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COVID-19 and the quantile connectedness between energy and metal markets

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ABSTRACT

This study analyzes the relationship between clean and dirty energy sources and energy metals during the COVID-19 pandemic. We document a sharp increase in connectedness after the COVID-19 pandemic, that is asymmetric at the lower and upper quantiles, with stronger dependence among the variables at the upper quantiles. Among the energy metals, cobalt is the least connected to the energy markets. Finally, our empirical results show a switch in the net connectedness indexes of energy metals and clean energy after January 2021. Our results have implication for investors and policy makers for energy and metal under various market conditions.

1. Introduction

A gigantic energy transition is awaiting us, as the goal of limiting global temperature increases to 1.5 °C looms large. Intuitively, this energy transformation will be primarily led by clean energy companies, which will lead to an increase in demand for specialized metals such as nickel, copper, and cobalt (International Energy Agency, 2021a). Consequently, leading to an increase in the interdependence between clean energy and metal prices, but also the interdependence between metal prices and fossil fuels, due to the importance of energy as an important input in metal production.

Theoretically, the metal markets can be linked to the energy markets through both the supply and demand channels. On the supply side, metal production is an energy-intensive industry, which requires a large amount of energy. Most metal production relies on fossil fuels such as coal, oil, and natural gas.[1] Thus, increasing fossil fuel prices can significantly alter the cost structure of metal production, thereby influencing the returns and volatilities of metal prices. Given the significance of fossil fuels in metal production, the role of fossil fuel prices in determining metal prices has been documented in previous studies.[2] On the demand side, the recent transition to clean energy technology implies that demand for metals used in clean energy technologies will likely increase. It is projected that the lithium reserve will deplete by 2040. Coupled with a low recycling rate, clean energy industries are reducing their reliance on lithium. Therefore, cobalt is set to enjoy a meteoric rise in demand by 2040 and possibly beyond (up to 1074%) (Månberger and Stenqvist, 2018). Moreover, silver used inside the paste of the cells will be replaced entirely by nickel-copper plating (Rehman and Lee, 2014). Thus, producing and deploying future clean energy technologies rely on a stable supply of energy metals such as cobalt, nickel, and copper. The COVID-19 pandemic has disrupted both the supply and demand channels through which metals and energy are linked, because of large fluctuations in fossil fuel prices coupled with the supply chain issues during this period. In particular, many clean energy

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[1] https://www.iea.org/data-and-statistics/charts/energy-consumption-in-the-iron-and-steel-sector-by-scenario

[2] For example, Shao et al. (2021), Dutta (2018), Zhang and Tu (2016), Umar et al. (2019); Naeem et al. (2020) Reboredo and Ugolini (2016), Umar et al. (2021a, b, c, d, e, f, g).

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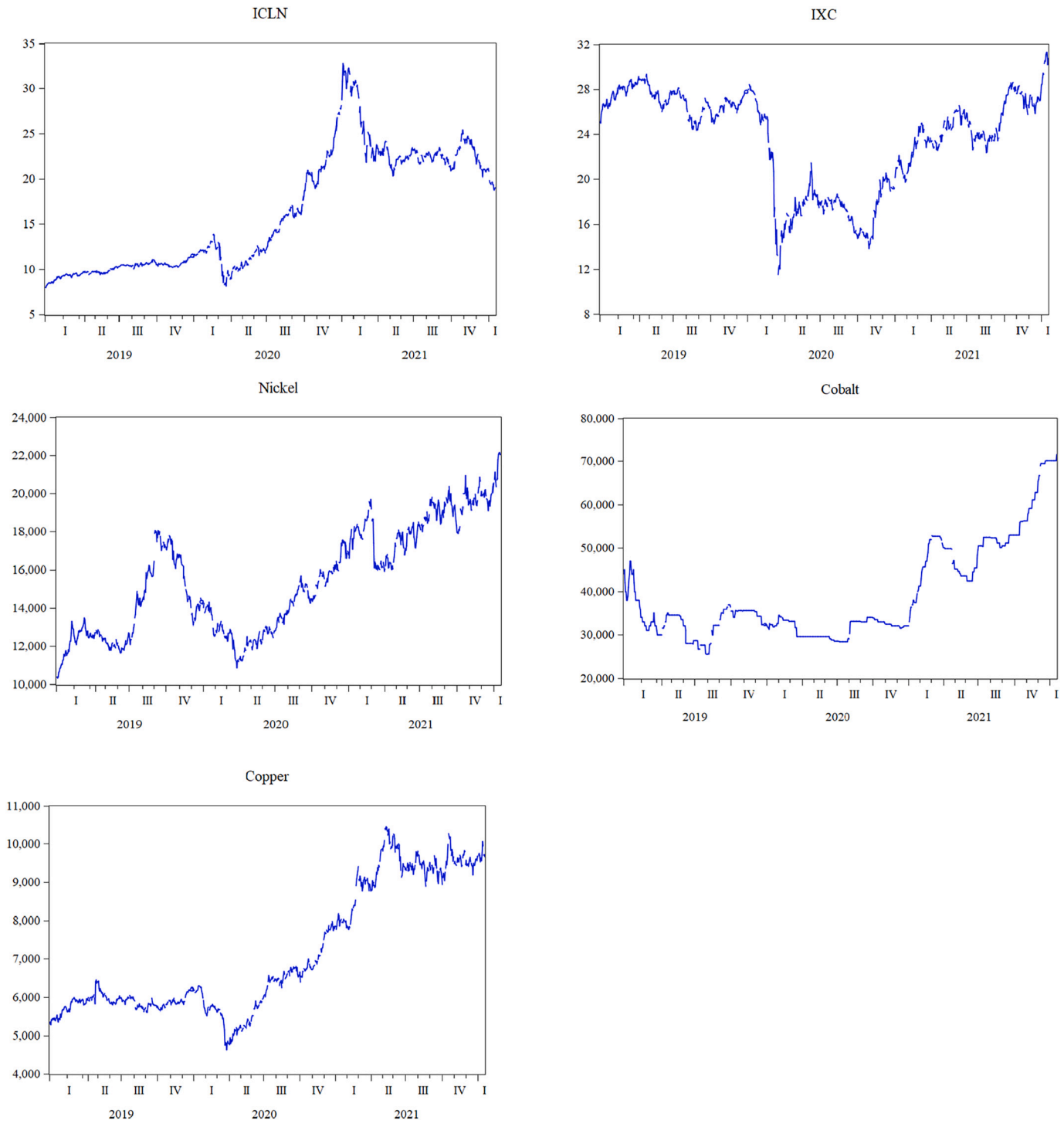

Fig. 1. (1.1.) Daily closing prices. (1.2.) Daily returns series.
Fig. 1(1.1 and 1.2) presents the prices and returns, respectively, of the energy and metal markets under study, where returns are calculated by log-differencing. ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt, respectively.

producers have suffered from supply chain glitches throughout the COVID-19 pandemic (Eroğlu, 2020).

Motivated by the aforementioned events, this paper investigates the connectedness between energy metal, clean energy, and dirty energy prices. Understanding this connectedness is central to risk measurement and management (Diebold et al., 2017). This is particularly relevant in the case of the metal and energy markets, as they rely heavily on one another through both the supply and demand channels. Given the catastrophic effect of the recent pandemic on financial markets, we zoom in on the relationship between metal and energy prices throughout

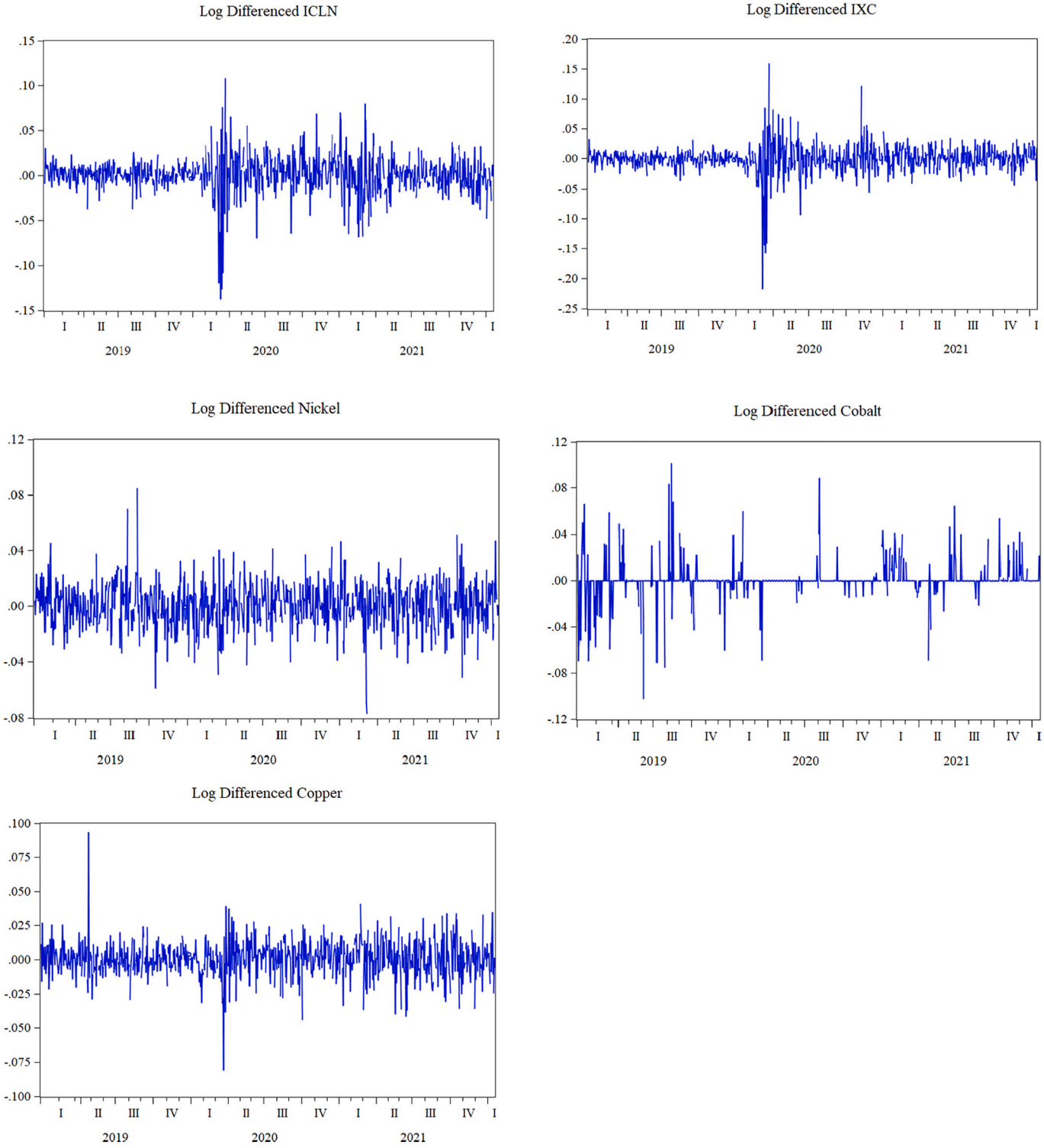

Fig. 1. (*continued*).

various phases of the COVID-19 pandemic.[3] Our motivation to study the relationship between metal and energy prices during extreme events like the COVID-19 crisis is based on several reasons. First, the pandemic has increased the level of uncertainty in energy markets, as illustrated by the high fluctuations in fossil fuel prices during this period. Highly volatile fossil fuel prices influence metal prices by making it difficult for metal producers to forecast their energy costs accurately. At the same time, highly volatile fossil fuel prices increase the volatility of clean energy prices, as fossil fuels and clean energy are considered substitutes. Moreover, the recent trends during the pandemic suggest an increasing inclination towards renewable energy firms (Wan et al., 2021). Thus, the transition to cleaner production amidst extreme events like the

[3] A number of studies have documented the impact of Covid-19 pandemic on various financial markets including socially responsible investments (See Karim et al., 2022; Umar and Gubareva, 2021a, 2021b; Gubareva and Umar, 2020; Umar et al., 2021c)

Table 1
Descriptive statistics.

1.1. Summary statistics of each variable

	ICLN	IXC	Nick	Copp	Cob
Mean	19.4	19.5	9.7	8.9	10.7
Variance	36.30	36.72	0.03	0.05	0.14
Skewness	−0.603***	−1.426***	−1.249***	−2.262***	−0.346***
Kurtosis	7.370***	20.856***	63.157***	38.035***	0.385*
JB	1601.08*	12,720.95	114,689.32	42,119.60	17.99***
ERS	−13.549**	−15.425**	−12.047**	−19.342**	−16.720***
Q (10)	156.155**	153.984**	100.123**	175.011**	359.166***
Q^2(10)	391.000**	188.725**	318.407**	374.760**	106.732***

1.2. Correlation matrix.

	ICLN	IXC	Nick	Copp	Cob
ICLN	1				
IXC	0.566451	1			
Nick	−0.0347	−0.04549	1		
Copp	−0.04111	−0.01453	0.24815	1	
Cob	−0.02067	−0.01484	0.026614	0.001086	1

ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt. JB stands for the Jarque-Bera test statistics, ERS stands for the Elliott, Rothenberg and Stock Unit Root test statistics. Q (10) and Q^2(10) stand for the Ljung-Box test statistics on returns and squared returns. ***, **, * indicate statistical significance at 1, 5, and 10% level.
ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt, respectively.

COVID-19 pandemic may shift the linkage between metal, clean and dirty energy prices. Therefore, understanding the metal-clean energy-dirty energy nexus during an extreme period like the COVID-19 crisis allows investors to adjust their strategies. This also provides valuable information for metal and energy producers to forecast their production costs.

To study the relationship between metal, clean and dirty energy prices during the COVID-19 period, we collect daily price data from 31st December 2019 to 19th January 2022. Specifically, we use the iShares Global Energy ETF(IXC) which is benchmarked against S&P Global 1200 Energy Sector Index as a proxy for fossil fuel energy or dirty energy, and the iShares Global Clean Energy ETF (ICLN) which is benchmarked against S&P Global Clean Energy Index as a proxy for clean energy. In addition, we consider closing prices of three metals namely cobalt, copper, and nickel, due to their significance in clean energy production, as explained above. Methodologically, we apply a generalised forecast error variance decomposition to a quantile vector autoregression model to study how the metal-clean energy-dirty energy nexus varies between extreme downward and upward movements.

Our results suggest that the connectedness among energy metal, clean energy, and dirty energy markets sharply increases at the extreme quantiles, compared to at the median quantile. This implies an increase in the contagion across the markets under extreme events. Moreover, on average, clean energy and dirty energy markets are shock transmitters while the energy metals are net shock receivers across all the quantiles. This highlights the importance of energy markets in the shock transmission patterns between energy and metal markets. Our results also show that the clean energy and dirty energy markets are highly connected to each other, while the three metal markets (nickel, copper, and cobalt) are highly connected to one another. Among the energy metals, the cobalt market is the least connected to the energy markets, thereby suggesting its potential hedging capacity for energy investments, particularly at the median quantile. Using a rolling window analysis to analyze how the market connectedness changes over time, we find that the connectedness across the markets sharply increased after the COVID-19 fallout, which is consistent with previous studies in other markets.[4] In addition, we find evidence of asymmetric connectedness at the lower and upper quantiles, with stronger dependence among the variables at the upper quantiles. This suggests that an extreme increase in energy and metal prices significantly increase the contagion across these markets. Finally, our empirical results show a switch in the roles of clean energy and metal markets after January 2021. Specifically, metal markets become the net shock transmitter while clean energy becomes the net shock receiver. This is consistent with the widening shortage of energy metals after January 2021, as a result of supply chain issues and increasing public preferences towards clean energy.

Our paper contributes to the literature in the following aspects. First, we contribute to the scant empirical evidence on the linkage between clean energy prices and energy metal prices. Specifically, we explore how the clean energy-metal relationship varies across quantiles. Our goal is to capture the tail and median dependence between clean energy stock and energy metal markets, which has implications for risk and portfolio management. Second, previous research has either considered the bi-sector nexus between clean energy – energy metal prices or between fossil fuel – energy metal prices, we consider the linkage between clean energy prices, dirty energy prices, and energy metal prices through a multivariate network framework, thereby identifying the primary shock receivers and transmitters in the system. Finally, our paper is among the first studies to document the evolution of the clean energy-dirty energy-energy metal nexus during the COVID-19 pandemic.[5]

The paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 presents the research methodology and data. Section 4 presents the empirical results and their implications, and section 5 concludes.

[4] For example, Baker et al. (2020), Bissoondoyal-Bheenick et al., 2021, Umar et al., 2022.

[5] Most studies that focus on the COVID-19 period have focused on the linkages in other markets, such as stock, oil, bonds, for example, Bissoondoyal-Bheenick et al., 2021; Umar et al., 2021; Costa et al., 2021; Youssef and Mokni, 2021; Umar et al., 2021; So et al., 2021; Bouri et al., 2021; Zhang et al., 2020; Umar et al., 2022; Umar et al., 2021.

Table 2
Average quantile connectedness.

2.1. Average connectedness for Quantile Q = 0.2

	ICLN	IXC	Nick	Copp	Cob	FROM
ICLN	47.72	23.92	9.64	9.23	9.49	52.28
IXC	24.03	49.1	8.9	9.68	8.29	50.9
Nick	10.85	11.78	45.35	20.92	11.1	54.65
Copp	11.09	12.8	20.63	45.29	10.19	54.71
Cob	8.35	8.94	12.5	10.92	59.3	40.7
TO	54.32	57.44	51.67	50.75	39.07	253.25
Inc. own	102.04	106.54	97.02	96.04	98.36	TCI = 45%
NET	2.04	6.54	−2.98	−3.96	−1.64	

2.2. Average connectedness for Quantile Q = 0.5

	ICLN	IXC	Nick	Copp	Cob	FROM
ICLN	63.45	22.96	6.57	4.41	2.6	36.55
IXC	22.1	66.53	3.98	3.37	4.02	33.47
Nick	8.7	8.82	64	15.16	3.32	36
Copp	9.05	8.22	15.67	63.13	3.93	36.87
Cob	4.95	4.93	4.93	3.35	81.84	18.16
TO	44.79	44.94	31.15	26.29	13.87	161.05
Inc. own	108.24	111.47	95.15	89.43	95.71	TCI = 35%
NET	8.24	11.47	−4.85	−10.57	−4.29	

2.3. Average connectedness for Quantile Q = 0.8

	ICLN	IXC	Nick	Copp	Cob	FROM
ICLN	46.44	25.56	11.17	8.67	8.17	53.56
IXC	24.96	50.02	7.99	8.44	8.59	49.98
Nick	12.28	11.16	44.31	19.78	12.46	55.69
Copp	12.78	13	18.1	45.58	10.54	54.42
Cob	11.17	9.82	10.22	9.57	59.22	40.78
TO	61.19	59.54	47.48	46.46	39.76	254.43
Inc. own	107.63	109.57	91.79	92.04	98.98	TCI = 58%
NET	7.63	9.57	−8.21	−7.96	−1.02	

ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt. Each cell represents the amount of spillovers from the market listed in the column to the market listed in the row. The column 'FROM others' captures the spillovers from all other variables to each row variable. The row 'TO others' captures the spillovers from each column variable to all other variables. The row 'Inc. own' captures the spillovers from each column variable to all variables, including itself. The row 'NET' captures the net connectedness, where a positive (negative) value indicates a shock transmitter (receiver).

2. Literature review

We segregate literature review into three main domains. We start with a discussion of the literature documenting the relationship of fossil fuels and metal markets, followed by literature documenting clean energy and metal markets. Lastly, we present discuss literature on spillover and extreme events.

2.1. Fossil fuel prices and metal markets

The empirical literature on the link between fossil fuel prices and metal markets can be summarized into three main themes.

First, a large literature documents the relationship between fossil fuel prices and precious metals such as silver, platinum, gold, and palladium, using various empirical approaches. For example, Shahzad et al. (2019) study the impact of oil price volatilities on precious metal prices using the VAR for VAR and the cross-quantilogram methods. Husain et al. (2019) study the connectedness among oil, stock, and precious metal markets and documented higher volatility spillovers during the global financial crisis. Using a DECO-GARCH model in a connectedness network framework. Yıldırım et al. (2020) study the time varying spillover between oil price and precious metal prices and find that oil prices Granger cause precious metal prices in both returns and volatilities. Shafiullah et al. (2021) show that the causality between oil and metal prices is variable across quantiles and precious metals. Ahmed et al. (2022) document the tail spillovers between oil and precious metals and find that precious metals experience lower tail risks during the COVID-19 pandemic, with gold having the lowest tail risks. Naeem et al. (2022) examine the safe-haven and hedging ability of oil and gold against commodities and show that oil is a safe haven for metals and agricultural commodities and has higher hedging effectiveness than gold. Mensi et al. (2021) study the asymmetric connectedness between oil, gold and sectoral stock markets in China and Europe.

Second, the literature also documents the relationship between fossil fuel prices and industrial or base metals such as aluminum, copper, lead, nickel, steel, tin, or zinc. Reboredo and Ugolini (2016) use copulas to characterize the dependence between oil and metal prices. They find that oil prices have spillover effects on the prices of six industrial and four precious metals both before and after the Global Financial Crisis. Cagli et al. (2019) study the short- and long-run behavior of energy and metal markets and find a non-linear relationship between futures and spot prices in these markets. They also show that energy and metal markets are informationally efficient. Umar et al. (2019) show that copper is a shock transmitter, while zinc is a shock receiver. Umar et al. (2021a, 2021b, 2021c, 2021d, 2021e, 2021f, 2021g) explore the dynamic return and volatility connectedness between metals and oil shocks. They show that oil demand shocks are transmitters of shocks while oil risk shocks are receivers of shocks. Tiwari et al. (2021) explore the frequency connectedness among oil, stock, and metal prices. They show that platinum, gold, palladium, and stock prices are net contributors of volatility, while oil, silver, steel, and titanium are net receivers. Shahzad et al. (2019) employ a rolling window autoregressive lag model and find varying cointegrations between oil and metal prices over time and across types of metal. Wang (2022) studies the efficiency and connectedness of energy, industrial metal, and financial markets and shows evidence for a relationship between market efficiency and connectedness. With respect to the evolution of the fossil fuel and metal markets during COVID-19, Cunado et al. (2021) analyze the connectedness between fossil fuel, precious and industrial metals markets during COVID-19 and find an increase in the connectedness across the markets during the pandemic. Farid et al. (2022) explore the quantile dependence between energy, metal and agriculture commodities during COVID-19 and find evidence of a stronger transmission pattern between these markets at the tails.

Recently, growing preferences for clean energy have led to higher demand for metals used in clean energy production, also known as clean energy metals. This has motivated several researchers to investigate the relationship between fossil fuels and clean energy metal prices. For example, Shao and Zhang et al. (2020) find evidence of spillovers from crude oil prices to clean energy metal prices at different time scales. Shao et al. (2021)explore the effect of oil price uncertainty and clean energy metal stocks in China.

2.2. Clean energy prices and metal markets

The literature on the relationship between fossil fuels and metal markets has been extensive, which documents the fossil fuel-metal nexus across a wide range of metals and market conditions (e.g. mean and tail dependence). In light of the increasing preference for clean energy, recently, researchers have started documenting the relationship between metals and clean energy prices. However, the majority of research so far has focused on the relationship between precious metals and clean energy, specifically the hedging and safe haven properties of precious metals against clean energy prices. Ahmad et al. (2018) is among the first to study the nexus between clean energy and gold prices and suggest that gold is not an effective hedge for clean energy stocks. Dutta (2019) shows the negative responses of solar energy stock prices to silver volatility. Dutta et al. (2020) examine the relationship between gold,

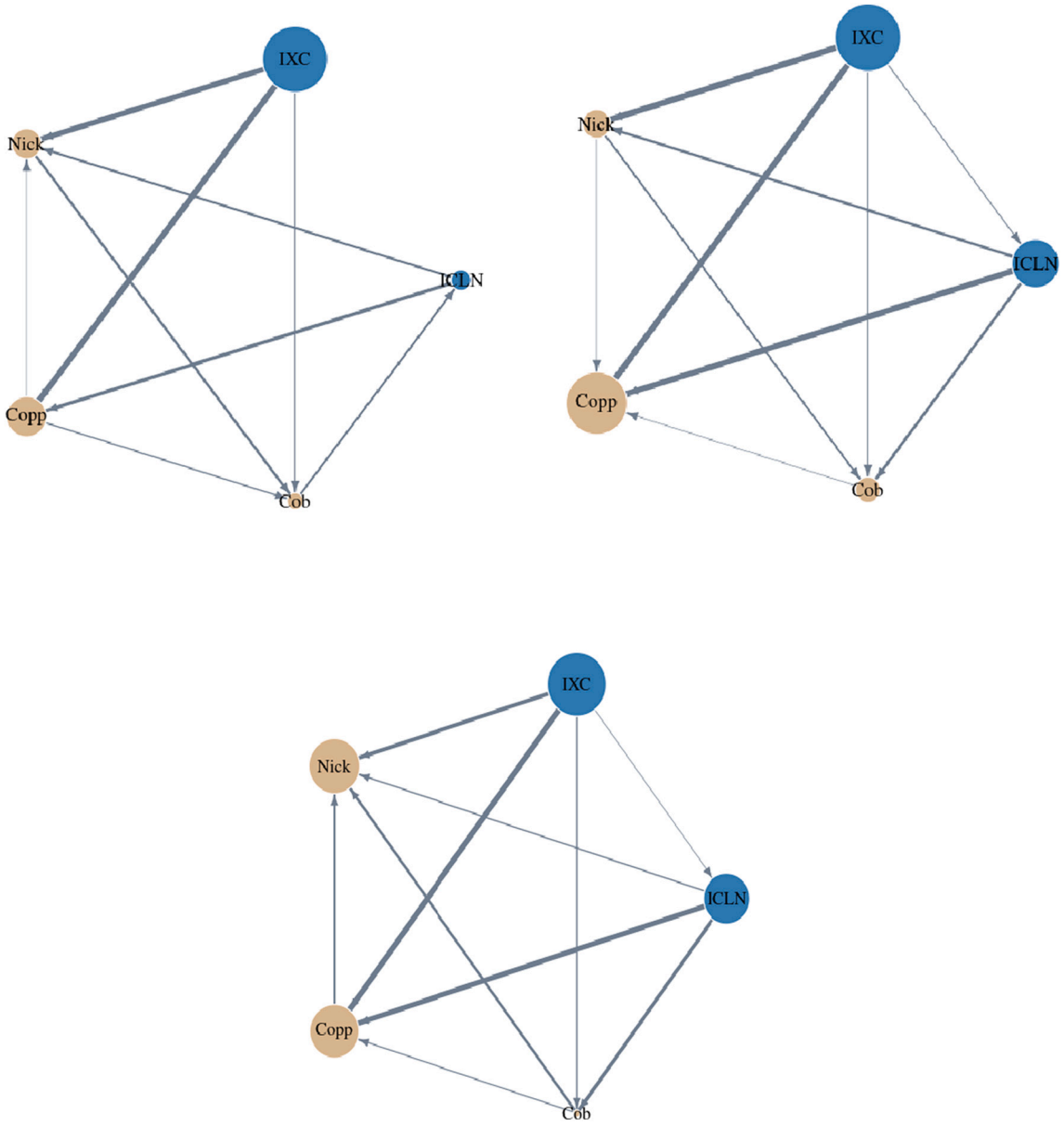

Fig. 2. Network plots of the quantile connectedness. (2.1.) Quantile = 0.2. (2.2.) Quantile = 0.5. (2.3.) Quantile = 0.8.
Note: The figure presents a network plot for the connectedness across the market across quantiles. Blue (yellow) nodes indicate net shock transmitters (receivers) and the size of the nodes corresponds to the absolute values of the NET connectedness index. The direction of the arrows indicates the direction of spillovers between two variables and the thickness of the arrows indicates the strength of these spillovers. IXC denotes the iShares Global Energy ETF (benchmarked against S&P Global 1200 Energy Sector Index); ICLN denotes iShares Global Clean Energy ETF (benchmarked against S&P Global Clean Energy Index). Cob, Copp, and Nick stand for cobalt, copper, and nickel.

silver, and oil volatilities and clean energy stock prices and show a negative relationship between the volatilities and clean energy stock prices. They conclude that gold, silver and oil volatilities can hedge against clean energy stock prices. In contrast, Erdoğan et al. (2022) analyze the causal relationship between precious metals and clean energy stocks and conclude that precious metals cannot be used to hedge the downside risk of clean energy stock investments.

As clean energy production continues to expand, it is expected that the demand for clean energy metals will increase.[6] This implies that the relationship between these metals and clean energy prices will become more significant, thus studying this relationship has important implications for environmentally conscious investors to effectively manage their portfolios, and for policymakers to stabilize the prices of clean energy. Gustafsson et al. (2022) study the hedge and safe-haven properties of energy metals against clean energy stock prices and find limited hedging capacity of energy metals against clean energy stock prices, because of the positive linkage between these markets. This is in line with the findings by Islam et al. (2022), who test the relationship between mineral import demand and the clean energy transition in 29 OECD countries. They find a significant response of mineral import demand to increasing solar and wind energy capacities.

[6] We define clean energy metals as those who are used in the production of clean energy, for example, nickel, cobalt and copper. See https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/executive-summary for examples of clean energy metals.

Table 3
Network plot analysis. (Refer to Figs. A.1-A.3 in the Appendix for the network plot)

Quantile (1)	Nodes (2)	Node Size (3)	Asset (4)	Interpretation (5)
Q1–0.20	Blue	Large	IXC	Significant net transmitter of shocks; high weighted average net total directional connectedness
		Medium	ICLN	Moderate net transmitter of shocks; moderate weighted average net total directional connectedness
	Yellow	Medium	Copper	Moderate net receiver of shocks; moderate weighted average net total directional connectedness
			Cobalt	Low net receiver of shocks; low weighted average net total directional connectedness
		Small	Nickel	
Q2–0.50	Blue	Large	IXC	Significant net transmitter of shocks; high weighted average net total directional connectedness
		Medium	ICLN	Moderate net transmitter of shocks; moderate weighted average net total directional connectedness
	Yellow	Large	Copper	Significant net receiver of shocks; high weighted average net total directional connectedness
			Cobalt	Low net receiver of shocks; low weighted average net total directional connectedness
		Small	Nickel	
Q3–0.80	Blue	Large	IXC	Significant net transmitter of shocks; high weighted average net total directional connectedness
		Medium	ICLN	Moderate net transmitter of shocks; moderate weighted average net total directional connectedness
	Yellow	Medium	Copper	Moderate net receiver of shocks; moderate weighted average net total directional connectedness
			Nickel	
		Small	Cobalt	Low net receiver of shocks; low weighted average net total directional connectedness

Note: IXC denotes the iShares Global Energy ETF (benchmarked against S&P Global 1200 Energy Sector Index); ICLN denotes iShares Global Clean Energy ETF (benchmarked against S&P Global Clean Energy Index). This table summarizes the findings of the network graphs in Figs. A.1-A.3. Column (1) indicates the quantiles, column (2) indicates node colors where 'Blue' ('Yellow') indicates that an asset is a shock transmitter (receiver). Column (3) indicates the node sizes (Large, Medium, Small), which corresponds to the size of the net connectedness index for each variable. Column (4) lists the assets and column (5) summarizes the interpretation for each asset in the network.

2.3. Spillovers under extreme events

In the wake of the extreme events since the emergence of COVID-19 in 2020, a booming literature is documenting the short- and long-term spillovers across financial markets under extreme market conditions.[7] As these extreme events alter investor risk appetite in energy and metal markets (Qadan and Nama, 2018; Qadan, 2019; Qadan and Idilbi-Bayaa, 2020; Umar et al., 2020), the analysis of the energy-metal linkage under extreme market movements provides useful information for effective portfolio management strategies. In the case of the clean energy market, studying the linkage between clean energy and energy metal prices has important implications for upholding the resilience of clean energy producing during turbulence periods. While several studies have shed lights on the relationship between energy markets and various metal markets such as precious metals and industrial metals during this period,[8] the linkage between energy and energy metal prices in the post-COVID-19 era has not been fully documented in the literature.

Our paper contributes to the scant empirical evidence on the linkage between clean energy prices and energy metal prices. First, previous studies on the clean energy-energy metal relationship have focused on documenting this relationship at a specific part of the return distribution (Gustafsson et al., 2022). We expand the empirical evidence by exploring how the clean energy-metal relationship varies across quantiles. Our goal is to capture how the dependence between clean energy stock and energy metal markets varies between normal and extreme market conditions. Our results show that the relationship among the variables vary across quantiles. This implies the necessity of changing investment strategies under different market conditions. Second, previous research has primarily focused on bi-sectoral relationships in the clean energy-dirty energy-energy metal nexus, while the interlinkage across all three sectors have not been fully explored. By exploring the clean energy-fossil fuel-energy metal price relationship in a multivariable network, our study shows the direct and indirect relationships among these markets and identifies the main drivers of shock transmission in the system. Finally, by focusing on the evolution of the clean energy-dirty energy-energy metal nexus during the COVID-19 pandemic, our paper provides useful information for the transition of finance towards cleaner economic activities.[9]

3. Research methodology

3.1. Empirical framework

Our methodology employs a modification of the connectedness framework by Diebold and Yilmaz (2012, 2014). Following Ando et al. (2022), we use quantile vector autoregression to study the connectedness among clean energy, dirty energy, and energy metal prices across the extreme lower, median, and extreme upper quantiles. This approach allows us to accommodate the extreme market movements during the COVID-19 pandemic.[10] The estimation of quantile vector autoregression, QVAR(p) is given as:

$$y_t(\tau) = \mu(\tau) + \sum_{j=1}^{p} \varphi_j(\tau)\, y_{t-j} + u_t(\tau) \quad (1)$$

where, t denotes time and τ denotes the quantiles; y_t is a vector of n endogenous variables, including clean energy, dirty energy, and energy metal prices $\mu(\tau)$; $\varphi_j(\tau)$ denote coefficient matrices while $u_t(\tau)$ represents the error vector. The maximum lag length p is 4 (Blanchard and Perotti, 2002; Linnemann and Winkler, 2016). Using Wold's theorem, we transform the QVAR(p) in eq. (1) to a quantile vector moving average representation, QVMA(∞): $Q_\tau\ (F_{t-1}) = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i}(\tau)$, with $A_i(\tau) = \Theta_1(\tau)A_{i-1}(\tau) + \Theta_2(\tau)A_{i-2}(\tau) + \ldots$ for $i = 1, 2, \ldots$; $A_0(\tau) = I_n$ and

[7] For example, see Baker et al. (2020); Chowdhury et al. (2022); Chortane et al. (2022); Yarovaya et al. (2022); Cheema et al. (2022); Boubaker et al. (2022).

[8] For example, Chen et al. (2022), Gustafsson et al. (2022), Erdogan et al. (2022), Fu et al. (2022), Jiang and Chen (2022).

[9] Most studies that focus on the COVID-19 period have focused on the linkages in other markets, such as stock, oil, bonds, for example, Bissoondoyal-Bheenick et al. 2021; Umar et al., 2021; Costa et al., 2021; Youssef and Mokni, 2021; Umar et al., 2021; So et al., 2021; Bouri et al., 2021; Zhang et al., 2020; Umar et al., 2022; Umar et al., 2021; Umar et al., 2022.

[10] Our choice of methodology stems from its simple and intuitive framework to account for spillover and interdependence between the variables under various market conditions. Moreover, this framework can simultaneously accommodate more than two variables with relatively low computational costs. This allows us to identify the direct and indirect linkages across all the variables in a multivariate system, and to identify the main sources of shock transmission across the variables. This approach has been used to study the extreme spillovers across different markets before and during the COVID-19 pandemic. For example, see Farid et al. (2022), Chen et al. (2022a), Chen et al. (2022b), Zhou et al. (2022).

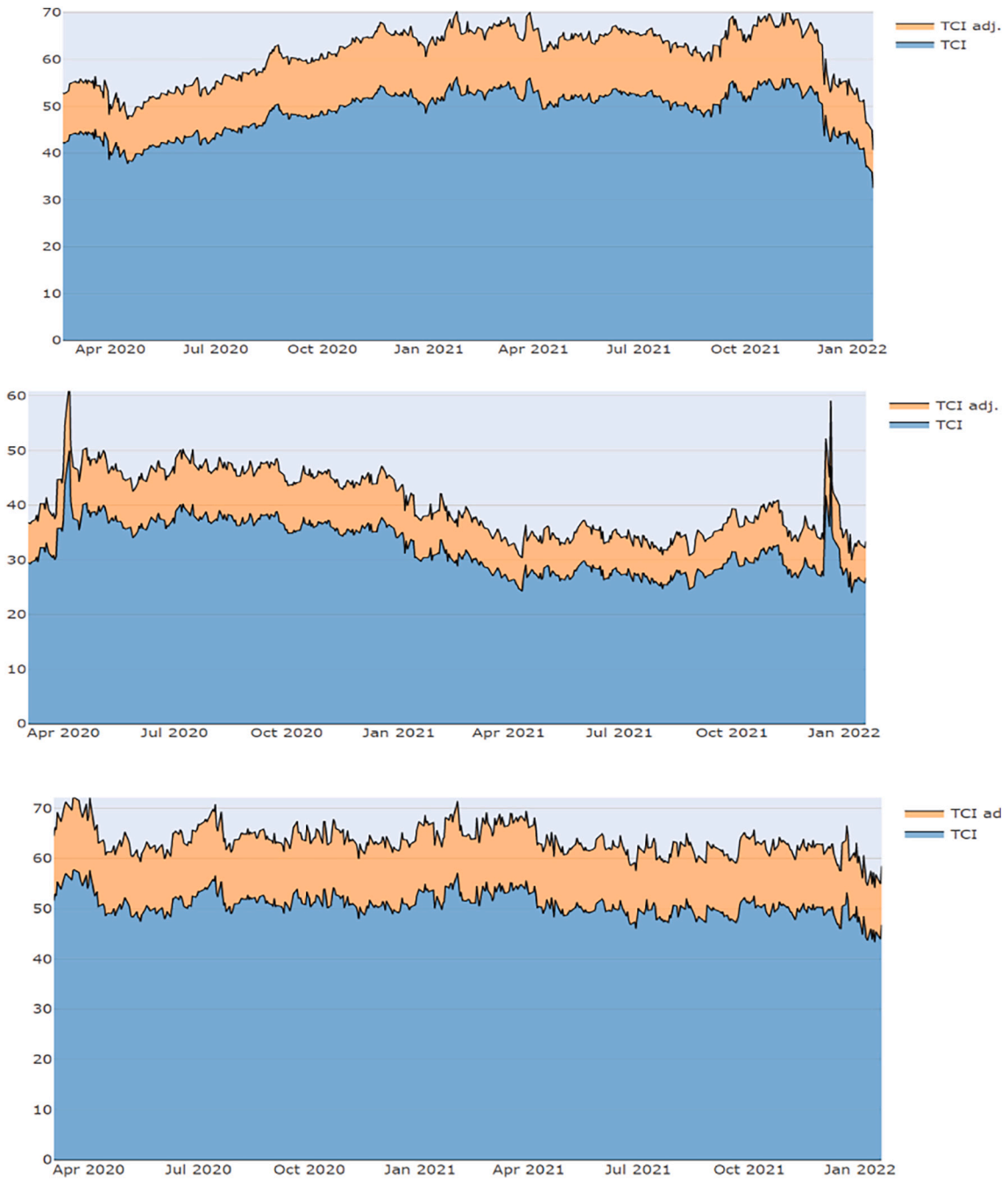

Fig. 3. Time-varying total connectedness indexes. (3.1.) Quantile = 0.2. (3.2.) Quantile = 0.5. (3.3)Quantile = 0.8.

$A_i(\tau) = 0$ for $i < 0$. I_n is an $n \times n$ identity matrix. From the QVMA(∞) representation, we calculate the H-step ahead generalised forecast error variance decomposition (GFEVD) as follows:

$$\psi^{g}_{i,j,\tau}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i^T A_h(\tau)\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i^T A_h(\tau)\Sigma A_h(\tau)^T e_i\right)} \tag{2}$$

where Σ is the variance matrix of the error term vector; σ_{jj} denotes the standard deviation of the error term of variable j. e_i is a $n \times 1$ vector that takes the value 1 for element i and 0 otherwise. Next, we compute the normalized generalised forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998).

$$\tilde{\psi}^{g}_{ij,\tau}(\mathrm{H}) = \frac{\psi^{g}_{ij,\tau}(H)}{\sum_{j=1}^{k}\varphi^{g}_{ij,\tau}} \tag{3}$$

$\psi^{g}_{ij,\tau}(\mathrm{H})$ illustrates the percent of forecast error variance in variable i that is explained by variable j when variable i is in quantile τ. Next, we calculate the following spillover indexes to capture the overall spillovers across the variables:

$$FROM_{i,\tau}(H) = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\psi}^{g}_{ij,\tau}(H)}{n} \times 100 \tag{4}$$

$$TO_{i,\tau}(H) = \frac{\sum_{j=1,j\neq i}^{n}\tilde{\psi}^{g}_{ji,\tau}(H)}{n} \times 100 \tag{5}$$

$$NET_{i,\tau}(H) = TO_{i,\tau}(H) - FROM_{i,\tau}(H) \tag{6}$$

$$TCI_{\tau}(H) = \frac{\sum_{i,j=1,j\neq i}^{n}\tilde{\psi}^{g}_{ji,\tau}(H)}{n} \times 100 \tag{7}$$

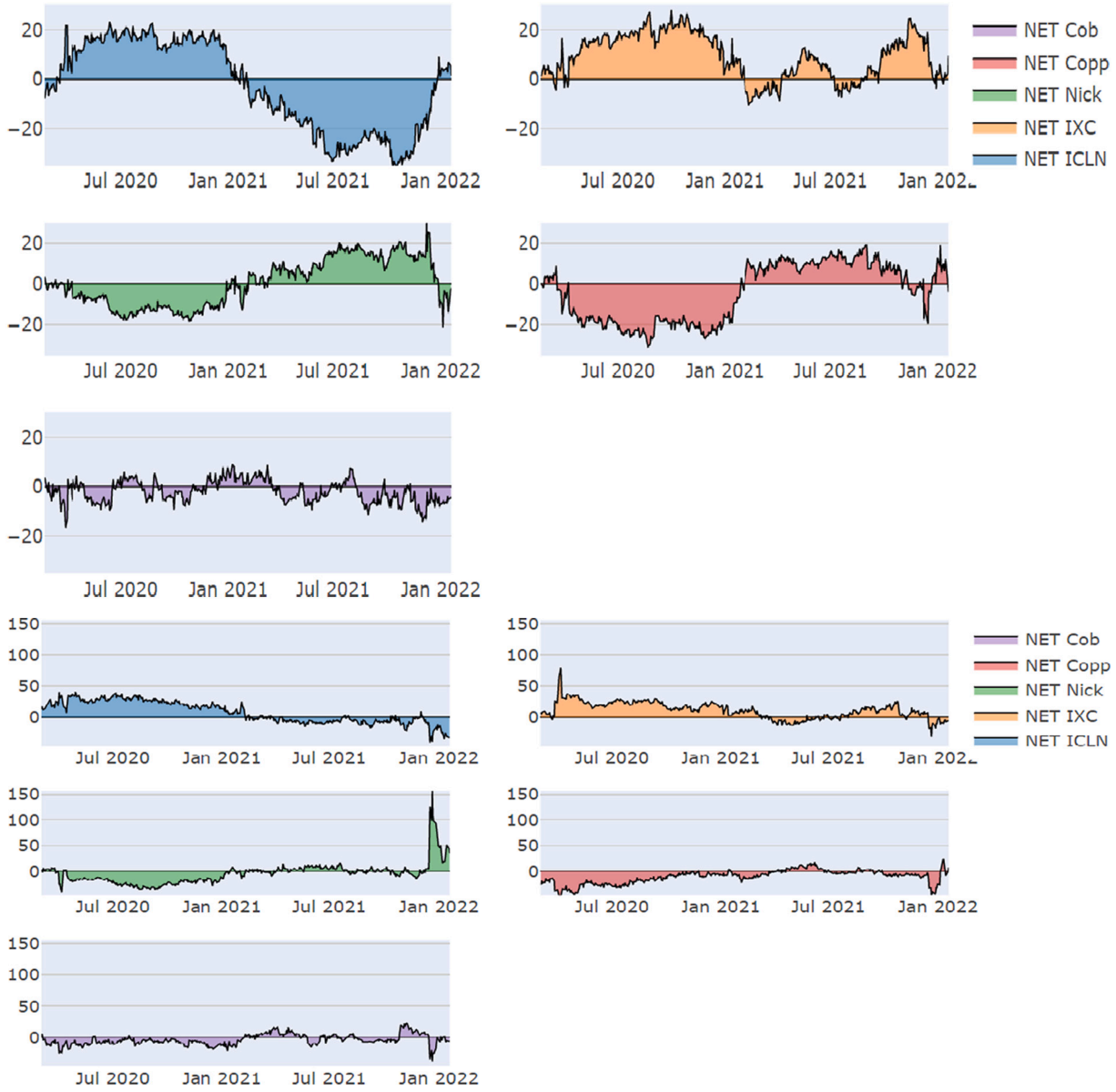

Fig. 4. Time-varying net connectedness. (4.1.) Quantile = 0.2. (4.2.) Quantile = 0.5. (4.3.) Quantile = 0.8.
Note: The figure captures the time-varying NET connectedness index, which is estimated from a dynamic quantile connectedness model with a 200-day rolling window. Positive (negative) values indicate that a market is a net shock transmitter (receiver). IXC denotes the iShares Global Energy ETF (benchmarked against S&P Global 1200 Energy Sector Index); ICLN denotes iShares Global Clean Energy ETF (benchmarked against S&P Global Clean Energy Index). Cob, Copp, and Nick stand for cobalt, copper, and nickel.

The *TO* connectedness index indicates the overall impact variable *i* has on all other variables *j*. The *FROM* connectedness index illustrates the impact of shocking all other variables *j* on variable *i*. The NET connectedness index captures the net spillovers from variable *i* to all other variables *j*, where a positive (negative) value indicate variable *i* is a shock transmitter (receiver) in the system. Finally, the total connectedness index (*TCI*) is capture the overall connectedness among the variables in the system and is used a proxy for market risk contagion.

In the empirical analysis, we focus on documenting the quantile connectedness at the 0.2, 0.5 and 0.8 quantiles. These quantiles capture the connectedness among metal and energy markets at the extreme negative, median and extreme positive movements. In addition to the static connectedness, we analyze the time-varying connectedness by calculating the rolling spillover indexes with a rolling window of 200 days.

3.2. Data

We choose the iShares Global Energy ETF (IXC) which is benchmarked against S&P Global 1200 Energy Sector Index as a proxy for fossil fuel energy or dirty energy markets. Further, the iShares Global Clean Energy ETF (ICLN) which is benchmarked against S&P Global Clean Energy Index as a proxy for clean energy markets. Both IXC and ICLN data have been procured from Bloomberg. To measure the performance of metal markets, we collect data on the daily closing prices of cobalt, copper, and nickel from Bloomberg. These metals are selected because of their significant use in the clean energy market (Boer et al., 2021b, 2021a). Since our goal is to capture the movements of energy and metal markets during the COVID-19 pandemic, our sample period ranges from 1st January 2019 to 19th January 2022. We calculate returns on the variables by log-differencing.

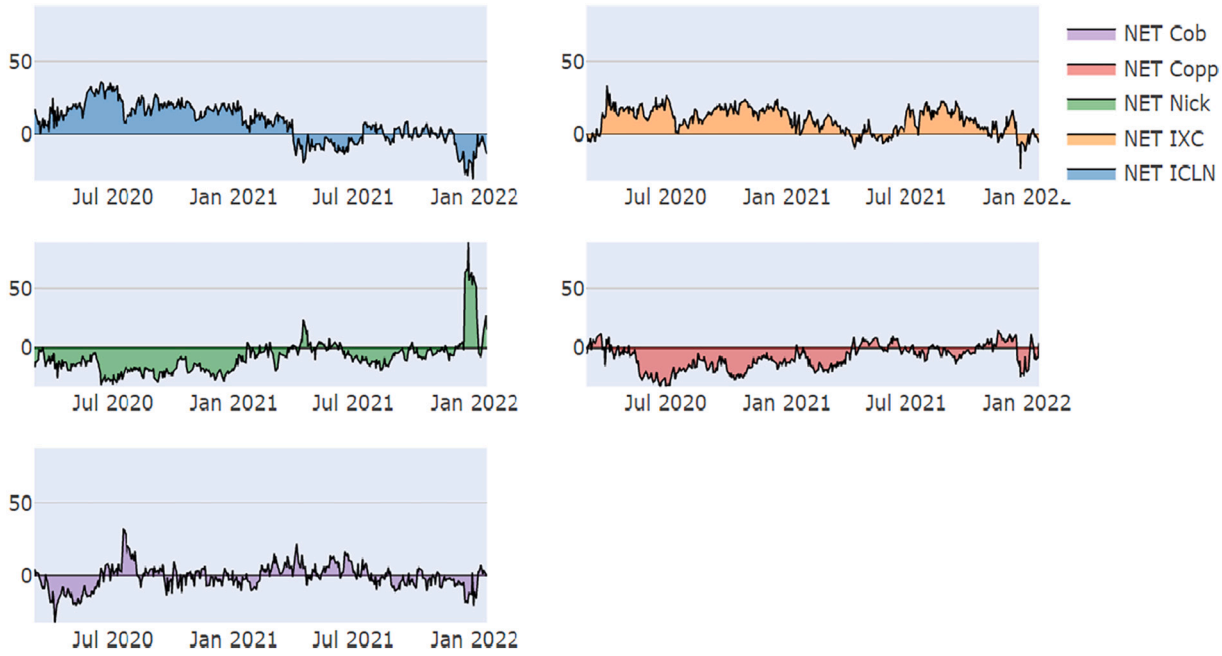

Fig. 4. (*continued*).

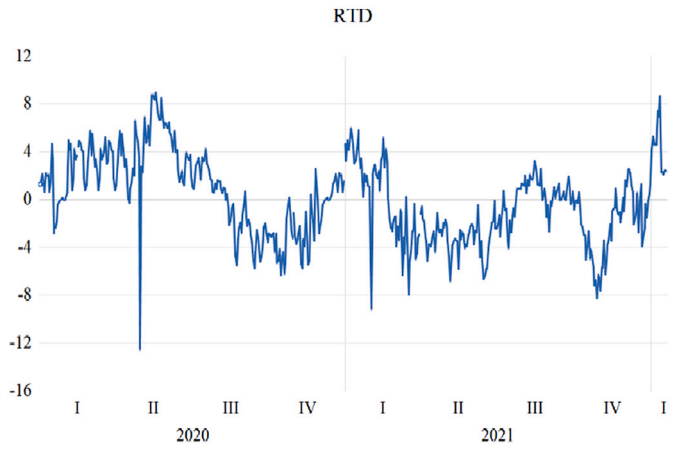

Fig. 5. Relative tail dependence.
The figure shows the difference between the TCI at the 80th quantile and 20th quantile, computed based on the dynamic quantile connectedness with a rolling window of 200 days.

Figure 1(1.1 and 1.2) display the time series of the prices and returns, respectively. Table 1(1.1 and 1.2) provides the descriptive statistics and correlation matrix, respectively. The average returns for all series are positive, which is in line with the increasing energy and metal prices throughout our sampling period. The clean energy and dirty energy indexes have the highest standard deviations, while the metal series have the lowest standard deviations. This is consistent with the large fluctuations in energy prices during the COVID-19 pandemic, which stems from unpredictable energy demand and the excess supply from the 2020 Russia-Saudi Arabia oil price war. All returns are negatively skewed. In addition, kurtosis is higher than 3 for most variables except Cobalt. Since most values of kurtosis are distanced from a typical mesokurtic distribution, all return series are not normally distributed, as illustrated by the Jarque-Bera test statistics. Finally, the ERS unit root tests indicate that all returns are stationary, while the Ljung-Box test statistics provide evidence of volatility clustering in returns. Table 1 (1.2.) shows positive correlations between the two energy indexes and between the three metal markets. However, the correlations between energy and metal markets are negative. Fig. 1 shows the evolution of the asset returns over time. The figure depicts sudden increase in volatility in copper and nickel prices following the International Energy Agency's COP26-Net Zero summit at the end of 2021.

4. Empirical results and interpretations

In this section, we report the results of our study followed by a discussion. We start this section with a review of the static (average) connectedness followed by dynamic (time-varying) connectedness.

4.1. Static quantile connectedness

The static contentedness analysis shows the average connectedness pattern of the variables using data from the entire sample period. To account for asymmetric connectedness, we quantify the average connectedness across various quantiles and report the results for the 20th, 50th, and 80th quantiles (Q = 0.2, 0.5 and 0.8) in Table 2 (2.1–2.3), and respectively. We notice that the total connectedness index (TCI) has a sizable difference across various quantiles, thus underscoring the use of quantile connectedness approach. Interestingly, the highest connectedness is at Q = 0.8, implying the level of comovement is exhibited during bullish market conditions. We attribute this to the interlinkage between energy and energy metal markets on both the demand and supply side. An increase in fossil fuel prices will increase the cost of production for metals, which in turn increase the volatility of clean energy prices.

Table 2(2.1). shows that at the lower quantile, cobalt receives the smallest amount of shock from the system (FROM spillover index = 40.7%), while the amount of shock received by other variables from the system exceeds 50%. Similarly, cobalt also transmits the least amount of shock to the system (TO spillover index = 39.07%). The NET connectedness index, which indicates whether a variable is a net shock transmitter or receiver, is closest to 0 for cobalt (−1.64%). Altogether, these results suggest the hedging potentials of cobalt for other assets under downward market movements, given its small connectedness to the system. Our results also shows that dirty energy prices are the largest net shock transmitter, with a NET connectedness index of 6.54%. Among the

pairwise connectedness, the two energy indexes (ICLN and IXC) are closely connected to each other, and nickel and copper are closely related to each other. The directional spillover indexes for these pairs of assets exceed 20%. In contrast, other pairwise spillover indexes are around 10%. Table 2(2.2. and 2.3). present the connectedness matrix at the median and upper quantile. Overall, the findings from Table 2(2.1). still hold, however, the connectedness indexes are smaller at the median quantile, than at the extreme quantiles.

To identify the role of each variable as a transmitter or receiver of spillover, we look at the row named (NET) of Table 2(2.1–2.3). We notice that across all quantiles the equity ETFs are net transmitters of spillover, whereas the metals are net recipients of spillover. Furthermore, the dirty energy ETF is the highest transmitter of spillover, which underscores its influential role in the dirty energy-energy metal-clean energy nexus. This is expected, as fossil fuels are an important input to metal production. Given that energy metals are an input to clean energy production, any shock to dirty energy will spill over directly or indirectly to all other markets.

Overall, our static analysis partially supports the findings of previous research on the increasing spillovers across markets under extreme conditions (e.g. Baker et al., 2020; Farid et al., 2022). Our result shows the importance of dirty energy as a shock transmitter to clean energy and energy metals. By studying the dirty energy-energy metal-clean energy nexus in a multivariate setting, our paper documents the direct and indirect linkage between fossil fuels and other markets.

The above analysis shows the overall connectedness and the role of each variable as a transmitter and receiver of spillover by accounting for the overall relationship of all the variables. To gain further insight, we look at the pairwise relation between different variables employed. We employ a network graph approach to distinguish between net transmitter and recipient of pairwise spillover across various quantiles, Q = 0.2, 0.5, 0.8, reported in Figs. 2(2.1–2.3), respectively. For ease of interpretation, we summarize the pairwise connectedness results in Table 3. This network plot analysis depicts the intensity and direction of shocks in this network. Both dirty and clean energy are found to propagate shocks to the system, where dirty energy is the largest net shock transmitter across all three quantiles. Metals were the net receiver of shocks, though the degree varies over the three quantiles and across metals. For example, copper is the largest net shock receiver across all three quantiles, while cobalt is the smallest net shock receiver across the quantiles. Interestingly, we notice that at the lower quantile, the clean energy and dirty energy ETFs seem to be unconnected, implying potential diversification benefits during periods of bearish market conditions.

4.2. Dynamic quantile connectedness

The previous section reported the average connectedness across various quantiles. In this section, we report the time-varying connectedness across various quantiles by estimating a dynamic quantile connectedness model with a rolling window of 200 days.

We start our discussion by analyzing the time-varying total connectedness (TCI) across Q = 0.2, 0.5, 0.8, which are depicted in Figs. 3(3.1.–3.3.), respectively. The TCI of all the variables (clear and dirty energy ETF and metals) exhibits sizable deviation both across time as well as across quantiles, thus underscoring the importance of time-varying and quantile connectedness analysis.

Overall, as expected, the connectedness across the extreme quantiles is higher compared to the median quantile. For the lower extreme quantile (Q1 = 0.2), we notice that the TCI increases steadily until April 2021, and fluctuates around 70% between April and October 2021, before dropping to 45% at the beginning of 2022.[11] One explanation for the increasing connectedness before October 2021 relies on the various events that influence the energy and metal markets during this period. For example, most countries implement varying degrees of travel restriction during this period. In addition, the high oil price volatilities caused by the Russia-Saudi Arabia oil price war, coupled with supply chain issues, increase the uncertainty and contagion across the markets. By October 2021, the acceleration of COVID-19 vaccination distributions partly contributes to the decline in spillovers across markets, as travel restrictions are lifted in many countries. Note that the emergence of the Omicron variant around the same time may not increase the spillovers across the markets, as this variant is more contagious but less deadly than the previous Delta variant, which is believed by many at the time to signal the end of the pandemic. Similar observations can be made for the upper quantile (Fig. 3(3.3)), however, the TCI tends to be higher at the upper quantile than at the lower quantile. The TCI in the upper quantile (Q = 0.8) remains relatively high and exhibits relatively less visible upward or downward trends during this period, compared to the TCI in the lower quantiles.

At the median quantile (Q2 = 0.5), the TCI exhibits a spike from 38 to 60% in April 2020, which corresponds to the first wave of the COVID-19 pandemic and the Russia-Saudi Arabia oil price war. Subsequently, it becomes relatively rangebound during both the Delta and Omicron phases (45–35%).

In summary, it is evident that TCI surged almost immediately after the declaration of COVID-19 as a pandemic in February 2020. This shows that COVID-19 has significantly impacted the connectedness between dirty energy, clean energy and energy metal markets. However, the TCI varies widely in magnitudes across quantiles, which implies an asymmetric impact of the pandemic on the connectedness among the variables. Note that any spike in the TCI at the median quantile is short term and reverts to their average value quickly. In contrast, the TCI at the extreme quantiles remains high for a long period of time. This suggests that shocks dissipate more quickly during normal market conditions, compared to bullish or bearish conditions. Thus, the diversification benefits among clean energy, dirty energy, and energy metal markets are larger at the median quantiles than at the extreme quantiles.

Next, we analyze the time-varying dynamics of the net connectedness indexes across the quantiles and report the results for quantiles Q = 0.2, 0.5, 0.8 in Fig. 4(4.1–4.3), respectively. A positive value indicates that a variable is a net shock transmitter. At the lower quantile (Fig. 4 (4.1.)), the clean energy and dirty energy markets are the net shock transmitters until January 2021. After that, the clean energy market becomes the net shock receiver, while the dirty energy market fluctuates between being a net shock transmitter and receiver. Copper and nickel are the net shock receivers until January 2021 and become net shock transmitters afterwards. The switch in the roles of clean energy, copper and nickel before and after January 2021 can be explained by the increasing preferences towards clean energy, which increases the demand for energy metals. This is consistent with International Money Fund's prediction that copper consumption would double, and nickel would quadruple, in line with International Energy Agency's 2050 net-zero roadmap (International Energy Agency, 2021b). After 2021, the emergence of serious supply chain issues implies that energy metal supply does not keep up with increasing demands, thus, any volatility in energy metal prices is transmitted into clean energy prices. Note that the net connectedness index for cobalt is the closest to 0 throughout the sampling period, which suggests its potential as a hedging instrument for other markets. We notice similar results at the median quantile (Fig. 4(4.2.)). At the upper quantile (Fig. 4(4.3.)), the markets exhibit

[11] The first wave of COVID-19 happens during the first half of 2020, the Delta variant starts in late 2020 until mid-2021, while the Omicron variant starts in late 2021.

similar patterns as at the lower and median quantiles until January 2021. However, after January 2021, while the roles of the markets as net shock transmitters and receivers are relatively stable at the lower and median quantiles, they fluctuate more frequently at the upper quantile. This provides evidence for asymmetric spillover effects across the markets between upward and downward market movements. In addition, our results also illustrate the more unpredictable nature of the spillover patterns during extreme increases in energy and metal prices.

To further identify and highlight the importance of asymmetric connectedness, we report the relative tail dependence (RTD) in Fig. 5 computed by taking difference of the TCI for the Q = 0.8 and Q = 0.2. We notice that the RTD is predominantly non-zero, which highlights the asymmetry in connectedness across quantiles. Positive RTD values indicate higher connectedness during bullish market conditions, whereas negative values indicate higher connectedness during bearish market conditions. Three lowest points (April 2020, February 2021 and October 2021) of RTD corresponds to the three phases of the COVID-19 pandemic: the first wave, the emergence of the Delta variant, and the emergence of the Omicron variant. The RTD is predominantly negative during August–December 2020, January–June 2021 and October 2021–January 2022, indicating stronger connectedness in the extreme lower quantiles. In contrast, they tend to be positive during other periods. Altogether, Fig. 4 shows evidence of asymmetric spillovers among clean energy, dirty energy and energy metal markets. However, the relative strength of the spillovers at the upper and lower quantiles varies throughout the sampling period. This implies that a timely forecast of market movements is important for effective risk and portfolio management. Our findings are in line with the findings of Bouri et al. (2021), who document similar results for cryptocurrencies under similar extreme conditions. Furthermore, similar risk transmission is observed between clean energy and dirty energy (crude oil) (Saeed et al., 2021). The divergent pattern in dynamic total connectedness index (TCI) for the three quantiles corroborates their findings.

We perform several robustness checks for the results. Specifically, we estimate the quantile connectedness models for other extreme quantiles such as the 5th and 95th quantiles. Our results in Appendix A shows that the extreme quantile connectedness becomes stronger at the 5th and 95th quantiles than at the 20th and 80th quantile, thereby confirming our conclusion of a stronger dependence among energy and energy metal markets at the tails. Moreover, our dynamic connectedness results at the 5th and 95th quantile also shows an increase in the connectedness at the early phase of the COVID-19 pandemic and during the Delta and early Omicron phases. We summarize the total connectedness indexes at various quantiles in Table A.3 and Fig. A.5. The table shows a higher total connectedness among the markets at the extreme quantiles compared to that at the median quantile. Table A.3 also presents evidence of asymmetric quantile connectedness, where the connectedness among the markets is higher at the upper extreme quantiles than at the lower extreme quantiles. Finally, we estimate the dynamic quantile connectedness using alternative rolling windows of 150 and 200 days. We find that the results are qualitatively similar under these alternative specifications (Table A.4).

Notes: The figure presents the time-varying total connectedness indexes across the quantiles, which are estimated using a rolling-window analysis of the quantile connectedness model. The size of the rolling window is 200 days, which corresponds to a trading year. The blue line captures the raw total connectedness index (Eq. (7)), while the orange line captures the adjusted total connectedness index, which is obtained by replacing the denominator n in Eq. (7) with n-1. n = 5 is the number of variables.

4.3. Discussion

The results reported in the previous sections underscore the importance of accounting for the asymmetric connectedness among clean energy, dirty energy, and energy metal markets across various quantiles. Our results have several implications for investors and policymakers.

First, our result shows that on average, the markets are more connected at the upper quantile, which suggests an increase in the contagion across the market in the event of an extreme increase in energy or metal prices. However, the relative strength of the connectedness between the extreme upper and lower quantiles varies over time throughout the sampling period. This implies that a timely forecast of market movements is important for effective portfolio management (Aharon et al., 2022; Bossman et al., 2022; Zhao et al., 2021). Moreover, since the spillovers across markets are stronger at the extreme quantiles than at the median quantiles, our results imply that policy efforts at stabilizing energy and metal prices under extreme market movements may lower the contagion across markets, thereby improving the hedging and diversification benefits between energy and metal markets. This, in turn, contributes to the direction of funding towards environmentally friendly economic activity.

Second, our results indicate that dirty energy is the main net transmitter of shocks across all quantiles and throughout most of the sampling period. This indicates the significance of dirty energy in the dirty energy-energy metal-clean energy nexus. Thus, movements in fossil fuel prices can be used to forecast movements in the energy metal and clean energy markets. The predominant role of dirty energy as the shock transmitter also implies that the energy metal and clean energy markets have not been fully independent from fossil fuels. Thus, to promote environmentally friendly activities, policy should promote the development technologies that increases the independence of energy metal and clean energy production from fossil fuels.

Third, our results show that the role of clean energy and energy metals switch before and after January 2021. Specifically, clean energy is the net shock transmitter before January 2021, while energy metals are the net shock transmitters after January 2021. As supply chain issues become more serious in 2021, this implies the importance of a stable energy metal supply for the production of clean energy. Our results also highlight the relevance of development in advanced materials that reduces the excessive reliance of clean energy production on energy metals. Finally, the low connectedness of cobalt to other markets across quantiles implies the potential use of cobalt as a hedging and diversification tools for energy and energy metal markets.

5. Concluding remarks

This study aims to understand the relationship between energy metals and clean/dirty energy assets during the periods around the COVID-19 pandemic. Using the quantile connectedness method, we find that dirty energy, clean energy, and energy metal markets are more connected at the extreme quantiles than at the median quantile. This indicates more contagion among these markets under bearish and bullish market conditions. Moreover, we find evidence of asymmetry in the connectedness among energy metals and energy markets, where on average, the connectedness is larger at the upper quantiles than at the lower quantiles. Thus, an extreme increase in energy or metal prices causes a significant increase in the spillovers across the markets. In addition, we find that dirty energy assets are the main transmitter of shocks across the quantiles. Finally, we find that copper and nickel are net transmitters of shocks in response to the supply chain issues and the increasing clean energy demand in early 2021. This is consistent with the IEA's projection of an increase in demand for copper and nickel in the transition from dirty to renewable energy.

Our paper contributes to the empirical evidence on the linkage between clean/dirty energy prices and energy metal prices. First, we document the dependence across these assets at various quantiles, thereby capturing their relationships under various market conditions. Second, by using a network approach, we identify the linkage between clean energy, dirty energy, and energy metal prices in a multivariate framework, thereby capturing the main receiver and transmitter of shocks in the system. Compared to other approaches such as wavelet

coherence or quantile-on-quantile models, this framework also allows us to capture the direct and indirect spillovers across the markets under various movements (extreme upward, normal, extreme downward). Finally, by focusing on the most recent crisis, namely the COVID-19 pandemic, our paper unravels the recent dynamics among clean energy, dirty energy, and energy metals, which have important implications for the sustainable recovery of the economy post-COVID-19.

Our empirical results have several implications for investors and policymakers. First, our results show that the connectedness among energy metals and clean/dirty energy equity assets increases during extreme periods. Therefore, investors and policymakers should not limit their analyses of these markets at the middle of the return distributions, since doing so would mask the asymmetric tail dependence among the markets. Second, the stabilization of energy and metal prices, particularly during periods of extreme upward market movements, will help stabilize the spillovers across the markets. This, in turn, improves the diversification benefits of an energy/energy metal portfolio. Third, as energy metals will play an important role in the transition to a carbon free economy, increasing the predictability of energy metal prices will be essential in attracting investors to the clean energy markets. Moreover, technological development that reduces the dependence of clean energy on metals and fossil fuels can foster the growth of clean energy markets. Fourth, our results indicate that cobalt is the least connected to other markets across quantiles. Thus, it can be used as a hedging tool for clean energy, dirty energy and other energy metals under a wide range of market conditions. Finally, the time-varying spillovers among the markets also provide important information for investors to adjust their investment positions across various market conditions. Future studies can extend our work by quantifying the portfolio implications and associated welfare effects for investors with various investment horizons and various risk aversion levels (Spierdijk and Umar, 2014). Another extension would be to study the relationship between energy and energy metal markets during other extreme events. Moreover, an analysis of the role of technologies on the nexus among clean energy, dirty energy and energy metal markets can provide useful information for the decarbonization of the economy. Finally, while the quantile connectedness model allows us to capture the spillovers across markets under various market conditions, our use of daily data may not fully account for the behavior of these markets at other time horizons. Future research can address this limitation by using data at other frequencies (intraday, weekly, monthly) and accounting for the heterogeneity in the nexus among energy and metal markets across investment horizons.

CRediT authorship contribution statement

Bikramaditya Ghosh: Conceptualization, Methodology, Software, Data curation, Validation, Investigation, Resources, Writing – review & editing, Visualization, Project administration. **Linh Pham:** Conceptualization, Supervision, Investigation, Resources, Data curation, Validation, Resources, Writing – review & editing, Visualization, Project administration. **Tamara Teplova:** Resources, Writing – review & editing, Visualization. **Zaghum Umar:** Resources, Writing – review & editing, Visualization.

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Appendix A. Robustness checks

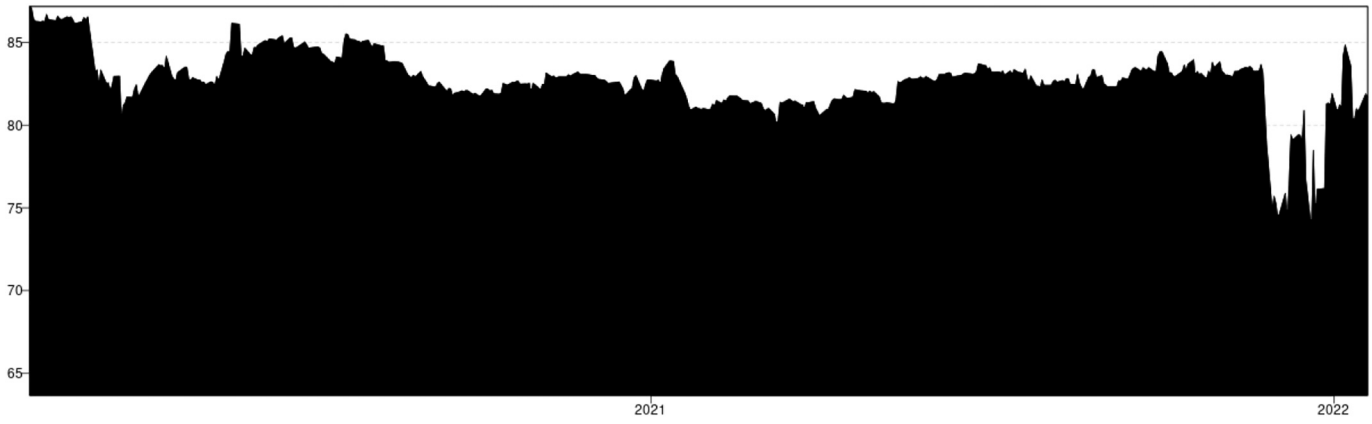

Fig. A.1 Total connectedness index plot for the extreme right quantile (Quantile = 0.95).
Notes: The figure presents the time-varying total connectedness indexes at the 95th quantile, which are estimated using a rolling-window analysis of the quantile connectedness model. The size of the rolling window is 200 days, which corresponds to a trading year.

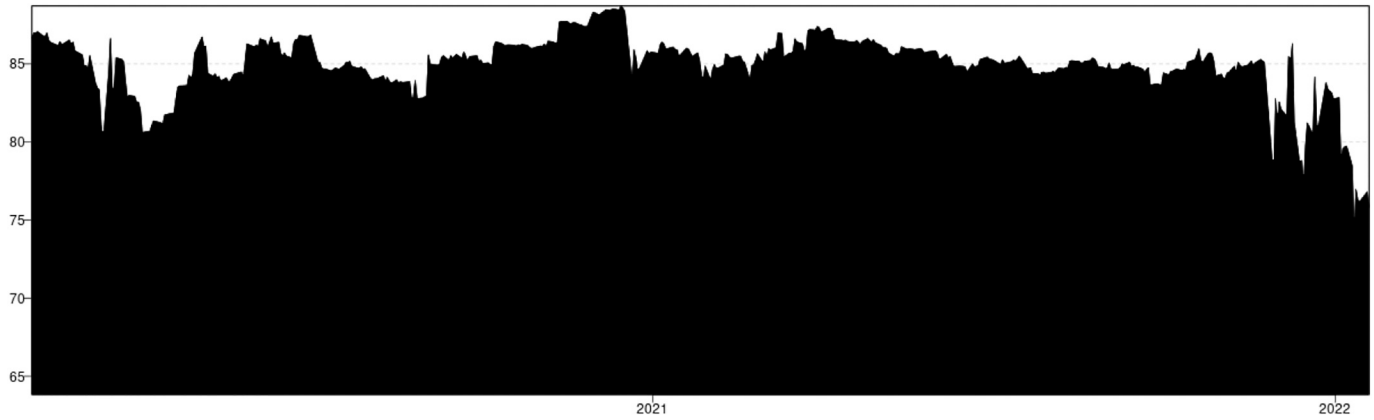

Fig. A.2. Total Connectedness Index Plot for the extreme left quantile (Quantile = 0.05).
The figure presents the time-varying total connectedness indexes at the 5th quantile, which are estimated using a rolling-window analysis of the quantile connectedness model. The size of the rolling window is 200 days, which corresponds to a trading year.

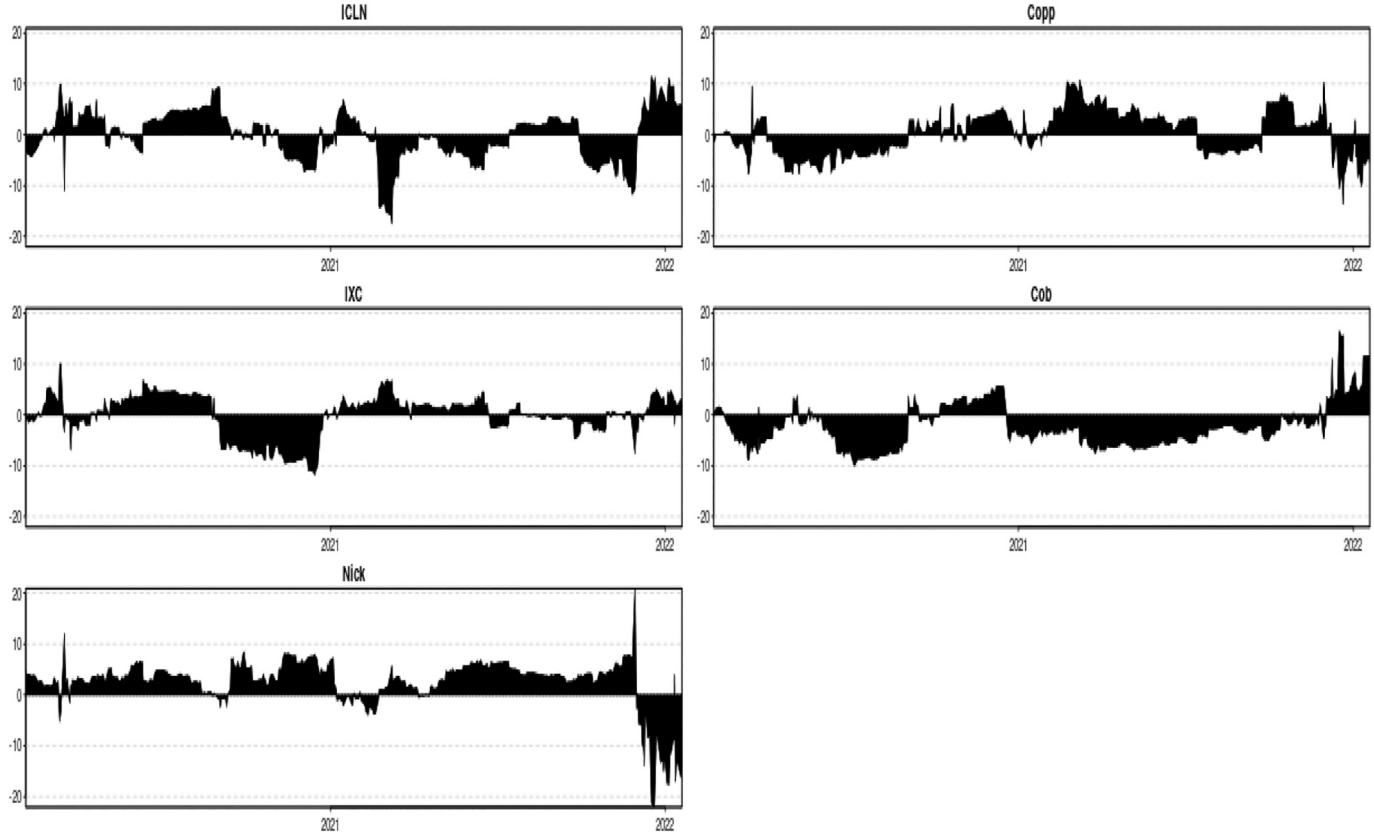

Fig. A.3. Net total directional connectedness at the extreme left quantile (Quantile = 0.05).

The figure captures the time-varying NET connectedness index, which is estimated from a dynamic quantile connectedness model with a 200-day rolling window. Positive (negative) values indicate that a market is a net shock transmitter (receiver). IXC denotes the iShares Global Energy ETF (benchmarked against S&P Global 1200 Energy Sector Index); ICLN denotes iShares Global Clean Energy ETF (benchmarked against S&P Global Clean Energy Index). Cob, Copp, and Nick stand for cobalt, copper, and nickel.

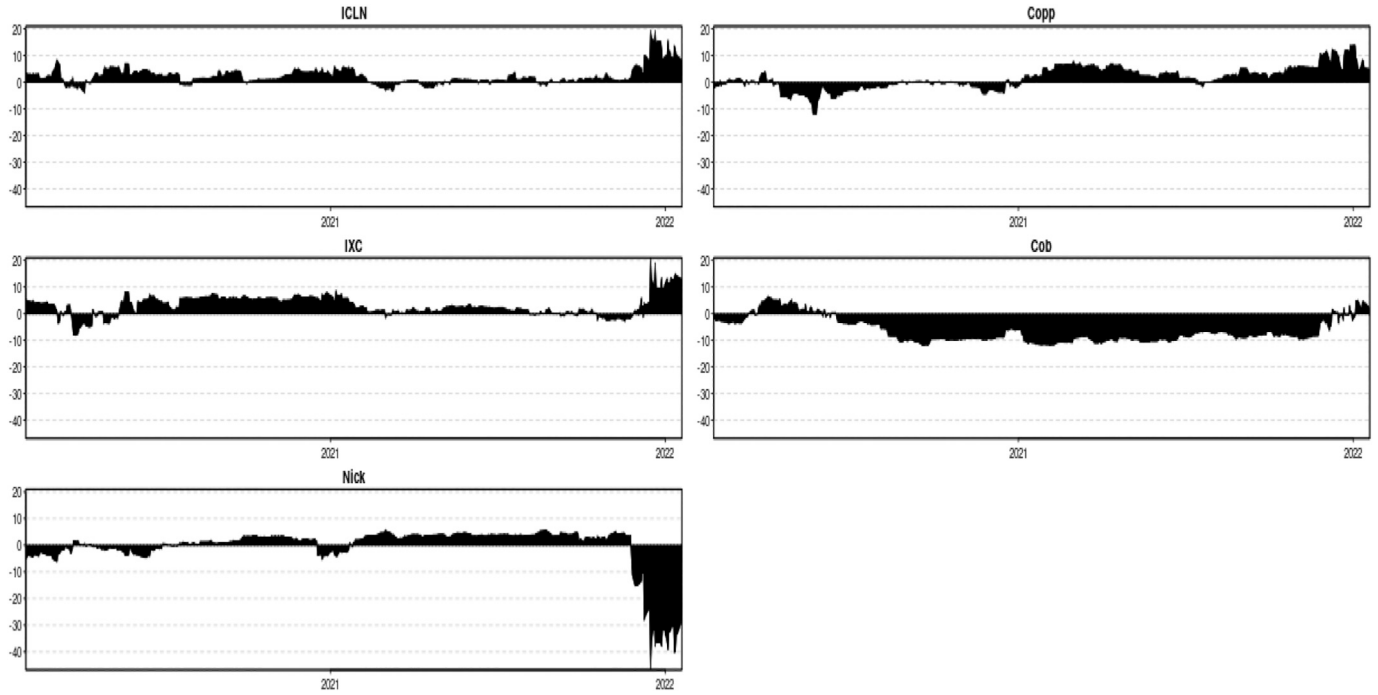

Fig. A.4. Net total directional connectedness at the extreme right quantile (Quantile = 0.95).

The figure captures the time-varying NET connectedness index, which is estimated from a dynamic quantile connectedness model with a 200-day rolling window. Positive (negative) values indicate that a market is a net shock transmitter (receiver). IXC denotes the iShares Global Energy ETF (benchmarked against S&P Global 1200 Energy Sector Index); ICLN denotes iShares Global Clean Energy ETF (benchmarked against S&P Global Clean Energy Index). Cob, Copp, and Nick stand for cobalt, copper, and nickel.

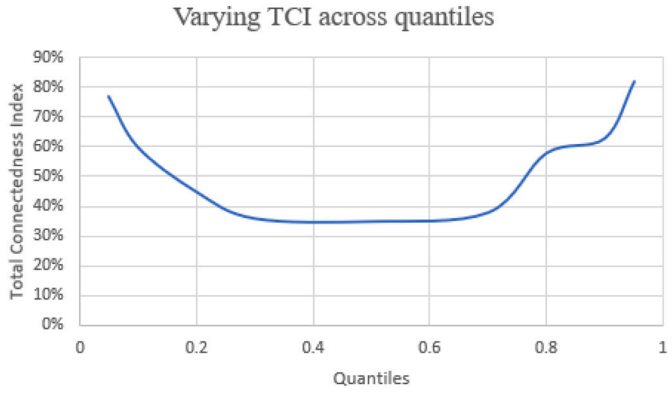

Fig. A.5 Varying TCI values across quantiles (graphical depiction of Table A.3).
The figure presents the total connectedness index across the quantiles.

Table A.1 Average connectedness for Quantile Q = 0.05.

	ICLN	IXC	Nick	Copp	Cob	FROM others
ICLN	30.34	22.27	15.76	16.22	15.41	69.66
IXC	23.07	32.23	15.25	15.07	14.37	67.77
Nick	14.91	14.63	32.1	21.98	16.38	67.9
Copp	15.66	15.56	22.14	30.39	16.25	69.61
Cob	15.8	15.18	17.22	16.65	35.15	64.85
TO others	69.44	67.63	70.38	69.91	62.41	339.78
Inc. own	99.78	99.87	102.48	100.31	97.56	TCI = 77%
NET	−0.22	−0.13	2.48	0.31	−2.44	

ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt. Each cell represents the amount of spillovers from the market listed in the column to the market listed in the row. The column 'FROM others' captures the spillovers from all other variables to each row variable. The row 'TO others' captures the spillovers from each column variable to all other variables. The row 'Inc. own' captures the spillovers from each column variable to all variables, including itself. The row 'NET' captures the net connectedness, where a positive (negative) value indicates a shock transmitter (receiver).

Table A.2 Average connectedness for Quantile Q = 0.95.

	ICLN	IXC	Nick	Copp	Cob	FROM others
ICLN	32.95	24.29	14.08	14.87	13.8	67.05
IXC	24.12	33.03	14.66	15.2	12.98	66.97
Nick	15.28	15.36	31.93	23.12	14.31	68.07
Copp	15.25	15.64	22.7	32.39	14.03	67.61
Cob	14.61	14.59	15.99	16	38.82	61.18
TO others	69.26	69.87	67.43	69.2	55.11	330.88
Inc. own	102.21	102.91	99.36	101.59	93.93	TCI = 82%
NET	2.21	2.91	−0.64	1.59	−6.07	

ICLN and IXC stand for the iShares Global Clean Energy ETF and the iShares Global Dirty Energy ETF. Nick, Copp, and Cob stand for nickel, copper and cobalt. Each cell represents the amount of spillovers from the market listed in the column to the market listed in the row. The column 'FROM others' captures the spillovers from all other variables to each row variable. The row 'TO others' captures the spillovers from each column variable to all other variables. The row 'Inc. own' captures the spillovers from each column variable to all variables, including itself. The row 'NET' captures the net connectedness, where a positive (negative) value indicates a shock transmitter (receiver).

Table A.3. Total Connectedness Index (TCI) across various quantiles.

Quantile	TCI
0.05	77%
0.1	60%
0.2	45%
0.3	36%
0.5	35%
0.7	38%
0.8	58%
0.9	63%
0.95	82%

The table summarizes the total connectedness indexes at various quantiles.

Table A.4 TCI values across alternative rolling windows.

Rolling Window (Days)	TCI (Q = 0.2)	TCI (Q = 0.5)	TCI (Q = 0.8)
150	45%	21%	43%
250	42%	20%	43%

The table summarizes the average total connectedness indexes at various quantiles using a dynamic quantile connectedness model at alternative rolling windows (150 and 250 days).

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106420.

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