies (see diBartolomeo, 2013; Gallo *et al.*, 2013; Thirimanna*et al.*, 2013; Christos, 2015; Spinelli, 2016; and Tu *et al.,* 2019). Researchers begin applying cointegration methods to cryptocurrencies to better understand their long-term relationships with traditional financial assets, as seen in studies by Fil and Kristoufek (2020), Kantaphayao and Sukcharoensin(2021), Lee and Rhee (2022), Miskiewicz *et al.*, (2022), Ante (2023), Panigrahi (2023), Panigrahi (2023a), Jiang *et al.,* (2023), Akbulaev and Abdulhasanov (2023) and Junior *et al.*, (2024),although a few studies, like those by Jayawardhana and Colombage (2024) and Wang and Wang (2024), present contradicting views.

As environmental concerns over cryptocurrencies' significant carbon footprints grow, a new category of "green" cryptocurrencies emerges. Cryptocurrencies like IOTA, Ripple, and Chia, which prioritize energy efficiency, offer an alternative to the high-power consumption of Bitcoin and Ethereum (see Ahmed MS *et al.,* 2025; Ali F *et al.,* 2024). Yet, despite their environmental benefits, investors continue to favour established cryptocurrencies, which, although environmentally costly, offer greater market capitalization and liquidity (see Zheng *et al.*, 2019; Ren Z, 2023). Very few studies highlight the long-term relationship between green and non-green cryptocurrencies, and this search for environmentally conscious cryptocurrency portfolios motivates our study. This paper aims to reduce this gap by exploring the cointegration between the top three non-green cryptocurrencies (Bitcoin, Ethereum, and Litecoin) and the leading three eco sustainable cryptocurrencies (IOTA, Ripple, and Chia). While Bitcoin and other non-green cryptocurrencies are known for their high energy consumption, IOTA, Ripple, and Chia consume significantly less energy per transaction, making them more eco-friendly alternatives. By exploring whether these two groups of cryptocurrencies are cointegrated, the study hopes to open the door to developing diversified and sustainable cryptocurrency portfolios that balance environmental concerns with financial goals.

The study's goal is to contribute to the creation of a more responsible and diversified cryptocurrency market. It seeks to provide insights into how green cryptocurrencies can be integrated into the growing digital asset class, enabling the development of sustainable investment strategies that do not compromise financial returns. Given the increasing importance of environmental considerations in investing, this research is timely, offering a roadmap for future studies on the behaviour of both green and non-green cryptocurrencies in the broader economic landscape.

2. LITERATURE SURVEY

The journey of cointegration studies in cryptocurrencies primarily revolves around the relationships between the most dominant digital currencies—those with the highest market capitalization and liquidity. Early work by Broek (2018) introduces cointegration, a method that highlights the long-term relationship between two non-stationary time series exhibiting mean reversion, while Gottfert (2019) expands this by applying the Engle-Granger and Johansen tests to study Bitcoin's relationships with five altcoins. His research uncovers that Bitcoin is cointegrated with Bitcoin Cash, Ethereum, Litecoin, and Ripple, indicating long-term price relationships between these currencies. The study by Hild and Olsson (2019) provides a different perspective, suggesting that cointegration relationships in cryptocurrencies are more likely to be short-lived. Hyunh (2019) also reflects on this uncertainty, noting that Bitcoin's cointegration with other assets is inconsistent, marked by inefficiencies in Bitcoin markets. Supporting this view, Cheah *et al.,* (2018) and other researchers find that Bitcoin's price behaviour is not always predictable when compared to other cryptocurrencies or financial assets. In 2019, Isaksen (2019) examines Bitcoin alongside Dashcoin, Dogecoin, and Litecoin, finding strong evidence of cointegration among these assets by using tests like the Augmented Dickey-Fuller and DF-GLS. Katsiampa*et al.,* (2019) echo this sentiment, indicating that Bitcoin markets are fractionally cointegrated, suggesting long memory in market dynamics, but also emphasizing the negative impact of uncertainty on these relationships, particularly during periods of volatility. This study is followed by some remarkable cointegration studies like Kumar and Ajaz (2019), Chu *et al.,* (2015), Dirican and Canoz (2017), Leung and Nguyen (2019), and Teker *et al.,* (2019). To study price movements, Yaya (2019) examines the evolving relationships in cryptocurrency markets post-crash, highlighting the market's efficiency, where past price information can no longer predict abnormal returns. The landscape of cryptocurrency research evolves significantly, with studies over the years focusing heavily on the relationships between the most widely traded digital currencies. During these years, all pairs demonstrate at least one cointegrating equation, indicating long-run co-movement between Bitcoin and selected altcoins. This shift plays a pivotal role in understanding the emerging interconnection of the cryptocurrency market.

A new dimension is provided by Christophe *et al.,* (2020), showing that Bitcoin's trading volume cointegrates with energy consumption, highlighting the impact of cryptocurrency trading on global energy use. Deniz and Teker (2020) find no significant cointegration between Bitcoin, Ethereum, Ripple, gold, and oil, suggesting these assets move independently over the studied period. The body of literature grows rapidly, with authors like Gil-Alana *et al.,* (2020) and Gonzalez *et al.,* (2020) contributing significant findings. The year 2020 is noted for the study of time-varying cointegrating coefficients by researchers like Hu *et al.,* (2020), Malladi and Dheeriya (2021), and Mendes and Carreiro (2020). Some unique studies point to strong dependency among cryptocurrencies and long-term relationships, as seen in Qureshi *et al.,* (2020), Sami and Abdallah (2020), and Teker and Teker (2020). While some advanced studies use more sophisticated models to explore long-run relationships among cryptocurrency prices, utilizing fractional integration techniques like Wu *et al.,* (2020), Adedokun (2021) and Yaya *et al.,* (2022). Carvalho (2021) shows the role of cointegration in statistical arbitrage strategies, particularly in pairs trading. His study compares three major cointegration tests—the Augmented Dickey-Fuller, Johansen’s, and Phillips Peron tests—highlighting their application in cryptocurrency markets. Similarly, to enhance the effectiveness of trading strategies, Demir *et al.,* (2021) apply cointegration tests, confirming a long-run relationship between Bitcoin and altcoin prices. Gonzalez *et al.,* (2021) find a significant long-term relationship between the returns of three cryptocurrencies—XRP, Tether, and Cardano—and Gold, while for further study, Gursoy and Sokmen (2021) explore the relationship between Bitcoin and gold prices, finding that although these assets do not exhibit direct causality, they move together in the long run, suggesting inclusion in the same investment portfolio. The relevance of cointegration for pairs trading reflects from the studies of Keilbar and Zhang (2021) and Nair (2021), while the arbitrage opportunities and speculative behaviour from cointegration relationships are shown by Tadi and Kortchemski (2021) and Waters and Bui (2021). Some studies apply the Johansen cointegration model to suggest potential opportunities for investment and diversification among cryptocurrencies, as seen in Aysan *et al.,* (2021), Gul (2022), and Horta *et al.,* (2022). Obeng and Attor (2022) reinforce this by confirming a long-term relationship between Bitcoin, Ethereum, and other altcoins, showing their significant influence on each other’s returns. Caporale *et al.,* (2023) explore the long-term relationships between major cryptocurrencies and U.S. stock indices, utilizing fractional cointegration methods, while Tadi and Witzany (2025) apply the Engle-Granger two-step method and Kapetanios-Shin-Shell tests, identifying cointegration relationships that enable the development of strong pairs trading strategies. Although very few studies are influenced by environmental regulations and investor sentiment, like Maheta and Mehta (2024) and Cheema *et al.,* (2024).

All the above-mentioned literature addresses two common questions:

- Is there any long-term relationship between green and non-green cryptocurrencies?
- Is there any potential for environmentally conscious cryptocurrency portfolios?

This paper seeks to answer this questions by taking into consideration the cointegration between the three leading non-green cryptocurrencies (Bitcoin, Ethereum, and Litecoin) and the top three environmentally sustainable cryptocurrencies (IOTA, Ripple, and Chia).

3. DATA AND METHODOLOGY

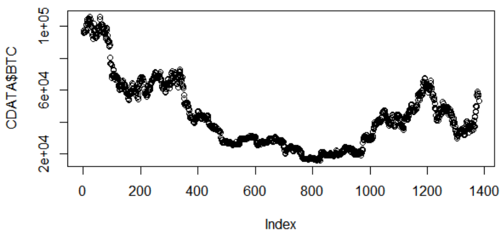
The study identifies the top three cryptocurrencies with the highest market capitalization and liquidity, namely Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). It also identifies three of the most environmentally friendly (in terms of power consumption) cryptocurrencies, namely IOTA (IOT), Ripple (XRP), and Chia (CHI). The research studies by Cohen & Pietrzak (2019), Agostinho *et al.,* (2020) and Dias *et al.,* (2024), and also motivate the selection of these six cryptocurrencies.

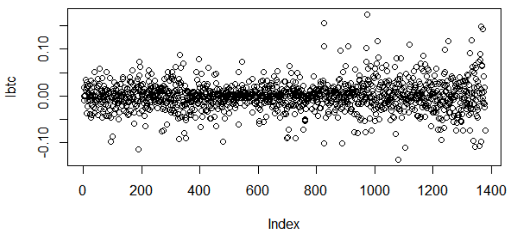
Daily closing prices of the six selected cryptocurrencies are considered from 10 November 2020 to 11 February 2025, providing 1555 data points for each series.

At the outset, the prices of the selected cryptocurrencies are tested for stationarity at levels 0 and 1. The results are appended below.

Testing for stationarity of the prices of the selected cryptocurrencies at levels 0 and 1

Figure 1 **Bitcoin Prices**	**Figure 2** **Bitcoin Prices after First Differencing**





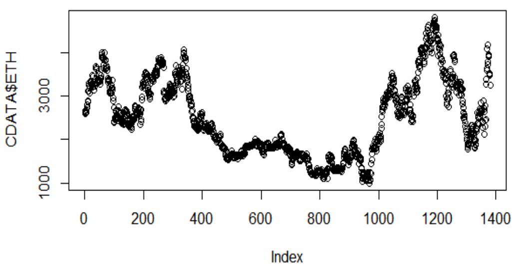
The ADF Test Results for Bitcoin prices before and after first differencing with H_0: The series is non stationary before first differencing which is reflected in Table 1

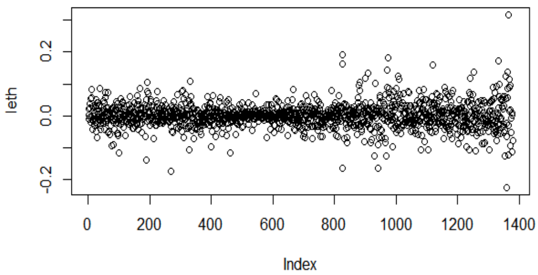
Table 1: ADF test results before and after first differencing of Bitcoin Prices

Particulars	Before 1st Differencing	After First Differencing
ADF Test Statistic	-1.5579	-38.416
Lag Order	0	0
p-Value	0.7654	0.01
Inference	H_0 is failed to be rejected	H_0 is rejected

Figure 1 plot seems to display Bitcoin prices over time, likely exhibiting clear trends or non-stationarity. Figure 2 plot, created by applying first differencing, reveals the modified prices, where trends and non-stationary patterns have been eliminated, resulting in a more random-seeming series, characteristic of stationary data.

Figure 3 **Ethereum Prices**	**Figure 4** **Ethereum Prices after First Differencing**





The ADF Test Results for Ethereum prices before and after first differencing with H_0: The series is not stationary before first differencing which is displayed in Table 2

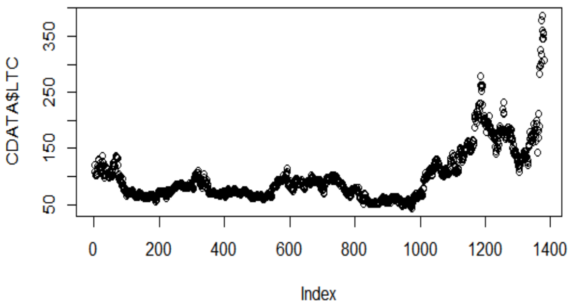
Table 2: ADF test results before and after first differencing of Ethereum Prices

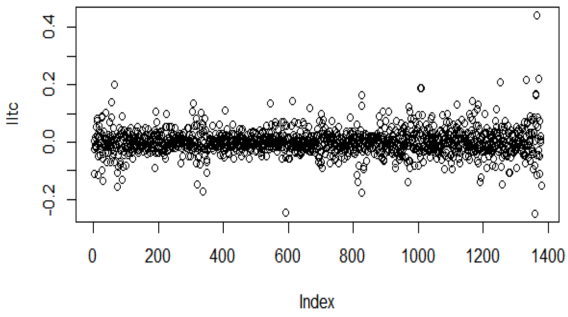
Particulars	Before 1st Differencing	After First Differencing
ADF Test Statistic	-2.1149	-38.918

Lag Order	0	0
p-Value	0.5297	0.01
Inference	H_0 is failed to be rejected	H_0 is rejected

Figure 3 plot seems to display Ethereum prices over time, likely exhibiting clear trends or non-stationarity. Figure 4 plot, created by applying first differencing, reveals the modified prices, where trends and non-stationary patterns have been eliminated, resulting in a more random-seeming series, characteristic of stationary data.

Figure 5 **Litecoin Prices**	**Figure 6** **Litecoin Prices after First Differencing**





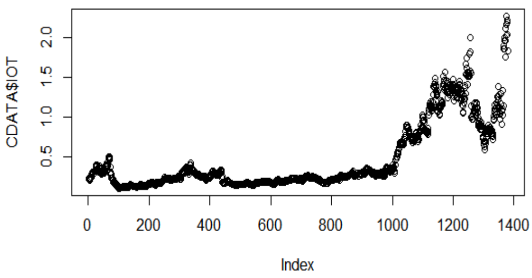
The ADF Test Results for Litecoin prices before and after first differencing with H_0: The series is not stationary before first differencing which is displayed in Table 3

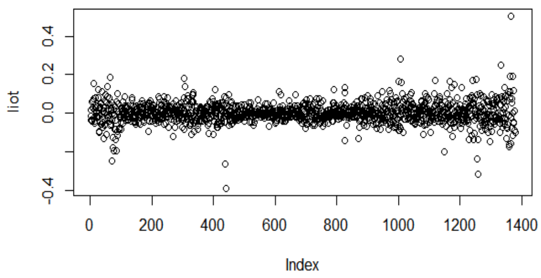
Table 3: ADF test results before and after first differencing of Litecoin Prices

Particulars	Before 1st Differencing	After First Differencing
ADF Test Statistic	-1.9872	-39.037
Lag Order	0	0
p-Value	0.5837	0.01
Inference	H_0 is failed to be rejected	H_0 is rejected

Figure 5 plot seems to display Litecoin prices over time, likely exhibiting clear trends or non-stationarity. Figure 6 plot, created by applying first differencing, reveals the modified prices, where trends and non-stationary patterns have been eliminated, resulting in a more random-seeming series, characteristic of stationary data.

Figure 7 **IOTA Prices**	**Figure 8** **IOTA Prices after First Differencing**





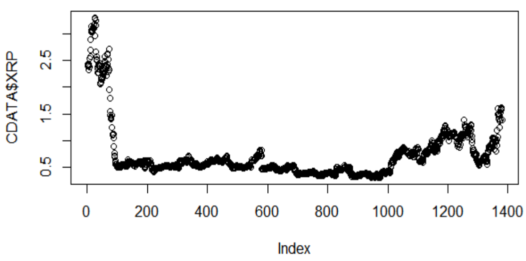
The ADF Test Results for IOTA prices before and after first differencing with H_0: The series is not stationary before first differencing reflected in Table 4

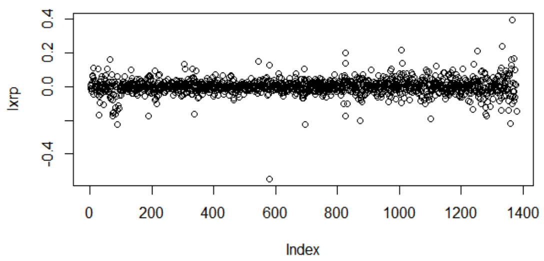
Table 4: ADF test results before and after first differencing of IOTA Prices

a. Particulars	b. Before 1st Differencing	c. After First Differencing
d. ADF Test Statistic	e. -2.4651	f. -38.034
g. Lag Order	h. 0	i. 0
j. p-Value	k. 0.3814	l. 0.01
m. Inference	n. H_0 is failed to be rejected	o. H_0 is rejected

Figure 7 and Figure 8 are supporting the Table 4 results which reflects the removal of non-stationary patterns after first differencing.

Figure 9 **XRP Prices**	**Figure 10** **XRP Prices after First Differencing**





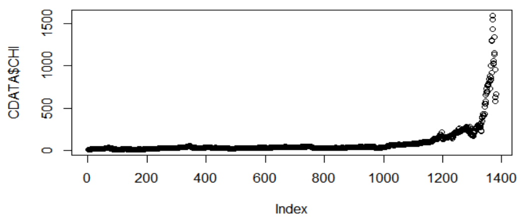
The ADF Test Results for XRP prices before and after first differencing with H_0: The series is not stationary before first differencing reflected in Table 5.

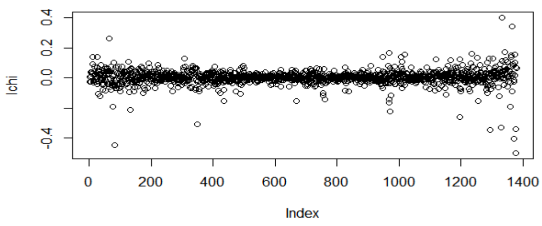
Table 5: ADF test results before and after first differencing of XRP Prices

Particulars	Before 1st Differencing	After First Differencing
ADF Test Statistic	-2.8238	-39.123
Lag Order	0	0
p-Value	0.2296	0.01
Inference	H_0 is failed to be rejected	H_0 is rejected

Figure 9 and Figure 10 are supporting the Table 5 results which reflects the removal of non-stationary patterns after first differencing

Figure 11 **Chia Prices**	**Figure 12** **Chia Prices after First Differencing**





The ADF Test Results for Chia prices before and after first differencing with H_0: The series is not stationary before first differencing are displayed in Table 6

Table 6: ADF test results before and after first differencing of Chia Prices

Particulars	Before 1st Differencing	After First Differencing
ADF Test Statistic	-2.9021	-36.607
Lag Order	0	0
p-Value	0.1965	0.01
Inference	H_0 is failed to be rejected	H_0 is rejected

Figure 11 and Figure 12 are supporting the Table 6 results which reflects the removal of non-stationary patterns after first differencing

As a result, the Engle-Granger 2-Step Method is used to detect cointegration between two time series. Comparisons are made across all pairs without any distinction. The analysis includes three types of pair combinations from the selected cryptocurrencies: green-green, non-green-non-green, and non-green-green. This results in the study of 15 pairs.

The Null Hypotheses H_0, is framed as:

H_0: No cointegration exists between two-time series

H_1: The two-time series are cointegrated.

Here initially the pair is tested for presence of unit root and for severity six tests have been done and they are Augmented Dickey Fuller (ADF) Test, Phillips-Perron (PP) Test, Pantula, Gonzales-Farias and Fuller (PGFF) Test, Elliott, Rothenberg and Stock DF-GLS (ERSD) Test, Johansen's Trace Test (JOT) Test and Schmidt and Phillips Rho (SPR) Test. (see Otoo *et al.*, (2020), Schmidt & Lee (1991) & (Gianfreda *et al.*, (2023)). The purpose is to assess the stationarity of price data of six cryptocurrencies and to examine the long-term movement of the cryptocurrency pair. For robustness, Phillips-Ouliaris (PO) (see Reimers (1992), & Caner (1998)) test for Cointegration is also carried out to validate the previous results. Finally, to find the presence of cointegrating factors among six cryptocurrencies Johansen Test for multivariate cointegration (see Aysan *et al.*, (2021) and Leung & Nguyen (2019)) has been performed.

4. FINDINGS AND ANALYSIS

Initially the pair is tested for presence of unit root. For stringency, the following six tests were done:

- Augmented Dickey Fuller (ADF) Test
- Phillips-Perron (PP) Test
- Pantula, Gonzales-Farias and Fuller (PGFF) Test

- Elliott, Rothenberg and Stock DF-GLS (ERSD) Test
- Johansen's Trace Test (JOT) Test
- Schmidt and Phillips Rho (SPR) Test

The results are appended below.

Cointegration results between Bitcoin and Ethereum

Results of Unit Root Test of the residuals with H_0: There is no cointegration between Bitcoin and Ethereum

Table 7: Cointegration Test results between Bitcoin and Ethereum

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-2.593	0.23846	H_0 is failed to be rejected	Bitcoin and Ethereum are not cointegrated
Phillips-Perron (PP)	-15.561	0.14593	H_0 is failed to be rejected	Bitcoin and Ethereum are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.993	0.38741	H_0 is failed to be rejected	Bitcoin and Ethereum are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.469	0.75593	H_0 is failed to be rejected	Bitcoin and Ethereum are not cointegrated
Johansen's Trace Test (JOT)	**-27.780**	**0.00767**	**H_0 is rejected**	**Bitcoin and Ethereum are cointegrated**
Schmidt and Phillips Rho (SPR)	-10.416	0.44146	H_0 is failed to be rejected	Bitcoin and Ethereum are not cointegrated

From Table 7 it is clear that the majority of tests indicate that Bitcoin (non-green) and Ethereum (non-green) are not cointegrated, only the Johansen's Trace Test suggests that, despite the other tests' results, there is a long-term relationship between the Bitcoin (non-green) and Ethereum (non-green).

Cointegration results between Bitcoin and Litecoin

Results of Unit Root Test of the residuals with H_0: There is no cointegration between Bitcoin and Litecoin

Table 8: Cointegration Test results between Bitcoin and Litecoin

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-0.101	0.98173	H_0 is failed to be rejected	Bitcoin and Litecoin are not cointegrated
Phillips-Perron (PP)	-1.169	0.96056	H_0 is failed to be rejected	Bitcoin and Litecoin are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.997	0.74943	H_0 is failed to be rejected	Bitcoin and Litecoin are not cointegrated

Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.194	0.84072	H_0 is failed to be rejected	Bitcoin and Litecoin are not cointegrated
Johansen's Trace Test (JOT)	-11.512	0.49666	H_0 is rejected	Bitcoin and Litecoin are not cointegrated
Schmidt and Phillips Rho (SPR)	-7.901	0.58516	H_0 is failed to be rejected	Bitcoin and Litecoin are not cointegrated

The results reflected from Table 8 indicates that Bitcoin (non-green) and Litecoin (non-green)are not cointegrated, implying that their prices do not move in tandem over the long term. This means there is no long-term relationship or shared stochastic trend between the two.

Cointegration results between Ethereum and Litecoin

Results of Unit Root Test of the residuals with H_0: There is no cointegration between Ethereum and Litecoin

Table 9: Cointegration Test results between Ethereum and Litecoin

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	0.436	0.99392	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated
Phillips-Perron (PP)	1.954	0.99889	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	1.000	0.94948	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.057	0.87326	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated
Johansen's Trace Test (JOT)	-6.799	0.90778	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated
Schmidt and Phillips Rho (SPR)	-9.465	0.48314	H_0 is failed to be rejected	Ethereum and Litecoin are not cointegrated

The results reflected from Table 9 indicates that Ethereum(non-green) and Litecoin (non-green) are not cointegrated, implying that their prices in long term do not move together.

Cointegration results between IOTA and XRP

Results of Unit Root Test of the residuals with H_0: There is no cointegration between IOTA and XRP

Table 10: Cointegration Test results between IOTA and XRP

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	**-5.851**	**0.00010**	**H_0 is rejected**	**IOTA and XRP are cointegrated**
Phillips-Perron (PfcP)	-13.280	0.21511	H_0 is failed to be rejected	IOTA and XRP are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	1.000	0.97693	H_0 is failed to be rejected	IOTA and XRP are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.029	0.87976	H_0 is failed to be rejected	IOTA and XRP are not cointegrated
Johansen's Trace Test (JOT)	-17.723	0.11319	H_0 is failed to be rejected	IOTA and XRP are not cointegrated
Schmidt and Phillips Rho (SPR)	-9.576	0.47828	H_0 is failed to be rejected	IOTA and XRP are not cointegrated

From table 10, IOT (green) and XRP (green) are found to be cointegrated only by ADF Test and not by any other five tests. ADF test is mainly based on individual time series behavior while the others are based on multiple series long term behavior. So, the co-integration is not so much significant.

Cointegration results between IOTA and Chia

Results of Unit Root Test of the residuals with H_0: There is no cointegration between IOTA and Chia

Table 11: Cointegration Test results between IOTA and Chia

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-2.927	0.12637	H_0 is failed to be rejected	IOTA and Chia are not cointegrated
Phillips-Perron (PP)	**-24.469**	**0.02356**	**H_0 is rejected**	**IOTA and Chia are cointegrated**
Pantula, Gonzales-Farias and Fuller (PGFF)	**0.976**	**0.00765**	**H_0 is rejected**	**IOTA and Chia are cointegrated**
Elliott, Rothenberg and Stock DF-GLS (ERSD)	**-2.503**	**0.04983**	**H_0 is rejected**	**IOTA and Chia are cointegrated**
Johansen's Trace Test (JOT)	**-29.819**	**0.00586**	**H_0 is rejected**	**IOTA and Chia are cointegrated**
Schmidt and Phillips Rho	-8.531	0.53970	H_0 is failed to be rejected	IOTA and Chia are not

(SPR)				cointegrated

Table 11 suggests a long-term relationship between IOT (green) and Chia (green) since they are cointegrated by four out of the six tests i.e. by PP, PGFF, ERSD and JOT tests.

Cointegration results between XRP and Chia

Results of Unit Root Test of the residuals with H_0: There is no cointegration between XRP and Chia.

Table 12: Cointegration Test results between XRP and Chia

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-0.087	0.98224	H_0 is failed to be rejected	XRP and Chia are not cointegrated
Phillips-Perron (PP)	-10.398	0.37128	H_0 is failed to be rejected	XRP and Chia are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.990	0.19792	H_0 is failed to be rejected	XRP and Chia are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.197	0.84021	H_0 is failed to be rejected	XRP and Chia are not cointegrated
Johansen's Trace Test (JOT)	**-22.455**	**0.02503**	**H_0 is rejected**	**XRP and Chia are cointegrated**
Schmidt and Phillips Rho (SPR)	-7.668	0.60202	H_0 is failed to be rejected	XRP and Chia are not cointegrated

From Table 12 it is found that XRP (green) and Chia (green) are cointegrated only under JOT and not by any of the other five tests which reflects a long-term equilibrium relationship between these two green cryptocurrencies.

Cointegration results between BTC and IOT

Results of Unit Root Test of the residuals with H_0: There is no cointegration between BTC and IOT

Table 13: Cointegration Test results between BTC and IOT

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-0.023	0.98463	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated
Phillips-Perron (PP)	-1.700	0.94295	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.977	0.75257	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated

Elliott, Rothenberg and Stock DF-GLS (ERSD)	0.302	0.93137	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated
Johansen's Trace Test (JOT)	-12.592	0.41731	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated
Schmidt and Phillips Rho (SPR)	-3.513	0.89819	H_0 is failed to be rejected	Bitcoin and IOT are not cointegrated

The results reflected from Table 13 indicates that BTC (non-green) and IOT (green) are not cointegrated, implying that their prices in long term do not move together.

Cointegration results between BTC and XRP

Results of Unit Root Test of the residuals with H_0: There is no cointegration between BTC and XRP

Table 14: Cointegration Test results between BTC and XRP

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	**-3.871**	**0.01024**	**H_0 is rejected**	**Bitcoin and XRP are cointegrated**
Phillips-Perron (PP)	-13.011	0.22968	H_0 is failed to be rejected	Bitcoin and XRP are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.994	0.46698	H_0 is failed to be rejected	Bitcoin and XRP are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.899	0.56965	H_0 is failed to be rejected	Bitcoin and XRP are not cointegrated
Johansen's Trace Test (JOT)	-20.208	0.05273	H_0 is failed to be rejected	Bitcoin and XRP are not cointegrated
Schmidt and Phillips Rho (SPR)	-13.820	0.29237	H_0 is failed to be rejected	Bitcoin and XRP are not cointegrated

From table 14, BTC (non-green)and XRP (green) are found to be cointegrated only by ADF Test and not by any other five tests. ADF test is mainly based on individual time series behavior while the others are based on multiple series long term behavior. So, the co-integration is not so much significant.

Cointegration results between BTC and Chia

Results of Unit Root Test of the residuals with H_0: There is no cointegration between BTC and Chia

Table 15: Cointegration Test results between BTC and Chia

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	0.177	0.99071	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated
Phillips-Perron (PP)	-9.109	0.44111	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.990	0.20603	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.836	0.59697	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated
Johansen's Trace Test (JOT)	-19.683	0.06425	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated
Schmidt and Phillips Rho (SPR)	-7.391	0.62201	H_0 is failed to be rejected	Bitcoin and Chia are not cointegrated

The results reflected from Table 15 indicate that BTC (non-green) and Chia (green) are not cointegrated, implying that their prices in long term do not move together.

Cointegration results between ETH and IOT

Results of Unit Root Test of the residuals with H_0: There is no cointegration between ETH and IOT

Table 16: Cointegration Test results between ETH and IOT

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	0.135	0.99018	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated
Phillips-Perron (PP)	-0.806	0.97081	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.997	0.72861	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	0.733	0.96977	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated

Johansen's Trace Test (JOT)	-6.666	0.91465	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated
Schmidt and Phillips Rho (SPR)	-16.085	0.19673	H_0 is failed to be rejected	Ethereum and IOT are not cointegrated

The results from Table 16 indicate that ETH (non-green) and IOT (green) are not cointegrated, implying that their prices in long term do not move together.

Cointegration results between ETH and XRP

Results of Unit Root Test of the residuals with H_0: There is no cointegration between ETH and XRP

Table 17: Cointegration Test results between ETH and XRP

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	**-5.260**	**0.00010**	**H_0 is rejected**	**Ethereum and XRP are cointegrated**
Phillips-Perron (PP)	-14.961	0.16213	H_0 is failed to be rejected	Ethereum and XRP are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	1.000	0.97627	H_0 is failed to be rejected	Ethereum and XRP are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.265	0.82417	H_0 is failed to be rejected	Ethereum and XRP are not cointegrated
Johansen's Trace Test (JOT)	-19.939	0.05864	H_0 is failed to be rejected	Ethereum and XRP are not cointegrated
Schmidt and Phillips Rho (SPR)	-8.448	0.54568	H_0 is failed to be rejected	Ethereum and XRP are not cointegrated

From Table 17, ETH (non-green) and XRP (green) are found to be cointegrated only by ADF Test and not by any other five tests. ADF test is mainly based on individual time series behavior while the others are based on multiple series long term behavior. So, the co-integration is not that much significant.

Cointegration results between ETH and Chia

Results of Unit Root Test of the residuals with H_0: There is no cointegration between ETH and Chia

Table 18: Cointegration Test results between ETH and Chia

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	0.353	0.99289	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated
Phillips-Perron (PP)	-8.885	0.45326	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	0.991	0.21405	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-0.487	0.74801	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated
Johansen's Trace Test (JOT)	-12.744	0.40611	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated
Schmidt and Phillips Rho (SPR)	-8.077	0.57247	H_0 is failed to be rejected	Ethereum and Chia are not cointegrated

The results from Table 18 indicates that ETH (non-green) and Chia (green) are not cointegrated, implying that their prices in long term do not move together.

Cointegration results between Litecoin (LTC) and IOT

Results of Unit Root Test of the residuals with H_0: There is no cointegration between LTC and IOT

Table 19: Cointegration Test results between Litecoin (LTC)and IOT

p. Tests	q. Test Statistic	r. p-Value	s. Results of Testing of Hypotheses	t. Implications from the testing of Hypotheses
u. Augmented Dickey Fuller (ADF)	v. -3.215	w. 0.06663	x. H_0 is failed to be rejected	y. Litecoin and IOT are not cointegrated
z. Phillips-Perron (PP)	**aa. -30.007**	**bb. 0.00925**	**cc. H_0 is rejected**	**dd. Litecoin and IOT are cointegrated**
ee. Pantula, Gonzales-Farias and Fuller (PGFF)	**ff. 0.975**	**gg. 0.00705**	**hh. H_0 is rejected**	**ii. Litecoin and IOT are cointegrated**
jj. Elliott, Rothenberg and Stock DF-GLS (ERSD)	kk. -1.355	ll. 0.37592	mm. H_0 is failed to be rejected	nn. Litecoin and IOT are not cointegrated

oo. Johansen's Trace Test (JOT)	pp. -18.439	qq. 0.09153	rr. H_0 is failed to be rejected	ss. Litecoin and IOT are not cointegrated
tt. Schmidt and Phillips Rho (SPR)	uu. -11.898	vv. 0.37655	ww. H_0 is failed to be rejected	xx. Litecoin and IOT are not cointegrated

The results from Table 19 are inconclusive. While the PP and PGFF tests suggest that Litecoin (non-green) and IOT (green) are cointegrated, the ADF, ERSD, JOT, and SPR tests do not provide evidence of cointegration, implying that there is no long-term relationship between the LTC (non-green) and IOT (green) cryptocurrency.

Cointegration results between Litecoin (LTC) and XRP

Results of Unit Root Test of the residuals with H_0: There is no cointegration between LTC and XRP

Table 20: Cointegration Test results between Litecoin (LTC) and XRP

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	**-5.588**	**0.00010**	**H_0 is rejected**	**Litecoin and XRP are cointegrated**
Phillips-Perron (PP)	-12.298	0.26833	H_0 is failed to be rejected	Litecoin and XRP are not cointegrated
Pantula, Gonzales-Farias and Fuller (PGFF)	1.000	0.98251	H_0 is failed to be rejected	Litecoin and XRP are not cointegrated
Elliott, Rothenberg and Stock DF-GLS (ERSD)	0.230	0.92210	H_0 is failed to be rejected	Litecoin and XRP are not cointegrated
Johansen's Trace Test (JOT)	-15.744	0.19222	H_0 is failed to be rejected	Litecoin and XRP are not cointegrated
Schmidt and Phillips Rho (SPR)	-8.876	0.51476	H_0 is failed to be rejected	Litecoin and XRP are not cointegrated

From Table 20, LTC (non-green) and XRP (green) are found to be cointegrated only by ADF Test and not by any other five tests. ADF test is mainly based on individual time series behavior while the others are based on multiple series long term behavior. So, the co-integration is not so much significant.

Cointegration results between Litecoin (LTC) and Chia

Results of Unit Root Test of the residuals with H_0: There is no cointegration between LTC and Chia

Table 21: Cointegration Test results between Litecoin (LTC) and Chia

Tests	Test Statistic	p-Value	Results of Testing of Hypotheses	Implications from the testing of Hypotheses
Augmented Dickey Fuller (ADF)	-2.854	0.14777	H_0 is failed to be rejected	Litecoin and Chia are not cointegrated

Phillips-Perron (PP)	**-33.796**	**0.00722**	**H_0 is rejected**	**Litecoin and Chia are cointegrated**
Pantula, Gonzales-Farias and Fuller (PGFF)	**0.970**	**0.00361**	**H_0 is failed to be rejected**	**Litecoin and Chia are cointegrated**
Elliott, Rothenberg and Stock DF-GLS (ERSD)	-1.890	0.17010	H_0 is failed to be rejected	Litecoin and Chia are not cointegrated
Johansen's Trace Test (JOT)	**-55.996**	**0.00010**	**H_0 is failed to be rejected**	**Litecoin and Chia are cointegrated**
Schmidt and Phillips Rho (SPR)	-17.647	0.16363	H_0 is failed to be rejected	Litecoin and Chia are not cointegrated

From Table 21, it is found that most of the tests (PP, PGFF, and JOT) indicate that Litecoin (non-green) and Chia (green) are cointegrated, whereas three tests (ADF, ERSD, and SPR) fail to find evidence of cointegration between these two cryptocurrencies.

Cointegration Results for all pairs of cryptocurrencies through Phillips-Ouliaris (PO) Test

In addition to the six tests as mentioned above, Phillips-Ouliaris (PO) Test for Cointegration are also carried out to see whether the results obtained above are corroborated by a more rigorous test.

Results of Phillips-Ouliaris Test for Cointegration are given below which have been carried out with H_0: There is no cointegration between the two-time series considered.

Table 22: Cointegration Results for all pairs of cryptocurrencies through Phillips-Ouliaris (PO) Test

Cryptocurrencies Pair	Phillips-Ouliaris Demeaned statistic	Truncation lag parameter	p-Value	Result of testing of Hypotheses	Inference
BTC-ETH	-11.5340	13	0.15000	H_0 is failed to be rejected	There is no cointegration
BTC-LTC	-4.5566	13	0.15000	H_0 is failed to be rejected	There is no cointegration
ETH-LTC	-5.0468	13	0.15000	H_0 is failed to be rejected	There is no cointegration
IOT-XRP	-2.9205	13	0.15000	H_0 is failed to be rejected	There is no cointegration
IOT-CHI	-16.3210	13	0.11620	H_0 is failed to be rejected	There is no cointegration
XRP-CHI	-13.9310	13	0.15000	H_0 is failed to be rejected	There is no cointegration
BTC-IOT	-5.7033	13	0.15000	H_0 is failed to be rejected	There is no cointegration

BTC-XRP	-6.4632	13	0.15000	H_0 is failed to be rejected	There is no cointegration
BTC-CHI	-5.8158	13	0.15000	H_0 is failed to be rejected	There is no cointegration
ETH-IOT	-7.8899	13	0.15000	H_0 is failed to be rejected	There is no cointegration
ETH-XRP	-11.5180	13	0.15000	H_0 is failed to be rejected	There is no cointegration
ETH-CHI	-8.8860	13	0.15000	H_0 is failed to be rejected	There is no cointegration
LTC-IOT	**-31.3470**	**13**	**0.01000**	**H_0 is rejected**	**There is cointegration**
LTC-XRP	-2.6743	13	0.15000	H_0 is failed to be rejected	There is no cointegration
LTC-CHI	**-28.0220**	**13**	**0.01099**	**H_0 is rejected**	**There is cointegration**

It is evident from Table 22 that LTC-IOT and LTC-CHI are cointegrated, as both tests reject the null hypothesis (H_0) with p-values of 0.01000 and 0.01099, respectively. Most other pairs, including BTC-ETH, BTC-LTC, ETH-LTC, IOT-XRP, XRP-CHI, BTC-IOT, BTC-XRP, BTC-CHI, ETH-IOT, ETH-XRP, and ETH-CHI, fails to reject the null hypothesis (H_0), indicating no cointegration between these pairs according to the Phillips-Ouliaris test. LTC-IOT and LTC-CHI are the only pairs in this group that show cointegration, implying a long-term equilibrium relationship between them. The remaining pairs do not exhibit cointegration, suggesting their prices do not follow a long-term stable relationship.

Multivariate cointegration results through Johansen Test

As a confirmatory exercise for the results obtained in the foregoing statistical tests for all the possible combinations of bivariate cointegration between the selected six cryptocurrencies, we subject the data set for Johansen Test for multivariate cointegration. As the number of variables is six, there can be upto (6 – 1) or 5 cointegrating factors.

To cover all the possible scenarios, the test has been done under two assumptions i.e.

1. Constant exists in the cointegrating; and
2. There is no intercept in the cointegration

Each of the two the assumption have been tested by using:

yy. Trace statistic; and

zz. Eigen statistic

In all the four situations, the framed hypotheses, tested at 5% Level of Significance, is:

H_0 : There is no Cointegrating Factor

The results are appended below.

Table 23: Multivariate cointegration results through Johansen Test

	Trace Statistic		Eigen Statistic	
	Intercept	No Intercept	Intercept	No Intercept

	Test	5%	Test	5%	Test	5%	Test	5%
$r \leq 5$	2.61	9.24	1.38	8.18	2.61	9.24	1.38	8.18
$r \leq 4$	7.78	19.96	6.09	17.95	5.16	15.67	4.71	14.90
$r \leq 3$	21.74	34.91	19.43	31.52	13.97	22.00	13.34	21.07
$r \leq 2$	41.05	53.12	37.78	48.28	19.31	28.14	18.35	27.14
$r \leq 1$	81.50	76.07	76.33	70.60	40.45	34.40	38.55	33.32
$r \leq 0$	166.19	102.14	160.42	90.39	84.69	40.30	84.09	39.43

From Table 23, it is observed that under all the four possible scenarios the test statistic is greater than the critical value at 5% till $r \leq 1$. From $r \leq 2$, the test statistic is found to be less than the critical value (5%.) This indicates that there are up to two cointegrating factors present between the six cryptocurrencies considered for this study. This result validates the findings from ADF, PP, PGFF, ERSD, JOT, SPR tests and Phillips-Ouliaris test.

The synopsis of the tests of 15 possible cointegrations between the six selected cryptocurrencies are contained in Table 24 below. The blank cells indicate no cointegration while the filled-in cells indicate cointegration between the concerned pair of cryptocurrencies and also the tests which confirm such cointegration.

Table 24: Summarized Cointegration Results between six cryptocurrencies

	BTC	**ETH**	**LTC**	**IOT**	**XRP**	**CHI**
BTC		**JOT**	******	************	**ADF**	********************
ETH			******	************	**ADF**	********************
LTC				**PP-PGFF-PO**	**ADF**	**PO-PP-PGFF-JOT**
IOT					**ADF**	**PP-PGFF-ERSD-JOT**
XRP						**JOT**
CHI						

The findings from Table 24 are jotted down below:

- ❖ The green cryptocurrency **CHI** demonstrates significant long-term co-movement with both **LTC** (a non-green asset) and **IOT** (another green asset), with the cointegration confirmed by four out of seven statistical tests.
- ❖ **IOT** (green) is also found to be cointegrated with **LTC** (non-green).
- ❖ Among the non-green cryptocurrencies analysed, **LTC** is unique in showing cointegration with all three green cryptocurrencies (**CHI, IOT, and XRP**), though the strength of these relationships varies.
- ❖ The long-term relationship between **LTC** and **XRP** (green) appears weak, as it is only supported by the ADF test and not by the other six tests performed.
- ❖ Within the green cryptocurrency group, **IOT** is significantly cointegrated with **CHI**.
- ❖ The cointegration between **IOT** and **XRP** (green) is not strong, confirmed solely by the ADF test, indicating a weak

connection.

- The observed weak cointegration between **IOT** and **LTC** suggests limited potential for effective pairs trading strategies due to the possibility of substantial and prolonged deviations from their equilibrium. While this pair could offer minor diversification benefits, it's not recommended as a central element for strategies relying heavily on long-term convergence.
- **XRP** (green) shows weak cointegration with several non-green cryptocurrencies (**BTC, ETH, LTC**) and also with **IOT** (green), pointing to a broad but tenuous link influenced by wider market sentiment and macroeconomic factors. This makes identifying consistently profitable trading pairs challenging, but **XRP** might aid portfolio diversification through its partial co-movement with major currencies. The weak connection with **IOT** restricts pairs trading opportunities between them.
- **CHI's** (green) strong cointegration with **LTC** (non-green) and **IOT** (green) offers more promising prospects for pairs trading, as price deviations from their equilibrium are likely to be smaller and correct more predictably, potentially yielding more frequent and profitable trading signals for market-neutral strategies.
- The weak cointegration between **CHI** (green) and **XRP** (green) implies that including both in a portfolio can provide better diversification benefits compared to pairing **CHI** exclusively with **LTC** or **IOT**.
- For investors interested in environmentally conscious portfolios, green cryptocurrencies like **IOT, XRP, and CHI** are available, but their varying degrees of cointegration with non-green assets complicate the creation of a portfolio that is both truly "green" and adequately diversified.
- Investors primarily focused on capturing relative value might consider allocating capital to strongly cointegrated green-non-green pairs like **CHI-LTC** and **CHI-IOT**, accepting indirect exposure to the environmental impact of the non-green components.
- Alternatively, a more diversified approach may incorporate weakly cointegrated pairs involving green cryptocurrencies (such as **IOT-LTC** and **XRP** with other coins) to balance environmental preferences with broader market exposure, acknowledging that this might result in less effective pairs trading.

The results effectively shows that weaker cointegration between cryptocurrencies imply portfolio diversification and the stronger co-integration between them imply long term equilibrium relationship for pair trading similar to the studies done by Pham *et al.*, (2022), Ilgin (2024), Ali F *et al.*, (2024) while the study contradicts with Li (2024) and Tadi *et al.*, (2025).

5. CONCLUSION

Based on objectives of the study, green cryptocurrencies (CHI, IOT, XRP) display diverse long-term equilibrium relationships with non-green counterparts such as LTC, affecting trading and portfolio decisions. CHI (green) stands out with strong cointegration to both LTC (non-green) and IOT (green), offering promising pairs trading setups. LTC (non-green) uniquely connects with all three green assets, albeit weakly with XRP (green). IOT (green) links strongly with CHI (green) but weakly with XRP (green) and LTC (non-green), limiting robust pairs trading for these latter pairs. XRP's (green) weak cointegration across the board implies broad market influence and challenges for consistent pairs trading, though it might support diversification. Building a truly green, diversified portfolio is difficult due to the varied interconnectedness. Investors can target strong green-non-green pairs (CHI-LTC, CHI-IOT) for relative value (accepting some non-green exposure) or use weakly cointegrated green pairs with non-green (IOT-LTC, XRP with others) for broader diversification, potentially with less effective pairs trading. This research underscores the complexity of building truly green cryptocurrency portfolios and highlights the need for further investigation into the underlying drivers of these cointegration dynamics to facilitate more informed and sustainable investment decisions in this rapidly evolving asset class.

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