



## Side Effects and Interactions: Exploring the Relationship between Dirty and Green Cryptocurrencies and Clean Energy Stock Indices

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### ABSTRACT

This study aimed to assess whether renewable energy cryptocurrencies such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA), and Stellar (XLM) can be considered hedging assets and safe havens for cryptocurrencies classified as “dirty,” such as Bitcoin Cash (BCH), Bitcoin (BTC) Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC) and the clean energy stock indices WILDERHILL Clean Energy (ECO) and Clean Energy Fuels (CLNE), from July 6, 2018, to July 6, 2023. The results show that the movements decreased significantly during the Stress period, which includes the events of 2020 and 2022. The Cardano cryptocurrency shows moderate movements, indicating stability and diversification, while Stellar shows moderate movements that suggest resilience. Conversely, XRP shows varied movements, requiring some caution, while IOTA stands out for significant movements associated with sustainable assets. These results interest players operating in these markets when they want to diversify and rebalance their portfolios.

**Keywords:** Cryptocurrencies, Clean Energies, Comovements, Safe Haven, Portfolio Rebalancing

**JEL Classifications:** C32, C38, G11, G14, Q42

## 1. INTRODUCTION

The rapid growth of cryptocurrencies has generated increasing demand. However, due to their significant environmental impact, traditional cryptocurrencies, characterised by high energy consumption and often called “dirty,” have been the subject of concern. These cryptocurrencies rely on the consensus mechanism known as “Proof of Work,” which has resulted in substantial environmental damage and raised significant concerns (Dias et al., 2023).

Literature on the link between cryptocurrencies and green markets is relatively scarce, even after the latter market has witnessed a considerable surge in recent years, especially for clean energy stocks that are sustainable alternatives to traditional carbon-intensive energy such as electricity, oil, and coal. Few papers can be considered closely related to this research. The authors (Symitsi

and Chalvatzis, 2018) show long-term volatility spillovers from Bitcoin to the energy markets and short-term volatility spillovers from the technology market to Bitcoin. Furthermore, the authors (Corbet et al., 2021) do not find a significant link between Bitcoin price volatility and the main green ETF markets. Complementarily, the authors (Naeem and Karim, 2021) do not identify a dependency between clean energy and Bitcoin but suggest that clean energy can be a diversification tool for Bitcoin. Meanwhile, the authors (Pham et al., 2021) also propose that green investments can offer diversification benefits for cryptocurrencies, especially during non-crisis periods. However, the question remains whether clean energy is a direct hedge or safe haven for cryptocurrencies such as Bitcoin or Ethereum.

If one discovers that certain clean energy stocks can act as a safe haven or hedge against certain types of cryptocurrencies, or vice

versa, this has implications for investors. For example, it might be practical to hedge against cryptocurrency declines using clean energy stocks or vice versa. However, the form of the currency matters. If it turns out that only dirty cryptocurrencies are a useful hedge or safe haven against clean energy, it suggests that the economic incentive to invest in clean energy will work against the ecological argument. Furthermore, although there has been much research into the interconnectedness of cryptocurrencies with other financial assets, the debate about whether the Bitcoin or cryptocurrency market is isolated from other assets (markets) is not over.

The rest of the paper is organised as follows. Section 2 provides the literature review; section 3 describes the data and the methodology used in the analysis. Section 4 shows the empirical results, and section 5 concludes and discusses the implications of this study.

## 2. LITERATURE REVIEW

Several studies have explored the potential of clean energy as a safe alternative to dirty energy. That analysis covers environmental issues such as sustainability and climate impact, as well as considerations related to energy security, technological innovation, stimulating a sustainable economy and the effectiveness of public policies. The term “safe haven” highlights the perception that the transition to clean energy sources can offer significant benefits, both environmental and economic, as opposed to traditional energy sources (Dias et al., 2023; Dias et al., 2023; Dias et al., 2023; Dias et al., 2023).

The studies by the authors (Angelini et al., 2022; Arfaoui et al., 2023; Ren and Lucey, 2022) explore the environmental and sustainability implications of the high energy consumption of cryptocurrencies, analysing whether clean energy stock indices can function as hedging assets against “dirty” assets. The authors (Angelini et al., 2022) identify financial contagion between clean energy and oil prices, with symmetrical and asymmetrical effects before the Paris Agreement. The authors (Ren and Lucey, 2022) indicate that clean energy does not act as a hedge for cryptocurrencies but can be considered a weak safe haven during market conditions, especially for “dirty” cryptocurrencies. Additionally, the authors (Arfaoui et al., 2023) reveal the importance of sustainable investments, such as the DJSI and ESG indices, during the COVID-19 pandemic, highlighting green bonds as potential sources of investment diversification.

In more recent studies, the authors (Farid et al., 2023; Sharif et al., 2023) explore the hedge and safe haven properties of clean energy stock indices against different asset classes. The authors (Sharif et al., 2023) investigated the correlations between green economy indices and dirty and clean cryptocurrencies in the US, European, and Asian markets from November 2017 to April 2022. The authors found strong comovements between green economy indices and clean cryptocurrencies during the 2020 pandemic. However, they raised doubts about the effectiveness of hedging and safe haven strategies, especially in Asia. The authors (Farid et al., 2023) examined the comovements between clean and dirty energy indices before and during the 2020 pandemic, revealing

weak short- and long-term links. They highlight a remarkable decoupling between the two energy markets, indicating that the clean energy market was relatively isolated during the pandemic, highlighting the benefits of portfolio diversification in the clean and dirty energy markets.

Studies on the hedging and safe haven properties of clean energy stock indices compared to energy-intensive and potentially “dirty” cryptocurrencies are gaining importance due to the recognition of the adverse environmental impacts associated with the high energy consumption of these cryptocurrencies. The growing interest of policymakers and market participants in sustainable and environmentally friendly investments drives this line of study. Understanding the hedging and safe-haven potential of clean energy stocks against these cryptocurrencies is crucial for investors seeking to manage risk and promote sustainable investment practices. By examining correlations, dependencies, and spillover effects between clean energy stocks and energy-intensive cryptocurrencies, researchers can assess whether clean energy stock indices are effective as hedges or safe havens during market uncertainty or crisis periods.

## 3. MATERIALS AND METHODS

### 3.1. Data

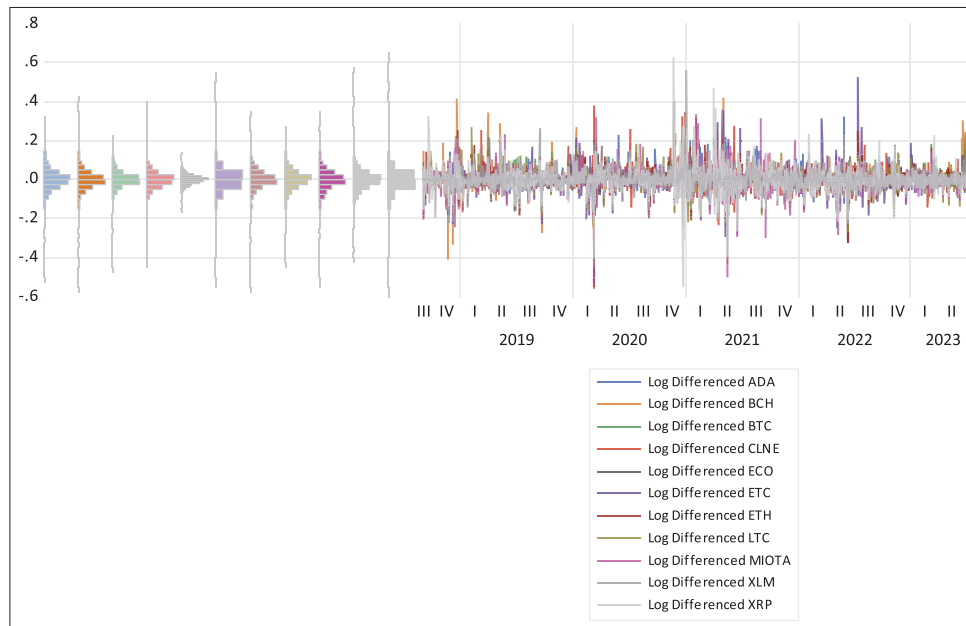
The sample data are the daily index prices of renewable energy cryptocurrencies such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA) and Stellar (XLM), cryptocurrencies classified as “dirty” such as Bitcoin Cash (BCH), Bitcoin (BTC) Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC) and the clean energy stock indices WIL-DERHILL Clean Energy (ECO) and Clean Energy Fuels (CLNE), from July 6, 2018 to July 6, 2023. The sample was divided into two sub-periods to provide more robustness to the study: Tranquil, which covers the period from July 6, 2018, to December 31, 2019, and Stress, which covers the years from January 2020 to July 2023. The daily quotations are in local currency to minimise exchange rate distortions that may occur and were retrieved from the Thomson Reuters Eikon database.

### 3.2. Methodology

This research will be developed in different stages. The panel unit root tests of the authors (Breitung, 2000; Levin et al., 2002) will be used to validate the stationarity of the time series and to validate the results, the tests of the authors (Dickey and Fuller, 1981; Phillips and Perron, 1988) with Fisher Chi-square transformation will be used. An IRF (Impulse Response Function) econometric model with Monte Carlo simulations (1000 repetitions) will be used to answer the research question, which involves specifying a VAR model, identifying shocks to the variables, estimating the parameters with real data, and simulating the impact by introducing random shocks. In addition, Monte Carlo simulations generate impulse response distributions, thus validating the robustness of the results.

## 4. RESULTS

Figure 1 shows the fluctuations of renewable energy cryptocurrencies, in levels, such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA),

**Figure 1:** Evolution, in levels, of the fluctuations of the markets analysed from July 6, 2018, to July 6, 2023

Source: Own elaboration

Note: Thomson Reuters Eikon: 1540 time data

and Stellar (XLM), cryptocurrencies classified as “dirty” such as Bitcoin Cash (BCH), Bitcoin (BTC) Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC) and the clean energy stock indices WILDERHILL Clean Energy (ECO) and Clean Energy Fuels (CLNE), from July 6, 2018, to July 6, 2023. Through graphical observation, growth peaks and significant falls can be seen, highlighting the presence of structural breaks. In 2021, cryptocurrencies experienced significant developments and events that shaped their market and overall perception. Bitcoin reached an all-time high price in April 2021, surpassing \$60,000, with Ethereum (ETH) and Ethereum Classic (ETC) following the same trend.

Table 1 shows the results of the panel unit root tests of the authors (Breitung, 2000; Levin et al., 2002), and for validation, the tests of the authors (Dickey and Fuller, 1981; Phillips and Perron, 1988) with Fisher Chi-square transformation. The intersection tests are robust to the level of lag of each time series until it reaches equilibrium (mean 0 and variance 1). The results show that the time series have unit roots when estimating the original price series. The logarithmic transformation in first differences had to be applied to achieve stationarity, and the null hypothesis was rejected at a significance level of 1%.

Tables 2 and 3 show the results of the VAR Lag Order Selection Criteria model and the VAR Residual Serial Correlation LM test for the Tranquil sub-period. In Table 2, the LR information criterion: sequential modified LR test statistic shows a 9-day lag for estimating the VAR model. Table 3 shows the results of the VAR Residual Serial Correlation LM and shows that the test validates the absence of autocorrelation with a 10-day lag, thus validating the VAR Lag Order Selection Criteria test at 9 lags.

Figure 2 shows the results of the IRF with Monte Carlo simulations (1000 repetitions) to understand whether renewable energy cryptocurrencies, such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA), and Stellar (XLM), can be considered hedging assets and safe havens for cryptocurrencies classified as “dirty,” such as Bitcoin Cash (BCH), Bitcoin (BTC) Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC) and the clean energy stock indices WILDERHILL Clean Energy (ECO) and Clean Energy Fuels (CLNE), in the tranquil period.

Overall, it was found that sustainable digital currencies comove among themselves but are divided into strong comovements where there is no possibility of hedging, and moderate comovements where they are classified as a weak hedging hypothesis.

Cardano (ADA) can be considered a (weak) hedging asset with the digital currencies BCH, BTC, ETC, and with the sustainable energy stock indices CLNE, ECO, but compared to the digital currencies ETH, LTC, MIOTA, XLM, and XRP the comovements are strong, thus suggesting that there are no hedging characteristics. The digital currency XRP cannot be considered a hedging asset for the digital currencies ADA, BCH, ETC, ETH, LTC, MIOTA, XLM, and for the sustainable energy indices CLNE and ECO because the comovements are very strong, but concerning the cryptocurrency BTC the smaller comovements are of lesser extent, which suggests that it could be a weak hedging asset. The MIOTA cryptocurrency shows strong comovements with the digital currencies ADA, BCH, BTC, ETH, LTC, XLM, and the CLNE and ECO energy indices, so there is no possibility of it being a hedging asset, but in relation to the ETC and XRP cryptos the comovements are less pronounced, which could be considered a weak hedging asset. Regarding the Stellar cryptocurrency (XLM), there were strong comovements with the digital currencies ADA,

**Table 1: Summary table of the unit root tests for the markets analysed from July 6, 2018, to July 6, 2023**

| Group unit root test: Summary                          |           |         |                |       |
|--|-----------|---------|----------------|-------|
| Method   | Statistic | Prob.** | Cross-sections | Obs   |
| Null: Unit root (assumes common unit root process)     |           |         |                |       |
| Levin, Lin and Chu t*                                  | -161.94   | 0.000   | 11             | 13346 |
| Breitung t-stat  | -58.36    | 0.000   | 11             | 13335 |
| Null: Unit root (assumes individual unit root process) |           |         |                |       |
| Im, Pesaran and Shin W-stat                            | -100.41   | 0.000   | 11             | 13346 |
| ADF - Fisher Chi-square                                | 2445.92   | 0.000   | 11             | 13346 |
| PP - Fisher Chi-square                                 | 2897.29   | 0.000   | 11             | 13376 |

Source: Own Elaboration. \*\*Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality

**Table 2: VAR lag order selection criteria, Tranquil period**

| Lag | LogL    | LR               | FPE      | AIC       | SC        | HQ        |
|-----|---------|------------------|----------|-----------|-----------|-----------|
| 9   | 8157.44 | <b>148.3984*</b> | 4.78e-33 | -43.43044 | -30.62365 | -38.31923 |
| 10  | 8251.64 | 124.0504         | 6.16e-33 | -43.26550 | -29.04996 | -37.59206 |

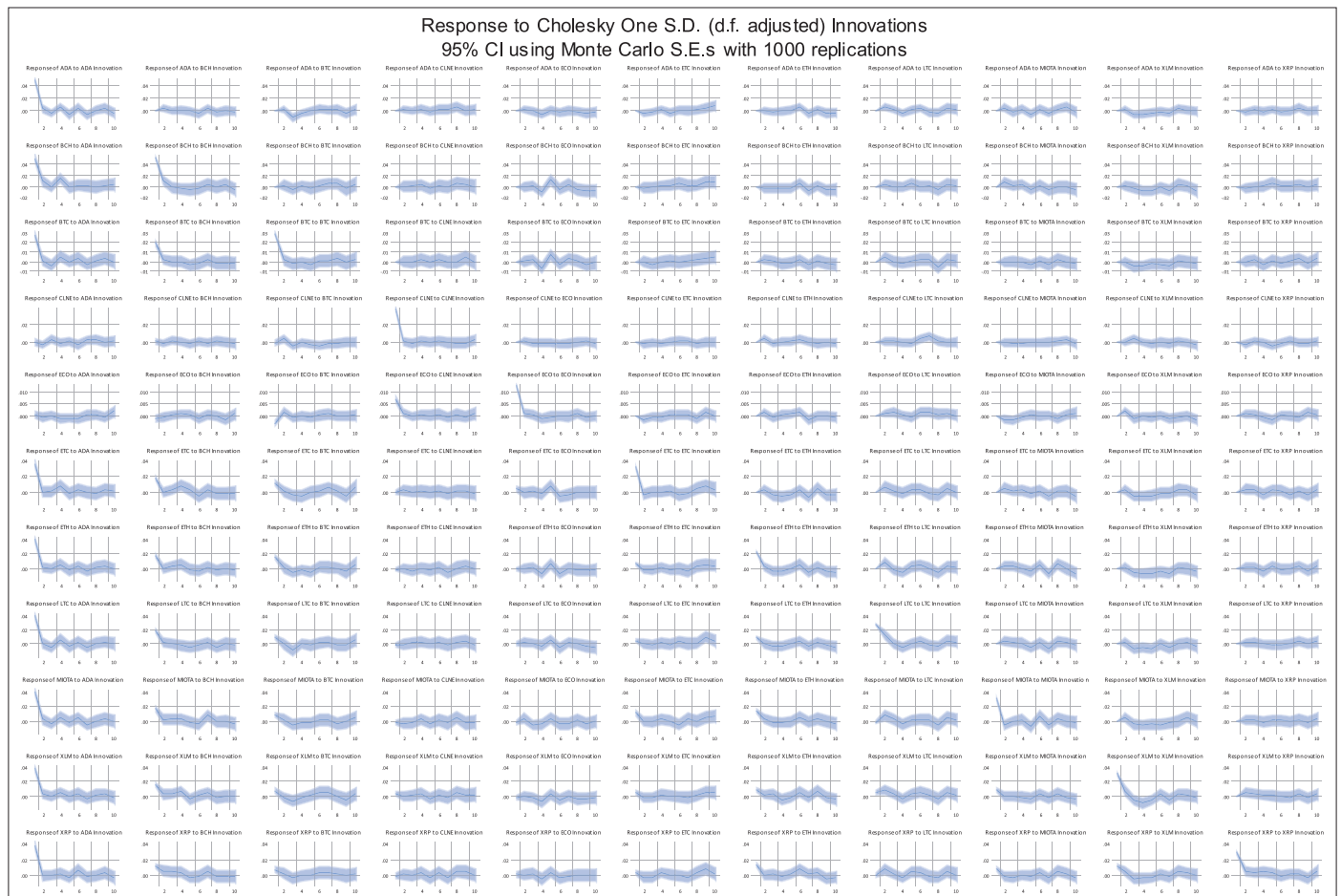
Source: Own Elaboration. Note: Data was worked on by the authors (software: Eviews12). \*Indicates lag order selected by the criterion. LR: Sequential modified, LR: Sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

**Table 3: VAR Residual Serial Correlation LM Tests, Tranquil period**

| Lag | LRE* stat | df  | Prob.  | Rao F-stat | df            | Prob.  |
|-----|-----------|-----|--------|------------|---------------|--------|
| 10  | 117.86    | 121 | 0.5637 | 0.97       | (121, 1626.2) | 0.5649 |

Source: Own Elaboration. Note: Data was worked on by the authors (software: Eviews12)

**Figure 2: Summary graphs for the estimation of the IRF model, with monte carlo simulations (1000 repetitions), for the tranquil period**



Source: Own elaboration

BCH, BTC, ETH, LTC, and MIOTA, and with the green energy indices CLNE and ECO, while with the digital currencies ETC and XLM, the comovements were moderate, which could be suggested as a weak hedging asset.

The results for the Stress sub-period of the VAR model are shown in Tables 4 and 5. In Table 4, the LR information criterion, represented by the modified LR sequential test statistic, shows that the VAR model is best estimated with a lag of 8 days. In Table 5, which shows the results of the LM Serial Residual Correlation test for the VAR, the test confirms the absence of autocorrelation with a lag of 9 days.

**Table 4: VAR lag order selection criteria, stress period**

| Lag | LogL     | LR               | FPE      | AIC       | SC        | HQ        |
|-----|----------|------------------|----------|-----------|-----------|-----------|
| 8   | 18582.33 | <b>162.9357*</b> | 8.55e-32 | -40.32837 | -34.97702 | -38.28113 |
| 9   | 18662.27 | 141.5640         | 9.42e-32 | -40.23430 | -34.22155 | -37.93403 |
| 10  | 18739.92 | 135.5591         | 1.04e-31 | -40.13499 | -33.46084 | -37.58170 |

Source: Own elaboration. Data was worked on by the authors (software: Eviews12). \*Indicates lag order selected by the criterion. LR: Sequential modified, LR: Sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

**Table 5: VAR residual serial correlation LM tests, stress period**

| Lag | LRE* stat | df  | Prob.  | Rao F-stat | df            | Prob.  |
|-----|-----------|-----|--------|------------|---------------|--------|
| 9   | 124.60    | 121 | 0.3926 | 1.03       | (121, 6027.1) | 0.3927 |

Source: Own elaboration. Note: Data was worked on by the authors (software: Eviews12)

Figure 3 shows the results of the IRF with Monte Carlo simulations (1000 repetitions) during the stress period. Overall, the comovements between sustainable crypto-currencies such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA), and Stellar (XLM), with dirty cryptocurrencies (Bitcoin Cash, Bitcoin, Litecoin, Ethereum, Ethereum Classic) and with clean energy stock indices (WILDERHILL Clean Energy, Clean Energy Fuels) decreased significantly. Cardano (ADA) now has moderate comovements with the digital currencies BCH, BTC, ETH, MIOTA, and XLM, and for the sustainable energy indices CLNE and ECO. Concerning the digital currencies ETC, LTC, and XRP, we suggest some caution either in hedging or safe haven.

**Figure 3: Estimation of the IRF model with monte carlo simulations (1000 repetitions), summary graphs for the stress period**



Source: Own elaboration

The digital currency XLM has moderate comovements with the cryptocurrencies ADA, BCH, CLNE, ECO, MIOTA, and XRP, and with the energy indices CLNE and ECO, while the comovements of the currencies BTC, ETC, ETH, and LTC are weak, which suggests that they have some safe haven characteristics. The digital currency XRP shows moderate comovements with the cryptocurrencies ADA, BCH, CLNE, ETC, ETH, MIOTA, and XLM, strong movements with LTC, and weak ones with BTC and ECO. The cryptocurrency IOTA (MIO-TA) shows strong comovements with BCH, XLM, XRP, and the CLNE index, and moderate comovements with the digital currencies ADA, BTC, ETC, ETH, LTC, and the ECO index.

## 5. CONCLUSION

This study aimed to assess whether renewable energy cryptocurrencies such as Cardano (ADA), Ripple (XRP), IOTA (MIOTA), and Stellar (XLM) can be considered hedging assets and safe havens for cryptocurrencies classified as “dirty,” such as Bitcoin Cash (BCH), Bitcoin (BTC) Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC) and the clean energy stock indices WILDERHILL Clean Energy (ECO) and Clean Energy Fuels (CLNE). In conclusion, a significant decrease in global movements during the stress period was observed between the sustainable cryptocurrencies (Cardano, Ripple, IOTA, Stellar) and those considered less sustainable (Bitcoin Cash, Bitcoin, Litecoin, Ethereum, Ethereum Classic), as well as with the clean energy stock indices. Cardano showed moderate movements, suggesting stability and diversification, while Stellar showed moderate movements, indicating resilience. XRP had varied comovements, calling for caution, while the digital currency IOTA stands out as having strong comovements with sustainable assets.

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