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Are green and dirty cryptocurrencies connected with climate risk attention?

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Abstract
This study examines the spillover effect of climate risk attention on green and dirty cryptocurrencies using the R-squared connectedness approach. We construct climate risk attention indices based on Google Trends data. Our findings unveil a dynamic and asymmetric nature of connectedness. We observe that climate risk attention serves as the net receiver of spillover across all market conditions. This result remains consistent even when employing alternative proxies and different methodologies. The study contributes to the ongoing efforts in sustainability, highlighting the significant role of climate risk attention in influencing investment and regulatory decisions.

Keywords: climate risk attention, green cryptocurrency, dirty cryptocurrency
JEL Classification Codes: C5, F3, G10, G12

1. Introduction

Cryptocurrency, a cost-effective and innovative digital financial tool, has accelerated global financial market integration (Ndubuisi and Urom, 2023; Doan et al., 2024). However, its environmental impact, stemming from high energy use and significant carbon emissions has raised concerns about its sustainability (Zribi et al., 2023; Ndubuisi and Urom, 2023; Corbet and Yarovaya, 2020). Bitcoin mining, driven by its Proof-of-Work blockchain framework,

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consumes more energy than gold mining, with an average energy footprint exceeding 600 kWh per transaction (Corbet et al., 2020). It accounts for approximately 0.5% of global energy consumption, and its carbon emissions could contribute to a potential 2°C temperature rise within three decades (Mora et al., 2018). This has spurred efforts to develop environmentally friendly alternatives, such as Proof-of-Stake blockchains, categorized as "green" cryptocurrencies due to their lower carbon footprint and positive investor reception (Ndubuisi and Urom, 2023; Ren and Lucey, 2022; Patel et al., 2023). However, the coexistence of "dirty" and "green" cryptocurrencies poses challenges for investment viability, particularly in assessing how climate risk impacts the cryptocurrency market.

While the efficient-market hypothesis (EMH) suggests media has limited influence on financial markets due to rapid information integration, empirical studies challenge this view. Research by Jiao et al. (2020) highlights the media's role in shaping investor behavior, revealing differing responses to positive and negative news, as well as the impact of emotions, attention, and media coverage on asset prices (Ndubuisi et al., 2022). Media attention also influences financial asset trading volumes (Dougal et al., 2012), aligning with agenda-setting and stakeholder theories, which emphasize the media's role in shaping public and stakeholder priorities. This study investigates whether investor attention to climate risk affects the returns of "dirty" and "green" cryptocurrencies.

Over the past decade, cryptocurrency markets have gained significant attention from academics, governments, investors, and the media, prompting extensive research. Studies have explored cryptocurrencies' safe-haven properties (Bouri et al., 2017; Demir et al., 2018; Urquhart and Zhang, 2019; Guesmi et al., 2019; Aysan et al., 2019; Akhtaruzzaman et al., 2020; Corbet et al., 2020; Su et al., 2020; Aloui et al., 2022), Bitcoin market efficiency (Nadarajah and Chu, 2017), volatility of green cryptocurrencies (Ahmed et al.,2025; Lee et al.,2025), its role as a medium of exchange (Baur et al., 2018), and their environmental impacts (Zribi et al., 2023; Krause and Tolaymat, 2018; Polemis and Tsionas, 2023). Research has also examined the relationship between environmental factors and cryptocurrency returns (Clark et al., 2023) and media attention on environmental awareness and returns (Clark and Mefteh-Wali, 2023). However, few studies address media attention and its connectedness between clean and dirty cryptocurrencies. Given the growing focus on sustainable investments, further research is needed on risk and return spillovers in this context.

This study contributes to existing literature in several ways. First, it examines the impact of climate risk attention on the returns of both dirty and green cryptocurrencies using novel attention indices. Second, we developed two climate risk attention indices the Physical Risk Attention Index (PRAI) and the Transition Risk Attention Index (TRAI) based on Google Trends search keywords. Both indices are used because climate risks have two dimensions: physical risks, involving direct climate impacts such as extreme weather and rising seas, and transition risks, arising from policy, regulatory, and technological changes in the move to a low-carbon economy. Third, this study specifically includes green cryptocurrencies along with dirty cryptocurrencies. The rise of environmentally sustainable cryptocurrencies, known as clean cryptocurrencies, addresses concerns over Bitcoin's environmental impact. These clean cryptocurrencies employ energy-efficient algorithms and integrate renewable energy sources into mining processes, offering ecological benefits alongside those of traditional cryptocurrencies (Ren and Lucey, 2022). Fourth, we utilize an asymmetric variant of the R^2 connectedness approach, enabling us to examine the overall spillover effect as well as the positive and negative impact of climate risk shocks (Adekoya et al., 2022). Finally, the study has policy implications for investors, policymakers, and portfolio managers.

2. Data and methodology

2.1. Data

To capture a comprehensive measure of climate risk attention, we construct two distinct indices: the Physical Risk Attention Index (PRAI) and the Transition Risk Attention Index (TRAI). The rationale for employing both indices stems from the dual nature of climate-related risks: physical risks, which refer to the direct impacts of climate change (e.g., extreme weather, sea level rise), and transition risks, which relate to policy, regulatory, and technological changes during the shift to a low-carbon economy. By distinguishing between these two dimensions, we are able to assess how public attention responds to different aspects of climate risk, thus enhancing the analytical depth and interpretive power of our study.

Both PRAI and TRAI are constructed using daily Google Search Trends (GST) data obtained through the trendecon R package. Following earlier studies by Zhang (2022), Santi (2023), and Bonato et al. (2023), we carefully selected keywords that are frequently used in discussions of physical and transition climate risks. For PRAI, these include "ecosystems," "sea level," "precipitation," "natural disaster," and "extreme weather." For TRAI, we include "climate policy," "carbon emissions," "hydrofluorocarbon," "bioenergy," "greenhouse gas," and "GHG." The selected keywords aim to reflect both the scientific and policy-related dimensions of climate discourse, thereby supporting the robustness and validity of our Climate Change Attention Indices (CCAI). We aggregate the keyword trends using principal component analysis (PCA) and normalize the indices to a 1–100 scale, where higher values denote elevated levels of climate risk attention. This dual-index framework allows us to isolate and analyze behavioral attention patterns toward both immediate and systemic climate threats.

For green and dirty cryptocurrency, following earlier studies by Ren and Lucey (2022), Patel et al. (2023), and Sharif et al. (2023) we selected 10 cryptocurrencies based on the market capitalization. Green cryptocurrencies are categorized by proof of stake (PoS)[1]. In contrast, dirty cryptocurrencies are categorized by proof of work (PoW)[2].

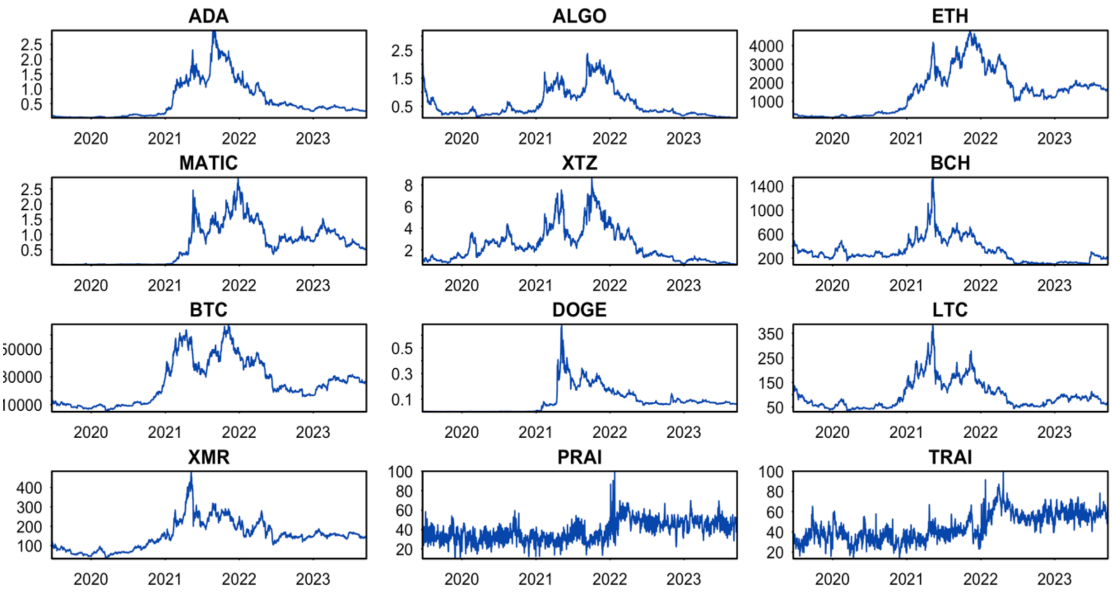
Based on the data availability of ALGO, we selected our sample period from June 21, 2019, to September 20, 2023. Our sample period included multiple financial turmoil events, such as COVID-19, the Russia-Ukraine War, the FTX Collapse, and the Silicon Valley Bank collapse,

[1] List of available PoW coin is available at https://coinmarketcap.com/view/pos/. Selected green cryptocurrencies are: Ethereum (ETH), Cardano (ADA), Tezos (XTZ), Polygon (MATIC), and Algorand (ALGO).
[2] List of available PoS coin is available at https://coinmarketcap.com/view/pow/. Selected dirty cryptocurrencies are: Bitcoin (BTC), Litecoin (LTC), Dogecoin (DOGE), Monero (XMR), Bitcoin Cash (BCH).

making it a significant period to study. The data for green and dirty cryptocurrencies were collected in USD from CoinMarketCap.

Figure 1 illustrates the closing value series for all variables, indicating similar patterns of peaks in all green and dirty cryptocurrencies. The peaks in PRI and TRI can be attributed to the 2022 European heatwaves[3]. Transform variables using: $r_{i,t} = (p_t - p_{t-1})/p_{t-1}$, are illustrated in Figure S.1 (see online supplementary material at https://reunido.uniovi.es/index.php/EBL/article/view/22304). Table S.1 depicts summary statistics and Figure S.2 illustrates correlation matrix.

Figure 1. Closing value series of the variables



Source: own elaboration

2.2. Methods

Our study aims to examine the spillover effect of climate risk on both green and dirty cryptocurrencies. There are various spillover estimation methods based on the Diebold and Yilmaz (2012, 2014); spillover index, including DCC-GARCH, TVP-VAR, and Q-VAR. However, according to Gabauer et al. (2023), these model-based spillover index methodologies are limited by the choice of the model and may not always converge to unity. To address these convergence issues, Gabauer et al. (2023) introduced a model-free version of the spillover index called the R^2 connectedness approach. R^2 is developed based on the assumptions of goodness-of-fit and a systematic upper limit. In this study, we utilize an asymmetric variant of

[3] Source: https://phys.org/news/2023-08-fastest-continent-europe-deadly.htm.

the R^2 connectedness, enabling us to examine the overall spillover effect as well as the positive and negative impact of climate risk shocks (Adekoya et al., 2022). A detailed methodology of asymmetric version of R^2 connectedness approach is presented in supplementary file.

3. Empirical results and discussions

3.1. Static connectedness results

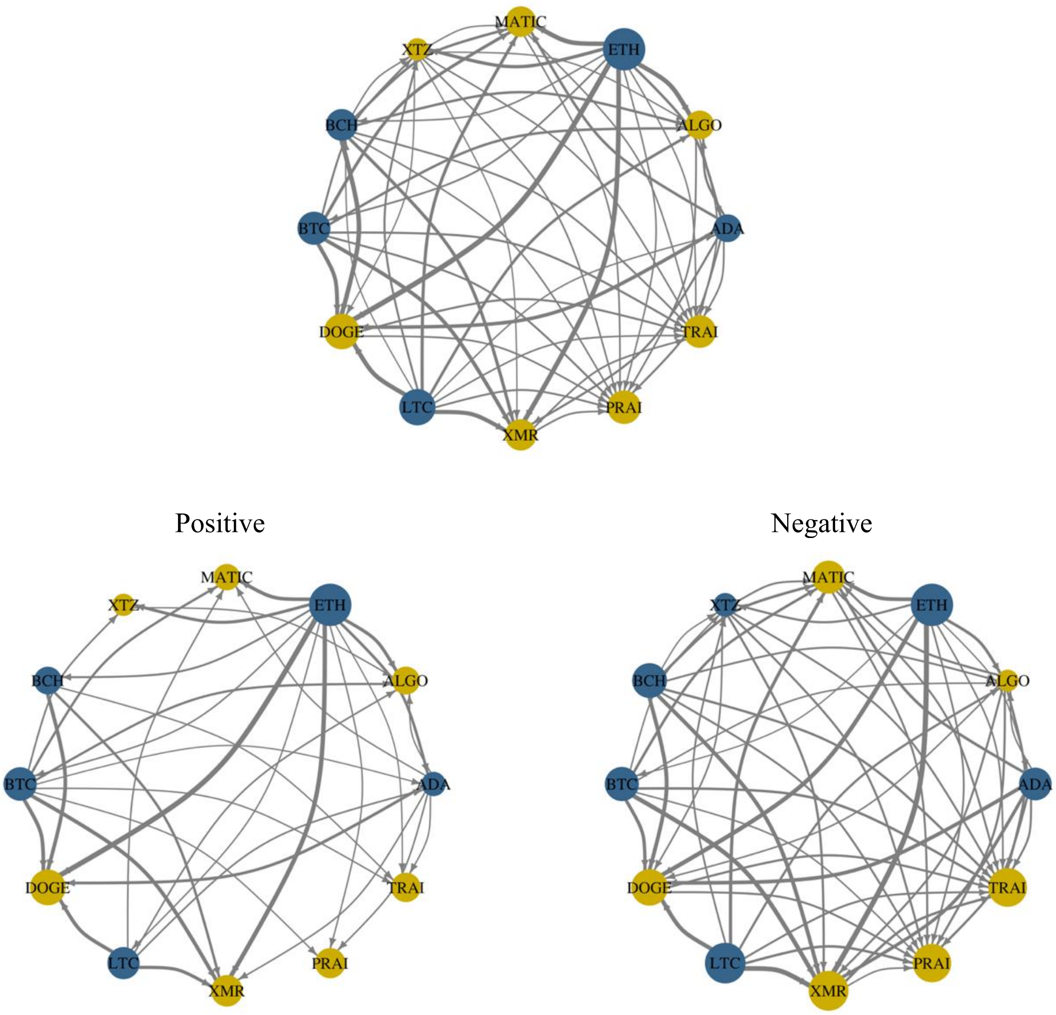
Table 1 reported in the appendix displays result for static spillover across overall, positive, and negative shocks. The total connectedness index (TCI) is 69.30%, 59.37%, and 72.60% for overall, positive, and negative market conditions, respectively. The TCI value indicates that positive market connectedness is lower than that of the overall and negative market, indicating the presence of an asymmetric nature of connectedness. The results show that in the overall market condition, TRAI has the highest own variance shock, indicating that 73.94% of shocks originate from its own innovation. However, in the case of positive and negative shocks, PRAI has the highest own variance shock.The "FROM" row indicates that ETH receives the highest spillover from other variables across all market conditions, while the "TO" row shows ETH also transmits the most spillover. The "NET" row reveals DOGE (-9.56%) as the main net receiver of shocks and ETH (14.33%) as the primary transmitter, consistent across positive market conditions. In negative markets, ETH remains the top transmitter, with XMR emerging as a net receiver. These findings align with asymmetric TCI values, highlighting asymmetric connectedness among green cryptocurrencies, dirty cryptocurrencies, and climate risk attention. PRAI and TRAI consistently act as net receivers of shocks in all market conditions.

Figure 2 demonstrates that spillovers primarily flow toward PRAI and TRAI, reflecting the significant influence of cryptocurrency market developments on climate-related attention. ETH, as the major transmitter, directs most shocks to MATIC, DOGE, XMR, and ALGO, especially in negative markets. During positive markets, PRAI and TRAI receive substantial spillovers mainly from BTC, ETH, and ADA, likely due to heightened environmental concerns during downturns. Sustainability-focused investors may diversify portfolios toward green cryptocurrencies to manage risks from negative climate sentiment and regulatory changes. These results align with prior research by André et al. (2021), Gunay et al. (2023), Agyei et al. (2023), and Lin et al. (2023), which highlight sentiment variables as key receivers in asset networks.

3.2. Dynamic connectedness results

Figure 3 illustrates the dynamic evolution of connectedness among green cryptocurrencies, dirty cryptocurrencies, and climate risk attention, with TCI values ranging from 40% to 85%, indicating significant time-varying spillovers. Connectedness increases notably during major events like COVID-19, the Russia-Ukraine war, European heatwaves, and America's landmark climate law[4]. Negative market connectedness surpasses positive and overall market levels, confirming the asymmetric nature of connectedness across the network.

Figure 2. Connectedness network plot

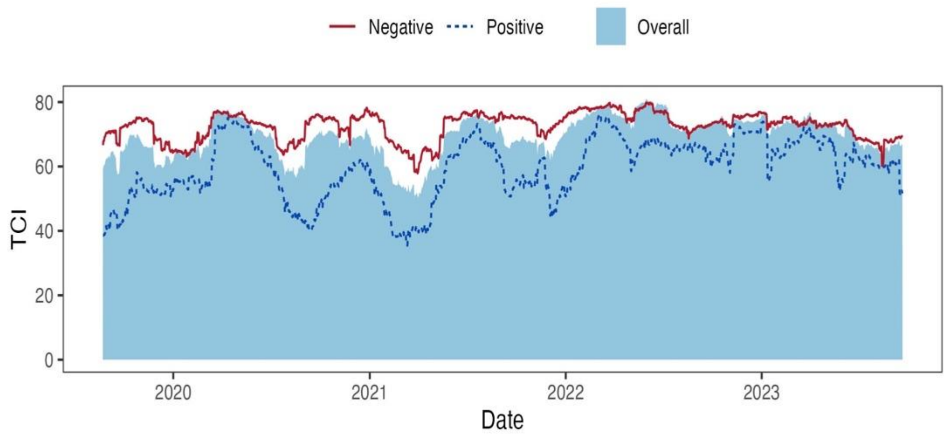


Source: own elaboration
Notes: The results are based on R^2 connectedness approach. The node size in the plot indicates spillover intensity, and the blue (yellow) hue indicates the net receiver (transmitter) of spillover. The direction of the arrow indicates the transmission direction, and the thickness indicates spillover intensity

[4] Source: https://www.imf.org/en/Publications/fandd/issues/2022/12/america-landmark-climate-law-bordoff and https://phys.org/news/2023-08-fastest-continent-europe-deadly.htm.

Figure 4 shows that PRAI and TRAI consistently act as net receivers of spillovers throughout the sample period, aligning with previous studies highlighting sentiment as a net receiver in asset networks (Agyei et al., 2023; André et al., 2021; Gunay et al., 2023; Lin et al., 2023). Figures S.3 and S.4 detail the time-varying net pairwise directional connectedness, influenced by economic and climate events, including COVID-19. Given this variability, investors should adopt dynamic strategies and incorporate risk management approaches that account for climate and economic event scenarios.

Figure 3. Dynamic total connectedness index



Source: own elaboration
Notes: The results are based on R^2 connectedness approach with 63 days quarterly trading window

3.3. Robustness test results

We conducted three sensitivity analyses for robustness testing. First, we conducted a robustness test based on different rolling windows and methodologies[5]. The results of the robustness test, using different sets of rolling windows and methodologies, are presented in Figure S.5. The results show that the TCI values deviate across a range of 40% to 85%, which is in line with our baseline findings, indicating the robustness of our results.

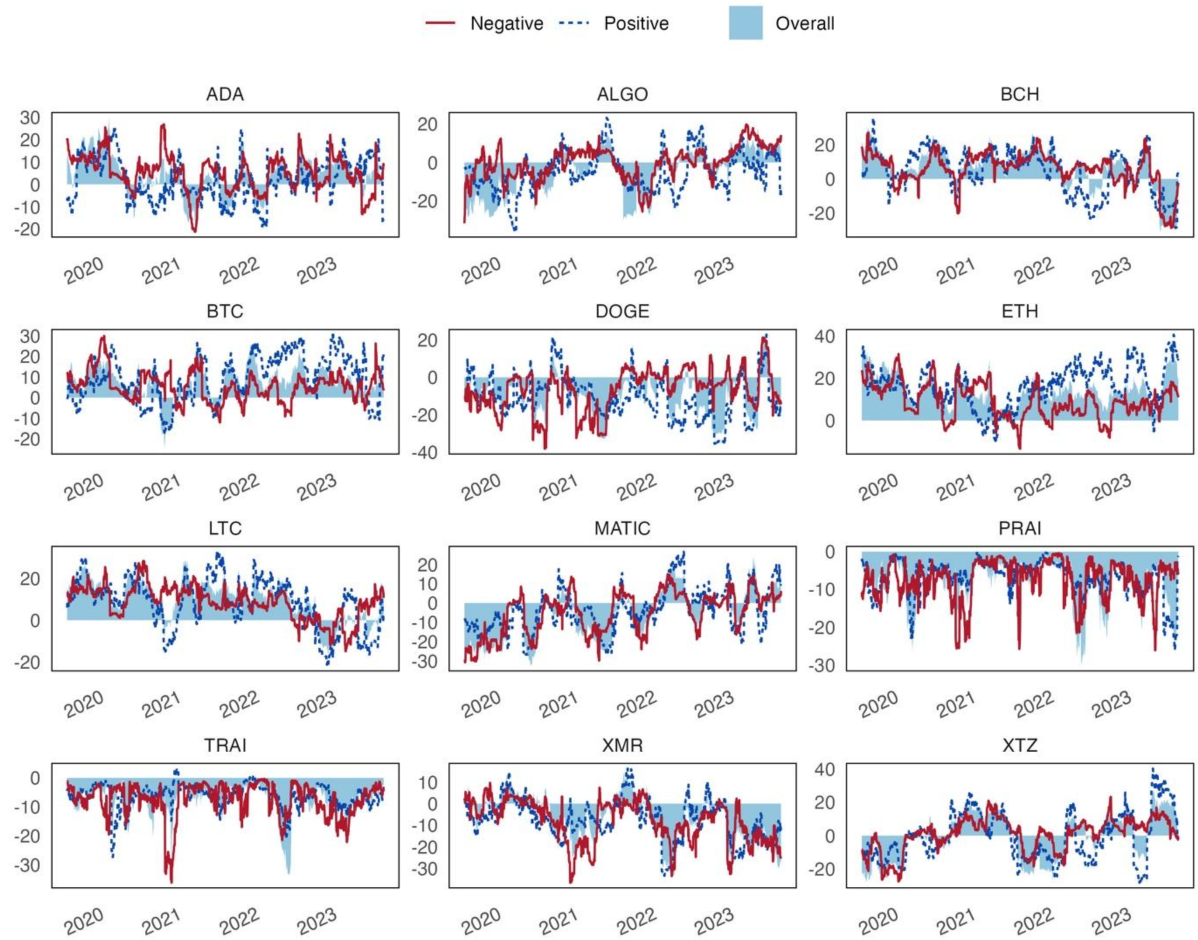
Second, we changed the proxy for climate risk attention. In the baseline model, we used PRAI and TRAI as the proxy for climate risk attention. For robustness, we developed a new proxy by combining PRAI and TRAI using principal component analysis into a Climate Risk Attention Index (CRAI). The findings using CRAI are presented in Figure S.6 and S.8, which again show a similar TCI and transmission nature of CRAI as a net receiver, indicating the robustness of our results.

[5] Our baseline model was estimated using a quarterly trading window with the Pearson methodology. For the robustness test, we used the Kendall and Spearman methodologies, along with Pearson, using rolling windows of 63, 189, and 252 days.

Finally, we introduced another proxy for climate risk attention using extreme weather keywords from Google Trends. We constructed a Climate Change Attention Index (CCAI) using keywords like "climate change," "climate risk," and "global warming," based on a similar methodology to PRAI and TRAI. The results of the robustness test using CCAI are presented in Figure S.7 and S.9. The results show a similar time-varying nature of TCI, which varies within the range of 40% to 85%. Moreover, the network connectedness results again show that CCAI acts as the net receiver in the system, corroborating our baseline findings and indicating the robustness of our results.

For further robustness testing, we separately examine the spillover effects for green and dirty cryptocurrencies. The results in Figure S.10 show that PRAI and TRAI consistently remain net receivers in the system, indicating that our findings are not biased by the classification of cryptocurrencies into green and dirty groups.

Figure 4. Dynamic net-direction connectedness results



Source: own elaboration
Notes: The results are based on R^2 connectedness approach with 63 days quarterly trading window

4. Conclusions

This study examined the spillover effects of climate risk attention on green and dirty cryptocurrencies. Green cryptocurrencies, especially ETH, are notably responsive to climate risk attention, while most spillovers originate from dirty cryptocurrencies. The TRAI shows the highest self-generated shocks overall, with PRAI as the main net receiver in both positive and negative market conditions. For regulators, these findings underscore the importance of policies addressing the environmental and sustainability aspects of cryptocurrencies, promoting eco-friendly practices and transparency. For investors, incorporating environmental and social factors, diversifying portfolios with green cryptocurrencies, and monitoring the dynamic interplay of climate events and market trends are critical strategies.

Note. Supplementary material is available online:
https://reunido.uniovi.es/index.php/EBL/article/view/22304

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References

Ahmed, M. S., Helmi, M. H., Tiwari, A. K. and Al-Maadid, A. (2025) Investor attention and market activity: evidence from green cryptocurrencies, *Studies in Economics and Finance*, 42(3), 397-426.

Adekoya, O. B., Akinseye, A. B., Antonakakis, N., Chatziantoniou, I., Gabauer, D. and Oliyide, J. (2022) Crude oil and Islamic sectoral stocks: asymmetric TVP-VAR connectedness and investment strategies, *Resources Policy*, 78, 102877. https://doi.org/10.1016/j.resourpol.2022.102877.

Agyei, S. K., Umar, Z., Bossman, A. and Teplova, T. (2023) Dynamic connectedness between global commodity sectors, news sentiment, and sub-Saharan African equities, *Emerging Markets Review,* 56, 101049. https://doi.org/10.1016/j.ememar.2023.101049.

Akhtaruzzaman, M., Sensoy, A. and Corbet, S. (2020) The influence of Bitcoin on portfolio diversification and design, *Finance Research Letters,* 37, 101344.

Aloui, C., Meo, M. S., Hamida, H. B. and Chowdhury, M. A. F. (2023) Bitcoin connectedness to traditional asset-classes in times of COVID-19, *International Journal of Trade and Global Markets*, 18(4), 315-338.

André, C., Gabauer, D. and Gupta, R. (2021) Time-varying spillovers between housing sentiment and housing market in the United States, *Finance Research Letters*, 42, 101925. https://doi.org/10.1016/j.frl.2021.101925

Aysan, A. F., Demir, E., Gozgor, G. and Lau, C. K. M. (2019) Effects of the geopolitical risks on Bitcoin returns and volatility, *Research in International Business and Finance*, 47, 511-518.

Baur, D. G., Hong, K. and Lee, A. D. (2018) Bitcoin: medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money,* 54, 177-189.

Bonato, M., Cepni, O., Gupta, R. and Pierdzioch, C. (2023) Climate risks and state-level stock market realized volatility, *Journal of Financial Markets,* 100854. https://doi.org/10.1016/j.finmar.2023.100854.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L. I. (2017) On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier? *Finance Research Letters,* 20, 192-198.

Clark, E., Lahiani, A. and Mefteh-Wali, S. (2023) Cryptocurrency return predictability: what is the role of the environment? *Technological Forecasting and Social Change*, 189, 122350.

Corbet, S. and Yarovaya, L. (2020) The environmental effects of cryptocurrencies, *Cryptocurrency and Blockchain Technology*, 1, 149.

Demir, E., Gozgor, G., Lau, C. K. M. and Vigne, S. A. (2018) Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation, *Finance Research Letters,* 26, 145-149.

Diebold, F. X. and Yilmaz, K. (2012) Better to give than to receive: predictive directional measurement of volatility spillovers, *International Journal of Forecasting,* 28(1), 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Diebold, F. X. and Yılmaz, K. (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms, *Journal of Econometrics,* 182(1), 119-134. https://doi.org/10.1016/j.jeconom.2014.04.012.

Doan, B., Jayasuriya, D., Lee, J. B. and Reeves, J. J. (2024) Cryptocurrency systematic risk dynamics, *Economics Letters*, 111788.

Dougal, C., Engelberg, J., Garcia, D. and Parsons, C. A. (2012) Journalists and the stock market, *The Review of Financial Studies,* 25(3), 639-679.

Fang, L. and Peress, J. (2009) Media coverage and the cross-section of stock returns, *The Journal of Finance,* 64(5), 2023-2052.

Gabauer, D., Chatziantoniou, I. and Stenfors, A. (2023) Model-free connectedness measures, *Finance Research Letters*, 54, 103804. https://doi.org/10.1016/j.frl.2023.103804.

Goodkind, A. L., Jones, B. A. and Berrens, R. P. (2020) Cryptodamages: monetary value estimates of the air pollution and human health impacts of cryptocurrency mining, *Energy Research and Social Science*, 59, 101281.

Guesmi, K., Saadi, S., Abid, I. and Ftiti, Z. (2019) Portfolio diversification with virtual currency: evidence from bitcoin, *International Review of Financial Analysis*, 63, 431-437.

Gunay, S., Goodell, J. W., Muhammed, S. and Kirimhan, D. (2023) Frequency connectedness between FinTech, NFT and DeFi: considering linkages to investor sentiment, *International Review of Financial Analysis*, 90, 102925. https://doi.org/10.1016/j.irfa.2023.102925.

Jiao, P., Veiga, A. and Walther, A. (2020) Social media, news media and the stock market, *Journal of Economic Behavior and Organization,* 176, 63-90.

Kachaner, N., Nielsen, J., Portafaix, A. and Rodzko, F. (2020) *The pandemic is heightening* *environmental awareness*, Boston Consulting Group.

Krause, M. J. and Tolaymat, T. (2018) Quantification of energy and carbon costs for mining cryptocurrencies, *Nature Sustainability,* 1(11), 711-718.

Li, R., Li, S., Yuan, D. and Zhu, H. (2021) Investor attention and cryptocurrency: evidence from wavelet-based quantile Granger causality analysis, *Research in International Business and Finance,* 56, 101389.

Lee, S., Lee, J. and Lee, W. (2025) Interconnected dynamics of sustainable cryptocurrencies: insights from transfer entropy analysis, *Finance Research Letters*, 76, 106914.

Lin, X., Meng, Y. and Zhu, H. (2023). How connected is the crypto market risk to investor sentiment? *Finance Research Letters,* 56, 104177. https://doi.org/10.1016/j.frl.2023.104177.

Lucey, B. and Ren, B. (2023) Time-varying tail risk connectedness among sustainability-related products and fossil energy investments, *Energy Economics,* 126, 106812.

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M. and Franklin, E. C. (2018) Bitcoin emissions alone could push global warming above 2 C, *Nature Climate Change,* 8(11), 931-933.

Moy, C. and Carlson, J. (2021) *Cryptocurrencies can enable global financial inclusion*, WEF. Will you participate.

Nadarajah, S. and Chu, J. (2017) On the inefficiency of bitcoin, *Economics Letters,* 150, 6-9.

Ndubuisi, G. and Urom, C. (2023) Dependence and risk spillovers among clean cryptocurrencies prices and media environmental attention, *Research in International Business and Finance,* 65, 101953.

Patel, R., Kumar, S., Bouri, E. and Iqbal, N. (2023) Spillovers between green and dirty cryptocurrencies and socially responsible investments around the war in Ukraine, *International Review of Economics and Finance,* 87, 143-162. https://doi.org/10.1016/j.iref.2023.04.013.

Polemis, M. L. and Tsionas, M. G. (2023) The environmental consequences of blockchain technology: a Bayesian quantile cointegration analysis for Bitcoin, *International Journal of Finance and Economics,* 28(2), 1602-1621.

Ren, B. and Lucey, B. (2022) Do clean and dirty cryptocurrency markets herd differently? *Finance Research Letters*, 47, 102795. https://doi.org/10.1016/j.frl.2022.102795.

Santi, C. (2023) Investor climate sentiment and financial markets, *International Review of Financial Analysis,* 86, 102490. https://doi.org/10.1016/j.irfa.2023.102490.

Sharif, A., Brahim, M., Dogan, E. and Tzeremes, P. (2023) Analysis of the spillover effects between green economy, clean and dirty cryptocurrencies, *Energy Economics,* 120, 106594. https://doi.org/10.1016/j.eneco.2023.106594.

Schinckus, C. (2021) Proof-of-work based blockchain technology and Anthropocene: an undermined situation? *Renewable and Sustainable Energy Reviews*, 152, 111682.

Smales, L. A. (2022) Investor attention in cryptocurrency markets, *International Review of Financial Analysis,* 79, 101972.

Urquhart, A. and Zhang, H. (2019) Is Bitcoin a hedge or safe haven for currencies? An intraday analysis, *International Review of Financial Analysis*, 63, 49-57.

Wan, D., Xue, R., Linnenluecke, M., Tian, J. and Shan, Y. (2021) The impact of investor attention during COVID-19 on investment in clean energy versus fossil fuel firms, *Finance Research Letters,* 43, 101955.

Wang, Y., Lucey, B., Vigne, S. A. and Yarovaya, L. (2022) An index of cryptocurrency environmental attention (ICEA), *China Finance Review International,* 12(3), 378-414.

Wu, S., Tong, M., Yang, Z. and Derbali, A. (2019) Does gold or Bitcoin hedge economic policy uncertainty? *Finance Research Letters*, 31, 171-178.

Yousaf, I., Suleman, M. T. and Demirer, R. (2022) Green investments: a luxury good or a financial necessity? *Energy Economics,* 105, 105745.

Zribi, W., Boufateh, T. and Guesmi, K. (2023) Climate uncertainty effects on bitcoin ecological footprint through cryptocurrency environmental attention, *Finance Research Letters*, 58, 104584.

Zhang, D., Chen, X. H., Lau, C. K. M. and Xu, B. (2023) Implications of cryptocurrency energy usage on climate change, *Technological Forecasting and Social Change*, 187, 122219.

Zhang, S. Y. (2022) Are investors sensitive to climate-related transition and physical risks? Evidence from global stock markets, *Research in International Business and Finance,* 62, 101710. https://doi.org/10.1016/j.ribaf.2022.101710.

Appendix

Table A1. Static asymmetric connectedness results

	Overall				Positive				Negative			
Variables	OWN	FROM	TO	NET	OWN	FROM	TO	NET	OWN	FROM	TO	NET
ADA	20.63	79.37	104.29	4.29	31.44	68.56	102.07	2.07	15.87	84.13	104.90	4.90
ALGO	24.76	75.24	95.13	-4.87	42.28	57.72	95.08	-4.92	16.96	83.04	99.95	-0.05
ETH	17.50	82.50	114.33	14.33	24.92	75.08	116.35	16.35	14.86	85.14	109.24	9.24
MATIC	26.35	73.65	93.77	-6.23	39.86	60.14	96.28	-3.72	19.86	80.14	94.92	-5.08
XTZ	23.25	76.75	99.63	-0.37	38.16	61.84	99.57	-0.43	17.77	82.23	100.88	0.88
BCH	19.69	80.31	106.94	6.94	28.72	71.28	104.76	4.76	15.99	84.01	105.88	5.88
BTC	18.91	81.09	107.90	7.90	27.46	72.54	109.31	9.31	15.46	84.54	105.54	5.54
DOGE	27.89	72.11	90.44	-9.56	41.87	58.13	88.92	-11.08	21.93	78.07	93.39	-6.61
LTC	18.35	81.65	110.13	10.13	27.14	72.86	108.32	8.32	15.05	84.95	108.47	8.47
XMR	23.28	76.72	93.27	-6.73	36.70	63.30	92.23	-7.77	18.93	81.07	91.91	-8.09
PRAI	73.83	26.17	91.75	-8.25	74.57	25.43	93.24	-6.76	78.40	21.60	92.53	-7.47
TRAI	73.94	26.06	92.41	-7.59	74.45	25.55	93.87	-6.13	77.77	22.23	92.38	-7.62
TCI	69.30				59.37				72.60			

Source: own elaboration
Note: OWN represents the variance shock generated internally or idiosyncratic spillover. The "FROM" row provides insights into the reception of shocks from other variables in the network, while the "TO" row illustrates the transmission of shocks to other variables. The "NET" row reveals the aggregated spillover and identifies whether a cryptocurrency or risk attention index is a net receiver or transmitter of shocks, based on the negative (receiver) or positive (transmitter) value of NET. Additionally, TCI refers to the Total Connectedness Index, representing the overall degree of connectedness within the network. The results are based on R^2 connectedness approach.