Interconnected Dynamics of Sustainable Cryptocurrencies: Insights from Transfer Entropy Analysis

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Abstract

This study introduces the concept of "sustainable cryptocurrencies", encompassing green and energy cryptocurrencies, and explores their dynamics alongside diverse assets using transfer entropy based network analysis, including pre- and post-COVID eras. The study reveals that sustainable cryptocurrencies commonly construct a dense transfer entropy network with major cryptocurrencies and the energy index. Meanwhile, they show distinct properties: green cryptocurrencies exhibit significant interconnectedness primarily among themselves, while energy cryptocurrencies show the energy index's emergence as a key component in the post-COVID volatility connectedness network. These insights offer valuable guidance for sustainable investing within cryptocurrency markets.

Keywords: Sustainable Cryptocurrency, Transfer Entropy, Network Analysis

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1. Introduction

The surge in carbon emissions due to rapid industrial expansion has intensified the global warming crisis, prompting a shift towards sustainable development and green finance concepts. This trend has made investors to increasingly prioritize sustainable investment strategies, aiming to align financial goals with environmental concerns. Consequently, the principles of Environmental, Social, and Governance (ESG) investing have garnered significant attention, reshaping investment approaches globally (Giese et al., 2019; Cerqueti et al., 2021). Convenient access to ESG investments via transparent and flexible ETFs has empowered retail investors, reshaping the investment landscape towards environmentally conscious practices (Pavlova & de Boyrie, 2022).

Meanwhile, since Bitcoin's emergence, cryptocurrencies have attracted investor attention for their potential for high returns and portfolio diversification (Andrianto & Diputra, 2017; Platanakis & Urquhart, 2020; Akhtaruzzaman et al., 2020). However, this enthusiasm is accompanied by growing concerns about their negative environmental impact. The security of Bitcoin's blockchain relies on an energy-intensive proof-of-work algorithm used in mining, which verifies transactions and generates new bitcoins as a reward (Nakamoto, 2008). This energy-intensive process of mining has been criticized for its substantial carbon footprint. Gallersdörfer et al. (2020) pointed out that not only Bitcoin but many other cryptocurrency projects also contribute significantly to environmental problems.

With growing concerns about the environmental impact of mining and a rising interest in sustainable investing in traditional financial markets, the cryptocurrency landscape is pivoting towards more environmentally friendly options. Investors and industry participants increasingly prioritize energy efficiency and sustainability, leading to the rise in popularity of "sustainable" cryptocurrencies. Two prominent types have gained attention: "green" cryptocurrencies, known for their low energy consumption, and "energy" cryptocurrencies, whose projects are linked to renewable energy sources. Ren & Lucey (2022) introduced the concept of "clean(green)" and "dirty" cryptocurrencies and analyzed them within the context of the clean energy market, exploring their safe haven properties and spillover patterns. Ali et al. (2024) analyzed their spillovers between G7 markets, revealing G7 markets as net transmitters and green cryptocurrencies as net recipients of return and volatility spillovers. Pham et al. (2022) demonstrated tail dependence among carbon prices, green and non-green cryptocurrencies, highlighting time-varying diversification benefits across carbon, green, and non-green cryptocurrencies. Yousaf et al. (2022) analyzed the relationship between energy cryptocurrencies with fossil fuel markets with spillover index and discovered tenuous connectedness between them. Naeem et al. (2023) measured the extreme downside risk among energy cryptocurrencies and diverse energy sectors, demonstrating the potential diversification benefits of energy cryptocurrencies, particularly concerning energy metals and fossil fuels.

Our paper makes several key contributions. First we introduce the concept of "sustainable cryptocurrency". While previous research has examined green and energy cryptocurrencies separately, we bridge this gap by analyzing their interrelationships within the sustainable cryptocurrency universe and in relation to other assets. Additionally, we extend the literature by incorporating a broader range of assets, including ESG ETFs and major cryptocurrencies, compared to prior studies that focused primarily on energy-related assets. This comprehensive approach offers a deeper understanding of the interplay between different types of sustainable and conventional investment options.

Furthermore, we utilize transfer entropy to analyze the return and volatility time series, providing deeper insights into market dynamics. Transfer entropy, a widely used tool in financial research for quantifying directional information flow, facilitates the construction of a network capturing these interactions (Shi et al., 2024; Jin & Xue, 2023; Lee et al., 2023). Through this network, we can observe the information flow between various assets and examine the topological features to understand overall market behavior. By analyzing the network's density and identifying key components, we offer a comprehensive overview of the dynamics surrounding sustainable cryptocurrencies. Lastly, we segment the entire period into pre-COVID and post-COVID eras to examine the evolving dynamics of interconnectedness. The COVID-19 pandemic significantly impacted financial markets in both the cryptocurrency and sustainable investment domains (Huang et al., 2021; Yarovaya et al., 2021; Rubbaniy et al., 2022; Bax et al., 2023). This division allows us to identify shifts or disruptions in information flow and network structure surrounding this pivotal event.

The rest of paper is organized as follows: Section 2 describes the data and methodology. Section 3 discusses our experimental results and main findings. Lastly, Section 4 concludes the paper.

2. Data and Methodology

2.1. Data

To gain insights into sustainable investing within cryptocurrency markets, we conducted a comprehensive data collection covering sustainable cryptocurrencies and various other asset types. We collect the daily market data for six categories: green and energy cryptocurrencies as sustainable cryptocurrencies, and major cryptocurrencies, ESG ETFs, commodities, and the energy index as external assets. The data collection period spans from January 1, 2018, to May 1, 2024, allowing for an extensive analysis that includes both pre- and post-COVID eras, with February 19, 2020, as the cutoff date based on Pavlova & de Boyrie (2022).

Green cryptocurrencies were selected based on criteria from Pham et al. (2022), Ren & Lucey (2022), and Ali et al. (2024), resulting in five assets. Energy cryptocurrencies were chosen using CoinMarketCap's energy filter, yielding 11 assets as of May 4, 2024. For major cryptocurrencies, we included BTC and ETH. ESG ETFs were chosen from U.S.-listed ETFs containing "ESG" in their names, with an intraday price exceeding $10, and possessing a Morningstar Performance Rating of four or five stars as of May 14, 2024, resulting in the inclusion of 12 ETFs. Additionally, six prominent commodity futures, including assets from fossil fuel markets, were included. The WilderHill Clean Energy Index was chosen to represent energy index, as per Naeem et al. (2023).

Data for green, energy, and major cryptocurrencies were acquired from CoinMarketCap, while commodities and ESG ETFs data were sourced from Yahoo Finance. Energy index data were collected from Google Finance. For a complete list of the assets included in this study, please refer to Table A.1.

In our study, we utilized daily logarithmic returns and volatility. Returns were calculated based on closing prices, while daily volatility was computed using the methodology introduced in Diebold & Yilmaz (2009):

$$\begin{aligned} V_t =& 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] \\ &- 0.383 \cdot (C_t - O_t)^2 \end{aligned}$$

where V_t denotes daily volatility, while H_t, L_t, C_t, and O_t signify the highest, lowest, closing, and opening prices, respectively, on day t.

Descriptive statistics of the log returns for sustainable cryptocurrencies are detailed in Table 1.

Table 1: Descriptive statistics

Panel A: Full Period		Obs	Mean	Median	S.D.	Min	Max	Skewness	Kurtosis	ADF	JB
Green Crypto	ADA	2307	-0.0002	-0.0002	0.0550	-0.5037	0.3218	-0.0311	6.0314	-18.2581***	3497.2149***
	IOTA	2307	-0.0012	0.0005	0.0579	-0.5436	0.3884	-0.4976	9.2268	-18.0592***	8278.6891***
	XNO	2307	-0.0013	-0.0015	0.0693	-0.5858	0.7461	1.1572	17.5845	-17.4959***	30238.0769***
	XLM	2307	-0.0005	-0.0003	0.0545	-0.4100	0.5592	0.9240	15.0721	-19.0718***	22164.9530***
	XRP	2307	-0.0006	-0.0010	0.0559	-0.5505	0.5486	0.3243	17.2248	-18.2151***	28560.1098***
Energy Crypto	POWR	2307	-0.0005	0.0019	0.0693	-0.7003	0.5826	-0.2942	16.1617	-36.8512***	25141.1613***
	SNC	2307	-0.0007	-0.0001	0.0681	-0.4986	0.9091	1.2435	24.4422	-12.2170***	58021.4695***
	TSL	2307	-0.0030	-0.0025	0.2026	-2.1061	2.8535	1.3198	49.0027	-10.5643***	231491.3341***
	ELEC	2239	-0.0023	-0.0035	0.0998	-0.6511	1.2540	1.5198	18.6780	-40.3022***	33408.2577***
	ROX	2044	-0.0006	-0.0003	0.3387	-3.9076	2.3263	-0.5833	27.0125	-21.4289***	62259.7294***
	SRM	368	-0.0002	-0.0068	0.0938	-0.3956	0.4041	0.3213	2.8348	-18.3559***	129.5556***
	EWT	1489	0.0007	-0.0034	0.0695	-0.6093	0.6740	0.9416	13.3039	-7.2998***	11200.9998***
	DIONE	617	0.0062	-0.0067	0.1136	-0.9686	0.5081	-0.5993	9.8713	-25.2782***	2542.0408***
	EVDC	783	-0.0006	-0.0100	0.4493	-7.7256	7.9218	1.0742	246.8695	-10.7514***	1988466.8968***
	RWN	1377	0.0027	-0.0026	0.1509	-1.3149	1.6862	1.2005	24.9329	-13.0013***	35997.8004***
	WOZX	1238	-0.0045	-0.0054	0.0720	-0.4794	0.8958	1.9643	26.4677	-42.6045***	36932.2910***
Panel B: Pre-COVID		Obs	Mean	Median	S.D.	Min	Max	Skewness	Kurtosis	ADF	JB
Green Crypto	ADA	778	-0.0032	-0.0023	0.0582	-0.2173	0.3218	0.2865	3.1565	-28.0766***	333.6301***
	IOTA	778	-0.0033	-0.0028	0.0573	-0.2918	0.2235	-0.3207	2.4785	-14.8097***	212.4610***
	XNO	778	-0.0040	-0.0034	0.0733	-0.3650	0.3363	0.0541	3.6828	-20.4872***	440.0349***
	XLM	778	-0.0021	-0.0036	0.0576	-0.3062	0.4618	0.7302	8.0045	-27.9422***	2146.1420***
	XRP	778	-0.0027	-0.0032	0.0535	-0.3520	0.3220	0.0133	7.5638	-27.1294***	1854.5966***
Energy Crypto	POWR	778	-0.0033	-0.0009	0.0643	-0.3346	0.3785	0.2197	4.4389	-10.4162***	644.9793***
	SNC	778	-0.0028	-0.0031	0.0834	-0.4078	0.9091	2.0877	23.7358	-6.5182***	18828.2445***
	TSL	778	-0.0074	-0.0065	0.0911	-0.4084	0.6010	0.8478	6.4894	-34.4792***	1458.3358***
	ELEC	710	-0.0064	-0.0084	0.0864	-0.3844	0.3628	0.1781	2.6340	-7.7231***	209.0026***
	ROX	515	0.0015	-0.0013	0.0668	-0.3408	0.2780	0.0125	3.6528	-12.3821***	286.3280***
Panel C: Post-COVID		Obs	Mean	Median	S.D.	Min	Max	Skewness	Kurtosis	ADF	JB
Green Crypto	ADA	1529	0.0013	0.0006	0.0532	-0.5037	0.2794	-0.2251	8.1047	-11.0305***	4197.6648***
	IOTA	1529	-0.0001	0.0020	0.0582	-0.5436	0.3884	-0.5860	12.4923	-11.1406***	10029.7086***
	XNO	1529	0.0001	-0.0008	0.0671	-0.5858	0.7461	1.8966	27.2722	-15.3939***	48301.0484***
	XLM	1529	0.0003	0.0011	0.0529	-0.4100	0.5592	1.0575	19.9527	-14.8051***	25647.9433***
	XRP	1529	0.0004	0.0005	0.0571	-0.5505	0.5486	0.4471	20.8970	-14.5990***	27871.5051***
Energy Crypto	POWR	1529	0.0009	0.0025	0.0717	-0.7003	0.5826	-0.4927	19.8353	-24.9760***	25127.3251***
	SNC	1529	0.0004	0.0012	0.0588	-0.4986	0.6093	-0.0564	16.9648	-46.7139***	18336.3863***
	TSL	1529	-0.0007	-0.0012	0.2403	-2.1061	2.8535	1.1472	36.5603	-9.6889***	85491.2319***
	ELEC	1529	-0.0004	-0.0016	0.1055	-0.6511	1.2540	1.8247	21.1858	-17.2521***	29443.1961***
	ROX	1529	-0.0013	-0.0003	0.3897	-3.9076	2.3263	-0.5066	19.8919	-18.6238***	25274.0194***
	SRM	368	-0.0002	-0.0068	0.0938	-0.3956	0.4041	0.3213	2.8348	-18.3559***	129.5556***
	EWT	1489	0.0007	-0.0034	0.0695	-0.6093	0.6740	0.9416	13.3039	-7.2998***	11200.9998***
	DIONE	617	0.0062	-0.0067	0.1136	-0.9686	0.5081	-0.5993	9.8713	-25.2782***	2542.0408***
	EVDC	783	-0.0006	-0.0100	0.4493	-7.7256	7.9218	1.0742	246.8695	-10.7514***	1988466.8968***
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	WOZX	1238	-0.0045	-0.0054	0.0720	-0.4794	0.8958	1.9643	26.4677	-42.6045***	36932.2910***

Note. Table 1 presents descriptive statistics of logarithmic returns for sustainable cryptocurrencies. S.D.: Standard deviation; ADF: Augmented Dickey Fuller test for unit root testing; JB: Jarque-Bera test for normality. Panels A, B, and C show the values for the full period(January 01, 2018 to May 01, 2024), the pre-COVID period(January 01, 2018 to February 19, 2020), and the post-COVID period(February 20, 2020 to May 01, 2024), respectively. It is noted that the list of assets may vary by the period since some cryptocurrencies may have been unavailable in certain periods. Asterisks indicate levels of statistical significance: *** : p-value < 0.01, ** : p-value < 0.05.

2.2. Methodology

In information theory, Shannon entropy $H(x)$ measures the average uncertainty in a sample of a discrete random variable. It represents the average amount of information necessary to predict the value of that variable. It is calculated as $H(x) = -\sum_{x \in X} p(x) \log_2 p(x)$. Based on Shannon entropy, Schreiber (2000) introduced Shannon Transfer Entropy (TE) to quantify the direction and the magnitude of information flows. It is a non-linear and model-free measure commonly used to assess the information flow between various financial categories. TE from time series J to I ($T_{J \to I}$) can be described as follows:

$$T_{J \to I}(k,l) = \sum_{i,j} p(i_{t+1}, i_t^{(k)}, j_t^{(l)}) \cdot \log_2 \Big(\frac{p(i_{t+1}|i_t^{(k)}, j_t^{(l)})}{p(i_{t+1}|i_t^{(k)})} \Big), \tag{1}$$

where k and l are the lags and $p(i)$ and $p(j)$ are the marginal probability distributions. We set the default values of k and l as 1.

Effective Transfer Entropy (ETE) extends TE by shuffling the time series J, thereby providing a more robust measure that mitigates the impacts of outliers (Marschinski & Kantz, 2002). In this paper, we applied ETE to measure the information flows between asset categories. ETE is described as follows:

$$ETE_{J\rightarrow I}(k,l) = T_{J\rightarrow I}(k,l) - T_{J_{\text{shuffled}}\rightarrow I}(k,l). \tag{2}$$

Rényi entropy generalizes Shannon entropy, allowing the sensitivity to the tail of the distribution to be adjusted through the hyperparameter q. It is described as follows:

$$H_q(x) = \frac{1}{1-q}\log_2 \sum_{x\in X} p^q(x), \tag{3}$$

where $q > 0$ and $q \neq 1$. For $0 < q < 1$, Rényi entropy gives more weight to the tail of the distribution. The lower the hyperparameter q, the more Rényi entropy gives weight to less probable events, making it more sensitive to the presence of even very low-probability events. As q approaches 1, Rényi entropy converges to Shannon entropy.

To measure the interactions between distinct categories in transfer entropy network, we used metric TOTO(Total-Out-To-Other) from Billio et al. (2012) in the following manner:

$$\text{TOTO}(j) = \sum_{i=1}^{N-N_m} E_{j\rightarrow i}, \forall i \in V \setminus \{j|j \in m\} \tag{4}$$

Here, N_m represents the number of nodes within the TE causal network. TOTO quantifies the aggregate number of TE causal relationships initiated by any node j associated with node i.

We also applied Network Density (ND) to quantify the degree of connectivity between categories similar to the style in Jin & Xue (2023). ND can be used to gauge the network when two categories comprise it, or when a single category exists within the network. The definitions for ND are as follows:

$$ND = \begin{cases} \frac{L}{2NM} & \text{between two categories with nodes } N \text{ and } M, \\ \frac{L}{2N(N-1)} & \text{within a single category with } N \text{ nodes.} \end{cases}$$

where L denotes the number of directed edges in the networks.

To calculate the systemic significance of asset k in the network and identify the key component of the network, we measure the transmission intensity WD^k within the network with the style of Liu et al. (2021). It is defined as follows:

$$WD^k_{in} = \sum_{i=1}^{N} T_{i\rightarrow j} \tag{5}$$

$$WD^k_{out} = \sum_{j=1}^{N} T_{i\to j} \tag{6}$$

Here, WD^k_{in} represents the total weights of the incoming edges to the node, WD^k_{out} indicates the total weights that the nodes send out, N is the number of nodes, and $T_{i\to j}$ is the TE from asset i to j. By combining these two metrics, we define the overall intensity of the inflow and outflow of the asset k as follows:

$$WD^k = WD^k_{in} + WD^k_{out} \tag{7}$$

3. Empirical Findings

3.1. Network Analysis

To understand the evolving dynamics of sustainable cryptocurrency investments, we utilized daily return and volatility series to construct a transfer entropy network. Across our asset universe, we calculated pairwise effective transfer entropy, filtering for significant information flows with a threshold p-value of 0.05. Table 2 presents the TOTO metric and network density derived from the transfer entropy networks in different periods.

Overall, the volatility network exhibits significantly higher density compared to the return network. Across all X and Y category combinations, Panel B consistently shows higher network density levels than Panel A. This suggests that volatility is much more interconnected among assets than returns within the sustainable cryptocurrency investing universe. Therefore, we concentrated our analysis on volatility.

For the full period, green cryptocurrencies show high network density with themselves, major cryptocurrencies, and the energy index. The high network density with major cryptocurrencies and the energy index is particularly notable, indicating the close association of green cryptocurrencies with both the broader crypto market and clean energy trends. This characteristic are also observed in energy cryptocurrencies. Although the values are lower, major cryptocurrencies and the energy index construct relatively dense networks while assets like commodities exhibit low connectivity consistent with previous findings (Yousaf et al., 2022). This common property in sustainable cryptocurrencies reveals the special characteristic of these tokens are sensitive to overall crypto market dynamics as well as specific developments in the clean energy sector, supporting our classification of these tokens as sustainable cryptocurrencies. The moderate network density between green and energy cryptocurrencies also supports this categorization.

In analyzing the pre and post-COVID landscape, we observe both notable distinctions and commonalities. While the density within green cryptocurrencies peaked, the internal density of energy cryptocurrencies decreased. Additionally, the density with major cryptocurrencies decreased for energy cryptocurrencies but remained stable for green cryptocurrencies. Interestingly both green and

Table 2: Effective transfer entropy causal network topology characteristics

Panel A: Return

X	Y	Full: ETE (X → Y)	Full: ETE (Y → X)	Full: Network Density	Pre-COVID: ETE (X → Y)	Pre-COVID: ETE (Y → X)	Pre-COVID: Network Density	Post-COVID: ETE (X → Y)	Post-COVID: ETE (Y → X)	Post-COVID: Network Density
Green Crypto	Green Crypto	7	7	0.3500	4	4	0.2000	4	4	0.2000
	Energy Crypto	15	11	0.2364	0	3	0.0600	12	11	0.2091
	Major Crypto	0	2	0.1000	0	4	0.2000	0	1	0.0500
	ESG ETF	2	13	0.1250	7	10	0.1417	1	0	0.0083
	Commodity	5	1	0.1000	1	0	0.0167	4	2	0.1000
	Energy Index	0	0	0.0000	0	0	0.0000	1	1	0.2000
Energy Crypto	Energy Crypto	10	10	0.0909	2	2	0.1000	9	9	0.0818
	Major Crypto	2	8	0.2273	1	2	0.1500	5	6	0.2500
	ESG ETF	19	17	0.1364	12	4	0.1333	13	21	0.1288
	Commodity	7	3	0.0758	1	2	0.0500	5	7	0.0909
	Energy Index	4	0	0.1818	0	0	0.0000	1	0	0.0455

Panel B: Volatility

X	Y	Full: ETE (X → Y)	Full: ETE (Y → X)	Full: Network Density	Pre-COVID: ETE (X → Y)	Pre-COVID: ETE (Y → X)	Pre-COVID: Network Density	Post-COVID: ETE (X → Y)	Post-COVID: ETE (Y → X)	Post-COVID: Network Density
Green Crypto	Green Crypto	20	20	1.0000	15	15	0.7500	20	20	1.0000
	Energy Crypto	31	32	0.5727	17	20	0.7400	31	25	0.5091
	Major Crypto	10	9	0.9500	10	5	0.7500	10	6	0.8000
	ESG ETF	36	16	0.4333	27	16	0.3583	18	8	0.2167
	Commodity	7	3	0.1667	3	2	0.0833	5	1	0.1000
	Energy Index	5	4	0.9000	2	0	0.2000	3	3	0.6000
Energy Crypto	Energy Crypto	45	45	0.4091	12	12	0.6000	40	40	0.3636
	Major Crypto	15	10	0.5682	8	5	0.6500	13	8	0.4773
	ESG ETF	47	43	0.3409	22	9	0.2583	22	23	0.1705
	Commodity	14	4	0.1364	2	0	0.0333	9	4	0.0985
	Energy Index	8	7	0.6818	3	0	0.3000	7	3	0.4545

energy cryptocurrencies exhibited increased density levels with the energy index in the post-COVID era. Moreover, despite the decrease in density values for energy cryptocurrencies, networks with major cryptocurrencies remained relatively dense, similar to the situation observed for green cryptocurrencies.

3.2. Key Component Analysis

We conducted a key component analysis using transmission intensity calculated within the transfer entropy network. Instead of encompassing every individual asset included in this study and constructing a large transfer entropy network, we reconstructed the network with valid assets demonstrating a moderate level of information flow with sustainable cryptocurrencies. The preceding section's findings highlight the volatility interconnectedness observed among both green cryptocurrencies and energy cryptocurrencies with major cryptocurrencies and the energy index. However, to further explore these dynamics and discern the distinct characteristics of the two types, we established two separate networks: "Green Crypto Universe" and "Energy Crypto Universe". Each universe comprises itself, along with major cryptocurrencies and the energy index.

Table 3 shows the transmission intensity in transfer entropy network for each universe. In Panel A, the intensity values of green cryptocurrencies surpass those of external assets throughout the entire period. This trend becomes more pronounced in the post-COVID era compared to the pre-COVID era. BTC ranked second-highest before COVID but notably dropped to second-lowest afterward,

Table 3: Transmission intensity in transfer entropy network

Panel A: Green Crypto Universe						Panel B: Energy Crypto Universe					
Full		Pre-COVID		Post-COVID		Full		Pre-COVID		Post-COVID	
Asset	TI	Asset	TI	Asset	TI	Asset	TI	Asset	TI	Asset	TI
IOTA	0.1573	XRP	0.1941	XNO	0.1692	SNC	0.1941	SNC	0.2583	ECO	0.1705
XNO	0.1529	BTC	0.1778	ADA	0.1639	ECO	0.1809	ELEC	0.2353	EWT	0.1313
XRP	0.1467	XNO	0.1644	IOTA	0.1616	ELEC	0.1472	POWR	0.2235	SNC	0.1284
XLM	0.143	ADA	0.1643	ETH	0.1615	TSL	0.1335	TSL	0.22	BTC	0.1276
ADA	0.1392	ETH	0.1575	XLM	0.1574	EWT	0.1305	ETH	0.2026	ELEC	0.1267
ETH	0.1211	IOTA	0.149	XRP	0.1322	POWR	0.1287	BTC	0.1425	WOZX	0.1088
BTC	0.0984	XLM	0.142	BTC	0.121	BTC	0.1278	ECO	0.041	RWN	0.1072
ECO	0.0972	ECO	0.032	ECO	0.0983	WOZX	0.117			ROX	0.1052
						RWN	0.1157			ETH	0.1012
						ETH	0.1115			POWR	0.1005
						ROX	0.1097			EVDC	0.0986
						EVDC	0.094			TSL	0.0902
						DIONE	0.0832			DIONE	0.0898
						SRM	0.0295			SRM	0.0419

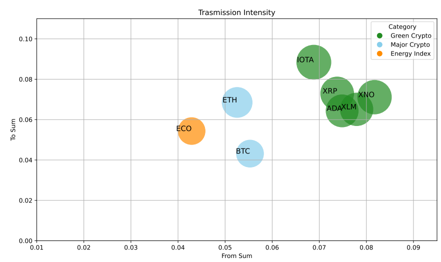
Note. Table 3 presents Transmission Intensity (TI) metrics, divided into two panels: one for the Green Crypto universe and one for the Energy Crypto universe.

while ETC maintained a middle position. Meanwhile, the energy index consistently held the lowest position. Despite establishing statistically valid information flow with green cryptocurrencies, the intensity levels remained relatively low. These results underscore the asymmetric nature of information transmission within the network, wherein green cryptocurrencies themselves serve as key components, exhibiting a high level of intensity in exchanging information among each other rather than with other assets.

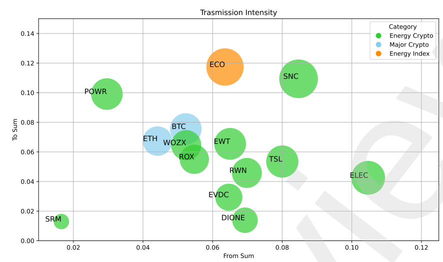
Panel B presents a divergent trend from Panel A, particularly notable in the behavior of the energy index. For the full period, the energy index ranks as the second-highest asset in transmission intensity. In the pre-COVID era, external assets displayed a low level of intensity, with the energy index exhibiting the least intensity. However, it surged to become the top asset in the post-COVID era. This indicates that post-COVID, the energy index becomes highly influential, fostering strong information flow relationships with energy cryptocurrencies. This positions it as a financial alternative mirroring issues in the energy sector.

Figure 1 illustrates the transmission intensity across various eras within two distinct universes. Each point represents a category's intensity, with the x-axis showing the sum of outgoing transmissions and the y-axis displaying the sum of incoming transmissions. The size of each point corresponds to the total transmission intensity, while colors denote different categories. Assets in the upper right quadrant are key components, significantly receiving and transmitting information flow within the selected universe.

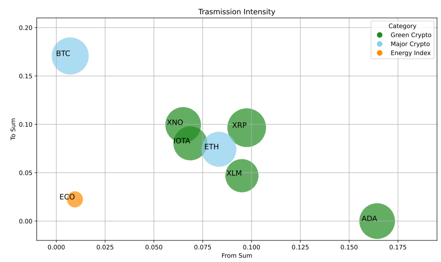
In the left column, within the green crypto universe, green cryptocurrencies are prominently clustered in the upper right quadrant, indicating their significant role compared to major cryptocurrencies and the energy index. This clustering intensifies post-COVID compared to pre-COVID. Conversely, in the right column, within the energy crypto universe, the energy index undergoes a marked shift in position. Initially in the bottom left quadrant during the pre-



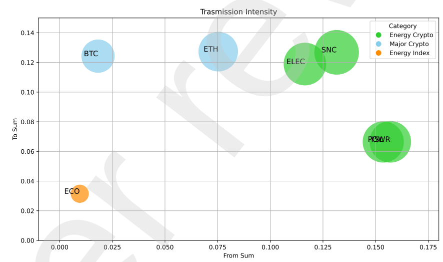
(a) Full Period: Green Crypto Universe



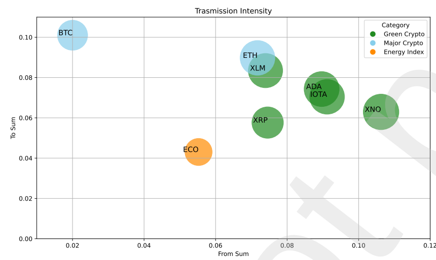
(b) Full Period: Energy Crypto Universe



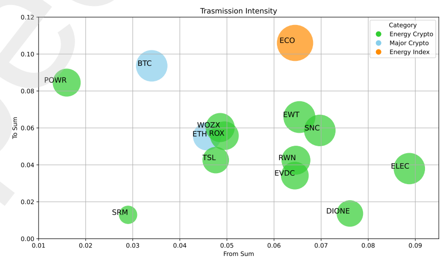
(c) Pre-COVID: Green Crypto Universe



(d) Pre-COVID: Energy Crypto Universe



(e) Post-COVID: Green Crypto Universe



(f) Post-COVID: Energy Crypto Universe

Figure 1: Transmission intensity across eras in green crypto and energy crypto universes

COVID era, it moves to the upper right quadrant post-COVID, highlighting its growing influence within the energy crypto universe.

3.3. Robustness Test

To add further robustness to our findings, we conducted a replication of the analytical process, this time employing Rényi entropy. By setting the hyperparameter q to 0.1, we aimed to assess the alignment of our findings, especially under circumstances where low probability events are given more weight. Table 4 presents the network topology characteristics and Table 5 illustrates the transmission intensity levels derived from the newly constructed network. Our results indicate that while there are minor variations in the values themselves, the overall trends observed in the experiment with Shannon entropy remain stable. Hence, we conclude that even with an emphasis on tail distributions, our

Table 4: Effective transfer entropy causal network topology characteristics with Rényi Entropy

Panel A: Return										
		Full			Pre-COVID			Post-COVID		
X	Y	ETE (X → Y)	ETE (Y → X)	Network Density	ETE (X → Y)	ETE (Y → X)	Network Density	ETE (X → Y)	ETE (Y → X)	Network Density
Green Crypto	Green Crypto	6	6	0.3000	2	2	0.1000	4	4	0.2000
	Energy Crypto	14	9	0.2091	1	3	0.0800	12	12	0.2182
	Major Crypto	0	2	0.1000	0	4	0.2000	0	1	0.0500
	ESG ETF	2	11	0.1083	8	10	0.1500	1	1	0.0167
	Commodity	5	1	0.1000	1	1	0.0333	4	2	0.1000
	Energy Index	0	0	0.0000	0	0	0.0000	1	1	0.2000
Energy Crypto	Energy Crypto	9	9	0.0818	0	0	0.0000	10	10	0.0909
	Major Crypto	3	8	0.2500	1	2	0.1500	4	6	0.2273
	ESG ETF	18	18	0.1364	10	5	0.1250	16	21	0.1402
	Commodity	7	4	0.0833	3	3	0.1000	6	7	0.0985
	Energy Index	4	0	0.1818	0	0	0.0000	2	0	0.0909
Panel B: Volatility										
		Full			Pre-COVID			Post-COVID		
X	Y	ETE (X → Y)	ETE (Y → X)	Network Density	ETE (X → Y)	ETE (Y → X)	Network Density	ETE (X → Y)	ETE (Y → X)	Network Density
Green Crypto	Green Crypto	20	20	1.0000	16	16	0.8000	20	20	1.0000
	Energy Crypto	29	31	0.5455	17	20	0.7400	30	25	0.5000
	Major Crypto	10	9	0.9500	10	5	0.7500	10	6	0.8000
	ESG ETF	36	17	0.4417	26	15	0.3417	19	10	0.2417
	Commodity	7	2	0.1500	4	0	0.0667	5	1	0.1000
	Energy Index	5	5	1.0000	3	0	0.3000	4	3	0.7000
Energy Crypto	Energy Crypto	47	47	0.4273	13	13	0.6500	42	42	0.3818
	Major Crypto	14	10	0.5455	8	5	0.6500	13	7	0.4545
	ESG ETF	53	39	0.3485	20	10	0.2500	23	21	0.1667
	Commodity	15	6	0.1591	2	1	0.0500	8	4	0.0909
	Energy Index	9	6	0.6818	3	0	0.3000	5	4	0.4091

Table 5: Transmission intensity in transfer entropy network with Rényi entropy

Panel A: Green Crypto Universe						**Panel B: Energy Crypto Universe**					
Full		Pre-COVID		Post-COVID		Full		Pre-COVID		Post-COVID	
Asset	TI	Asset	TI	Asset	TI	Asset	TI	Asset	TI	Asset	TI
IOTA	0.1600	XRP	0.1964	XNO	0.1691	SNC	0.1935	SNC	0.2577	ECO	0.1590
XNO	0.1525	BTC	0.1787	ADA	0.1640	ECO	0.1925	ELEC	0.2332	SNC	0.1353
XRP	0.1471	XNO	0.1780	IOTA	0.1610	ELEC	0.1536	POWR	0.2313	EWT	0.1301
XLM	0.1421	ADA	0.1693	ETH	0.1608	POWR	0.1328	TSL	0.2206	BTC	0.1226
ADA	0.1401	ETH	0.1576	XLM	0.1566	TSL	0.1317	ETH	0.2004	ELEC	0.1201
ETH	0.1208	IOTA	0.1489	XRP	0.1368	EWT	0.1300	BTC	0.1428	WOZX	0.1187
ECO	0.1014	XLM	0.1407	BTC	0.1223	BTC	0.1258	ECO	0.0415	RWN	0.1149
BTC	0.0977	ECO	0.0390	ECO	0.1032	WOZX	0.1171	ROX	0.0070	POWR	0.1013
						RWN	0.1155			ROX	0.1002
						ROX	0.1082			ETH	0.0994
						ETH	0.1061			EVDC	0.0981
						EVDC	0.0913			TSL	0.0931
						DIONE	0.0848			DIONE	0.0772
						SRM	0.0428			SRM	0.0283

insights into the volatility dynamics of the sustainable cryptocurrency universe remain consistent.

4. Conclusion

This study introduces the novel concept of sustainable cryptocurrency and investigates their dynamics with various assets. The shared trait of substantial volatility interconnection with major cryptocurrencies and the energy index validates our proposed categorization. However, they also exhibit unique characteristics, such as the pronounced interconnectedness within green cryptocurrencies and the significant influence of the energy index within the energy crypto universe. This investigation offers crucial insights for investors, highlighting the need to consider both the shared and unique aspects when making investment decisions in sustainable investment strategies.

5. Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT for proofreading and enhancing the writing. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A.

Table A.1

Table A.1: Asset categories, names, and tickers as sourced

Category	Name	Ticker	Category	Name	Ticker
Green Crypto	Cardano	ADA	Commodity	Crude Oil	CL=F
	IOTA	IOTA		Gold	GC=F
	Nano	XNO		Silver	SI=F
	Stellar	XLM		Copper	HG=F
	XRP	XRP		Natural Gas	NG=F
Energy Crypto	Powerledger	POWR		Brent Crude Oil	BZ=F
	SunContract	SNC	ESG ETF	Nuveen ESG Large-Cap Growth ETF	NULG
	Energo	TSL		Nuveen ESG Small-Cap ETF	NUSC
	Electrify.Asia	ELEC		Nuveen ESG International Developed Markets Equity ETF	NUDM
	Robotina	ROX		FlexShares STOXX Global ESG Select Index Fund	ESGG
	Solareum	SRM		iShares ESG Aware MSCI USA ETF	ESGU
	Energy Web Token	EWT		Columbia U.S. ESG Equity Income ETF	ESGS
	Dione Protocol	DIONE		iShares MSCI USA ESG Select ETF	SUSA
	Electric Vehicle Direct Currency	EVDC		SPDR S&P Oil & Gas Exploration & Production ETF	XOP
	Rowan Token	RWN		Nuveen ESG Mid-Cap Growth ETF	NUMG
	Efforce	WOZX		iShares ESG Aware MSCI EAFE ETF	ESGD
Major Crypto	Bitcoin	BTC		FlexShares STOXX US ESG Select Index Fund	ESG
	Ethereum	ETH		iShares ESG 1-5 Year USD Corporate Bond ETF	SUSB
Energy Index	WilderHill Clean Energy Index	ECO			

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