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Full length article

Dependence and risk spillovers among clean cryptocurrencies prices and media environmental attention

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ABSTRACT

This paper examines the relationships among cryptocurrency environmental attention and clean cryptocurrencies prices using Time-Varying Parameter Vector Auto-Regression (TVP-VAR) and wavelets techniques. Results show strong connectedness among these variables, implying that the prices of clean cryptocurrencies are influenced by attention on cryptocurrency sustainability. Connectedness is stronger with positive shocks on environmental attention than negative shocks. Also, in the short-term, clean cryptocurrencies prices lead environmental attention, especially after 2021. However, there are notable periods when environmental attention led clean cryptocurrency prices before 2021. In the long-term, clean cryptocurrencies such as Hedera, Polygon, Cosmos, IOTA, TRON, Stellar, Tezos and Ripple lead environmental attention. In the presence of bitcoin, the degrees of connectedness increased across both shocks on cryptocurrency environmental attention. In all cases, the bitcoin market is the main destination of shocks from the system. We highlight some crucial implications of these results.

1. Introduction

Cryptocurrency represents one of the latest and most promising digital inventions in the financial space in recent times. Among others, it has reduced financial transaction costs, enabled greater speed and efficiency in financial transactions as well as facilitated the security of financial operations. Ultimately, this has contributed significantly to expediting global financial integration, especially in integrating developing economies into the global financial system. Arguing along this line, Moy and Carlson (2021) note that the emergence of cryptocurrency is leading to the development of an alternative financial and technological infrastructure that is global, open source, and accessible to all who have access to the internet, regardless of nationality, ethnicity, race, gender, and socioeconomic class. Akin to this, cryptocurrency is offering investment opportunities to investors and market participants that are interested in combining different classes of assets (Urom et al., 2022a). Indeed, evidence abounds to show that cryptocurrency provides alternative investment opportunities as well as provide safe-haven and hedging roles for different assets (e.g., Bouri et al., 2017; Guesmi et al., 2019; Urom et al., 2020; Khelifa et al., 2021).

Despite the above benefits, cryptocurrencies create a series of challenges and risks. Of particular interest is its negative environmental impact due to its high energy consumption and heavy carbon footprint (Mora et al., 2018; Gallersdörfer et al., 2020). As of 31st December 2021, statistics from Digiconomist indicates that Bitcoin, which is the most widely-mined cryptocurrency, consumes about 204.5 TWh of energy per year, while Ethereum, which is the second-largest cryptocurrency, consumes about 81.25 TWh of energy per year. The high energy consumption of cryptocurrency intensifies fossil fuel use, leading to an increase in carbon

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footprint. Cryptocurrency also increases carbon footprint through the significant electronic waste it generates, as mining hardware quickly becomes obsolete (see De Vries and Stoll, 2021). In fact, while there is still no consensus among the scientific community on the exact contribution of cryptocurrencies to the global carbon emission, the predominant view is that they pose a threat to environmental sustainability (Mora et al., 2018; Krause and Tolaymat, 2018; Stoll et al., 2019; Baur and Oll, 2022). Baur and Oll (2022), for instance, reviewed past studies and concluded that carbon footprint estimates from Bitcoin span from 1.2 to 130.50 Mt CO2 per year.

The environmental sustainability concerns about cryptocurrency have led to an emerging class of cryptocurrencies that are considered environmentally sustainable (hereafter referred to as clean cryptocurrency). This new cryptocurrency class is built on energy-efficient algorithms and aims to incorporate renewable energy into the mining process (Ren and Lucey, 2022a). Some examples of such cryptocurrencies include Cardano, Ripple, and IOTA. Their respective estimated energy consumption is 0.5479 kWh, 0.0079 kWh, and 0.00011 kWh per transaction, compared to the 707 kWh per transaction of Bitcoin (Ren and Lucey, 2022a). Hence, these clean cryptocurrencies offer environmental benefits alongside other benefits conventional cryptocurrencies may offer. More than ever before, economic actors are now required to decouple the pursuit of economic prosperity from environmental degradation and carbon footprint (Yoshino et al., 2021; Ndubuisi and Owusu, 2022). As the pressure to achieve this intensifies through the global call for a green economic recovery, the environmental sustainability threats of cryptocurrencies entail that sustainability of the economic recovery plans through cryptocurrencies must also be considered. As clean cryptocurrencies offer investment and exchange opportunities without compromising the global agenda of making the planet greener and more environmentally sustainable, it calls for a better understanding of its market fundamentals as well as the factors that shape its developments. Consequently, this paper's objective is to contribute to the cryptocurrency literature in this regard by examining how clean cryptocurrencies' pricing is influenced by media attention on cryptocurrency environmental concerns. The paper tests this relationship by examining the dependence and risk spillover between clean cryptocurrencies' prices and the media attention on cryptocurrency environmental concerns

How the media influences financial assets have long been an important area of inquiry in the finance literature. Although the efficient-market hypothesis suggests that the media plays no significant role in driving the developments in financial markets as public news is quickly and fully incorporated into asset prices even before the media report it, several studies have found that the media do influence developments in the financial market. In this case, the financial markets are not efficient in a way that all available information is instantaneously integrated into prices as assumed by proponents of the EMH (Strycharz et al., 2018). For instance, studies have found that the media influences investing behavior (Tetlock, 2007; Fang and Peress, 2009; Jiao et al., 2020) as well as impacts asset prices through investors' reactions, sentiments, and attention (Peress, 2014; Wu and Lin, 2017; Liu and Han, 2020; Ndubuisi et al., 2022). Others have shown that media attention on financial assets can affect their trading volume as well as drive their share price reactions (Engelberg and Parsons, 2011; Dougal et al., 2012; Fang and Peress, 2009). Thus, media coverage and attention can be seen as important sources to inform investors. From an agenda-setting and stake-holder theory perspective, it is thus safe to argue that topics that are salient on the media agenda are transferred to the public agenda as well as influence the decision-making processes of stakeholders such as investors (see Strycharz et al., 2018; Gao et al., 2021). Consistent with this view, and as extant studies suggest that cryptocurrencies have asset-like prosperities, this paper asks whether clean cryptocurrencies' pricing is influenced by the media attention on cryptocurrency environmental concerns.

To our best knowledge, this is the first paper to analyze the aforementioned relationship. However, the paper is related to nascent but growing literature on the behaviors of and factors affecting clean cryptocurrencies. Notable in this literature include Ren and Lucey (2022a,b) and Pham et al. (2022). Ren and Lucey (2022a) investigate the herding behavior of dirty and clean cryptocurrencies. Although they found that herding generally exists only in the dirty cryptocurrency market, and is more significant in down markets, they did find that clean cryptocurrencies' investors herd to dirty crypto markets, especially when both markets are generating positive returns. Ren and Lucey (2022b) examine whether clean energy serves as a hedge or safe-haven for cryptocurrencies, differentiating between dirty and clean cryptocurrencies. They found that except during extreme bearish markets where clean energy serves as at least a weak safe-haven for both, clean energy stocks are not a direct hedge for either of the types of cryptocurrencies. Pham et al. (2022) examine the extreme tail dependence among carbon prices, dirty and clean cryptocurrencies. They found that carbon prices are largely disconnected from cryptocurrencies during low volatility periods. They also found that except during the COVID-19 pandemic, clean cryptocurrencies are weakly connected to dirty cryptocurrencies.

Unlike these studies that focus on either the herding behavior of green cryptocurrency, how clean energy stocks hedge for clean cryptocurrencies, or the tail connectedness among clean and dirty cryptocurrencies, the focus of the current paper is on the connectedness and time–frequency domain relationship between media attention on the environmental concerns of cryptocurrencies and clean cryptocurrencies' prices. Moreover, to offer a more rounded discussion, this paper provides some additional analyses, where we incorporate the price evolution of dirty cryptocurrencies using Bitcoin into the system containing both cryptocurrency environmental attention index and clean cryptocurrencies' prices. This enables us to shed light on the effects of bitcoin prices on the dynamic connectedness between environmental concerns on cryptocurrency and clean cryptocurrencies' prices as well as the net pairwise connectedness and coherency between this index and bitcoin across both time and frequency domains. Our empirical analysis unfolds as follows: First, we estimate the degree of connectedness among cryptocurrency environmental attention index and 12 clean cryptocurrencies. Secondly, we retrieve and plot the time-varying net pairwise connectedness between each clean cryptocurrency and the cryptocurrency environmental attention index. Thirdly, we explore the asymmetric degrees of connectedness among these variables by distinguishing between positive and negative shocks on the cryptocurrency environmental attention index. Fourthly, we analyze the degree of coherency and lead–lag co-movement between each clean cryptocurrency and cryptocurrency environmental attention index across both time and frequency domains. Lastly, we re-estimate all our analysis while introducing bitcoin as an additional variable to represent the effects of conventional cryptocurrency prices on these relationships.

Results from TVP-VAR show a strong risk spillover among the chosen clean cryptocurrencies and media attention on cryptocurrencies environmental concern, implying that the price formation of the chosen clean cryptocurrencies is due to risk spillovers from others in the system as well as media's attention on the sustainability of the cryptocurrencies markets. Also, across all the sample period, shocks from CEAI were dominated by shocks from TRON while shocks from ADA, ALGO, COSM, EOS, IOTA, VECH, STEL, TEZO and RIPP dominated shocks from CEAI. However, these findings are different for HEDE and POLY which exhibit significant periods of positive net pairwise connectedness with CEAI, suggesting that shocks from CEAI dominated shocks from these clean cryptocurrencies, especially for POLY. From the MODWT, we show that clean cryptocurrencies lead media environmental attention in the short term, especially after 2021. However, before 2021, there are notable periods in which cryptocurrency environmental attention leads green cryptocurrency prices, especially Algorand, ESO, Polygon, VeChain, and Tezos while the prices of Hedera, Polygon, Cosmos, IOTA, TRON, Stellar, Tezos, and Ripple lead media attention on cryptocurrency environmental concerns in the long term. Our additional analyses show that regardless of the specification, the degrees of connectedness increase, following the inclusion of bitcoin in the system and that positive net pairwise connectedness significantly dominates negative net pairwise connectedness between bitcoin and cryptocurrency environmental attention index.

The rest of this paper is structured as follows. The next section describes the data as well as presents the empirical techniques adopted for this study. The third section presents and discusses the results, while section four contains the conclusions and policy implications.

2. Data and methods

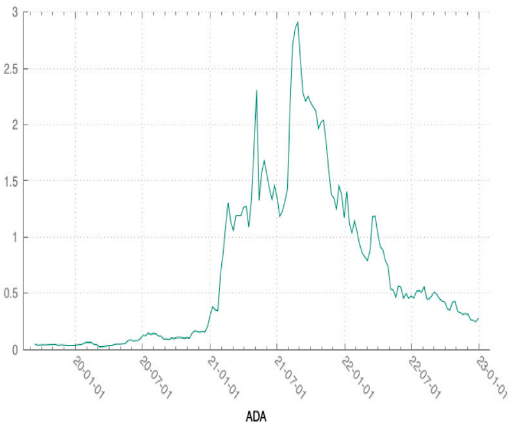
2.1. Data

Ren and Lucey (2022a) recently identified 12 cryptocurrencies that are ranked among the top 50 by market capitalization and are considered clean. They include, Cardano (ADA), Algorand (ALGO), Cosmos (COSM), EOS (EOS), Hedera (HEDE), Polygon (POLY), IOTA (IOTA), TRON (TRON), VeChain (VECH), Stellar (STEL), Ripple (RIPP) and Tezos (TEZO). Unlike dirty cryptocurrencies (e.g., Bitcoin and Ethereum), these cryptocurrencies are considered clean because they are built on energy-efficient consensus algorithms, including Proof-of-Stake (PoS), Proof-of-Authority (PoA), Ripple Protocol, Stellar Protocol, and some other alternatives. In particular, Wendl et al. (2023) document that researchers have increasingly recognized PoS as a sustainable alternative that offers a solution to the environmental concerns related to Proof-of-Work (PoW) cryptocurrencies such as bitcoin, which are historically associated with an increasing climate footprint. Inspired by Ren and Lucey (2022a), this paper used weekly closing prices of these 12 clean cryptocurrencies and Bitcoin (BTC) as measures of clean and dirty cryptocurrencies prices, respectively. The sample period covered is from September 20, 2019 to December 30, 2022. As per the empirical measure of media attention on cryptocurrencies' environmental concern, the study relies on the newly proposed weekly index of cryptocurrency environmental attention (CEAI) by Wang et al. (2022). The CEAI captures the relative extent of media discussions concerning the environmental impact of cryptocurrencies using over 778.2 million news stories about sustainability concerns of cryptocurrency markets' growth from the LexisNexis News and Business database.

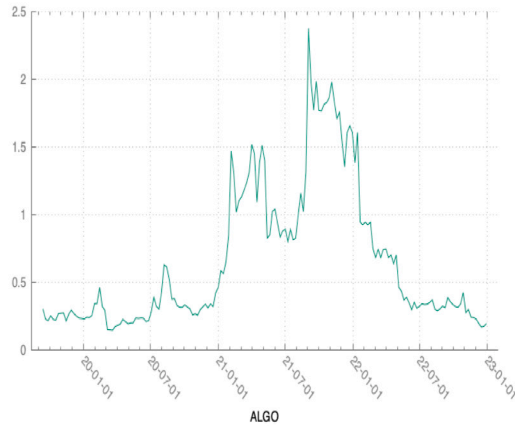
The beginning of our sample period is due to the availability of data of some clean cryptocurrencies selected for this study while the end date is due to the CEAI, which is only available up to the end of December 2022 as at the time of analysis for this study. Figs. 1 and 2 present the time series plots of clean cryptocurrencies prices, bitcoin prices and environmental attention index, respectively. These plots show evidence of significant upward trend in the prices of all the selected clean cryptocurrencies as well as bitcoin. These upward trends in prices appear to have reversed, however, with prices dropping to their pre-2020 levels across all these cryptocurrencies. Regarding cryptocurrency environmental attention, this index appears to have also risen profoundly during this same period, reaching its highest levels in early 2021, but has remained above its pre-2020 levels. This suggests an increase in the level of media attention on energy consumption and mining pollution of cryptocurrencies, especially since early 2021.

In Table 1, we present the descriptive statistics for all the variables while Fig. 3 shows the unconditional correlations among them using a heat-map. As may be seen in Table 1, the mean logged difference in the degree of cryptocurrency environmental attention for the period of this study is about 0.0003. Also, among the chosen clean cryptocurrencies, in descending order, EOS, ALGO, IOTA and TEZO exhibit negative mean returns while the rest possess positive mean returns. While POLY has a highest positive return of about 0.0242, HEDE has the least positive mean return of about 0.00O1. Bitcoin has a mean return of about 0.0027. Coefficients of the standard deviation tests suggest that POLY is the most volatile clean cryptocurrency and that environmental attention on cryptocurrencies is less volatile than the returns of clean cryptocurrencies. Whereas the coefficients of the excess kurtosis tests are positive for all the variables, indicating that all the series depart from the normality condition, the skewness test show that ALGO, COSM, EOS, POLY, VECH, TEZO and BTC are positively skewed.

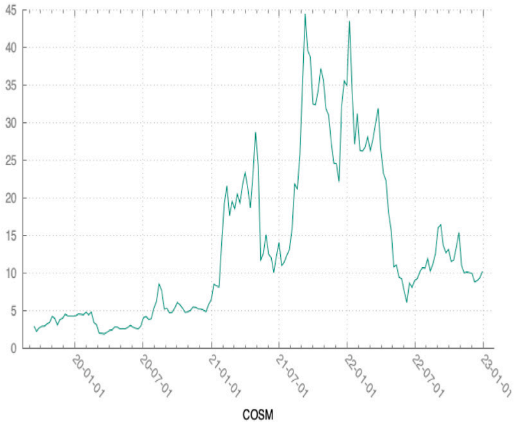
The Jarque–Bera tests corroborates the excess kurtosis tests results, with positive coefficients for all the variables. Finally, the Augmented Dickey–Fuller (ADF) test for unit roots also shows that all the series become stationary after at the first difference, making it suitable for the two econometric methods applied in this study. Results of the contemporaneous correlation matrix as shown in Fig. 3 indicate that all the chosen clean cryptocurrencies and bitcoin have negative correlation with cryptocurrency environmental attention. The negative correlation appear to be stronger between CEAI and ADA, followed by TEZO and BTC while it is least with POLY, followed by RIPP. Among clean cryptocurrencies, return correlations are positive and strongest between EOS and TRON, followed by EOS and IOTA. It is also evident that correlations are weaker between HEDE and other clean cryptocurrencies, followed by the correlations between POLY and other clean cryptocurrencies. Correlations are negative between BTC and CEAI, POLY and RIPP while there are positive with the remaining cryptocurrencies.



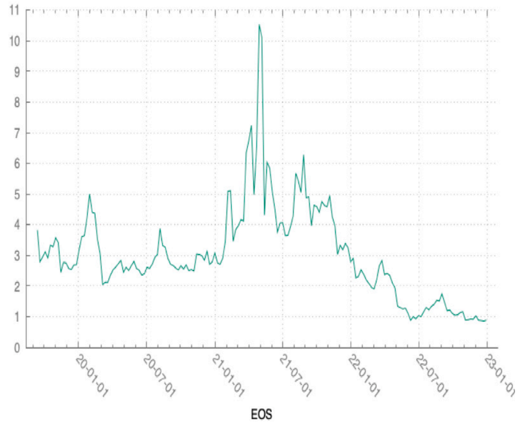
(a) Plot of ADA prices



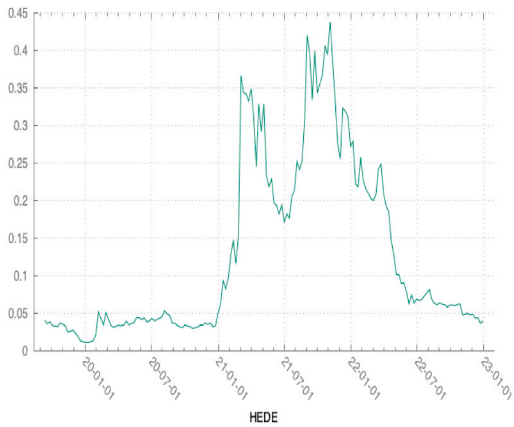
(b) Plot of ALGO prices



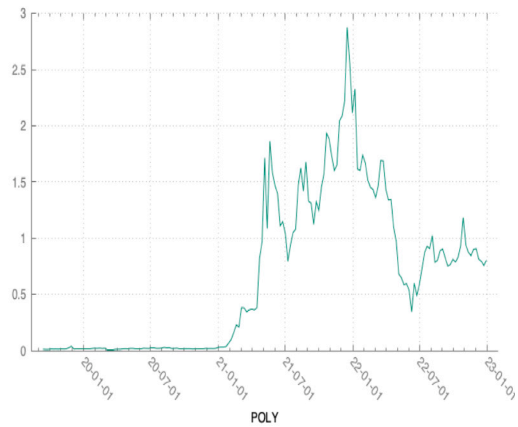
(c) Plot of COSM prices



(d) Plot of EOS prices

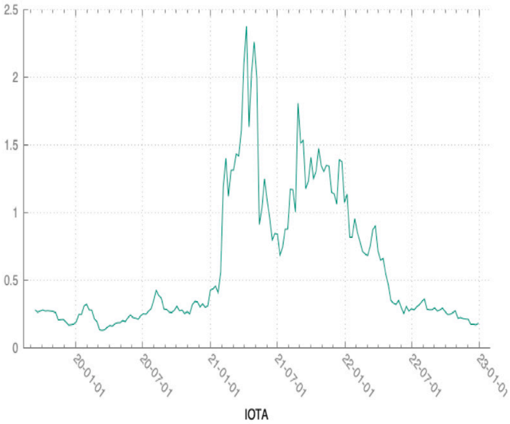


(e) Plot of HEDE prices

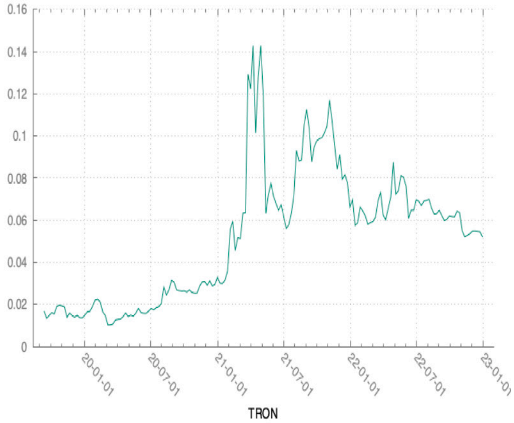


(f) Plot of POLY prices

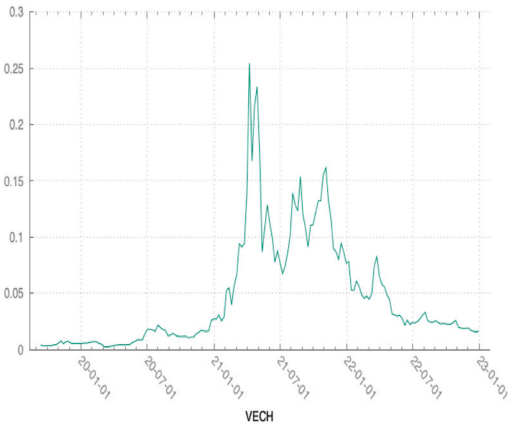
Fig. 1. Plots of clean cryptocurrencies prices.



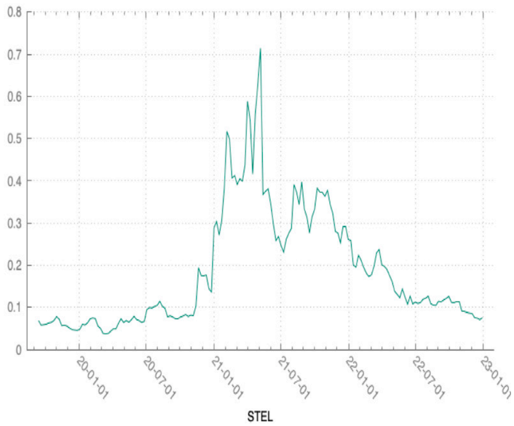
(g) Plot of IOTA prices



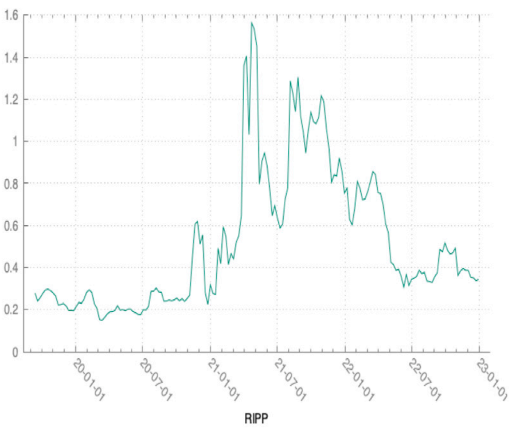
(h) Plot of TRON prices



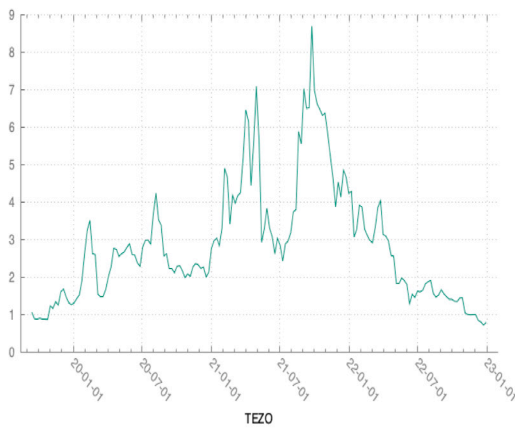
(i) Plot of VECH prices



(j) Plot of STEL prices



(k) Plot of RIPP prices



(l) Plot of TEZO prices

Fig. 1. (*continued*).

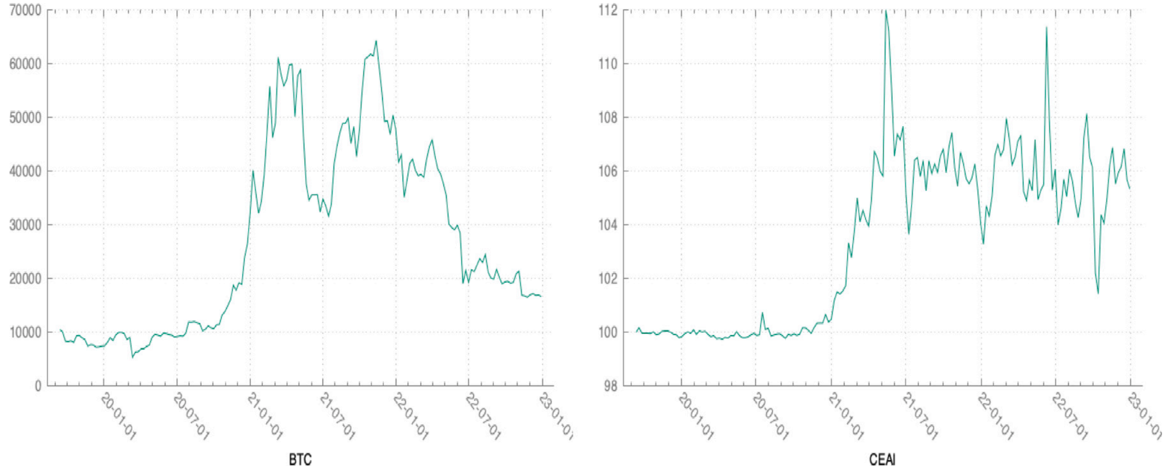


Fig. 2. Plots of Bitcoin and cryptocurrency environmental attention index.

Table 1
Descriptive statistics.

Variable	Mean	Min.	Max.	Std. dev.	Skew.	Ex. kurt.	JB	ADF
CEAI	0.0003	−0.0378	0.0568	0.0106	1.0900	8.9036	602.18***	−12.202***
ADA	0.0101	−0.5551	0.6539	0.1510	0.3202	2.7860	58.565***	−11.477***
ALGO	−0.0026	−0.6821	0.5918	0.1708	−0.2602	2.7679	56.849***	−13.165***
COSM	0.0073	−0.7286	0.5366	0.1643	−0.4604	2.3833	46.785***	−11.690***
EOS	−0.0085	−0.8511	0.4782	0.1523	−0.9226	5.7554	261.79***	−10.800***
HEDE	0.0001	−0.3500	0.9197	0.1705	1.8711	7.8989	547.51***	−11.864***
POLY	0.0242	−1.0702	0.7671	0.2160	−0.3435	5.2044	197.49***	−8.3483***
IOTA	−0.0026	−0.7848	0.7558	0.1610	0.0869	5.7184	234.57***	−12.608***
TRON	0.0065	−0.6374	0.7107	0.1325	0.0998	7.4509	398.14***	−13.465***
VECH	0.0081	−0.7095	0.6000	0.1880	−0.0772	2.1564	33.496***	−12.442***
STEL	0.0005	−0.6638	0.7498	0.1457	0.8182	7.1075	381.234***	−10.086***
RIPP	0.0012	−0.6753	0.7437	0.1617	0.5144	5.8671	254.28***	−12.851***
TEZO	−0.0017	−0.6630	0.4370	0.1548	−0.5021	2.2235	42.660***	−12.814***
BTC	0.0027	−0.5360	0.2354	0.1031	−1.1355	4.8149	203.11***	−12.854***

Note JB and ADF represent the Jarque–Bera and Augmented Dickey–Fuller tests statistics for normality and unit roots, respectively.
***Indicates significance at the 1% level.

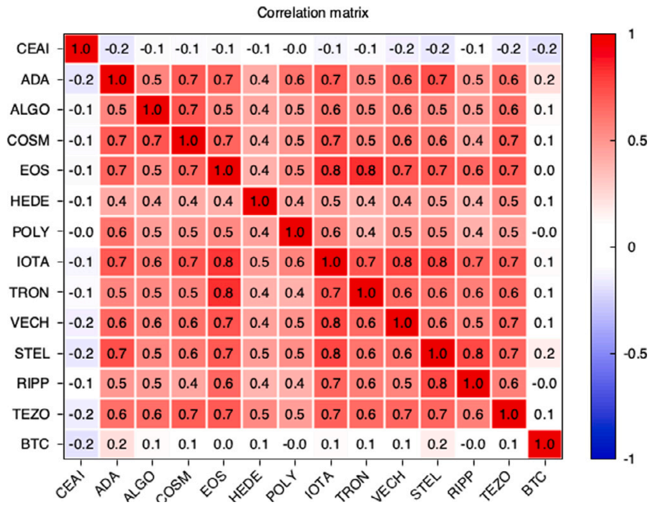


Fig. 3. Plot of correlation matrix among the variables.

2.2. Methods

Consistent with the paper's objective of testing empirically the dependence and risk spillover between clean cryptocurrencies' prices and the media attention on cryptocurrency environmental concerns, two empirical approaches are employed: the Bayesian Time-varying Parameter Vector Autoregressive (TVP-VAR) of Antonakakis et al. (2020) and the Maximum Overlap Discrete Wavelet Transform (MODWT) of Whitcher and Craigmile (2004). Beginning with the former, it is used to test the sphere of shocks or risk propagation between two or more variables while the latter is used to explore the dependence and coherency between two variables across both time and frequencies. These two econometric frameworks are described in details below.

2.2.1. The TVP-VAR connectedness model

The TVP-VAR based spillover approach offers several advantages over other spillover models, such as the Diebold and Yilmaz (2012) spillover model. For instance, it permits the variations in variances using the stochastic volatility Kalman Filter estimation with forgetting factors of Koop and Korobilis (2014), and it is not sensitive to outliers, but adjusts swiftly to events. Also, unlike other spillover models that may either overreact when the rolling-window size is too small or flattens the effects out when a large rolling-window size is selected, there is no burden of arbitrary selection of the rolling window-size and no loss of observations.

Following these features, the TVP-VAR has gained significant application in recent studies (see e.g., Mishra and Ghate, 2022; Adekoya et al., 2022). Basically, The TVP-VAR model evolves with a basic VAR model with lag p as follows:

$$x_t = \phi + \theta_1 x_{t-1} + \cdots + \theta_p x_{t-p} + \mu_t \qquad \mu_t | F_{t-1} \sim N(0, S_t) \tag{1}$$

where, x_t represents the N variables at time t. θ_t is a $N \times N$ dimension of time-varying coefficient matrix while μ_t is the error term. S_t is an $N \times N$ time-varying variance–covariance matrix; R_t denotes an $Np \times Np$ variance–covariance matrix while F_{t-1} is the one period lag of available information set.

The Generalized Impulse Response Function (GIRF) is used to retrieve the responses of all variables after a shock in variable i and the differences between a H-step-ahead error forecast assuming that variable i is shocked and another where it is not. Thus, the resulting difference may be attributed to the shock in variable i, defined as follows:

$$GIR_t = (H, \lambda_{j,t}, F_{t-1}) = E(x_{t+H} | \mu_{j,t} = \lambda_{j,t}, F_{t-1}) - E(x_{t+H} | F_{t-1}), \tag{2}$$

$$\Psi^g_{j,t}(J) = \frac{A_{J,t} S_t \mu_{j,t}}{\sqrt{S_{jj,t}}} \frac{\lambda_{j,t}}{\sqrt{S_{jj,t}}} \qquad \lambda_{j,t} = \sqrt{S_{jj,t}} \tag{3}$$

where J is the forecast horizon, $\lambda_{j,i}$ denotes the selection vector, with 1 on the jth position and 0 otherwise. If one variable is shocked x_j while the other is not, the contribution of this variable to the variance in another variable x_i is given by the Generalized Forecast Error Variance Decomposition (GFEVD) defined as follows:

$$\tilde{\gamma}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}} \times 100 \tag{4}$$

where $\sum_{j=1}^{N} \tilde{\gamma}^g_{ij,t}(J) = 1$ and $\sum_{i.j=1}^{N} \tilde{\gamma}^g_{ij,t}(J) = N$. The normalization of the variance shares makes each role to add up to 100, indicating that all variables jointly reflect the total forecast error variance of variable i.

$$C^J_{i\leftarrow} = \sum_{j=1}^{n} \gamma^J_{ij} \times 100, \qquad and \qquad C^J_{i\rightarrow} = \sum_{j=1}^{n} \gamma^J_{ji} \times 100, \quad j \neq i; \quad 0 \leq C^J_{i\leftrightarrow} \leq 1 \tag{5}$$

Following this, the net directional connectedness (*Net*), which shows the differences between $C^J_{i\leftarrow}$ and $C^J_{i\rightarrow}$ is: $C^J_i = C^J_{i\rightarrow} - C^J_{i\leftarrow}$. Intuitively, if $C^J_i > 0$, variable i influences the system than it is being influenced, and vice versa. Further, the total connectedness index ($Total$) which measures the total connectedness of the system, with higher values denoting higher connectedness, is given as:

$$Total = \frac{1}{k} \sum_{i,j=1}^{k} \gamma^J_{ij} \times 100, \qquad i \neq j \tag{6}$$

We retrieve and plot the net directional connectedness of all clean cryptocurrencies with the index of CEAI. Finally, in a further analysis, the paper also account for asymmetric risk spillover among the variables by distinguishing between positive and negative shocks on CEAI. Thus, we also consider the degree of risk spillover when either positive or negative shocks occur to CEAI. Following Urom et al. (2021), positive and negative shocks to CEAI are denoted by:

$$CEAI_{pos} = \begin{cases} CEAI_t, & if \quad CEAI_t > 0 \\ 0, & if \quad otherwise \end{cases}$$

$$CEAI_{neg} = \begin{cases} CEAI_t, & if \quad CEAI_t < 0 \\ 0, & if \quad otherwise \end{cases} \tag{7}$$

Table 2
Connectedness among clean cryptocurrencies and cryptocurrency environmental attention index.

	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	FROM
CEAI	67.41	2.69	2.17	2.87	4.49	0.37	0.57	2.42	4.41	2.39	4.02	2.11	4.08	32.59
ADA	0.88	21.09	5.80	9.44	8.79	2.51	6.42	9.93	5.96	8.16	10.10	4.26	6.63	78.91
ALGO	1.36	6.97	21.17	11.82	7.92	3.09	4.55	8.39	6.95	7.55	6.56	4.27	9.41	78.83
COSM	0.96	9.49	10.85	20.45	8.76	2.29	3.84	9.93	5.88	7.67	7.56	3.64	8.68	79.55
EOS	1.69	7.29	6.04	7.46	17.33	1.99	3.62	11.17	11.68	8.17	8.32	7.14	8.08	82.67
HEDE	1.12	5.85	5.33	4.13	5.22	36.14	5.50	5.74	5.62	5.50	5.90	4.79	9.16	63.86
POLY	2.42	9.72	6.83	5.87	7.03	4.68	31.88	7.24	3.57	6.04	6.18	3.50	5.02	68.12
IOTA	0.77	9.05	6.37	8.39	11.21	2.34	3.94	17.47	8.60	9.04	8.88	6.95	6.99	82.53
TRON	1.69	6.27	5.99	5.77	13.83	2.92	2.31	10.35	20.48	7.94	7.44	7.35	7.65	79.52
VECH	0.86	8.21	6.64	7.76	9.63	2.84	3.99	10.67	7.95	20.49	7.19	5.42	8.35	79.51
STEL	1.41	10.20	5.27	7.12	9.36	2.88	3.45	9.77	7.17	6.85	18.90	10.36	7.26	81.10
RIPP	1.88	5.13	4.08	3.86	10.23	3.08	2.36	9.78	8.12	6.25	13.07	25.02	7.14	74.98
TEZO	1.48	6.88	8.50	8.49	9.60	4.59	3.29	8.05	7.51	8.59	7.47	5.84	19.71	80.29
TO others	16.54	87.74	73.86	82.97	106.07	33.59	43.86	103.44	83.42	84.16	92.70	65.64	88.46	962.45
Inc.Own	83.95	108.83	95.03	103.42	123.41	69.73	75.74	120.91	103.90	104.65	111.60	90.66	108.17	TCI = 74.03
NET	−16.05	8.83	−4.97	3.42	23.41	−30.27	−24.26	20.91	3.90	4.65	11.60	−9.34	8.17	

2.2.2. *The wavelet coherence analysis*

Concerning the MODWT technique, it is used to analyze the dependence between each clean cryptocurrency and the CEAI. The choice of wavelets technique is premised on the fact that while most traditional financial econometric models permit the use of one dimensional analysis such as time or frequency, which limits the multiscale information of an original time series, the wavelets approach enables a joint dimensional analysis in both time and frequency domains. Hence, the method conveys information in the time domain as well as information in the frequency domain (Chen et al., 2019). Therefore, wavelets are effective mathematical tools in the analysis of dynamic interaction between two time series at different time and frequency domains. Following Caraiani (2012), therefore, that denotes the wavelet coherence as the ratio of cross-spectrum to the product of each individual series spectrum, the wavelet coherence model that guides the second analysis of this study is defined as:

For a series $x(t)$, the continuous wavelet transform for a wavelet ψ is:

$$W_{s,\tau} = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi * \left\{\frac{t-\tau}{s}\right\} dt \tag{8}$$

where $*$ is a sign of complex conjugation, s denotes the scaling parameter while τ is the location parameter. Thus, for a discrete time series, x_n, with N observations, $n = 0, \dots, N-1$, with a time step δt, the wavelet power spectrum may be retrieved by discretizing the integral of Eq. (8) as follows:

$$W_m^s(s) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \psi^* \left\{(n-m)\frac{\delta t}{s}\right\} \tag{9}$$

Thus, the cross wavelet transform (W_n^{xy}) for two time series, such as x_n and y_n, is defined as:

$$W_n^{xy} = W_n^x W_n^{y*} \tag{10}$$

$$R_n(s) = \frac{|S(s^{-1}W_n^{xy}(s))|}{S(s^{-1}|W_n^x|)^{\frac{1}{2}} S(s^{-1}|W_n^y|)^{\frac{1}{2}}} \tag{11}$$

where S is the smoothing operator in both scale and time. Lastly, the study complements the MODWT with the concept of phase difference to explore the lead–lag relationship between each clean cryptocurrency and CEAI. The phase difference is defined as:

$$\phi_{x,y} = tan^{-1}\left\{\frac{\Im(W_n^{xy})}{\Re(W_n^{xy})}\right\} \tag{12}$$

where $\Im(\cdot)$ and $\Re(\cdot)$ denote the real and imaginary parts of the cross wavelet spectrum.

3. Results and discussion

3.1. *Dynamic connectedness and coherency between CEAI and clean cryptocurrencies prices*

Table 2 presents the results of the risk spillover between clean cryptocurrencies and CEAI estimated based on 100 weeks rolling window, 1 lag length and 10 steps-ahead forecasts horizon. In all cases, we follow Pham et al. (2022) to interpret our results in the light of increased levels of price volatility of cryptocurrency prices during the period of COVID-19 pandemic from February 2020 to February 2021, which captures all the recurrent phases of COVID-19 during the whole year. The result shows that the total

Table 3
Connectedness among clean cryptocurrencies and positive shocks on cryptocurrency environmental attention index.

	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	FROM
CEAI	55.69	4.28	2.65	4.18	6.31	0.49	1.04	3.69	4.94	3.34	4.99	2.62	5.79	44.31
ADA	2.18	20.65	5.67	9.33	8.96	2.37	6.35	9.80	5.93	8.07	9.85	4.26	6.59	79.35
ALGO	1.31	6.94	21.40	11.99	7.82	3.06	4.64	8.37	6.93	7.49	6.59	4.24	9.21	78.60
COSM	2.05	9.42	10.79	20.14	8.64	2.30	3.91	9.89	5.86	7.57	7.49	3.58	8.36	79.86
EOS	2.44	7.53	5.91	7.38	17.18	1.90	3.63	11.18	11.65	8.06	8.34	7.01	7.81	82.82
HEDE	1.30	5.82	5.26	4.19	4.90	36.70	5.47	5.45	5.63	5.42	5.85	4.60	9.40	63.30
POLY	2.78	9.66	6.81	5.98	7.09	4.58	31.36	7.25	3.67	6.23	6.08	3.47	5.03	68.64
IOTA	1.59	9.01	6.26	8.40	11.15	2.22	3.95	17.26	8.58	8.87	8.80	6.92	6.99	82.74
TRON	2.62	6.18	5.92	5.72	13.73	2.88	2.33	10.29	20.27	7.82	7.38	7.28	7.59	79.73
VECH	1.70	8.15	6.56	7.72	9.48	2.77	4.10	10.49	7.95	20.37	7.17	5.34	8.22	79.63
STEL	2.43	10.10	5.18	7.07	9.34	2.81	3.44	9.66	7.11	6.76	18.64	10.35	7.09	81.36
RIPP	2.52	5.19	3.97	3.86	10.03	3.00	2.37	9.75	8.16	6.17	13.13	24.73	7.13	75.27
TEZO	3.28	6.96	8.14	8.17	9.33	4.64	3.27	8.03	7.47	8.40	7.32	5.69	19.31	80.69
TO	26.20	89.23	73.12	83.98	106.77	33.04	44.49	103.83	83.88	84.20	92.98	65.36	89.21	976.30
Inc.Own	81.88	109.88	94.53	104.12	123.95	69.75	75.85	121.09	104.15	104.57	111.63	90.09	108.52	TCI = 75.10
NET	−18.12	9.88	−5.47	4.12	23.95	−30.25	−24.15	21.09	4.15	4.57	11.63	−9.91	8.52	

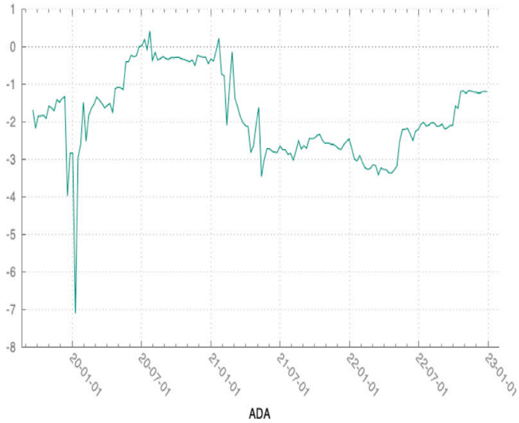
connectedness index (*Total*) is about 74.03%, indicating a strong level of shocks transmission among clean cryptocurrencies prices and media attention on cryptocurrency environmental sustainability concerns. This result shows that about 74.03% forecast error variance in the price formation of the chosen clean cryptocurrencies are due to risk spillovers from others in the system as well as from media attention on cryptocurrency environmental sustainability concerns. Also, the results of net connectedness *Net* indicate that, in descending order, EOS, IOTA, STEL, ADA, TRON, VECH, TEZO and COSM are the net-transmitters of shocks while HEDE, POLY, CEAI, RIPP and ALGO are net-receivers of shocks to the system. This shows that EOS, IOTA, STEL, ADA, TRON, VECH, TEZO and COSM influences the system containing the remaining clean cryptocurrencies and CEAI more than they are being influenced by the system. On the other hand, HEDE, POLY, RIPP, ALGO as well as CEAI receive stronger shocks from the system than they send to the system.

Fig. 4 presents the time-varying net pairwise connectedness between CEAI and each clean cryptocurrency. The key finding is that for most of the study period, there is negative net pairwise connectedness between CEAI and most of the clean cryptocurrencies. A negative net pairwise connectedness between CEAI and a clean cryptocurrency indicates that in a system consisting of CEAI and the concerned clean cryptocurrency, CEAI receives stronger shocks than it sends to the system. Our results show that across all the sample period, shocks from CEAI were dominated by shocks from TRON. Shocks from most other clean cryptocurrencies including ADA, ALGO, COSM, EOS, IOTA, VECH, STEL, TEZO and RIPP dominated shocks from CEAI, except for a brief period during which shocks from CEAI dominated shocks from these clean cryptocurrencies, mainly during the first half of 2020. This suggests that although the prices of clean cryptocurrencies leads to greater media attention on concerns about cryptocurrency environmental sustainability, during the peak of the COVID-19 pandemic, media attention on cryptocurrency environmental sustainability appears to have led clean cryptocurrency prices. However, these findings are different for HEDE and POLY which exhibit significant periods of positive net pairwise connectedness with CEAI, suggesting that shocks from CEAI dominated shocks from these clean cryptocurrencies, especially for POLY.

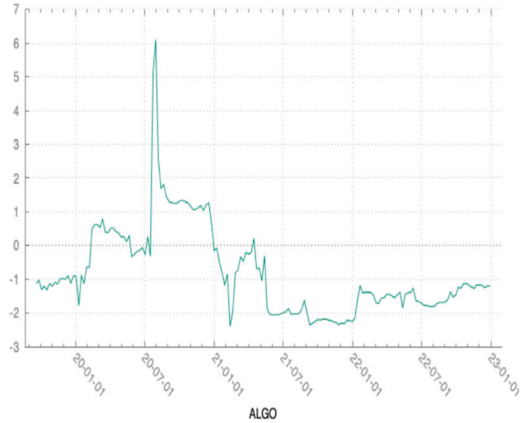
As hinted in Eq. (7) of the methods section, we explore changes in the degree of connectedness under positive and negative shocks on media attention on cryptocurrencies environmental sustainability. Connectedness under positive and negative shocks are presented in Tables 3 and 4, respectively. The key findings are, first, the degree of connectedness is stronger with positive CEAI shocks (75.10%) than with negative CEAI shocks (72.78%). Secondly, under both positive and negative CEAI shocks, net-receivers and net-transmitters remain the change. When we consider positive CEAI shocks, Tezo remains a stronger shocks transmitter than TRON while VECH influences the system more than COSM. However, when we consider negative CEAI shocks, TEZO becomes more important than ADA in net shocks transmission into the system.

Moving on, Fig. 5, Panel a-l presents the results of the wavelet coherency and phase difference analysis. The thick shaded contours show regions of statistically significant dependence. Colder colors (blue) indicate areas of less dependence (coherence) while warmer colors (red) represent regions of high dependence. Further, phase arrows indicate the lead/lag co-movement. Following, Urom et al. (2022a,b,c), right arrows → show *in-phase*, suggesting co-movement in a particular scale while left arrows ← are associated with *anti-phase*, indicating otherwise. In particular, *right-down* ↘ or *left-up arrows* ↖ indicates that CEAI leads, while *right-up* ↗ or *left-down* ↙ arrows indicate that the associated clean cryptocurrency leads CEAI. As can be seen, dependence between clean cryptocurrencies prices and cryptocurrency environmental attention is generally stronger in the short-term (between 1–8 weeks).

There is also notable evidence of medium-term (8–16 weeks) dependence between CEAI and POLY, STEL and ADA. In the long-term (>16 weeks), significant dependence exists between CEAI and HEDE, POLY, COSM, IOTA, TRON, STEL, TEZO and RIPP. Regarding the lead–lag relations, in the short-term, the phase arrows mostly face left-downwards, suggesting that clean cryptocurrencies lead CEAI, especially after 2021. However, before 2021, there are notable periods with left-upwards facing arrows, indicating that CEAI leads green cryptocurrency prices, especially ALGO, ESO, POLY, VECH and TEZO. This suggests that during the COVID-19 crisis, media attention on cryptocurrency sustainability led the price formation of these green cryptocurrencies. The

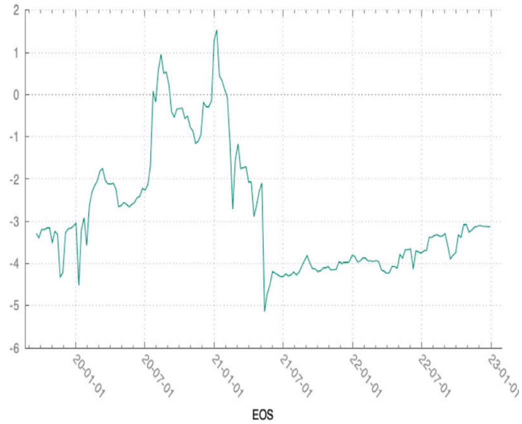


(a) Plot of net connectedness with ADA

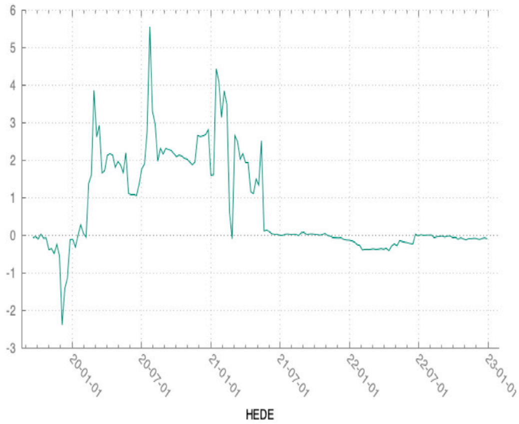


(b) Plot of net connectedness with ALGO

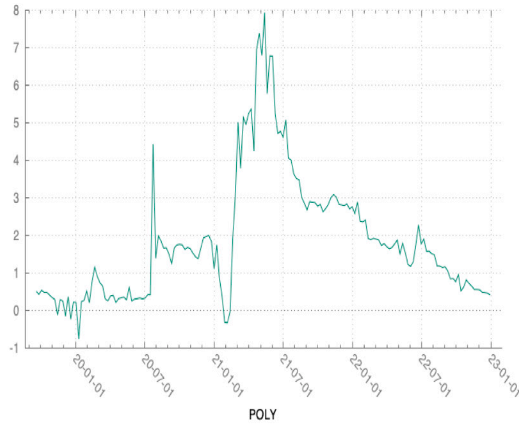
(c) Plot of net connectedness with COSM



(d) Plot of net connectedness with EOS

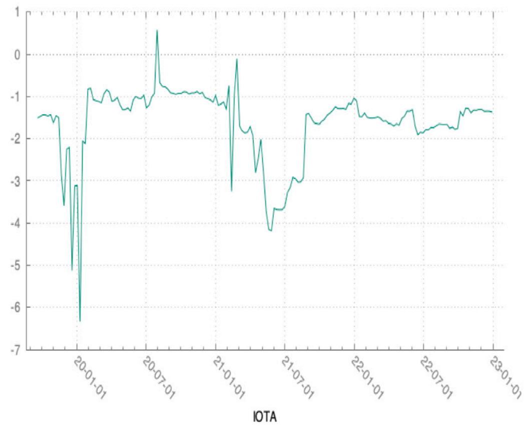


(e) Plot of net connectedness with HEDE

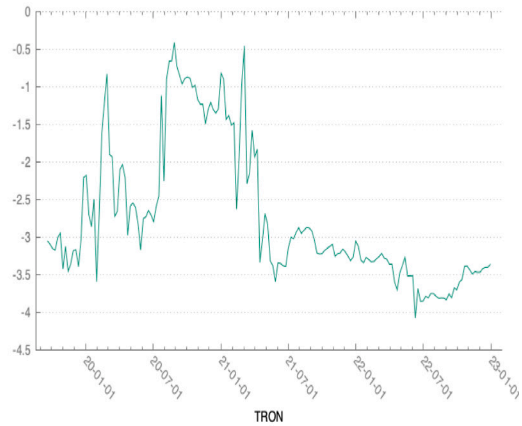


(f) Plot of net connectedness with POLY

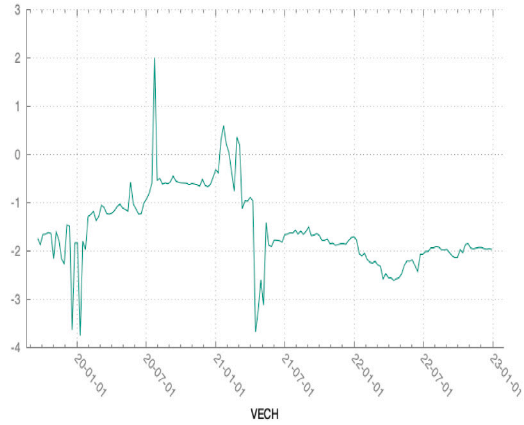
Fig. 4. Plots of CEAI net pairwise connectedness with clean cryptocurrencies.



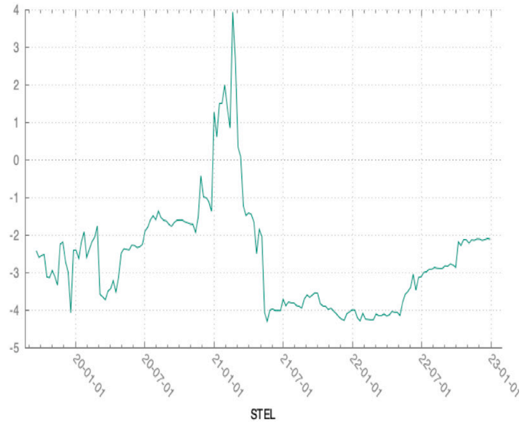
(g) Plot of net connectedness with IOTA



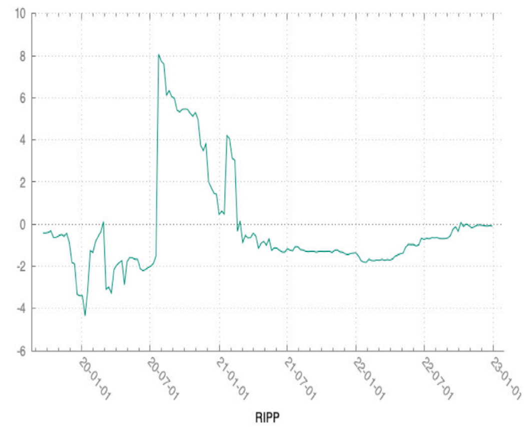
(h) Plot of net connectedness with TRON



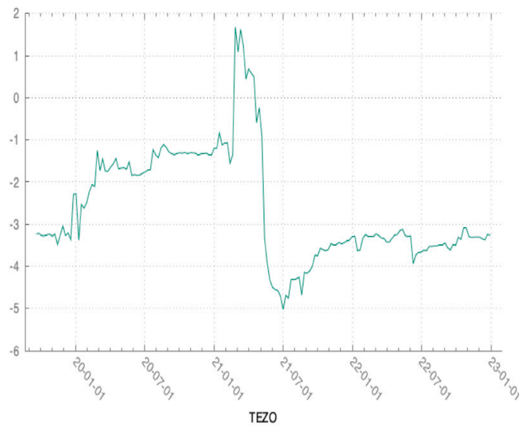
(i) Plot of net connectedness with VECH



(j) Plot of net connectedness with STEL



(k) Plot of net connectedness with RIPP



(l) Plot of net connectedness with TEZO

Fig. 4. (*continued*).

phase arrows associated with the observed long-term dependence are mostly right upwards, suggesting that in the long-term, the prices of HEDE, POLY, COSM, IOTA, TRON, STEL, TEZO and RIPP lead CEAI.

Table 4
Connectedness among clean cryptocurrencies and negative shocks on cryptocurrency environmental attention index.

	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	FROM
CEAI	85.59	1.21	0.87	1.14	0.56	1.17	0.62	0.86	1.37	1.45	1.67	1.45	2.03	14.41
ADA	1.35	20.64	5.74	9.50	8.92	2.67	6.65	9.88	5.91	8.12	9.66	4.43	6.53	79.36
ALGO	0.18	6.96	21.25	11.99	7.79	3.44	4.72	8.42	7.17	7.61	6.57	4.27	9.64	78.75
COSM	0.41	9.59	10.90	20.20	8.70	2.68	3.97	10.07	5.99	7.67	7.42	3.64	8.77	79.80
EOS	0.49	7.58	5.95	7.55	17.42	2.21	3.95	11.23	11.82	8.15	8.32	7.14	8.20	82.58
HEDE	0.67	6.08	5.06	4.70	4.88	35.65	6.01	6.62	5.64	5.79	6.14	5.03	7.73	64.35
POLY	1.10	10.03	6.91	6.00	7.43	5.29	31.05	7.49	3.76	6.30	5.86	3.84	4.94	68.95
IOTA	0.42	9.01	6.24	8.53	11.16	2.61	4.17	17.37	8.59	8.95	8.69	7.16	7.09	82.63
TRON	0.43	6.40	5.98	5.88	13.93	3.15	2.49	10.50	20.57	8.02	7.51	7.33	7.82	79.43
VECH	0.77	8.21	6.53	7.75	9.35	3.08	4.15	10.51	8.05	20.36	7.27	5.37	8.58	79.64
STEL	0.83	9.90	5.30	7.09	9.35	3.17	3.45	9.63	7.37	6.98	18.95	10.32	7.66	81.05
RIPP	0.60	5.60	4.03	3.93	10.19	3.45	2.84	10.08	8.19	6.25	12.91	25.05	6.88	74.95
TEZO	1.90	6.83	8.47	8.50	9.45	4.47	3.21	8.00	7.68	8.55	7.71	5.52	19.74	80.26
TO	9.15	87.41	71.97	82.55	101.70	37.39	46.23	103.29	81.55	83.82	89.75	65.51	85.87	946.18
Inc.Own	94.73	108.05	93.21	102.74	119.12	73.04	77.28	120.66	102.12	104.19	108.70	90.56	105.61	TCI = 72.78
NET	−5.27	8.05	−6.79	2.74	19.12	−26.96	−22.72	20.66	2.12	4.19	8.70	−9.44	5.61	

Table 5
Connectedness among clean cryptocurrencies, Bitcoin and cryptocurrency environmental attention index.

	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	BTC	FROM
CEAI	65.71	2.81	2.39	3.01	4.58	0.47	0.61	2.48	4.25	2.58	3.98	2.20	3.89	1.05	34.29
ADA	0.94	20.76	5.77	9.30	8.91	2.27	6.00	9.86	6.10	8.10	9.93	4.35	6.50	1.20	79.24
ALGO	1.54	6.96	21.00	11.67	8.04	2.92	4.37	8.37	7.05	7.50	6.45	4.37	9.31	0.44	79.00
COSM	1.07	9.44	10.80	20.25	8.81	2.18	3.65	9.93	6.01	7.61	7.47	3.84	8.61	0.34	79.75
EOS	1.71	7.29	6.09	7.41	17.27	2.01	3.58	11.10	11.64	8.14	8.29	7.26	7.94	0.26	82.73
HEDE	1.16	5.77	5.24	4.10	5.85	34.55	5.71	5.81	5.79	5.54	5.68	4.60	8.92	1.29	65.45
POLY	2.54	9.31	6.72	5.64	7.16	4.80	32.70	6.89	3.53	6.12	6.13	3.37	4.75	0.34	67.30
IOTA	0.83	9.09	6.36	8.34	11.22	2.26	3.71	17.50	8.65	8.87	8.90	7.00	6.77	0.53	82.50
TRON	1.73	6.33	6.10	5.74	13.73	2.89	2.25	10.42	20.20	7.89	7.35	7.55	7.50	0.32	79.80
VECH	0.90	8.03	6.66	7.67	9.63	2.72	3.89	10.50	8.06	20.41	7.11	5.56	8.21	0.64	79.59
STEL	1.49	10.18	5.12	7.01	9.41	2.70	3.37	9.73	7.15	6.80	18.73	10.41	7.15	0.74	81.27
RIPP	2.12	5.10	4.10	3.82	10.21	2.99	2.22	9.72	8.13	6.15	13.04	24.91	7.06	0.44	75.09
TEZO	1.47	6.91	8.40	8.48	9.69	4.42	3.17	7.89	7.63	8.58	7.42	5.86	19.61	0.47	80.39
BTC	1.43	7.99	5.38	5.16	10.86	3.35	4.51	9.35	8.70	8.17	6.79	7.26	6.17	14.88	85.12
TO	18.94	95.21	79.13	87.33	118.11	35.98	47.03	112.05	92.70	92.03	98.54	73.63	92.79	8.05	1051.53
Inc.Own	84.64	115.98	100.13	107.58	135.38	70.53	79.73	129.55	112.90	112.44	117.27	98.54	112.40	22.93	Total = 75.11
NET	−15.36	15.98	0.13	7.58	35.38	−29.47	−20.27	29.55	12.90	12.44	17.27	−1.46	12.40	−77.07	

A number of probable interpretations of the causality mechanisms between media attention on the environmental sustainability of cryptocurrencies and the price formation of clean cryptocurrencies across time and financial market conditions may be concluded from several fronts. First, given the recent evolution of cryptocurrencies as portfolio diversifiers under climate change and green energy transition, increasing investors' attention and concerns towards climate-related risks emanating from cryptocurrency market suggest that investors consider clean cryptocurrencies safer hedging tools against multifaceted risks, including financial risks, climate risks and rare disasters such as COVID-19 pandemic. This causes increases in the prices of clean cryptocurrencies, which are more environmentally friendly because they out-perform conventional cryptocurrencies that possess increasing carbon footprint. However, the increasing media attention on cryptocurrency market has important implications for media-driven investors' behavior and asset pricing. Indeed, increases in the prices and volatility of clean cryptocurrencies has the potential of increasing awareness and environmental attention on the evolution of their energy footprint, which, may influence their prices. Hence, increase in clean cryptocurrencies' prices may lead to a spike in environmental awareness of the their climate footprint. This is because increasing clean cryptocurrencies' prices, which largely reflect increase in their demand and deployment raise public awareness of potential environmental issues as investors seek maximum protection from multifaceted risks while generating possible returns in line with their risk preferences.

3.2. Effects of bitcoin prices on the dynamic connectedness and coherency between CEAI and clean cryptocurrencies prices

In this subsection, we measure the effects of changes in the price of bitcoin on the dynamic connectedness between cryptocurrency environmental attention and prices of clean cryptocurrencies. Thus, we carried out all the analysis again while introducing bitcoin as an additional variable to represent the dirty cryptocurrency family. As shown in Tables 5–7, we examine the changes in the degree of connectedness and shocks transmission within the system in the presence of bitcoin. In particular, Table 5 shows that when we

Table 6
Connectedness among clean cryptocurrencies, Bitcoin and positive shocks on cryptocurrency environmental attention index.

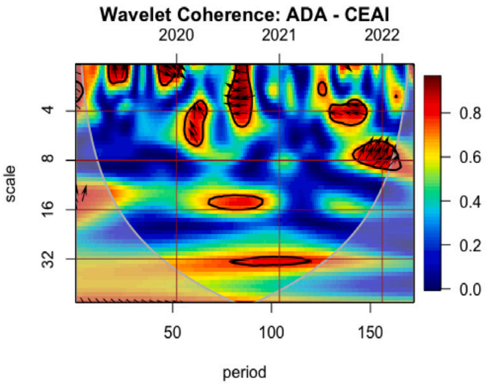
	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	BTC	FROM
CEAI	56.16	4.04	2.61	3.80	6.02	0.50	1.17	3.39	4.50	3.14	4.75	2.60	5.42	1.91	43.84
ADA	2.09	20.37	5.67	9.23	9.08	2.17	5.90	9.72	6.08	8.01	9.71	4.32	6.44	1.22	79.63
ALGO	1.43	6.96	21.21	11.81	8.00	2.88	4.42	8.39	7.06	7.46	6.50	4.34	9.13	0.41	78.79
COSM	2.17	9.36	10.73	19.91	8.74	2.18	3.68	9.89	6.00	7.51	7.40	3.76	8.30	0.37	80.09
EOS	2.43	7.52	5.96	7.35	17.11	1.91	3.53	11.10	11.61	8.03	8.30	7.15	7.64	0.35	82.89
HEDE	1.12	5.92	5.17	4.17	5.47	35.29	5.64	5.58	5.80	5.47	5.65	4.42	9.05	1.26	64.71
POLY	2.94	9.23	6.69	5.77	7.13	4.66	32.34	6.90	3.60	6.31	5.99	3.35	4.74	0.34	67.66
IOTA	1.69	9.04	6.25	8.35	11.17	2.14	3.68	17.29	8.63	8.69	8.81	6.95	6.78	0.54	82.71
TRON	2.76	6.26	6.01	5.68	13.64	2.85	2.24	10.35	19.95	7.76	7.28	7.46	7.41	0.35	80.05
VECH	1.66	8.01	6.57	7.63	9.53	2.64	3.97	10.33	8.07	20.29	7.11	5.50	8.05	0.64	79.71
STEL	2.40	10.11	5.05	6.99	9.44	2.63	3.33	9.63	7.12	6.72	18.45	10.38	7.01	0.74	81.55
RIPP	2.75	5.18	3.96	3.84	10.06	2.90	2.22	9.70	8.17	6.06	13.09	24.60	7.06	0.40	75.40
TEZO	3.03	7.01	8.07	8.19	9.45	4.43	3.14	7.91	7.60	8.40	7.31	5.75	19.19	0.51	80.81
BTC	2.49	8.05	5.22	5.19	10.84	3.26	4.56	9.19	8.72	7.98	6.77	7.09	6.06	14.59	85.41
TO	28.97	96.69	77.97	88.00	118.56	35.14	47.48	112.09	92.96	91.55	98.68	73.06	93.09	9.04	1063.26
Inc.Own	85.13	117.05	99.18	107.91	135.67	70.43	79.82	129.37	112.91	111.84	117.13	97.66	112.28	23.63	Total = 75.95
NET	−14.87	17.05	−0.82	7.91	35.67	−29.57	−20.18	29.37	12.91	11.84	17.13	−2.34	12.28	−76.37	

Table 7
Connectedness among clean cryptocurrencies, Bitcoin and negative shocks on cryptocurrency environmental attention index.

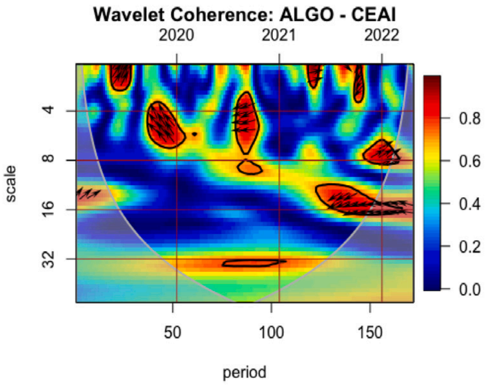
	CEAI	ADA	ALGO	COSM	EOS	HEDE	POLY	IOTA	TRON	VECH	STEL	RIPP	TEZO	BTC	FROM
CEAI	80.17	1.33	1.00	1.27	1.28	0.97	0.83	1.22	1.48	1.71	2.08	2.00	1.89	2.77	19.83
ADA	0.88	20.50	5.67	9.45	9.10	2.45	6.52	9.77	5.99	8.06	9.69	4.60	6.24	1.07	79.50
ALGO	0.21	6.89	21.12	11.79	7.93	3.30	4.60	8.30	7.26	7.58	6.60	4.53	9.48	0.41	78.88
COSM	0.41	9.60	10.86	20.19	8.77	2.41	3.70	10.07	6.14	7.65	7.52	3.85	8.50	0.34	79.81
EOS	0.23	7.61	6.02	7.47	17.47	2.23	4.02	11.19	11.81	8.13	8.30	7.39	7.87	0.26	82.53
HEDE	0.87	5.41	5.52	4.26	5.87	34.14	5.83	5.79	5.84	5.73	5.98	4.84	8.94	0.97	65.86
POLY	0.91	10.00	6.82	5.58	7.69	4.91	31.79	7.45	3.69	6.43	5.82	3.56	5.07	0.27	68.21
IOTA	0.32	9.01	6.19	8.43	11.22	2.49	4.13	17.56	8.63	8.79	8.79	7.31	6.74	0.38	82.44
TRON	0.46	6.26	6.07	5.83	13.87	3.07	2.40	10.43	20.37	7.95	7.57	7.74	7.61	0.35	79.63
VECH	0.72	8.00	6.51	7.63	9.41	2.97	4.12	10.28	8.12	20.33	7.30	5.63	8.33	0.65	79.67
STEL	0.59	9.95	5.19	7.08	9.36	2.96	3.43	9.62	7.31	6.94	18.88	10.59	7.35	0.76	81.12
RIPP	0.57	5.49	4.02	3.86	10.31	3.26	2.59	10.00	8.27	6.18	13.07	24.94	7.04	0.39	75.06
TEZO	0.97	6.59	8.56	8.33	9.40	4.71	3.38	7.71	7.76	8.57	7.76	5.94	19.96	0.35	80.04
BTC	1.03	8.12	5.18	5.32	10.58	3.91	4.96	9.24	8.94	7.98	6.43	7.07	6.63	14.61	85.39
TO	8.16	94.27	77.61	86.31	114.80	39.65	50.52	111.07	91.22	91.71	96.90	75.07	91.70	8.98	1037.97
Inc.Own	88.33	114.77	98.73	106.50	132.26	73.79	82.31	128.63	111.59	112.04	115.78	100.00	111.66	23.60	TCI = 74.14
NET	−11.67	14.77	−1.27	6.50	32.26	−26.21	−17.69	28.63	11.59	12.04	15.78	0.00	11.66	−76.40	

introduce bitcoin to the system, a number of observations can be drawn. First, the degree of connectedness increases to 75.11, implying that about 75.11% of forecast error variance in the value of each of the variables may be attributed to shocks emanating from the system. Secondly, bitcoin is the most vulnerable variable in the system as it becomes the highest net-receiver of shocks from the system. It is crucial to note that bitcoin receives about 77.07 of net-shocks, which is more than the sum of all the net-shocks received by the remaining net-receivers of shocks. This implies that the market for dirty cryptocurrencies is significantly vulnerable to shocks transmission between clean cryptocurrencies and attention to cryptocurrency environmental attention. Lastly, while the lists of net-receivers and net-transmitters remain unchanged, ALGO, which was a net-receiver of shocks, becomes a net-transmitter of shocks in the system with bitcoin while TRON becomes more influential on the system than VECH and TEZO, which were more influential in the system without bitcoin.

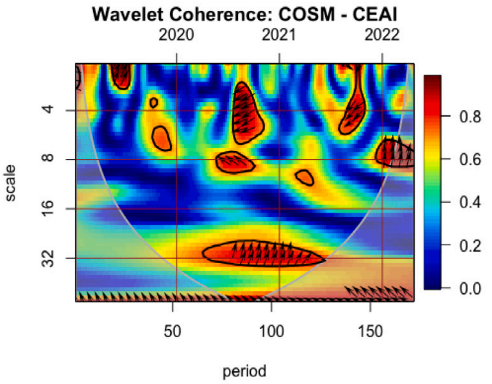
Furthermore, Table 6 displays the degree of connectedness with positive CEAI shocks in the presence of bitcoin. Relative to the results of connectedness with positive CEAI shocks in Table 3, we can deduce that the inclusion of bitcoin raises the degree of connectedness to 75.95. While the lists of net-receivers and net-transmitters of shocks remain the same, bitcoins remains the highest net-receiver of shocks and that ALGO reverses to its position as a net-receiver of shocks. On the other hand, Table 7 shows some interesting observations. First, compared to Table 4, the degree of connectedness increases to 74.14 when we introduce bitcoin to the system with negative CEAI shocks. Also, while bitcoin remains the most influenced variable by the system, EOS becomes the most influential variable in the system, followed by IOTA. Similarly, unlike in the system without bitcoin, where COSM was more influential than TRON, TRON becomes more influential than COSM. It is also interesting to note that with the introduction of bitcoin, RIPP becomes neutral, as it sends to the system an equal amount of shock that it receives from the system. This is in contrast to the system with negative CEAI shocks without bitcoin, where RIPP was significantly more influenced by the system than both CEAI and ALGO.



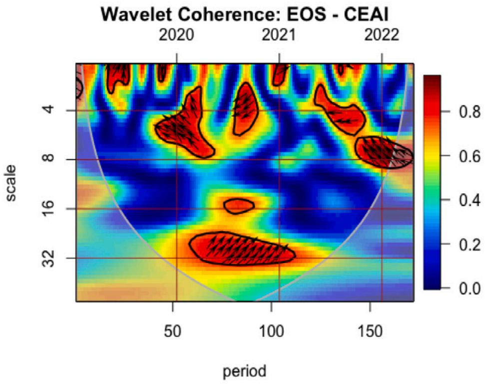
(a) Coherency of ADA with CEAI



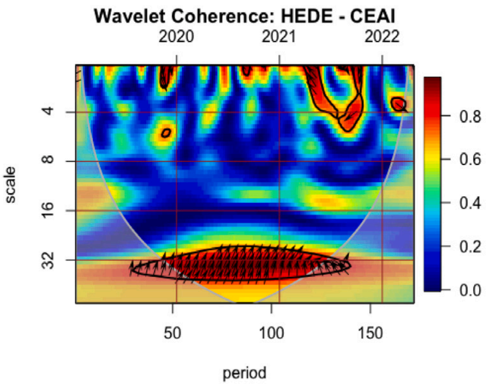
(b) Coherency of ALGO with CEAI



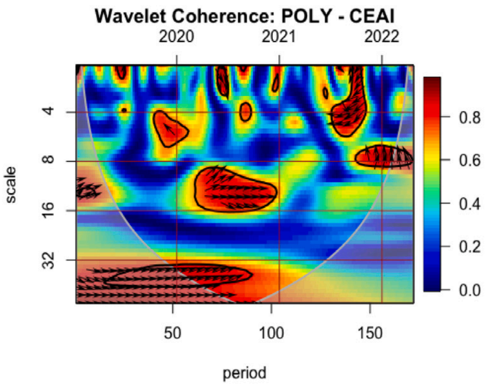
(c) Coherency of COSM with CEAI



(d) Coherency of EOS with CEAI

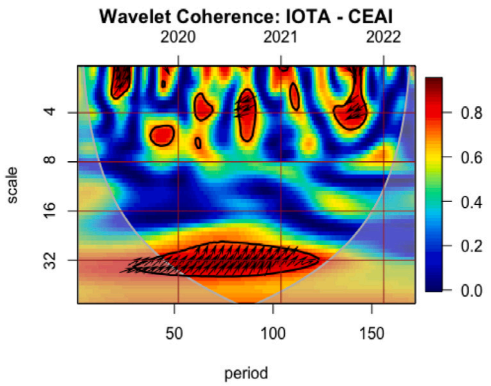


(e) Coherency of HEDE with CEAI

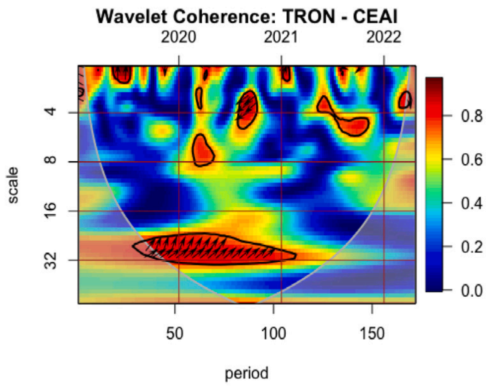


(f) Coherency of POLY with CEAI

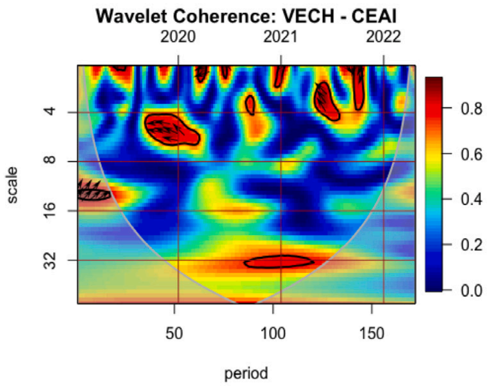
Fig. 5. Coherency of clean cryptocurrencies with cryptocurrency environmental attention.



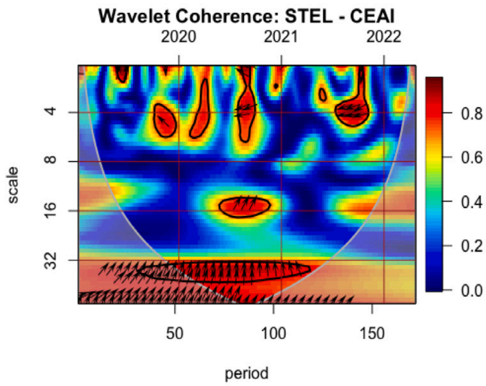
(g) Coherency of IOTA with CEAI



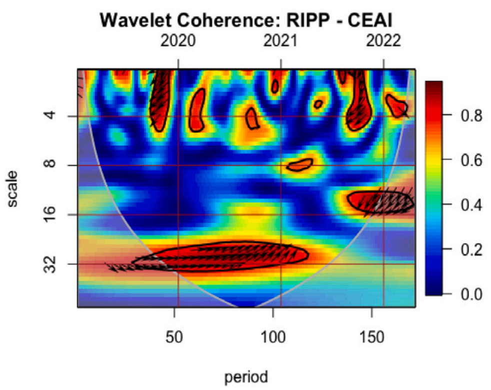
(h) Coherency of TRON with CEAI



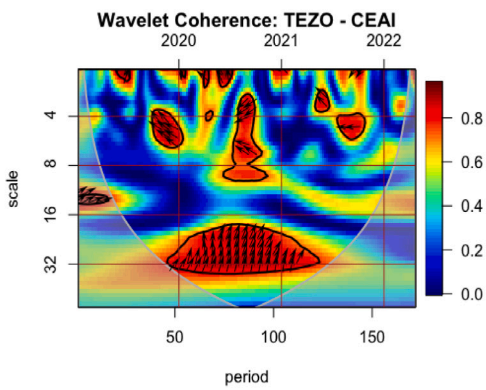
(i) Coherency of VECH with CEAI



(j) Coherency of STEL with CEAI



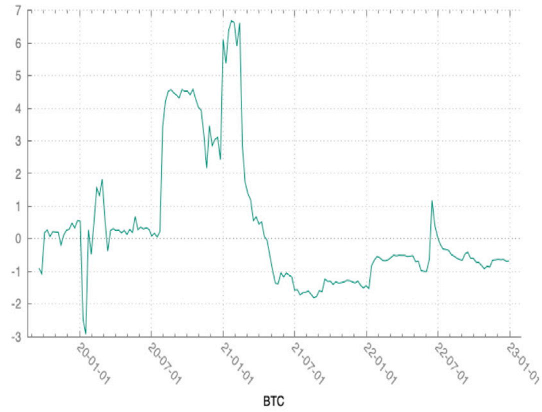
(k) Coherency of RIPP with CEAI



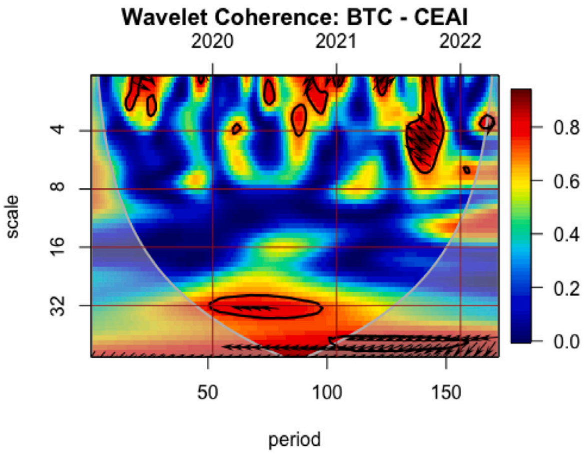
(l) Coherency of TEZO with CEAI

Fig. 5. (*continued*).

Fig. 6 Panel a-b displays the plots of time-varying net pairwise connectedness and wavelet coherency between clean cryptocurrency environmental attention and bitcoin prices, respectively. A number of insights may be drawn from both plots. First, Panel (a) shows notable periods of positive net connectedness especially from early January 2020 till towards the end of 2021. For most of the



(a) Plot of net connectedness with Bitcoin



(b) Coherency of Bitcoin with CEAI

Fig. 6. Plots of net-connectedness and coherency between bitcoin and clean cryptocurrency environmental attention.

periods from 2022 till the end of our sample, net pairwise connectedness was negative. However, there was a brief period of positive net connectedness. Positive net pairwise connectedness between clean cryptocurrency environmental index and bitcoin suggest that investors attention on the sustainability of cryptocurrencies had significant effects on the price evolution of bitcoin, especially between early 2020 and late 2021, which corresponds with the period of increased market volatility due to the COVID-19 pandemic. This result corroborates the findings of Wang et al. (2022), which document a significantly positive relationship between bitcoin and the index of cryptocurrency environmental attention, indicating that the prices of dirty cryptocurrencies respond to public concerns expressed in relation to the environmental effects of increasing energy consumption and mining pollution of traditional cryptocurrencies.

On the other hand, negative net connectedness denotes periods in which bitcoin prices exerted greater influence on cryptocurrency environmental attention. The magnitude of this influence is, however, found to be significantly below the levels of the influence from environmental attention on dirty cryptocurrency prices. Lastly, Fig. 6 Panel (b) shows the time and frequency domain co-movement and lead–lag relationship between environmental attention index and bitcoin. This result corroborates the findings of net pairwise connectedness between the environmental attention and bitcoin prices. Indeed, there are notable periods of significant co-movement and lead–lag relationships, especially in the short- and long-term as shown by thick shaded contours. During these periods, arrows face right downwards, especially from the start of our data sample till 2021. This indicates that during this period, concerns about the sustainability of cryptocurrencies led bitcoin prices. This finding can also be seen around 2022, during which arrows face left upwards, indicating a similar pattern of influence, which appears to extend towards the medium term.

4. Conclusion

This paper employs the Bayesian Time-varying Parameter Vector Autoregressive (TVP-VAR) and Maximal Overlap Discrete Wavelet Transform (MODWT) to investigate the dependence and risk spillover between clean cryptocurrencies pricing and media attention on cryptocurrency environmental concern. As an empirical measure of media attention on cryptocurrency environmental concern, the paper employed the newly proposed weekly index of cryptocurrency environmental attention (CEAI) by Wang et al. (2022). For clean cryptocurrencies, it employed weekly closing price data for 12 clean cryptocurrencies including Cardano, Algorand, Cosmos, EOS, Hedera, Polygon, IOTA, TRON, VeChain, Stellar, Ripple, and Tezos. At first, we estimated the level of connectedness among cryptocurrency environmental attention index and the chosen clean cryptocurrencies. Then, we retrieved and plotted the evolution of net pairwise connectedness between each clean cryptocurrency and the cryptocurrency environmental attention index. Further, we assess the asymmetric degrees of risk spillovers among these variables by differentiating between positive and negative shocks on the cryptocurrency environmental attention index. We also analyzed the coherency and lead–lag co-movement between each clean cryptocurrency and cryptocurrency environmental attention index across both time and frequency domains. In some further analyses, we re-estimated all our analysis while including bitcoin as an additional variable to proxy the effects of dirty cryptocurrency prices on these relationships.

Results from the TVP-VAR model show evidence of strong risk spillover among the chosen clean cryptocurrencies and media attention on cryptocurrencies environmental concern, implying that the price evolution of the chosen clean cryptocurrencies is influenced by risk spillovers from others in the system as well as media's attention on the sustainability of the cryptocurrencies markets. More importantly, our results also show that across all the sample period, shocks from CEAI were dominated by shocks from TRON. Shocks from most other clean cryptocurrencies including ADA, ALGO, COSM, EOS, IOTA, VECH, STEL, TEZO and RIPP dominated shocks from CEAI, except for a brief period during which shocks from CEAI dominated shocks from these clean cryptocurrencies, mainly during the first half of 2020. This suggests that although the prices of clean cryptocurrencies leads to greater media attention on concerns about cryptocurrency environmental sustainability, during the peak of the COVID-19 pandemic, media attention on cryptocurrency environmental sustainability appears to have led clean cryptocurrency prices. However, these findings are different for HEDE and POLY which exhibit significant periods of positive net pairwise connectedness with CEAI, suggesting that shocks from CEAI dominated shocks from these clean cryptocurrencies, especially for POLY.

Concerning results from MODWT, the result showed that clean cryptocurrencies lead media environmental attention in the short term, especially after 2021. However, before 2021, there are notable periods in which cryptocurrency environmental attention leads green cryptocurrency prices, especially Algorand, ESO, Polygon, VeChain, and Tezos. This suggests that during the COVID-19 crisis, attention to cryptocurrency sustainability led the price formation of these clean cryptocurrencies. In the long term, however, the prices of Hedera, Polygon, Cosmos, IOTA, TRON, Stellar, Tezos, and Ripple lead media attention on cryptocurrency environmental concerns. Results from our additional analyses show that regardless of the specification, the degree of connectedness increases, following the inclusion of bitcoin in the system containing clean cryptocurrencies and cryptocurrency environmental attention index. Risk spillover is strongest in the case of negative shocks on cryptocurrency environmental attention. Also, although there are notable periods of positive and negative net pairwise connectedness between bitcoin prices and cryptocurrency environmental attention index, the magnitude of positive net pairwise connectedness significantly dominates negative net pairwise connectedness, suggesting that the conventional cryptocurrency market receives stronger influence than it gives to media cryptocurrency environmental attention index.

These results hold practical investment and policy implications. From an investment perspective, these results suggest that media attention on cryptocurrency environmental concern is an important determinant of clean cryptocurrencies prices. In this regard, investors interested in clean cryptocurrencies should pay close attention to changes in media attention on cryptocurrency environmental sustainability concern. From a policy perspective, the results show that CEAI is a viable instrument to drive investments in clean cryptocurrency as the environmental concerns on cryptocurrency continue to pose threat to making the planet greener and environmentally sustainable. This is corroborated by the findings of a significantly large degree of positive net pairwise connectedness between cryptocurrency environmental attention and bitcoin prices, which indicates that increasing attention to the environmental sustainability of conventional cryptocurrencies influences their prices. Finally, this study can be extended in different ways. For instance, future studies can examine whether media attention on cryptocurrency environmental concerns influences clean and dirty cryptocurrencies differently. Future studies can also examine whether this relationship differs across market conditions and investment horizon.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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