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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) Litcoin (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 carbonintensive 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

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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).

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 ESGL 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) Litcoin (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 ran-dom 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) Litcoin (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. 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) Litcoin (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 oury of 2010, to oury of 2023

Group unit root test: Summary										
Method	Statistic Prob.** Cross-sections									
Null: Unit root (assumes common un	nit root process)									
Levin, Lin and Chu t*	-161.94	0.000	11	13346						
Breitung t-stat	-58.36	0.000	11	13335						
		0.000								
Null: Unit root (assumes individual u	init 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	148.3984*	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

Response to Cholesky One S.D. (d.f. adjusted) Innovations 95% CI using Monte Carlo S.E.s with 1000 replications										
Response of AGA to ADA is novation	Reponse of AGA to BCH Isnovation	Response of ADA to BTC Isnovation	Response of ADA to CLNE Innovation	Response of ADA to ICO Innovation	Response of ADA to EIC Innovation	Response of ADA to ETH Innovation	Response of ADA to LTC Innovation	Reponse of ADA to MCRA knows ba	Response of ADA to XUM Innovation	Reponse of ADA to XRP Innovation
Response of BCH to ADA Isnovation	Response of BCH to BCH isnovation	Response of BCH to BTC Isnovation	Response of BCH to CLNE knowline	Response of BCH to BCO Innovation	Response of BCH to ETC Innovation	Response of BCH to ETH Innovation	Response of BCH to LTC Innovation	Reponse of BCH to MOTA knows ion	Response of BCH to XLM Innovation	Response of BCH to XRP Innovation
Reponse of BTC to ADA Innovation	Response of BTC to BCH Innovation	Response of B/C to B/C hnowthin 42 41 41 42 41 41 42 4 4 4 4 4 4 4 4 4 4 4 4 4	Response of BTC to CLNE innovation	Response of 81C to ECO Innovation	Response of BTC to ETC Innovation	Response of BTC to ETH Innovation	Response of BTC to LTC Innovation	Response of BTC to MIOTA Innovation	Response of BTC to XLM knowthin 42 41 41 41 42 4 6 8 2 4 6 8 20	Response of BTC to XRP Innovation
Reponse of CLNE to ADA Innovation	Response of CUNE to BCH Innovation	Response of CLNE to BTC innovation	Response of CLME to CLME innovation	Response of CLNE to ECO Innovation 01 02 2 4 6 8 10	Response of CIMI to ETC Innovation 02 02 2 4 6 8 50	Response of CLMI to CTH Innovation	Response of CLNE to LTC innovation	Response of CLNE to MOTA hnows bin	Reponse of EUK to XUM knowline 42 2 4 6 8 20	Response of CLINE to XRP Innovation 42
Response of ECO to ADA Innovation 400 005 000 2 4 6 8 10	Reponse of 6C0 to 8CH knowlon 000 005 2 4 0 8 20	Response of KCOto BX: Innovation	Response of ECO to CLNE Innovation	Response of ICO to ICO innovation 400 400 2 4 6 8 50	Response of ECOto EC Innovation	Response of ECD to EN Insortion	Response of IC Dto LT: Innovation	Reponse of BCO to MIXTA Innovation	Reponse of 600 to XLM knowthon 500 500 2 4 6 8 50	Reponse of ECO to XRP Innovation
Reponse of ITC to ADA Innovation	Reponse of ITC to BCH Innovation	Response of EX to BX binovition .64 .62 .00 .2 4 6 8 10	Response of ETC to CLNE Innovation	Response of ITC to IECOInnovation	Response of EC to EC innovation	Reponse of ETC to ETH Innovation	Reponse f ITC to LK: Innovation 54 52 2 4 9 8 10	Reponse of ETC to MDIA hnowshipe	Response of ITC to XUM knowskipn .04 .02 .00 2 4 5 8 20	Reponse of EX: to XRP Innovation .04 .02 .00 .0 .0 .0 .0 .0 .0 .0 .0
Response of ETH to ADA Innovation	Response of ETH to BCH Innovation	Response of EDI to BIC Innovation	Response of ETH to ELNE Innovation	Response of EHts ECOInnovation	Response of ETH to ETC innovation	Response of ETH to ETH Innovation	Response of ETHto LX: Innovation	Response of ETH to MDTA Innovation	Response of EMHto XLM knowskipn 	Response of EM to XRP Innovation
Reponse of LTC to ADA Innovation	Response of LTC to BCH Innovation	Response of LK to BK Innovelian	Response of LIX to CLNE innovation	Response of LIC to ECO innovation	Response of LTC to ETC innovation .04 .02 .00 2 4 6 8 10	Response of LTC to EIN Innovation	Response of LTC to LKC Innovelian	Response of LTC to MDIA hnowlide	Response of LTC to XLM knowking	Response of LIC to XRP Innovation
Response of MIDTA to ADA Innovation	Response of MCIA to 8CH innovation	Response of MDIA to BIC Innovation 44 42 40 2 4 6 8 10	Response of MOTA to CLNE Innovation	Response of MORA to ECO Innovation	Response of MCRA to ETC Innovation	Response of MIDTA to ETH Innovation	Response of MUDIA to LITC innovation	Response of MOTA to MOTA the Novition	Response of MOTA to XUM Innovation	Response of MCRA to XRP Innovation
Response of XUM to ADA Isnovation	Response of XUM to BCH Innovation	Response of XLM to BTC Innovation	Response of XLMto CLNE Innovation	Response of XUM to ECO innovation	Response of XUM to EIC Innovation	Response of XLMto ETH Innovation	Response of XLM to ETC Innovation	Response of XLM to MOTA Innovation	Response of XLM to XLM Innovation	Response of XUM to XRP Innovation
Response of XRP to ADA Isnowtion	Response of XRP to BCH Innovation	Response of XRP to BTC Innovation	Response of XRP to CLNE Innovation	Response of XRP to ECO Innovation	Response of XRP to ETC Innovation	Response of XRP to ETH Innovation	Response of XRP to LTC Innovation	Reponse of XRP to MOTA Innovation	Response of XRP to XLM Innovation	Response of XRP to XRP innovation

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. 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, Litcoin, 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.

Table 4: VAR lag order selection criteria, stress period

Lag	LogL	LR	FPE	AIC	SC	HQ
8	18582.33	162.9357*	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: Estimation of the IRF model with monte carlo simulations (1000 repetitions), summary graphs for the stress period

Response to Cholesky One S.D. (d.f. adjusted) Innovations 95% CI using Monte Carlo S.E.s with 1000 replications										
Response of ADA to ADA innovation 06 04 02 00 2 4 6 8 10	Response of ADA to BCH Innovatio n D6 D4 D2 D0 2 4 6 8 10	Response of ADA to BTC Innovatio n 06 04 02 00 2 4 6 8 10	Response of ADA to CLNE Innovation .06 .04 .02 .00 .2 .4 .6 .8 .10 .05 .05 .05 .05 .05 .05 .05 .0	Response of ADA to 8CO Innovation D6 D4 D2 D0 2 4 6 8 20	Response of ADA to ETC Innovation	Response of ADA to ETH Innovatio n 04 02 00 2 4 6 8 10	Response of ADA to LTC innovation D6 D4 D4 D2 D0 2 4 6 8 10	Response of ADA to MIOTA Innovation 06 04 02 00 2 4 6 8 10	Reponse of ADA to XLM Isnovetio n .06 .04 .02 .00 .2 .4 .6 .8 .05 .05 .05 .05 .05 .05 .05 .05	Response of ADA to XRP Innovation D6 D4 D2 D2 D0 Z 4 6 8 10
Reponse of BCH to ADA Innovation	Response of BCH to BCH knows is n 04 02 00 2 4 6 8 10	Response of BCH to BTC Innovation 04 02 00 2 4 6 8 10	Response of BCH to CLNE Innovation	Response of BCH to BCOInnovation	Response of BCH to ETC Innovation	Response of BCH to EH Innovation	Response of BCH to LTC Innovation 04 02 00 2 4 6 8 10	Response of BCH to MUTA knowth on 04 02 00 2 4 6 8 10	Reponseof BCH to XLMIsnovetion	Response of BCH to XRP Innovation 04 02 00 2 4 6 8 10
Reponse of BIC to A0A knowski e 03 04 01 0 2 4 6 8 10	Reponse of BTC to BCH Innovation 03 01 01 02 2 4 6 8 10	Response of BTC to BTC Innovation 01 01 02 01 02 2 4 6 8 10	Response of BTC to CLNE Innovation	Regense of BIC to ECOInnovation 03 01 02 01 02 2 4 6 8 20	Response of BTC to ETC Innovation .03 .01 .01 .01 .02 .01 .03 .04 .05 .05 .05 .05 .05 .05 .05 .05	Response of BTC to EH Innovation .03 .01 .01 .00 .01 .02 .01 .02 .01 .03 .03 .03 .03 .04 .05 .05 .05 .05 .05 .05 .05 .05	Response of BTC to LTC Innovation 03 01 01 02 2 4 6 8 10	Reponsed BTC to MI0TA Innovation	Reponse of BIC to XLM Innovation .03 .02 .01 .00 .00 .00 .02 .01 .00 .03 .02 .01 .03 .02 .01 .03 .03 .03 .04 .05 .05 .05 .05 .05 .05 .05 .05	Bit Image: Constraint of the second sec
Reponse of LIME to ADA Innovation	Response of CLNE to BCH Innovation	Response of CLNE to BTC Innovation 04 02 00 2 4 6 8 10	Reponse of LIME to CLNE innovation	Response of CLNE to ECO knowskin 04 02 00 2 4 6 8 10	Response of CURE to ETC Innovation	Response of CLNE to ETH Innovation 04 02 00 2 4 6 8 10	Reponse of UME to LIC innovation 04 02 00 2 4 6 8 10	Response of CLNE to MIDTA Innovation	Reponse of CURE to XLMIsmovation	Response of CLNE to X8P knowled n
Reponse of ECO to A0A knoweb m	Response of ECD to BCH Innovation	Response of ECO to BTC Innovation	Response of ECO to CLNE Innovation	Reponse of ECO In ECO Innovation	Response of ECO to ETC Innovation	Response of ECO to EH Innovation	Response of ECO to LTC Innovation 02 01 02 2 4 6 8 10	Response of ECOto MIDTA Innovation	Reponse of ECO to XLM Innovation	Responsed ECOto XRP Innovation
Response of ETC to ADA knower is a 04 02 02 00 00 00 00 00 00 00 00 00 00 00	Response of ETC to BCH Innovation	Response of ETC to BTC Innovation .04 .02 .00 .04 .02 .00 .04 .04 .05 .04 .04 .04 .04 .04 .04 .04 .04	Response of ETC to CUAE Innovation	Response of ETC to ECOInnovation D4 D2 D0 2 4 6 8 10	Reponse of ETC to ETC hnowskipn	Reponsed ETC to EH Innovation .04 .02 .00 .02 .00 .04 .02 .04 .04 .04 .04 .04 .04 .04 .04	Response of ERC to LPC Innovation 04 02 00 2 4 6 8 10	Response of ETC to MIOTA Innovation	Response of ETC to XUM knowetb n .04 .02 .00 .04 .02 .00 .04 .04 .04 .04 .04 .04 .04	Response of ETC to XRP innovation D4 D2 D0 2 4 6 8 10
Response of EH to ADA knowb on 04 02 0 2 4 6 8 10	Response of ETH to BCH Innovation	Response of ETH to BTC Innovation	Response of EIH to CUAE Innovation	Response of EH to ECO Innovation D4 D2 D0 2 4 6 8 10	Response of ETH to ETC hnove bin 04 02 00 2 4 6 8 10	Reponsed ETH to ETH hnowking	Response of EIH to LTC Innovation .04 .02 .00 .04 .04 .04 .04 .04 .04 .04	Response of ETH to MOTA Innovation	Response of EIH to XUM knowtion	Reponse of ETH to XRP Innovation D4 D2 D0 2 4 6 8 10
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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) Litcoin (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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