Research in International Business and Finance 73 (2025) 102547

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Connectedness and frequency connection among green bond, cryptocurrency and green energy-related metals around the COVID-19 outbreak

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ARTICLE INFO

JEL classification:
Q01
Q42
Q56
G10

Keywords:
Green Bond
Cryptocurrency
Green energy-related metals
Return Connectedness
Wavelet Coherence
Quantile

ABSTRACT

We investigate the return interdependence among green bonds, cryptocurrency indices and green energy-related metals. We apply time-varying parametric vector autoregression (TVP-VAR) conenctedness, wavelet coherence, Wavelet Quantile Correlation (WQC) and Quantile on Quantile (QQR) Connectedness Methods. Our empirical findings show that return connectedness has become even stronger after the outbreak of COVID-19, with both green bonds and cryptocurrency indices acting as net receivers of return spillovers. Surprisingly, Copper functioned as a net sender of return spillovers over the entire observation period. Findings revealed that the cryptocurrency index exhibited a consistent positive correlation with the green energy-related metals market at medium to short-term frequencies, whereas green bonds showed a negative correlation with metals market at short-term frequencies and a positive correlation at long-term frequencies.

1. Introduction

The direction and size of spillovers can assist market participants, including policymakers and portfolio managers, in managing and responding to systemic risk during times of crisis. This can affect the lives of millions. The outbreak of the COVID-19, during which global economic activity was disrupted, saw many governments undertaking temporary policy measures to support economic recovery as market uncertainty spiked. As many economies were commodity dependent, commodity and equity markets plunged simultaneously, and the global financial cycle entered a downward phase (Zeng et al., 2024a). This significantly impacted both these economies' social and financial stability. The COVID-19 pandemic differed from prior turmoils, which were primarily financial crises, because it was a systemic crisis with widespread economic fallout and devastating social and economic consequences. As a

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https://doi.org/10.1016/j.ribaf.2024.102547
Received 1 September 2023; Received in revised form 25 August 2024; Accepted 28 August 2024
Available online 30 August 2024

consequence, investors, portfolio managers, and policymakers faced unprecedented challenges in asset allocation and risk appetite during COVID-19. Notably, standard risk management techniques were vulnerable to large-scale failures as volatility soared and correlations converged. COVID-19's extreme negative shocks have generated new research and industry interest in systemic risk behaviour during major financial distress. To mitigate systemic risk, it is critical that we understand the dependency structure of various assets and the transmission paths to preserve investment portfolio sustainability. Therefore, examining these issues has significant indications for policy making, portfolio construction, and market regulation.

With climate change risks now a common global agenda, green energy-related industries are one of the most promising and explosive areas for the future of the world economy in the context of carbon peaking and carbon neutrality. This is attracting increasing attention from investors and policy makers. Among the many green investment targets, green bonds have minimal investment risk, minimal default risk and stable cash flow (Braga et al., 2021). Previous literature has highlighted that green bond differs significantly from traditional bonds in offering low-risk chances in times of crisis (Hachenberg and Schiereck, 2018). In addition to offering investors with a sustainable investment alternative, green bonds are also viewed as a key tool in tackling climate change and transitioning to a low carbon economy. The global experience of many extreme environmental and climate events in recent years, combined with the growing investor interest in sustainable investments during the COVID-19 pandemic (Pham and Do, 2022), has made green bonds one of the products receiving the most attention in global capital markets. They have also shown excellent investment returns during the COVID-19 period (Kanamura, 2021).

Along with green investments, cryptocurrency investment has gained much attention as an underlying investment concept. In particular, as the cryptocurrency market continues to grow in size, the influence of the cryptocurrency index on other financial assets has also come under scrutiny of investors and regulators (Bohte and Rossini, 2019; Hafner, 2020; Umar et al., 2020). Previous studies have reported time-varying correlations between cryptocurrencies and financial assets (Zeng et al., 2024b), as well as dynamic connections between cryptocurrencies and financial assets during periods of market stress (Corbet et al., 2018; Caferra and Vidal-Tomás, 2021). Moreover, during the COVID-19 outbreak, there seemed to be a dynamic link between cryptocurrency markets and financial markets (Zeng et al., 2024c). However, the connection between the cryptocurrency index and energy consumption and sustainability is highly controversial. Specifically, cryptocurrency mining is a process of verifying transactions and generating new cryptocurrencies through computer arithmetic, a process that requires a lot of computing power and electricity as computers need to constantly perform complex calculations to solve mathematical puzzles in order to verify transactions and generate new coins. In addition, as the cryptocurrency market grows, more and more people are becoming involved in the mining process. This leads to ever-increasing energy consumption. Bitcoin's individual energy consumption amounted to 127 terawatt hours (TWh) annually, surpassing the energy usage of numerous countries, Norway among them. Notably, within the United States, cryptocurrency operations were approximated to generate between 25 and 50 million tons of carbon dioxide (CO_2) emissions each year. This is comparable to diesel fuel emissions used by US railways. This increase in energy consumption will not only impact the environment, but also on energy supply and prices. There is therefore a strong link between cryptocurrency market development and energy consumption.

As a result, many works have considered the environmental sustainability impacts of cryptocurrencies, such as increased energy consumption and mining pollution (Wang et al., 2022). Essentially, the high energy consumption of mining cryptocurrencies pushes up electricity costs for everyone, so green bond returns, and cryptocurrency returns can establish an expected association. So, return spillover mechanisms between cryptocurrency and metals markets have been documented. Rehman and Vo (2020) find a positive correlation among cryptocurrencies and precious metals under normal market states, reducing diversification returns over all investment horizons. However, there are more diversification gains under extreme negative returns. Mensi et al. (2019) investigated the interconnectedness of risk between bitcoin and the principal precious metals, encompassing gold, silver, palladium, and platinum. Their study revealed substantial transmission of volatility between bitcoin and precious metals, with bitcoin predominantly assuming the role of a net recipient. Further insights provided by Fasanya et al. (2021) indicate a robust correlation between the bitcoin market and precious metals markets. However, this correlation does not operate as a hedge or a safe haven during ranges of market turmoil. Rehman (2020) determined that the transmission of upside risk connectedness from bitcoin to precious metals surpasses that of the downside risk spillover. Conversely, when scrutinizing the spillover impact of precious metals onto bitcoin, the significance lies more in the transfer of downside risk rather than upside risk.

Our work contributes to the literature that focuses on connectedness estimates that report the amount and direction of connectedness among markets during crises (e.g., Bouri et al., 2021). Firstly, we assess the financial system's response to a catastrophic event connected with the COVID-19 outbreak, which is an emerging and widely followed topic. Secondly, our research will add incremental value to recent research that has estimated the role of COVID-19 on green bonds, cryptocurrency markets and metals closely related to new energy sources. In particular, we examine financial incentives, energy-related risks, and stability of green financing investment in this carbon-neutralization era. There are limited studies studying the impact of ESG practices on green bond stability. Our research will fill this gap and our contribution is timely as the market focuses on new energy resources and future climate mitigating innovations. Thirdly, we compliment and extend the existing studies that consider cross-market and asset transmission using approaches such as dynamic conditional correlation (DCC), conditional value-at-risk (CoVaR), and more advanced Diebold and Yılmaz's (2012, 2014) technique. Significantly, our TVP-VAR framework overcomes the limitations inherent in connectedness estimations derived from variance decomposition within conventional VAR models. Our current methodology addresses outlier sensitivity arising from the Kalman filter, the vulnerability of outcomes due to arbitrary rolling window size selections, and data loss resulting from rolling window analyses. Additionally, it captures the dynamic aspects of comprehensive connectedness measurement and the interconnections among different assets. Furthermore, our initial exploration delves into the degree of correlation between the green bond asset, the cryptocurrency market, and green energy-related metals. We also undertake a comprehensive investigation into the temporal-frequency phase relationship between these paired markets. Specifically, we employ cross-wavelet analysis to scrutinize both the direction and extent of causality between the two markets. This analysis helps us ascertain whether the lead-lag relationships between their respective time-series co-evolve across varying time intervals and frequencies, in accordance with the approach outlined by Rua (2013). Several prior studies have also examined the structural aspects of connectedness between markets and the temporal-frequency relationships among markets, utilizing methodologies consistent with our approach (e.g., Zeng et al., 2023).

Another significant aspect of the contributions to this research lies in its methodology. After examining the spillover structure and lead-lag relationships of the studied markets using the TVP-VAR connectedness framework and wavelet coherence approach, we employed two unique and novel approaches to further enhance the contribution of this work at a research level. Firstly, unlike the methods of traditional quantile regression, which can only show the relationships between two variables within every quantile, the wavelet quantile correlation method we used overcomes the limitations of traditional quantile or wavelet methods. These earlier methods failed to simultaneously explore the frequency (investment horizon) correlations of two variables across different quantiles (market conditions) (Kumar and Padakandla, 2022). Thus, the wavelet quantile correlation approach provided a cross-quantile and frequency correlation structure, providing a more comprehensive and precise portrayal of market dynamics. Secondly, unlike the widely used quantile connectedness method, which often assumes positive correlations between systems and restricts its range to specific quantile levels, the QQR connectedness framework proposed by Gabauer and Stenfors (2024) explored how the cryptocurrency index and green bonds at different quantile levels ($\tau 1, \tau 2, \ldots, \tau k$) influenced the market performance of metal commodities at various quantile levels, and vice versa. While similar to the quantile-on-quantile regression function introduced by Sim and Zhou (2015), the innovation of the QQR connectedness method lies in exploring the spillover effects between different quantiles of predictor and response variables. By utilising these advanced econometric methods, our research aimed to make a significant contribution to the existing literature. Our empirical results highlighted the potential market risks of cryptocurrency and green bond assets and their heterogeneous impacts on the green energy-related metal commodity markets. Additionally, our findings provided important references for developing risk management strategies for sustainable assets and cryptocurrency finance.

In summary, this study made a significant contribution to understanding the complex relationships among the green bond, cryptocurrency, and green energy-related metals markets through multidimensional analysis and innovative methodologies. Firstly, we employed the TVP-VAR connectedness framework and wavelet coherence analysis to check the spillover structure and lead-lag connections between these markets. Secondly, we introduced two advanced econometric methods: wavelet quantile correlation and QQR connectedness analysis. The wavelet quantile correlation method overcame the limitations of traditional quantile and wavelet approaches, simultaneously exploring the correlation structure under heterogeneous market states and investment horizons. The QQR connectedness method innovatively investigated the spillover effects between markets at various quantile levels, providing a more comprehensive description of market dynamics than traditional quantile connectedness methods. The combination of these methods allowed us to gain deep insights into the heterogeneous shocks of market risks, offering crucial references for the risk management of sustainable assets and cryptocurrencies. Through this multi-angle, multidimensional analysis, this study not only extended the existing literature but also provided new perspectives on the interactions of financial markets in the era of carbon neutrality, with important practical implications for investment decision-making and policy formulation.

Our research concludes the COVID-19 crisis was a key driver of increased connectedness in the markets we analysed. We see the total and cross-asset dynamic connection becoming increasingly strong after COVID-19 outbreak. These results are intuitive and show that the assets we examined saw a quick surge in risk accumulation due to the COVID-19 outbreak. This is distinct from the long-term buildup of systemic risk in the financial system. Across the duration of the study period, copper exhibited a role as a net sender of spillovers, while all other variables assumed positions as net recipients. Furthermore, the wavelet analysis revealed noteworthy connections between the green bond and cryptocurrency markets concerning most metals intimately associated with emerging energy sources (excluding iron). These connections were identified across various frequency domains subsequent to the onset of the COVID-19 outbreak. Predictably, this underscores the notion that the abrupt emergence of the pandemic escalated market uncertainty and introduced greater diversity in linkage patterns. Lastly, our findings using the quantile correlation method revealed a generally positive connection between the cryptocurrency index and the green energy-related metals market at medium to short-term frequencies, albeit with some heterogeneity in certain frequency ranges. In contrast, the green bond market exhibited a negative connection with the green energy metals market at short-term frequencies, but a significant positive connection at long-term frequencies. Notably, both the cryptocurrency index and the green bond index demonstrated substantial hedging potential against the metals market under stable market conditions, enhancing our understanding of their risk management strategies amidst market price shocks.

Following are the remaining sections. Section 2 provides research data and frameworks for empirical analysis. In Section 3, we explore the results and the underlying analysis. Section 4 summarizes the significant findings and policy implications.

2. Methodological and data

2.1. TVP-VAR Connectedness method

While following a recent study by Antonakakis et al. (2020), we use the TVP-VAR connectedness approach to explore the time-varying transmission mechanisms and interactions among key variables. We adopt the TVP-VAR and use the Bayesian Information Criterion (BIC) as outlined in the following equation:

$$x_t = \Phi_t x_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, U_t)$$

$$\text{vec}\ (\Phi_t) = \text{vec}\ (\Phi_{t-1}) + \rho_t, \rho_t \sim N(0,_t) \tag{1}$$

Where, x_t, ε_t and ρ_t are $N \times 1$ vectors, and U_t and Φ_t are $N \times N$ matrices of two dimensions.

We then apply the Generalized Forecast Error Variance Decomposition (GFEVD), which will be described as the variance sharing of asset i over asset j, as captured by the formula:

$$\phi^g_{ij,t}(J) = \frac{U^{-1}_{ii,t}\sum_{t=1}^{J-1}\left(\nu_i' A_t U_t \nu_j\right)^2}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\left(\nu_i' A_t U_t A_t' \nu_j\right)}$$

$$\widetilde{\phi}^g_{ij,t}(J) = \frac{\phi^g_{ij,t}(J)}{\sum_{j=1}^{N}\phi^g_{ij,t}(J)} \tag{2}$$

Where, ν_j is a zero vector and is uniform in position i, $\sum_{j=1}^{N}\widetilde{\phi}^N_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\phi}^N_{ij,t}(J) = N$.

The Total Connectedness Index (TCI) estimates the inter-connectedness of a network and is formulatedby:

$$TCI^g_t(J) = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\phi}^g_{ij,t}(J)}{\sum_{i,j=1}^{N}\phi^g_{ij,t}(J)} \tag{3}$$

To be precise, the TCI can be described as the average (non-diagonal) spillover effect of a particular asset on all other assets, representing the spillover effect of variable i on all other j. This can be outlined as:

$$CI^g_{i\rightarrow jt}(J) = \sum_{j=1,i\neq j}^{N}\widetilde{\phi}^g_{jit}(J)$$

$$CI^g_{i\leftarrow jt}(J) = \sum_{j=1,i\neq j}^{N}\widetilde{\phi}^g_{ijt}(J) \tag{4}$$

The net value of the total directional connectedness is then obtained by estimating the difference between $CI^g_{i\rightarrow jt}(J)$ and $CI^g_{i\leftarrow jt}(J)$.We apply a formula whereby:

$$CI^g_{it}(J) = CI^g_{i\rightarrow jt}(J) - CI^g_{i\leftarrow jt}(J) \tag{5}$$

2.2. wavelet coherence

The study then explores the leading lag and correlation of prices between different markets by considering the implementation of a method that considers both the frequency and time domain relationships of the time series. We use wavelet coherence approach for this purpose. Specifically, we first define the crossed wavelet transform (CWT), which has been introduced by Torrence and Compo (1998) as a transformation that can be expressed through two time series, *a(t)* and *b(t)*, with the following equation:

$$N_{ab}(p,q) = N_a(p,q)N^*_b(p,q) \tag{6}$$

Where, $N_a(p,q)$ and $N_b(p,q)$ denotes the continuous transformation of two time series of *a(t)* and *b(t)*. p denotes the position index and q denotes the evaluate. The complex coherence is then denoted by (*). The cross-wavelet transform will be applied to measure wavelet power, i.e., $|N_a(p,q)|$. The cross-wavelet power spectrum can be separated out in the time domain with respect to time frequency to show a strong concentration of energy. This will help us observe the unexpected and significant changes in the co-movement pattern of the variables. Torrence and Webster (1999) utilized the adjusted wavelet coherence coefficient formula where:

$$W^2(p,q) = \frac{|\,M\left(M^{-1}Nab(p,q)\right|^2}{M\left(M^{-1}|N_a(p,q)|^2\right)M\left(M^{-1}|N_b(p,q)|^2\right)} \tag{7}$$

where, M is the smoothing mechanism and the formula $0\leq W^2(p,q)\leq 1$, which indicates the squared range of the wavelet coherence coefficients. $W^2(p,q)$ closer to 0 indicates a lower correlation, while closer to 1 indicates the presence of a high degree of correlation.

2.3. Wavelet Quantile Correlation

Kumar and Padakandla (2022) improved upon the Quantile Correlation (QC) method, which was initially developed by Li et al. (2015), by introducing the Wavelet Quantile Correlation (WQC). This novel approach refined the original framework, enabling a more precise examination of the interrelationships between two variables, X and Y. According to Li et al., within this context, one can believe that $Q_{\tau,X}$ corresponds to the τ^{th} quantile of X, and $Q_{\tau,Y}(X)$ in line with the τ^{th} quantile of Y, given that X serves as the precondition. Furthermore, X frameworks as the series that is independent.

Quantile covariance is defined as follows,

$$q_{cov_t}(Y,X) = \text{cov}\left\{I\left(Y - Q_{\tau,Y} > 0, x\right)\right\} = E\left(\varphi_\tau\left(Y - Q_{\tau,Y}\right)(X - E(Y)\right) \tag{8}$$

where $0 < \tau < 1$.

$$\varphi_\tau(w) = \tau - I(w < 0) \tag{9}$$

Then Li et al. (2015) defined the QC in following,

$$\text{qcov}_t(Y,X) = \frac{\text{qcov}_t(Y,X)}{\sqrt{\left(\text{v a r}\left(\varphi_\tau\left(Y - Q_{\tau,Y}\right)\text{var}(X)\right)\right.}} \tag{10}$$

Kumar and Padakandla (2022) extended the QC method by utilising the maximal overlapping discrete wavelet transform, which was developed by Percival and Walden (2000), to decompose the variables X_t, and Y_t. Subsequently, they decompose the pairs X_t, and Y_t at level j^{th}, applying specific techniques to calculate the WQC for every level j. Consequently, the computation of WQC is as follows,

$$WQC_\tau\left(d_j[X], d_j[Y]\right) = \frac{qcov_\tau\left(d_j[Y], d_j[X]\right)}{\sqrt{\text{var}\left(\phi_\tau\left(d_j[Y] - Q_{\tau,d_j[Y]}\right)\right)\text{var}\left(d_j[X]\right)}} \tag{11}$$

where X, and Y indicate the independent and dependent markets, respectively.

2.4. Quantile-on-Quantile Connectedness Method

To evaluate the quantile-on-quantile connectedness (QQR) structure between the CCI, ESG, and the specified metal market, we utilised the QQR connectedness framework introduced by Gabauer and Stenfors (2024). Initially, we outlined a QVAR(p) function that facilitated the estimation of dependencies across different quantiles,

$$x_t = \mu(\tau) + \sum_{j=1}^{p} B_j(\tau)x_{t-j} + u_t(\tau) \tag{12}$$

Here, x_t and x_{t-j} are $K \times 1$ dimensional vectors of endogenous variables, τ represents a vector of quantiles within the range $[0,1]$, p indicates the lag length, $\boldsymbol{\mu}(\tau)$ points out the conditional mean vector of $K \times 1$ dimensional, $\boldsymbol{B}_j(\tau)$ is a $K \times K$ dimensional QVAR parameter matrix.

To calculate the GFEVD as introduced by Koop et al. (1996), the QVAR model is transfer into a QVMA model applying the Wold theorem as follows:

$$x_t = \mu(\tau) + \sum\nolimits_{j=1}^{p} B_j(\tau)x_{t-j} + u_t(\tau) = \mu(\tau) + \sum\nolimits_{i=0}^{\infty} A_i(\tau)u_{t-i}(\tau) \tag{13}$$

Then, the F-step ahead GFEVD illustrates the effect a shock in market j has on market i:

$$\phi^g_{i\leftarrow j,\tau}(F) = \frac{\sum\limits_{f=0}^{F-1}\left(e_i'A_f(\tau)H(\tau)e_j\right)^2}{H_{ii}(\tau)\sum\limits_{f=0}^{F-1}\left(e_i'A_f(\tau)H(\tau)A_f(\tau)'e_i\right)} \quad gSOT_{i\leftarrow j,\tau}(F) = \frac{\phi^g_{i\leftarrow j,\tau}(F)}{\sum\limits_{j=1}^{k}\phi^g_{i\leftarrow j,\tau}(F)} \tag{14}$$

where e_i is a zero vector of $K \times 1$ dimensional with unity in its i th option. Given that the row amount of $\phi^{gen}_{i\leftarrow j,\tau}$ does not equal unity, then normalizing $\phi^{gen}_{i\leftarrow j,\tau}(H)$ by dividing by the row amount to achieve the scaled GFEVD, gSOT $T_{i\leftarrow j,\tau}(F)$.

The TO indicates the influence series i has on others, while the FROM reflects the influence all markets have on market i. These connectedness calculates are provided as follows:

$$\begin{aligned} S^{gen,to}_{i\rightarrow,\tau\tau} &= \sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \\ S^{gen,from}_{i\leftarrow,\tau} &= \sum_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau}. \end{aligned} \tag{15}$$

The NET total directional connectedness of market i was calculated by determining the discrepancy between the FROM and TO aggregate directional connectedness measures:

$$S^{\text{gen,net}}_{i,\tau} = S^{gen,to}_{i\rightarrow\bullet,\tau} - S^{\text{gen},from}_{i\leftarrow,\tau} \tag{16}$$

where $S^{\text{gen,net}}_{i,\tau} > 0\left(S^{\text{gen,net}}_{i,\tau} < 0\right)$ denotes that market i exerts more (less) influence on all other markets than it receives, and is thus regarded as a net sender (receiver) of shocks.

At last, the TCI, spanning between [0,1], is estimated by:

$$TCI_{\tau}(F) = \frac{K}{K-1}\sum_{k=1}^{K} S_{k\leftarrow,\tau}^{gen,from} \equiv \frac{K}{K-1}\sum_{k=1}^{K} S_{k\leftarrow,\tau}^{gen,to}. \tag{17}$$

This measure quantified the extent of network interconnectedness. Therefore, an elevated TCI indicated an increased level of market risk.

2.5. Data

To achieve the study objective, we have selected four metals closely related to new (renewable) energy sources. We utilize daily data from the aluminium, copper, lead, and iron commodity markets, extracted from Refinitiv Datastream. These metals were chosen because they are most closely associated with the new energy industry given their potential to help switch to low carbon and supporting the renewable energy transition. Graaf (2019) says only four metals are relevant to the important new energy segments: solar, wind, electric vehicles, and energy storage. Therefore, to support green revolutionary and energy efficiency, we consider these four metals essential for the new energy sector. We divided the sample into two to elucidate the differences in correlations between green bonds, cryptocurrency markets, and green energy-related metals before and during the COVID-19 outbreak. The initial subsample encompasses the timeframe ranging from 1 January 2015–22 January 2020, representing the period prior to the emergence of the COVID-19 outbreak. The subsequent subsample covers the span from 23 January 2020–4 February 2022, corresponding to the period marked by the occurrence of the COVID-19 outbreak. Our dataset for green bonds is derived from the S&P Green Bond Index, while cryptocurrency indices are sourced from CCi30. We adopt the approach of continuous compounding, achieved through the computation of the logarithmic difference between consecutive price points. Table 1 provides an overview of acronyms, index names, and the respective data sources for the indices.

3. Empirical results and major Analysis

Table 2 provides that the J-B statistic is significant at the 1 % level of significance for both variables, and the statistic is very large, which indicates that the distribution of log returns for all variables does not follow a normal distribution. Mean values of copper, ESG, and CCI skewness are less than 0, indicating that these series are all left-skewed to varying degrees. It is worth noting that the skewness of aluminum and lead is greater than 0, which indicates that these series are all right biased to varying degrees when the skewness coefficient is greater than 0. This means that the heavy tail is on the right. There is a large kurtosis for all variables, showing a spike. Overall, the return series for each market does not follow a normal distribution and exhibits a spiky thick tail. Table 2

The results of the ERS test clearly show that the unit root test is significant. This indicates that all log series are smooth. Also from the results, we can see that the statistical values of the Ljung-Box Q test and the Q-squared test clearly confirm that the log series are all significantly auto-correlated.

The heat map in Fig. 2 illustrates the unconditional correlation matrix. This matrix is based on the Pearson correlation of examining the log return series through the entire sample period. It is noted that all variables (except iron) are positively correlated with all other assets under consideration. Copper has the highest correlation with both the Cryptocurrency Market Index and the Green Bond Index over the whole sample period.

Table 3 represents estimates of average return connectedness. The main diagonal line shows the impact of the independent variable of the return shock and the off-diagonal line shows the interaction between financial indices. In order to assess alterations in average connectedness pre and post the COVID-19 outbreak, the dataset was divided into two segments. The augmented correlations between individual markets subsequent to the COVID-19 outbreak are presented in Table 2. Preceding the onset of the pandemic outbreak, the TCI stood at 19.19 %. This figure underwent a shift to 22.37 % following the outbreak of the pandemic. After the COVID-19 outbreak, the interaction of all other assets can be blamed for an average of 22.37 % of the error in a financial asset's forecast.

Notably, within the sample period, the copper market stands out as the exclusive net propagator of shocks. Shocks to other markets increase sharply after the COVID-19 outbreak (2.07 %–8.22 %). In addition, our detailed analysis shows that both the cryptocurrency and green bond markets are net receivers of return spillovers throughout the sample period. Interestingly, the exposure of the cryptocurrency and green bond markets to other variables in the system increases after the pandemic outbreak. This evidence suggests that the price of copper on the market, which is a crucial industrial raw material and the basis of green energy, is affected by copper inventory pressures, supply and demand, and other factors that form unique cycles.

Table 1
Description of indices.

Acronym	Index	Source
Copper	Copper Futures	Datastream
ESG	S&P Green Bond Index	https://www.spglobal.com/spdji/en/indices/esg/sp-green-bond-index/
CCI	CCi30	https:// cci30.com/
Aluminum	Aluminum Futures	Datastream
Lead	Lead Futures	Datastream
Iron	Iron Futures	Datastream

Table 2
statistics analysis.

	Copper	ESG	CCI	Aluminum	Lead	Iron
Mean	0.026	0.005	0.295	0.03	0.009	0.042
Variance	1.637	0.103	27.258	1.352	2.028	3.765
Skewness	−0.414	−0.564	−1.431	0.089	0.061	−1.757
Kurtosis	3.839	5.672	11.526	2.114	1.496	25.010
J-B	1114.943***	2417.705***	10195.697***	325.413***	162.915***	46109.764***
ERS	−5.252***	−6.821***	−2.512**	−9.071***	−6.696***	−15.371***
Q (20)	12.303*	35.117***	32.664***	11.032*	10.470*	50.474***
Q^2 (20)	30.025***	453.404***	47.290***	378.351***	28.576***	5.006*

Note: The Jarque-Bera (JB) test, the Elliot, Rothenberg and Stock (ERS) test, and the Ljung-Box Q test. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

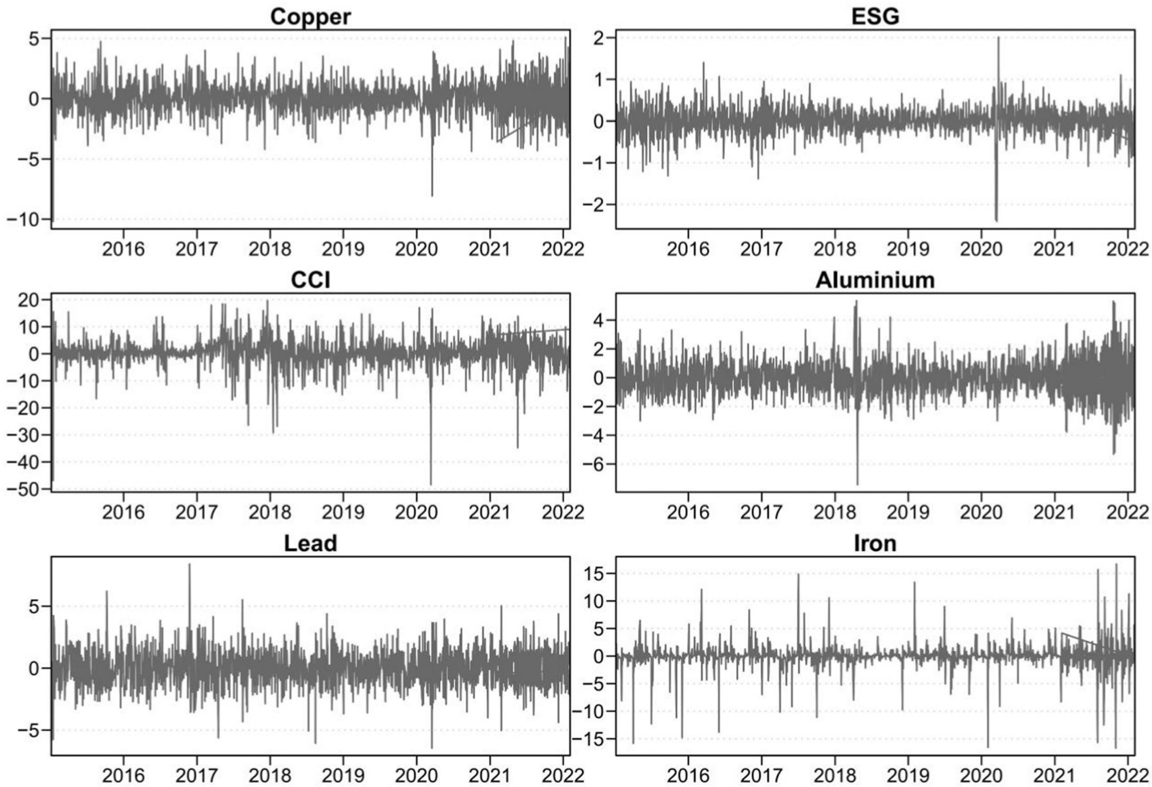

Fig. 1. Daily log returns.

However, Table 3 only presents static results and does not capture time-varying TCI values. We note that financial market connectedness is not fixed and may trend up or down in response to perturbations by endogenous or exogenous factors. It is therefore essential to use a rolling window approach. In Fig. 3, we can observe a process of variation in the TCI over the sample range. The lack of stability of the spillover indices, particularly after the COVID-19 outbreak, suggests a time-varying nature of interdependent relationships. Further, we find that total connectedness is distributed between 10 % and 30 %. Notably, in early 2020, we can observe that the TCI reaches its lowest point, close to 10 %. This indicates that the tTCI experienced a brief decline after the COVID-19 outbreak in 2020. However, it spikes to close to 30 % during 2021, which we believe is related to the global economic recovery and increased liquidity as observed by Barua (2020).

We also observe that the highest point of the return connectedness index occurs during 2015, at over 30 %. This is a period of major crisis with the Chinese stock market crash. Increased concerns about the Chinese economic bubble and a slowdown in the Chinese economy caused the index to rise to 30 %.

Subsequently, as depicted in Fig. 4, an investigation is conducted into the comprehensive aggregate directional connectedness of each market within the system. The net spillover is estimated as the disparity between the directional spillover transmitted to other markets in the system and the directional spillover index received from these markets. This computation quantifies the net spillover impact of a given market upon all other markets. A positive amount representing that market as a transmitter of information

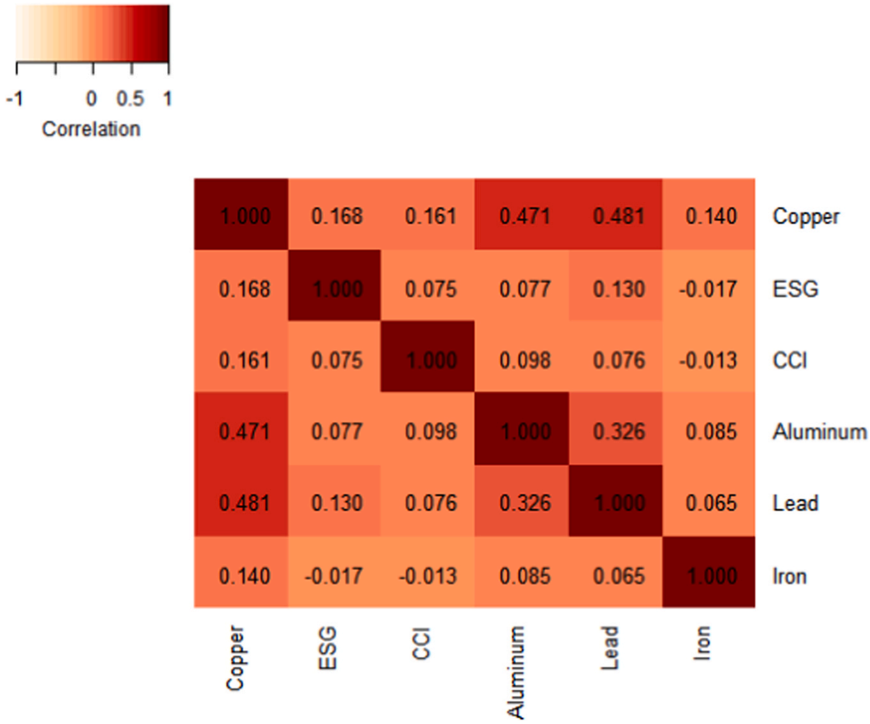

Fig. 2. Heat-map of Unconditional correlations.

Table 3
Summary of connectedness index.

Before COVID-19 outbreak (02/01/2015–22/01/2020)							
	Copper	ESG	CCI	Aluminum	Lead	Iron	From Others
Copper	64.07	1.77	1.89	12.88	18.13	1.26	35.93
ESG	3.07	91.96	0.73	1.47	2.05	0.73	8.04
CCI	2.73	0.82	92.97	0.97	1.51	1.00	7.03
Aluminum	14.73	1.53	1.29	72.50	9.22	0.74	27.50
Lead	19.43	1.78	1.18	8.66	67.94	1.01	32.06
Iron	3.44	0.75	1.28	1.01	1.27	92.24	7.76
TO Others	43.40	6.65	6.37	24.99	32.17	4.74	118.33
NET	7.47	−1.39	−0.66	−2.52	0.11	−3.01	***TCI***=19.72 %
NPDC	0.00	2.00	3.00	4.00	1.00	5.00	
During COVID−19 period (23/01/2020–04/02/2022)							
	Copper	ESG	CCI	Aluminum	Lead	Iron	From Others
Copper	63.90	5.14	2.61	15.46	9.59	3.29	36.10
ESG	8.22	79.65	4.72	2.72	3.39	1.30	20.35
CCI	3.97	4.73	87.50	1.79	1.52	0.49	12.50
Aluminum	17.34	2.08	1.68	68.41	7.61	2.88	31.59
Lead	11.70	3.52	2.26	7.26	73.72	1.54	26.28
Iron	4.95	1.25	0.79	3.91	2.01	87.09	12.91
TO Others	46.17	16.73	12.06	31.15	24.11	9.49	139.73
NET	10.07	−3.62	−0.44	−0.44	−2.17	−3.41	***TCI***=23.29 %
NPDC	0.00	3.00	3.00	2.00	3.00	4.00	

Note: Results are presented based on a TVP-VAR with first-order lag length and a generalized FEVD with 20 steps ahead.

throughout the system. Meanwhile, a negative value represents that market as a receiver of information throughout the system. Fig. 4 offers that the Green Bond Index, Aluminum, and Lead were information recipients for most of the entire sample period. With some brief exceptions, they all had sharp declines at the beginning of the COVID-19 outbreak in 2020.

Meanwhile, we see that the copper has been a net sender during the entire sample period. We believe this is due to copper's widespread use as an essential basic raw material in multiple industries. In addition to the continued growth in copper demand driven by the upward boom in sectors such as photovoltaics, wind power, and new energy vehicles in a carbon neutral context, showing the importance of this commodity in the energy transition. Fig. 4 also suggests that cryptocurrency has been a net sender of spillovers for most of the range. It has driven the network following the COVID-19 outbreak. This was due to the plummeting prices of conventional

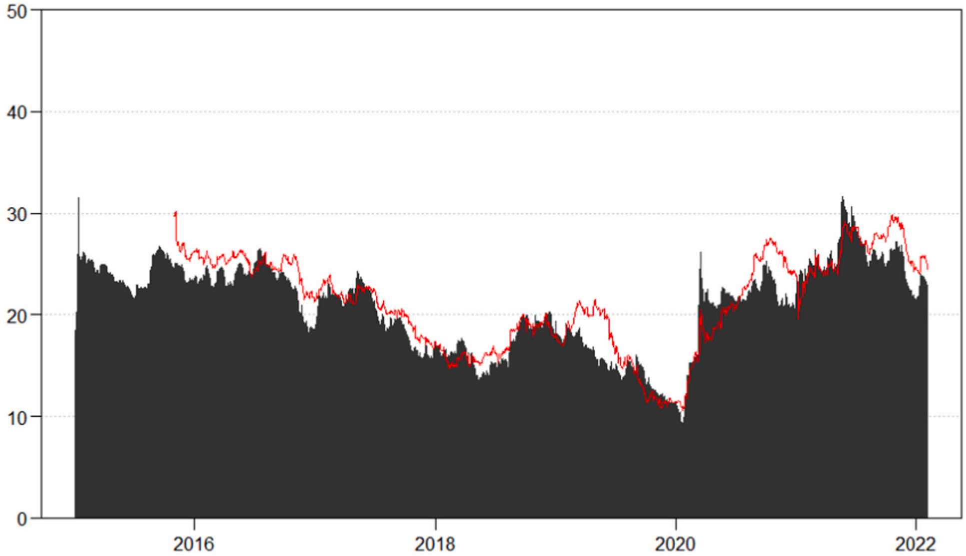

Fig. 3. Total connectedness index. Notes: Outcomes are based on a TVP-VAR with order one lag and a 20-step-ahead GFVED. The red line shows the original DY12 technique utilising a 200-day rolling-window VAR with a BIC lag duration and a 20-step-ahead GFVED.

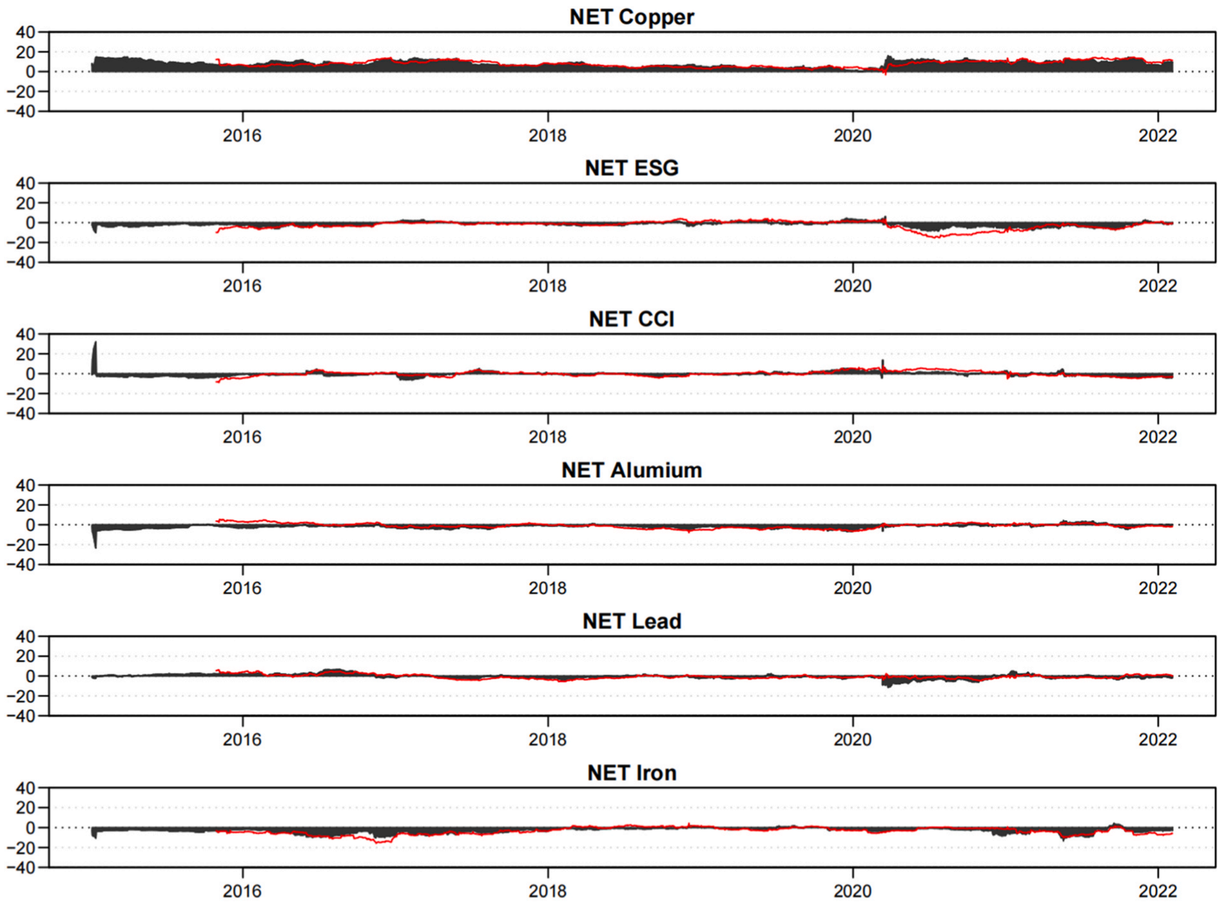

Fig. 4. Net directional connectedness. Notes: Outcomes are based on a TVP-VAR with order one lag and a 20-step-ahead GFVED. The red line shows the original DY12 technique utilising a 200-day rolling-window VAR with a BIC lag duration and a 20-step-ahead GFVED.

investment products as COVID-19 continued to rage across the globe, forcing investors to seek safe havens for their capital.

While the net spillover indices for each variable provide a clear trend over time, they do not provide connectedness for the paired variables. In this regard, the following section elucidates the dynamic bilateral relationships amongst the variables under scrutiny. A positive amount assigned to the net pairwise spillover index, within the paired markets, designates the former as the beneficiary of information transmission. Thus, its value denotes the extent of spillover from the latter to the former. A negative value represents the former as the transmitter of information and its value marks the extent of spillover from the former to the latter. Fig. 5 shows spillovers across pairs of our key financial variables. We can clearly see that Copper is an information receiver most of the time in the paired market. This is except for spillovers with natural gas where it is an information sender most of the time. In addition, the shocks received after the pandemic outbreak are more significant. This finding is in line with Hung's (2021). Furthermore, with specific attention directed towards the ESG and the CCI, it becomes apparent that the green bond serves as an originator of spillover effects. Thoroughly scrutinizing our findings pertaining to the green bond and the CCI, we ascertain that the green bond index predominantly operates as a transmitter of return spillovers. However, it becomes a return receiver at the beginning of the pandemic outbreak. This could be interpreted as investors' response to the increased speculative investment in precious metals due to the market panic. However, after the initial panic subsides, investors resume green investments with long-term value as before.

In this case, the return connectedness between CCI and the precious metals market is more complex. We find that CCI became a net recipient of spillover for aluminum and lead in the period following the pandemic outbreak. In contrast, CCI was a net recipient of spillover for natural gas for most of the sample range; For copper, on the other hand, CCI continued to be a net sender of shock. Overall, during the COVID-19 outbreak, we found profoundly high connectedness in most market portfolios. This was due to the market turmoil caused by the outbreak. This was due to many investors applying precious metals to hedge against cryptocurrency return uncertainty as highlighted by Umar et al. (2021). Due to this, cryptocurrency markets receive increased shocks from other precious metal markets.

To our surprise, copper pairs positively with the Green Bond Index, a finding that deserves further attention, especially at the beginning of the pandemic outbreak. Close observation of the pairing connectedness shows that the copper market dominated the shock to the green bond market. This was especially the case after copper prices fell sharply due to a contraction in aggregate economic demand. However, after investors recovered from COVID-19 panic, investors rekindled interest in green bonds.

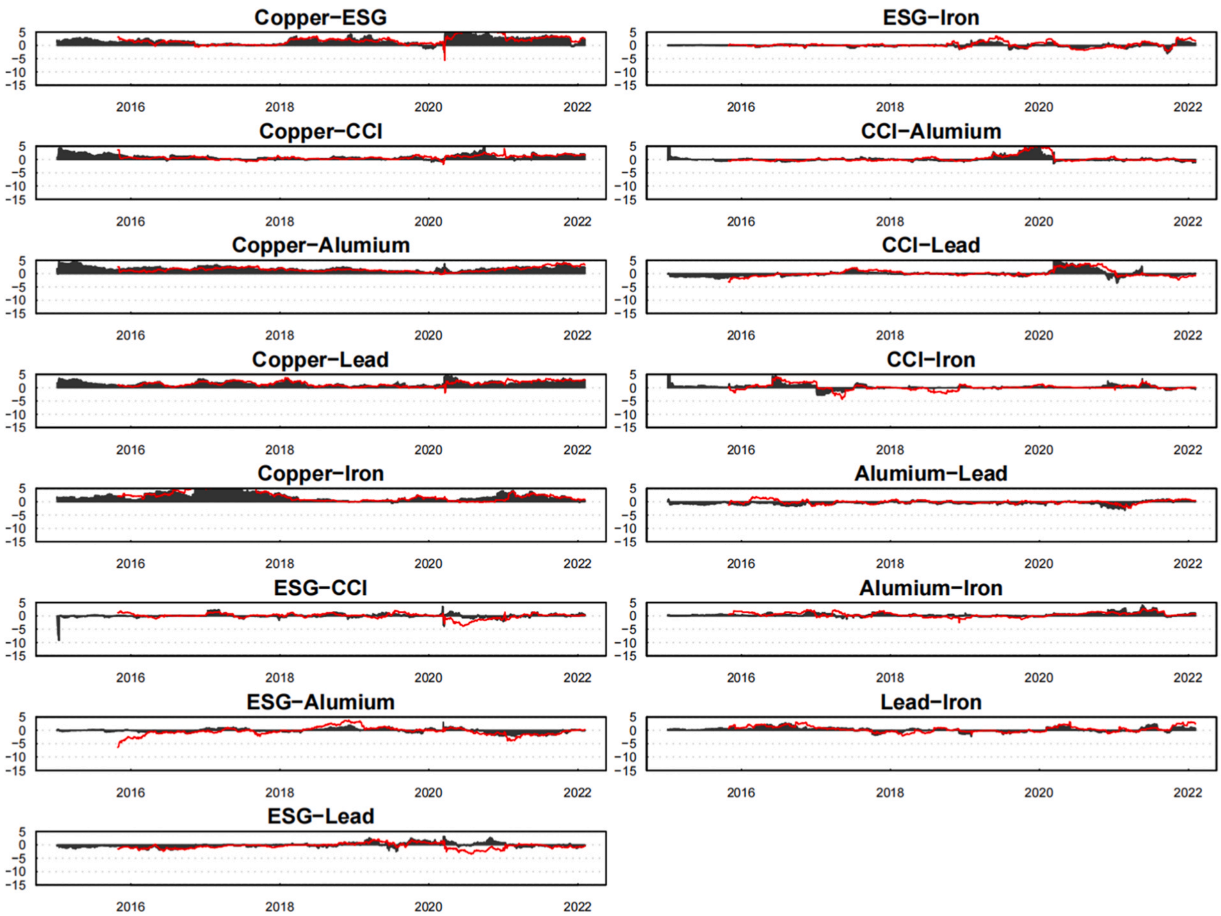

Fig. 5. Net total directional connectedness. Notes: Outcomes are relied on a TVP-VAR with order one lag and a 20-step-ahead GFVED. The red line shows the original DY12 technique utilising a 200-day rolling-window VAR with a BIC lag duration and a 20-step-ahead GFVED.

Overall, our results may provide investors with valuable insight into creating suitable portfolios based on their own risk appetite. For example, investors can observe and estimate the overall pairing spillover effect to determine portfolio weights. In addition, connectedness is not constant over the sample period, indicating that risk-hedging strategies are needed in portfolio management. Furthermore, Figs. 3–5 show the volatility trend of the TVP-VAR-based return spillover result is broadly similar to that of the VAR-

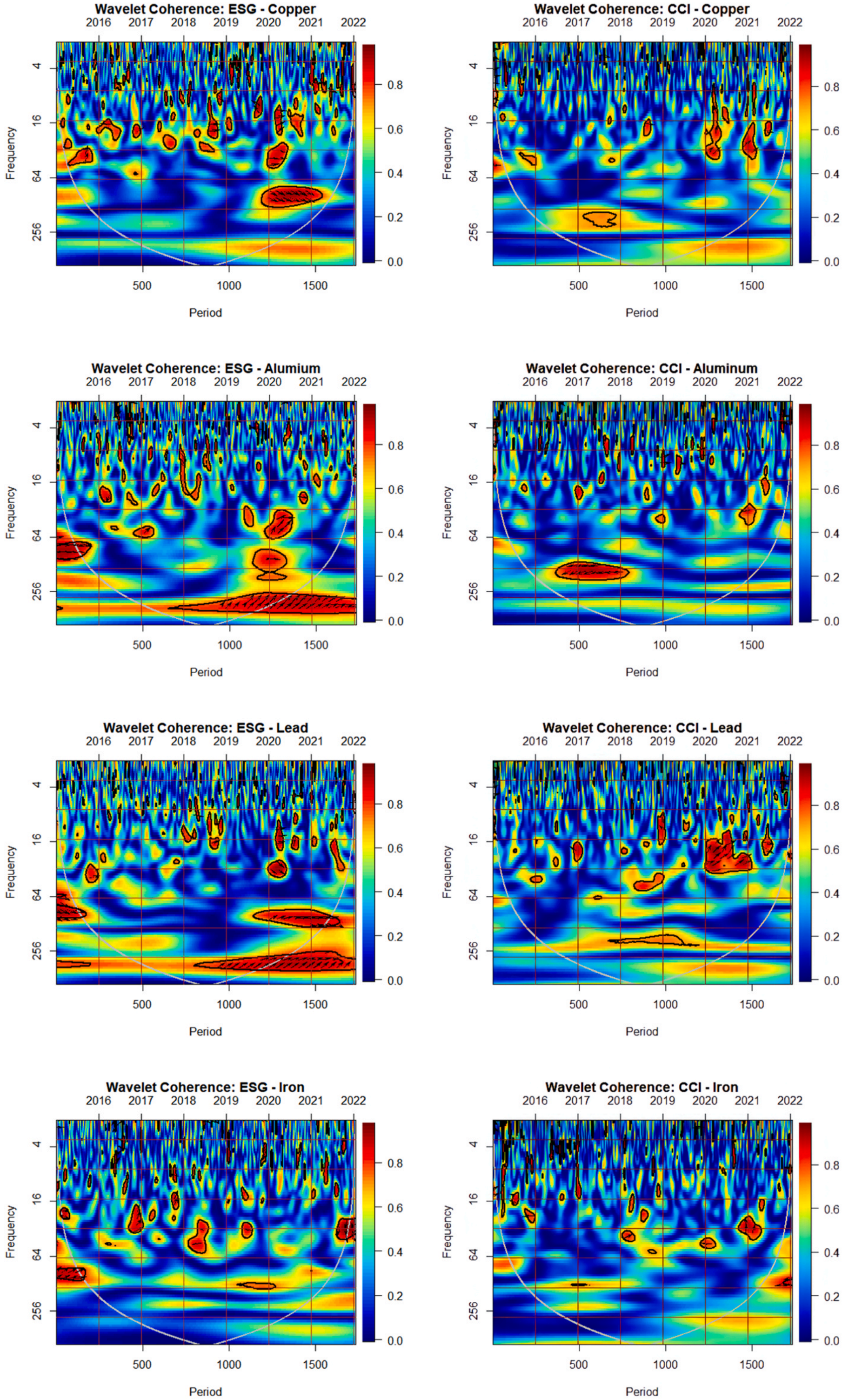

Fig. 6. Wavelet coherence for paired markets.

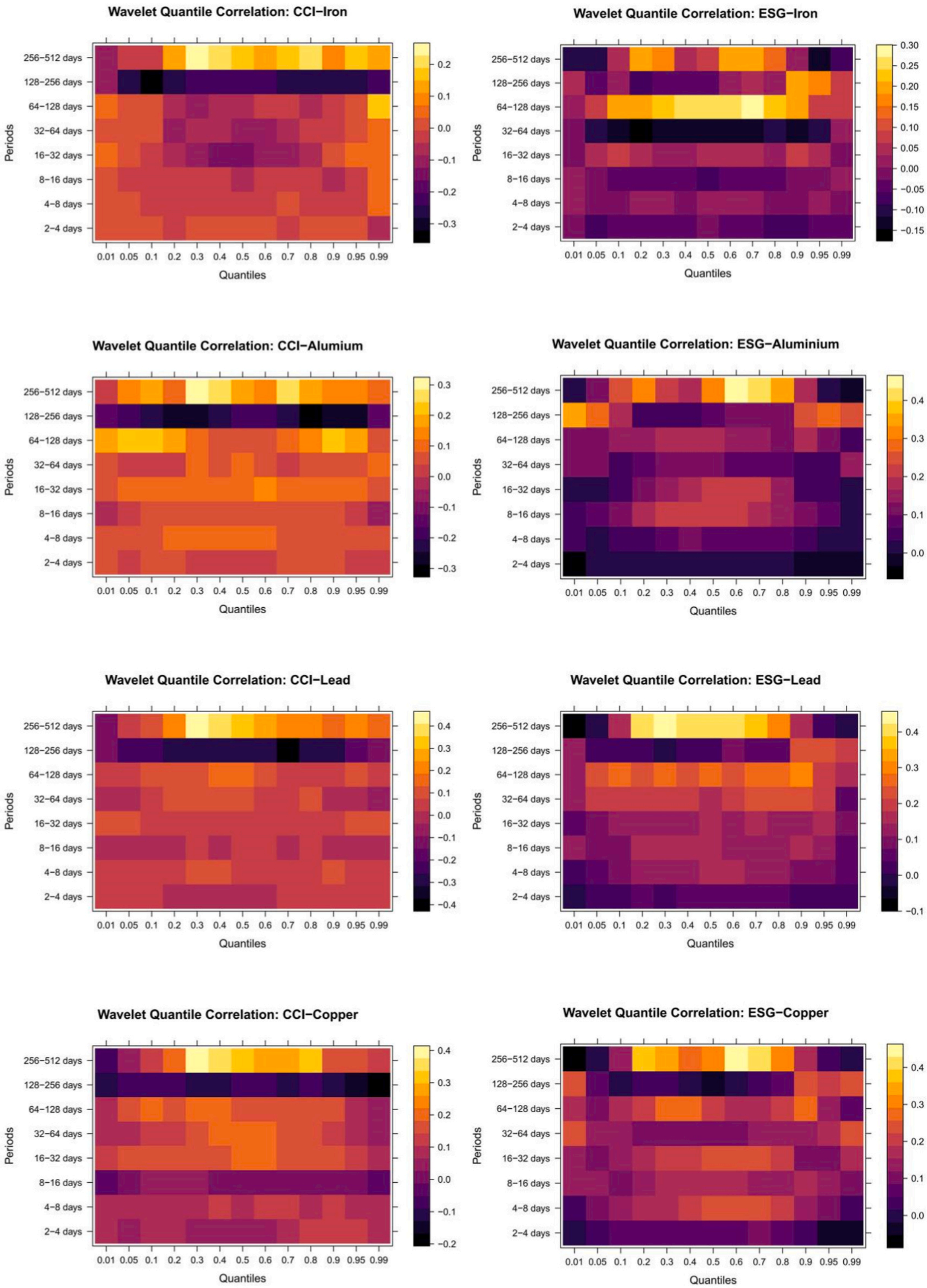

Fig. 7. Results of WQC method. Notes: The heat map displays the estimated slope coefficients, transitioning from purple to orange. In Fig. 7, the heat map depicts how the CCI and ESG influenced carbon emissions across different metal commodity markets at varying frequencies and quantiles. The right vertical axis represents the relationship coefficients, while the left vertical axis indicates different frequencies (short-, medium-, and long-term). The horizontal axis represents market conditions (quantiles).

based spillover approach (red line). This shows that our connectedness results are robust.

In the next part, we process wavelet coherence to analyse the time-varying correlations and lead-lag relationships among the Green Bond, the Cryptocurrency Index (CCI) and the most important green energy- associated metals. An excellent opportunity is provided by the current COVID-19 crisis to check the dynamic linkages between assets. Importantly, wavelet coherence evaluation can provide new insights into how green bond indices, cryptocurrency markets, and prices of major green energy-related metals vary over time and frequency. It should be noted that the bivariate wavelet coherence framework allows us to capture the correlation dynamics of co-movement and leading lags between the selected variables. Fig. 7 shows wavelet coherence plots for pairs of the Green Bond, the cryptocurrency market, and the major green energy-related metals.

As in Fig. 6, we use wavelet coherence/cross wavelet transform to investigate co-movement between different commodity markets. The phase difference is denoted by the black arrow present on the wavelet coherence plot. A phase difference of zero signifies the synchronized movement of the two series. In instances where two series are in-phase (anti-phase) or possess positive (negative) correlation, the arrows are oriented towards the right (left) direction. The blue colour indicates a weak dependence between different markets. The darker the red colour, the higher the dependence. As shown in the diagram below, the horizontal axis provides time, and the vertical axis shows frequency. The phase arrows indicate phase differences, with the right arrow indicating in-phase, suggesting two markets trending towards the same movement at a given scale. The left arrow indicating in-phase, opposite movements at a given scale. Different arrows indicate different markets leading in different time series, with the (→) arrow showing that the two markets are moving in the same phase, while (←) denotes that the two markets are out of phase. (↗) = the former market is leading; (↘) = the latter market is leading; (↖) = the latter market is leading; (↙) = the former market is leading.

Fig. 6 depicts the outcomes of our correlation estimation pertaining to ESG-Copper. Within the medium-term frequency domain (64–256 days) and during the sample time span of 2020–2021, distinct clusters of notable red regions become evident in the high and medium frequency bands concerning ESG-Copper. This concurrent observation implies that the copper market maintains a lead over the green bond index in the context of pricing dynamics (located at the bottom right of the arrow). A possible reason for this is that after the initial recession, the economic recovery in the post-COVID-19 era has driven demand growth in the copper market (Song and Zhou, 2020). We then evaluate the case for ESG-Aluminum. An arrow pointing downward in the medium to long term frequency domain (64–256 days) is identified at the start of the sample horizon (corresponding to 2015). This suggests that the aluminum price leads the ESG market. Notably, the wavelet coherence plot shows some significant red islands between the novel corona-virus outbreak in 2020 and the beginning of 2021. Additional findings pertaining to the medium frequency domain reveal a correlation of medium-term nature between the green bond index and the aluminum market. This outcome underscores a robust correlation existing between the Green Bond Index and the Aluminum market within the medium frequency spectrum. This is following the COVID-19 outbreak. Green Bond Index price is ahead of Aluminum market price in the upper right corner of the arrow.

We investigate causality and phase differences between the ESG and Lead markets. We see a brief period of synergistic movement in the medium-term frequency domain (64 days) during 2015–2016, with the arrow pointing primarily to the right, indicating lead market prices are leading the ESG market. In addition, we also observe the most significant periods of coherent and synergistic movement in the medium-term frequency domain (64 days) as well as in the long-term frequency domain (around 256 days) during 2019–2021. According to this arrow, the ESG market price leads the Lead market price in terms of medium- and long-term returns.

As a related analysis, we check the multi-scale dependence structure of the Cryptocurrency Index (CCI) with respect to the green energy-related metals. By looking at the CCI-Copper, we find intermittent significant correlations in the short-term frequency domain (4–64 days) corresponding to the COVID-19 outbreak period in the time domain between 2020 and 2021. In addition, these arrows on the right denote the short-term returns of the CCI index ahead of the copper market. We observe a correlation in the bands of the short-term frequency domain (4–16 days) at the beginning of the sample time domain (corresponding to early 2015) in the period prior to COVID-19. The arrows show down to the right when the copper price leads the CCI index in the short term. Both market correlations occur during the short-term frequency band, suggesting that they are not long-term correlated and that there is a strong dependency in the short-term band.

We then investigated the CCI-Aluminum market. We observe a strong correlation in the long-term band (64–256 days) in the period spanning 2016–2017 prior to the COVID-19 outbreak, with the arrow pointing mainly to the lower left. This shows that the crypto-currency market leads the long-term returns of the Aluminum market. For the CCI and Lead as highlighted in the coherence plot, a large red island appears on the medium-term wavelet scale (16–64 days) over the period 2020–2021. This points out to a high degree of coherence between the two variables over the medium-term horizon in the range following the pandemic outbreak. The arrow to the right of the chart illustrates that primary market prices lag the cryptocurrency market. Clearly, the post COVID-19 outbreak implies a unidirectional causal effect between CCI and lead.

Finally, we focus on wavelet coherence and phase relationships for ESG-Iron and CCI-Iron, respectively. The red colour indicates strong coherence, while the dark blue colour indicates low coherence between market pairs. Upon examining the ESG-Iron pairs, it becomes evident that connections within the long-term frequency domain (64–256 days) manifested at the inception of the sample period, accompanied by lagging returns within the iron market. Furthermore, the association between the ESG and iron markets displayed a lack of strength, barring the medium-term frequency domain (16–64 days). The same is the case towards the end of the sample period when iron market returns lead the green bond index. Whereas the CCI-Iron pair only shows small islands of red in 2020–2021, in the medium-term frequency domain (16–64 days), the cryptocurrency market index leads the Iron market. Based on the empirical results above, it can be summarized that in general, the short, intermediate, and long-term coherence between market pairs varies frequently. Therefore, we do not see clear evidence of a definitive causal relationship. However, the correlation between the Green Bond Index compared to the Cryptocurrency Index and our selection of green energy-related metals was more active after the COVID-19 outbreak, especially for the aluminium and lead markets.

We introduced the WQC, which effectively addressed the issue of cross-quantile tail dependency structures between two variables. Fig. 7 illustrates the results of the WQC analysis.

Regarding the relationship between CCI and metal commodity markets, a consistent positive correlation was generally observed

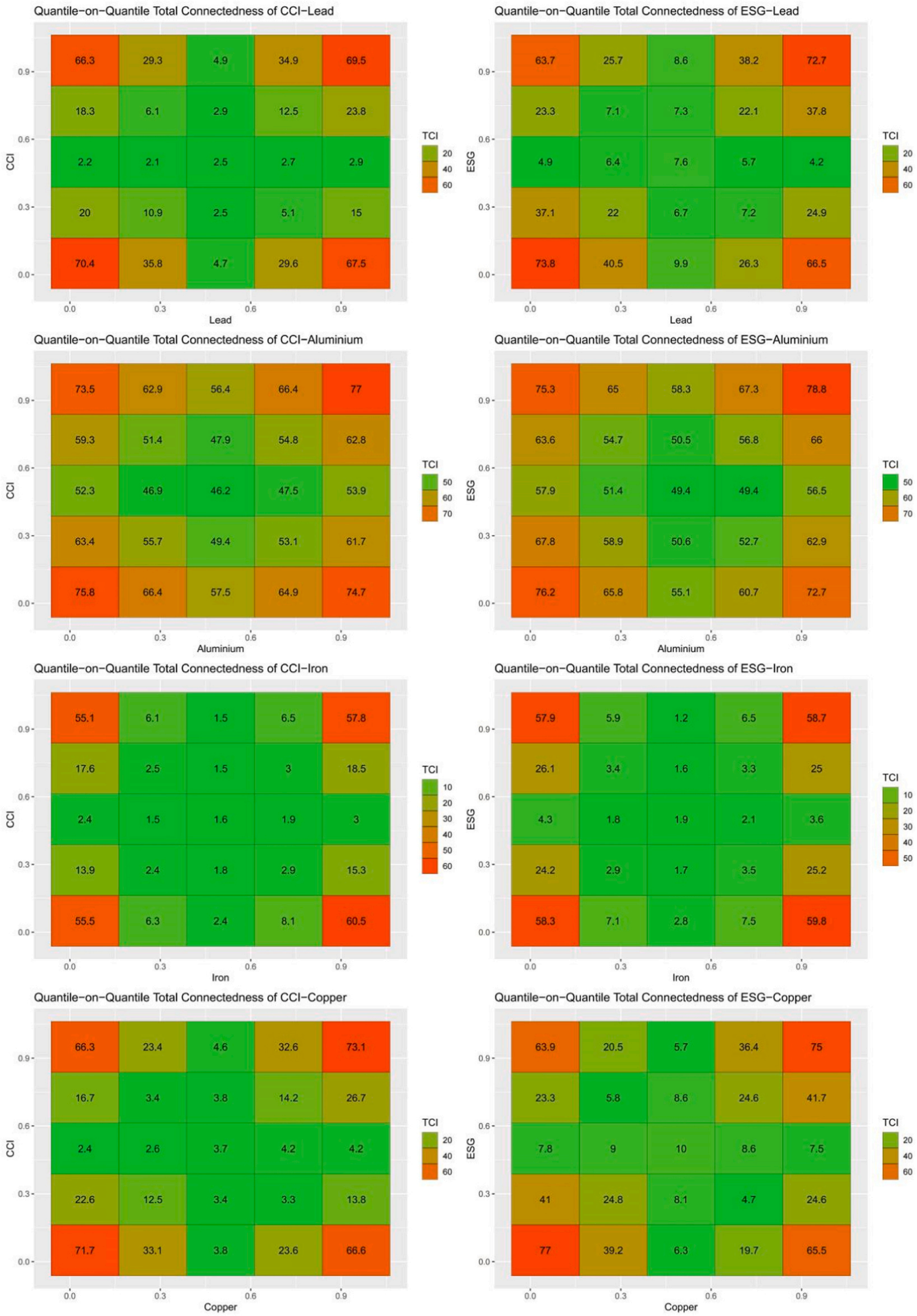

Fig. 8. Results of QQR connectedness. Notes: Our findings are based on a 200-day rolling window method for the QVAR function. This function was configured with lag 1 and 20 steps ahead, consistent. τ1 is CCI or ESG index, and τ2 denotes the specify metal commodity market.

across all quantiles and periods before the frequency range of half a year to one year (128–256 days). However, there was heterogeneity among specific metal commodity markets, with some frequency intervals exhibiting negative linkage structures. For example, the impact of CCI on copper showed a noticeable decline over a period of one week to half a month (8–16 days), but over time, this relationship became increasingly tight until the frequency of half a year. Notably, the WQC analysis highlighted the cross-quantile short- to medium-term significance of CCI impacts, particularly during short-term shocks, where the cross-quantile linkage was close. This finding aligns with previous studies (e.g., Mo et al., 2022; Zeng et al., 2024d), which primarily confirmed the significant net spillover effects of cryptocurrencies on commodity markets at different frequencies.

Additionally, our results indicated that, in contrast to CCI, ESG exhibited a negative correlation with the metal commodity markets across all quantiles at short-term frequencies (less than 8 days). Furthermore, at various quantiles and medium- to short-term frequencies (less than 64 days), the influence of ESG on metal commodity markets was mostly positive but weak. Our observations further demonstrated that ESG had a consistently significant positive impact on metal commodity markets at long-term frequencies and near middle quantiles. The stronger correlation and more significant impact of ESG measures on metal commodity markets over extended time periods could be attributed to this phenomenon (Naeem et al., 2021).

Then, we employed the QQR connectedness methodology. Our analysis started with an examination of the average connectedness metrics, exploring the complexities of connections between directly and inversely related quantiles to understand their dynamic interactions.

Fig. 8 displayed the average TCI between the CCI and the metal commodities market. The results revealed that, with the exception of CCI-Iron, the TCI between CCI and other metal commodity market indices at inversely related quantiles ([$\tau1 = 10$ %, $\tau2 = 95$ %] to [$\tau1 = 90$ %, $\tau2 = 25$ %]) was weaker than at directly related quantiles ([$\tau1 = 5$ %, $\tau2 = 5$ %] to [$\tau1 = 95$ %, $\tau2 = 95$ %]). However, for CCI-Iron, the TCI at directly related quantiles ([$\tau1 = 5$ %, $\tau2 = 5$ %] and [$\tau1 = 95$ %, $\tau2 = 95$ %]) showed significant connectedness. Our findings suggest that during periods of extreme market risk, there was a closer relationship between CCI and the metal commodities market. This finding is supported by Rehman and Vo (2020), who found that precious metals under extreme positive return distributions did not converge with cryptocurrencies under extreme negative returns, thus providing diversification opportunities for investors.

A comparable trend was identified in the relationship between ESG and the metal commodities market, where inversely related quantiles ([$\tau1 = 5$ %, $\tau2 = 95$ %] and [$\tau1 = 95$ %, $\tau2 = 5$ %]) showed more significant correlations than directly related quantiles ([$\tau1 = 5$ %, $\tau2 = 5$ %] to [$\tau1 = 95$ %, $\tau2 = 95$ %]), except for Iron. This mirroring pattern highlights the asymmetry and heterogeneity in their interconnected structures. This result partially aligns with Naeem et al. (2021), who found that green bonds and industrial metals have diversification potential under stable market and extreme uptrend conditions.

In conclusion, our analysis revealed several notable results: except for Iron, the directly related quantile pairs ([$\tau1 = 5$ %, $\tau2 = 5$ %] to [$\tau1 = 95$ %, $\tau2 = 95$ %]) between CCI and ESG and other metal commodity markets exhibited more significant connectedness than inversely related quantile pairs. Furthermore, our results indicated that during non-extreme market periods or moderate oil price shocks, there was minimal connectedness between CCI, ESG, and other metal commodity markets, except for aluminium. This suggests that CCI and ESG may have strong hedging potential against various metal commodity markets during stable market conditions. As Hernandez et al. (2019) noted, the relatively small volatility in commodity markets during stable periods is insufficient to cause significant financial shocks to the green bond market. Our study enhances our understanding of risk management strategies for cryptocurrency and green bonds concerning price shocks in the metal commodities market.

4. Conclusions and policy implications

Our research was the first to combine the TVP-VAR connectedness approach, wavelet coherence, wavelet quantile correlation, and QQR connectedness method to analyse the frequency and quantile dependency and spillover effects of the green bond, cryptocurrency index, and green energy-related metals over an extended period. We conclude with the following findings and policy recommendations.

Firstly, the connectedness among the green bond and cryptocurrency indices and the green energy-related metals market was influenced by economic performance, which shaped the nature of their interactions. Following the COVID-19 outbreak, these connections became stronger. In both the green bond and cryptocurrency markets, risk shocks were absorbed. Notably, the copper market acted as a net sender of connectedness throughout the sample period, transmitting persistent shocks to other markets. This effect was most evident after the COVID-19 outbreak, demonstrating the increasing interdependence among the sample markets. Secondly, findings based on cross-wavelet transformation showed that unique risk shocks between markets had different lead-lag relationships. The direction of these spillovers changed over time and across frequency breakdowns, influenced by the strength of the interactions and changes in economic fundamentals. Specifically, the green bond market was strongly correlated with lead and aluminium at medium to long-term frequencies, respectively, particularly after the COVID-19 outbreak. However, shocks in the green bond market drove the lead and aluminium markets. Interestingly, the cryptocurrency market was closely correlated with copper and lead prices in the short-term following the COVID-19 outbreak, with the cryptocurrency market leading in terms of shock transmission. The third and most surprising result of our analysis was that COVID-19 altered the dependency of green bonds and cryptocurrencies on green energy-related metals. Since the outbreak, our analysis indicated that the market has increasingly focused on the energy transition and the green energy industry. Finally, our empirical results based on quantile correlation indicated that the cryptocurrency index exhibited a consistent positive correlation with metal commodity markets, except for lead, at medium to short-term frequencies, despite some heterogeneity in certain frequency intervals. In contrast, green bonds displayed a negative correlation with metal commodity markets at short-term frequencies and a positive correlation at long-term frequencies. Our analysis revealed the hedging potential of the cryptocurrency index and green bonds against metal commodity markets under heterogeneous market states, particularly when market states were stable.

From the perspective of policymakers, the empirical results of this research hold significant implications for governments and regulatory bodies. The research reveals a complex interdependence among the green bond, cryptocurrency, and green energy-related metals markets, providing a critical basis for forward-looking policy formulation. Particularly under the structural shocks imposed by COVID-19 on the entire financial system, the strengthened market linkages indicate that policymakers need to adopt a more comprehensive view, considering the practical implications of policies across different markets. For instance, our findings demonstrate a strong correlation between the green bond market and the markets for lead and aluminium at medium to long-term frequencies, suggesting that policies aimed at promoting the green bond market may significantly impact these metal markets. Additionally, the short-term association between the cryptocurrency market and the prices of copper and lead indicates that regulators need to closely monitor the potential impacts of crypto assets on traditional commodity markets. Furthermore, our results underscore the necessity of formulating long-term sustainable development policies. The influence of green bonds on the metals market implies that policymakers must balance the advancement of green technologies with the stability of critical metal supplies. This may involve developing strategic metal reserve policies or supporting the research and development of sustainable mining technologies.

For investors and market makers, this work provides valuable perspectives into optimising portfolio investment and risk management. Firstly, the role of copper as a persistent net risk sender highlights the importance of including copper in investment portfolios, especially during periods of global economic turbulence. Investors might consider leveraging this characteristic of copper to diversify risk, particularly in the context of the heightened market linkages post-COVID-19. Secondly, the growing signaling role of the green bond offers investors new tools for risk assessment. By closely monitoring fluctuations in the green bond market, investors can anticipate potential trends in other related markets, especially when evaluating investment opportunities associated with metals such as lead and aluminium. Additionally, the study’s findings on the correlations between the CCI and the metal commodities market at different frequencies, and the varying correlation patterns between ESG and the metals market in both short-run and long-run contexts, provide investors with new hedging strategies. For example, in the short term, investors might consider using cryptocurrencies to hedge against the price volatility of copper and lead. In contrast, for long-term investment strategies, incorporating green bond into metal commodity investment decisions could help balance short-term fluctuations with long-run trends.

Finally, the study emphasizes the need for market participants to adopt more dynamic and multidimensional risk management approaches. Given the varying relationships among markets across different time scales and frequencies, investors should develop analytical tools and models capable of capturing these complex interactions. This might involve integrating multiple methods used in this study, such as TVP-VAR, wavelet quantile correlation, and QQR connectedness analysis, to comprehensively assess investment risks and opportunities.

Overall, this study provides new perspectives for understanding the intricate relationships among green finance, cryptocurrencies, and commodity markets, aiding in the formulation of more effective policies and equipping investors with essential tools to optimise investment strategies. Future research could further extend to more indices or metal markets related to green energy, offering a more comprehensive view of market dynamics.

Ethics approval and consent to participate

Not applicable.

Funding

This paper was supported by the Major Program of the National Social Science Foundation of China (Grant No. 23&ZD175), the National Natural Science Foundation of China (Grant Nos. 72173096, 72303139, 71873103).

CRediT authorship contribution statement

Hongjun Zeng: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Qingcheng Huang:** Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdullahi D. Ahmed:** Writing – review & editing, Supervision, Project administration, Methodology, Data curation, Conceptualization. **Brian Lucey:** Writing – review & editing, Supervision, Resources, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data Availability

Data will be made available on request.

Acknowledgements

We will be grateful to the anonymous reviewers who will comment on this manuscript. Hongjun Zeng acknowledges the support of

RMIT Research Stipend Scholarships (RRSS-SC).

Consent for publication

All authors are very positive to publish this manuscript on this journal.

Competing interests

There is no competing interest among the authors.

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