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Dependence of transition minerals on global clean energy and technology stocks

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ABSTRACT

Using both cross-quantilograms and Granger-causality in-mean and in-quantiles techniques, this paper investigates the dynamic dependence of transition minerals on global clean energy and technology markets for the period from December 28, 2018 to October 4, 2024. The results reveal asymmetric responses of transition minerals to changes in the global clean energy and technology markets, with a notably stronger and more consistent positive linkage to the global technology market. Transition minerals such as aluminum, cobalt, copper, and zinc tend to move in tandem with technology market returns, underscoring their strategic role in tech-driven growth. Interestingly, we found more compelling evidence of Granger causality from the clean energy market to transition minerals across several market states than we found from the technology market. For investors and commodity traders, these results suggest a forward-looking informational edge in the use of clean energy market signals to anticipate price movements in specific mineral markets, particularly in hedging or timing strategies. For policymakers, especially in mineral-rich economies, the results also highlight the importance of tracking global clean energy demand trends as early shock signal in the transition mineral market.

1. Introduction

The global economic landscape is undergoing a profound transformation driven by technological innovation, the push towards sustainability, and the urgent imperative to combat climate change. At the core of this global shift lies the surging demand for a group of minerals now widely recognized as “transition minerals”. Notable examples of these minerals include lithium, cobalt, rare earth elements (REE), copper, manganese, platinum, graphite, and nickel. These minerals have unique physical and chemical properties that make them indispensable for the production and performance of clean energy and advanced manufacturing technologies that define the ongoing transformation. Hence, transition minerals arguably constitute the material foundation of the ongoing global shift.

One of the widely held views in the literature is that high technologies and transition-oriented technology systems that underline the ongoing global shift are mineral intensive (Arrobas et al., 2017; Hund et al., 2023; Ndubuisi and Avenyo, 2024). Central to this discourse is the observation that many of these minerals have limited substitutability, which means that their functional roles in emerging technologies cannot be easily replicated or replaced. Hence, transition minerals are not merely auxiliary inputs; they are critical backbones of the global transformation, as without them, the technological advancements and innovations that characterize and define the global shift would neither be possible nor scalable.

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This is mirrored in the surging stock values of transition mineral companies and the increasing investment flows into mineral extraction, processing and trading as the global development and deployment of high technologies and transition-oriented technologies intensify. Concurrently, these minerals' demand and market size have also surged exponentially, with these technologies being the main driver (IEA, 2023a). For example, the Critical Minerals Market Review by the International Energy Agency (IEA, 2023a) revealed that between 2017 and 2022, the demand for lithium tripled, while cobalt and nickel saw respective increases of 70% and 40%. Furthermore, the market size of key transition minerals doubled during this period, reaching \$320 billion by 2022. Looking ahead, Hund et al. (2023) further predict that the average annual demand for 17 minerals related to the energy transition will continue to rise steadily through 2050.

The trends presented above underscore the strategic value of transition minerals and their growing significance as alternative investment and trading assets. In fact, as the global shift intensifies, transition mineral stocks have emerged as strategic assets. However, their economic value is largely contingent and fundamentally shaped by the development, commercialization, and diffusion of high-tech technologies and transition-oriented innovations. In this interdependent dynamic, the asset value of transition minerals is derivative of the technological systems that rely on them, positioning these technologies as both demand drivers and directional signals for transition minerals. That is, transition mineral stock values are far from linear or autonomous. They are intricately linked to and determined in many ways by developments in high-tech and transition technology systems.

Accordingly, this paper critically examines the dependence of transition minerals on global clean energy and technology markets. The paper relates to a rapidly evolving academic literature that examines the behavior, risk-return characteristics, and diversification potential of transition minerals in an increasingly complex financial system (e.g., Reboredo and Ugolini, 2020; Sohag et al., 2023; Saadaoui et al., 2025; Pham and Hsu, 2025; Zhang et al., 2025; Zhu et al., 2025). For example, Reboredo and Ugolini (2020) applied a Markov-switching vector autoregressive model to examine price transmission dynamics between REE stocks and a range of other markets, including base metals, gold, oil, clean energy, and the MSCI global index. They found that price connectedness between REE and other stock markets varied significantly across different volatility regimes, highlighting the complex interactions between critical mineral markets and broader financial systems.

Caglar (2023) explored volatility spillovers between future mobility stocks and battery metals using a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. The study revealed that lithium and copper were dominant net transmitters of volatility, emphasizing their centrality to the energy transition. More recently, Pham and Hsu (2025) demonstrated that extreme upward movements in geopolitical risks Granger-cause extreme fluctuations in the prices of cleantech metal stocks in China. Their findings also suggest that geopolitical risks contribute to synchronized volatility across these markets, especially at the distribution's tails. Attilio (2025) utilized a Global Vector Autoregressive (GVAR) model to examine the macroeconomic impacts of critical mineral price shocks. They found that such shocks significantly hinder the energy transition, especially in the major producer countries with potential transmission channels, including financial markets and industrial production.

This paper contributes to the growing literature on transition minerals in three key ways. First, while existing studies focus predominantly on clean energy markets, we expand the scope to incorporate the influence of global technology markets in shaping the dynamics of transition mineral markets. As previously noted, the application of transition minerals goes beyond clean energy technologies to include other advanced manufacturing technologies, such as defense or aerospace, that may not have direct implications for the green transition. For instance, REE performs an indispensable function in permanent magnets used in wind turbines and advanced electronics. Accordingly, by accounting for global technology markets in our analysis, we capture technological innovations in non-energy sectors. This allows us to better understand the cross-sectoral dependencies that influence price formation and volatility.

Second, we employ the cross-quantilegram methodology proposed by Han et al. (2016) to investigate the dependence structure between transition mineral prices and global clean energy and technology indices. The method offers a flexible and comprehensive framework to assess not only the strength and directionality of dependence but also how these relationships evolve across different quantiles and time horizons. In doing so, we evaluate the potential of technology sector assets to serve as hedging instruments or safe havens for transition mineral investments, especially under varying investment horizons and market conditions as captured by the time scales and tail distributions.

Third, we introduce a quantile-based Granger causality analysis to examine whether observed dependencies are underpinned by causal relationships. This allows us to go beyond correlation and assess the predictive and informational content of technology and clean energy markets with respect to transition mineral price behavior. The insights derived from this multi-method approach are particularly valuable for investors, policymakers, and researchers seeking to navigate the complexities of this emerging asset class and its implications for the broader transition to a sustainable, technologically advanced global economy.

The rest of this paper is structured so that the next section presents the research design. Section 3 presents and discusses the results of the study, while the conclusion is presented in Section 4.

2. Data and empirical strategy

2.1. Data

We used weekly prices from December 28, 2018, to October 4, 2024, for nine transition minerals: aluminum, cobalt, copper, lithium, nickel, palladium, platinum, uranium, and zinc. The start of the sample period enables us to capture crucial transition minerals such as cobalt, whose price index is only available from this period, while the end date corresponds to the commencement of our analysis. For the global clean energy market, we rely on S&P Global Clean Energy Index (SPGCEI), while for the global

Table 1
Descriptive statistics.

Variable	Mean	Minimum	Maximum	Std. Dev.	Skewness	Ex. kurtosis	ADF
Aluminum	0.0012	-0.1006	0.1366	0.0309	0.3207	1.8901	-13.450***
Cobalt	0.0014	-0.2497	0.1394	0.0428	-0.9221	4.3935	-16.978***
Copper	0.0016	-0.1263	0.0948	0.0283	-0.2801	1.6011	-16.977***
Lithium	0.0018	-0.2085	0.1449	0.0450	-0.4093	3.2038	-10.751***
Nickel	0.0016	-0.2614	0.4960	0.0549	2.1873	22.529	-13.576***
Palladium	-0.0006	-0.4802	0.3551	0.0649	-0.6449	12.650	-16.053***
Platinum	0.0008	-0.1861	0.1736	0.0430	-0.2796	2.3481	-19.486***
Uranium	0.0035	-0.1847	0.2325	0.0392	0.5846	7.4792	-12.972***
Zinc	0.0014	-0.1280	0.1865	0.0380	0.1774	1.7453	-16.747***
DJGTI	0.0041	-0.1253	0.0999	0.0267	-0.4856	1.7132	-13.877***
SPGCEI	0.0003	-0.0370	0.0331	0.0084	-0.0222	2.0065	-10.191***

Note: Descriptive statistics of weekly return series for the study period from December 28, 2018 to October 4, 2024. SPGCEI denotes S&P Global Clean Energy Index while DJGTI is the Dow Jones Global Technology Index. Std. Deviation represents standard deviation while ADF is the Augmented Dickey–Fuller test for stationarity.

technology market, we use the Dow Jones Global Technology Index (DJGTI). All transition mineral price indexes were retrieved from the Bloomberg database, while SPGCEI and DJGTI were both taken from S&P Global database. Table 1 displays the descriptive statistics for all return series. Among the transition minerals, uranium has the highest mean return, while only palladium is associated with negative mean return over the study period. Also, the global technology stock may have offered a higher mean return than the global clean energy stock. Regarding the level of risks, palladium was the most risky, while copper was the least. The global technology market appears riskier than the clean energy market, as shown by the standard deviation values. Also, although all return series have kurtosis values greater than 3, aluminum, nickel, uranium, and zinc are rightly skewed, while the remaining assets are negatively skewed. Kurtosis values above the threshold of 3 is indicative of flatter tails that those of normal distribution (Enwo-Irem and Urom, 2024). We also confirm that all return series are stationary, as the Augmented Dickey–Fuller (ADF) test shows. The evolution of all series of returns is shown in Fig. 1, which shows a considerable increase in volatility around the periods of the COVID-19 pandemic in early 2020 and the Russia–Ukraine war in 2022. Lastly, the correlation heatmap in Fig. 2 shows strong positive correlations among transition minerals, except with uranium. It also shows positive and stronger correlations with global technology than the global clean energy market.

2.2. Empirical strategy

2.2.1. The cross-quantilogram

The cross-quantilogram of Han et al. (2016) measures the dependence and directional predictability between quantiles of the variables of interest and extends the quantilogram approach of Linton and Whang (2007). This method has some crucial advantages over other approaches to measuring dependence and directional predictability. For instance, it is easy to interpret and conceptually more appealing than other methods, as noted by Han et al. (2016). Also, Mikosch and Starica (2000) argue that since it is based on quantile hits that do not require moment conditions like ordinary correlogram, it is more suitable for financial time series that exhibit heavy tails such as those considered in this study, as shown in the previous section using the Excess Kurtosis test. Indeed, as shown in past studies, the rationale for using this method stems from the need to go beyond the mean and variances of return distributions to focus on potential dependence on the left and right tails of return distribution (see, e.g., Uddin et al., 2019; Urom et al., 2020, 2022). Moreover, the empirical design of this type of method also permits the consideration of longer lags to offer insights about the duration of the dependence between variables.

Assume that $\theta_{1,t}$ and $\theta_{2,t}$ are two strictly stationary time series and that $q_{i,t}(\tau_i)$ is the τ_i -quantile for $\theta_{i,t}$ with $i = 1, 2$. Given an arbitrary pair of quantiles $\tau = (\tau_1; \tau_2)$ and an k , the cross-quantilogram measures the serial dependence between two events such as $\{\theta_{1,t} < q_{1,t}(\tau_1)\}; \{\theta_{2,t-k} < q_{2,t-k}(\tau_2)\}$. The quantile-hit process as in Linton and Whang (2007) may be denoted in terms of indicator function $1[\cdot]$ as $\{1[\theta_{i,t} < q_{i,t}(\tau_i)]\}$. Thus, the cross-quantilogram may be defined as follows:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(\theta_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(\theta_{2,t-k} - q_{2,t-k}(\tau_2))]}{\sqrt{E[\psi_{\tau_1}(\theta_{1,t} - q_{1,t}(\tau_1))]} \sqrt{E[\psi_{\tau_2}(\theta_{2,t-k} - q_{2,t-k}(\tau_2))]}} \quad (1)$$

For $k = 0, \pm 1, \pm 2, \dots$ where $\psi_a(v) \equiv 1[v < 0] - a$.

The sample counterpart of the above equation is denoted as:

$$\hat{\rho}_\tau(k) = \frac{\sum_{t=k+1}^T \psi_{\tau_1}(\theta_{1,t} - \hat{q}_{1,t}(\tau_1))\psi_{\tau_2}(\theta_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}{\sqrt{\sum_{t=k+1}^T \psi_{\tau_1}^2(\theta_{1,t} - \hat{q}_{1,t}(\tau_1))} \sqrt{\sum_{t=k+1}^T \psi_{\tau_2}^2(\theta_{2,t-k} - \hat{q}_{2,t-k}(\tau_2))}} \quad (2)$$

where $\hat{\rho}_\tau(a)$ represents a suitable estimate for the a -quantile, which is easily obtained via sample quantiles.

Given that the asymptotic distribution $\sqrt{T}(\hat{\rho}_\tau(k) - \rho_\tau(k))$ cannot be analytically derived and is not free of noise parameters, Han et al. (2016) depends on the stationary bootstrap of Politis and Romano (1994). For instance, assume that $[\theta_t^* = (\theta_{1,t}^*; \theta_{2,t}^*)]_{t=k+1}^T$

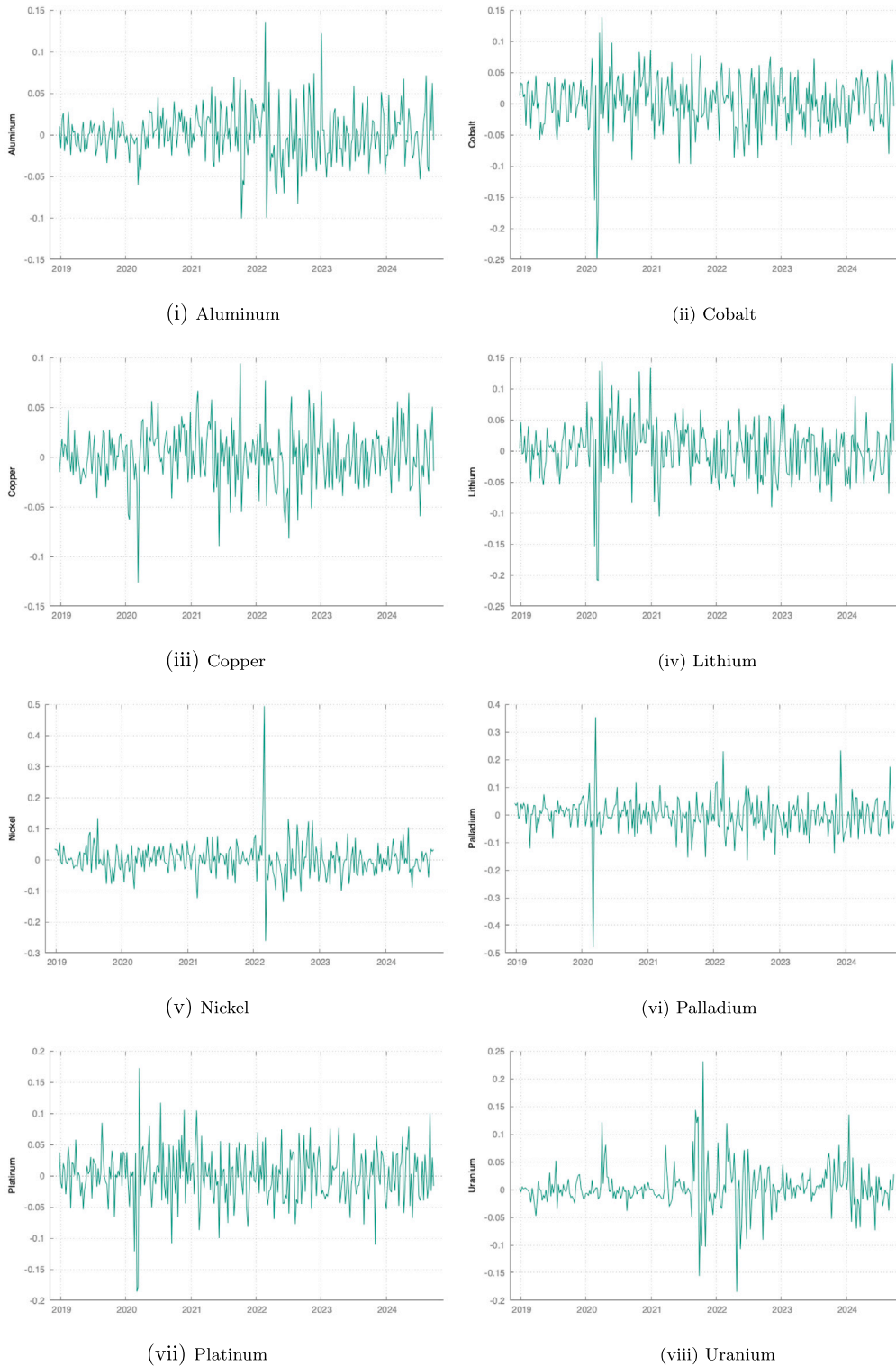


Fig. 1. Plots of weekly return series of transition minerals, global clean energy and technology indexes for the study period from December 28, 2018 to October 4, 2024.

Note: SPGCEI denotes S&P Global Clean Energy Index while DJGTI is the Dow Jones Global Technology Index.

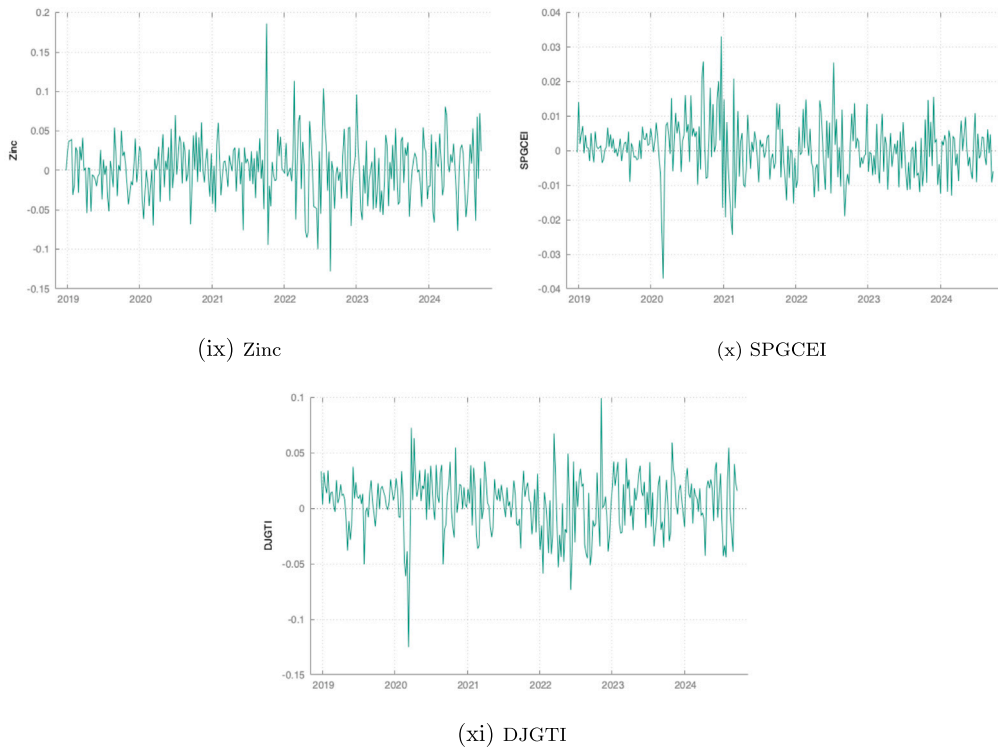


Fig. 1. (continued).

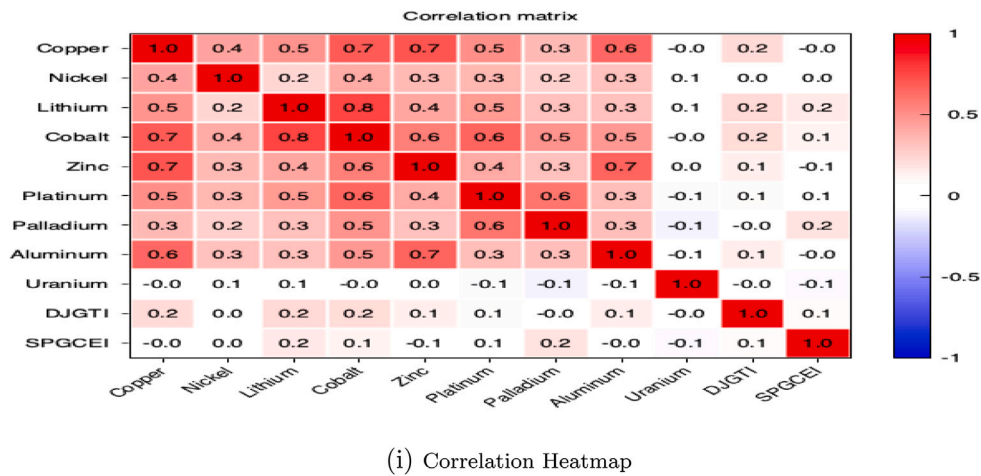


Fig. 2. Heatmap plot of correlation among transition minerals and global clean energy and technology indexes for the study period from December 28, 2018 to October 4, 2024.

Note: SPGCEI denotes S&P Global Clean Energy Index while DJGTI is the Dow Jones Global Technology Index.

denotes the bootstrap samples while $\hat{q}_{1,t}^*(\tau_1); \hat{q}_{2,t-k}^*(\tau_2)$ is the corresponding quantile estimates, the bootstrapped cross-quantilogram may be stated as:

$$\hat{\rho}_\tau^*(k) = \frac{\sum_{t=k+1}^T \psi_{\tau_1}(\theta_{1,t}^* - \hat{q}_{1,t}^*(\tau_1)) \psi_{\tau_2}(\theta_{2,t-k}^* - \hat{q}_{2,t-k}^*(\tau_2))}{\sqrt{\sum_{t=k+1}^T \psi_{\tau_1}^2(\theta_{1,t}^* - \hat{q}_{1,t}^*(\tau_1))} \sqrt{\sum_{t=k+1}^T \psi_{\tau_2}^2(\theta_{2,t-k}^* - \hat{q}_{2,t-k}^*(\tau_2))}} \tag{3}$$

Further, to determine the significance of dependence at different quantiles, Han et al. (2016) proposes a quantile-based version of the Ljung–Box–Pierce statistics based on the hypothesis of $H_0 : \rho_\tau(k) = 0$ for all $k \in 1, \dots, p$ against the alternative $H_1 : \rho_\tau(k) \neq 0$

for some $k \in 1, \dots, p$, which may be defined as:

$$\hat{Q}_\tau^{(p)} \equiv \frac{T(T+2) \sum_{k=1}^p \hat{\rho}_\tau^2(k)}{T-k} \tag{4}$$

where $\hat{Q}_\tau^{(p)}$ denotes the portmanteau test for significance of serial dependence at each pair of quantiles up to p lags.

2.2.2. Granger-causality in-mean and in-quantiles

We rely on the Granger causality test in mean and in quantiles by Troster (2018), which notes that a series X_t does not Granger-cause another series Y_t if past values of X_t do not predict the future values of Y_t . Following Yahya et al. (2020), the justification for the choice of this method over the conventional Granger causality test is the need to differentiate between causality in the mean and causality impacting the tails of the distribution. This is in consonance with our first objective, which focuses on quantile-based dependence. Assume an explanatory vector $I_t \equiv (I_t^Y, I_t^X) \in \mathbb{R}^d$, $d = s + q$, where I_t^Y and I_t^X denotes the past values of Y_t and X_t , respectively. The hypothesis of no causality from X_t to Y_t evolves as:

$$H_0^X \not\Rightarrow^Y : F_Y(y|I_t^Y, I_t^X) = F_Y(y|I_t^Y), \quad \forall y \in \mathbb{R},$$

where $F_Y(\cdot|I_t^Y, I_t^X)$ represents the conditional distribution function of Y_t given (I_t^Y, I_t^X) . Assume also that $Q_\tau^{Y,X}(\cdot|I_t^Y, I_t^X)$ denotes the τ -quantile of $F_Y(\cdot|I_t^Y, I_t^X)$, the quantile-based form of the above equation may be stated as:

$$H_0^{QC:X} \not\Rightarrow^Y : Q_\tau^{Y,X}(Y_t|I_t^Y, I_t^X) = Q_\tau^Y(Y_t|I_t^Y), \quad a.s. \quad \forall \tau \in T,$$

where the limitations below must be satisfied by $T \subset [0, 1]$, and the τ -quantile of Y_t :

$$Pr\{Y_t \leq Q_\tau^Y(Y_t|I_t^Y)|I_t^Y\} := \tau, \quad a.s. \quad \forall \tau \in T,$$

$$Pr\{Y_t \leq Q_\tau^{Y,X}(Y_t|I_t^Y, I_t^X)|I_t^Y, I_t^X\} := \tau, \quad a.s. \quad \forall \tau \in T,$$

Following Yahya et al. (2020), the conditional τ -quantile, $Q_\tau^Y(\cdot|I_t^Y)$ can be expressed in terms of a quantile parametric model $m(I_t^Y, \theta_0(\tau))$, which depends only on the information set I_t^Y . Hence, the null hypothesis of no causality may be rewritten as:

$$H_0^X \not\Rightarrow^Y : E1\{Y_t \leq m(I_t^Y, \theta_0(\tau))\}|I_t^Y, I_t^X = \tau, \quad a.s. \quad \forall \tau \in T, \tag{5}$$

where $m(I_t^Y, \theta_0(\tau))$ is the conditional quantile of $Q_\tau^Y(\cdot|I_t^Y)$, for all $\tau \in T$. If Ψ is a matrix of $T \times n$, with components $\psi_{ij} = \Psi_{\tau_j}(Y_t - m(I_t^Y, \theta_T(\tau_j)))$, where $\Psi_{\tau_j}(\epsilon) := 1(\epsilon \leq 0) - \tau_j$. As in Troster (2018), we rely on the following test statistics:

$$S_T = \frac{1}{T_n} \sum_{j=1}^n |\psi_{\cdot j} \mathbf{W} \psi_{\cdot j}|, \tag{6}$$

where \mathbf{W} denotes a $T \times T$ matrix containing $w_{t,s} = \exp[-0.5(I_t - I_s^2)]$ and $\psi_{\cdot j}$ as the respective column j th of Ψ . Under the null hypothesis of no causality from global clean energy and technology markets to each transition mineral in this study, we use S_T to test the quantile autoregressive model (QAR) $m(\cdot)$, for all $\tau \forall T \subset [0.1]$ stated as:

$$QAR(1) : m^1(I_t^Y, \theta(\tau)) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t \Phi_u^{-1}(\tau), \tag{7}$$

where $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \sigma_t)$ are the parameters estimated using the maximum likelihood in an equally spaced quantile grid.

3. Results and discussion

3.1. Dependence of transition minerals on the global clean energy and technology markets

The results of the serial dependence obtained using the cross-quantilogram approach are presented as heat map matrices. Our discussions are based on the normalized cross-quantilograms, which reveal areas of true statistical significant dependence across all decile combinations.

Fig. 3 displays the quantile response of transition minerals to changes in the global clean energy market. The heatmaps reveal asymmetric responses of transition minerals to changes in clean energy market returns, as they encompass both positive and negative significant serial dependence. Notably, lithium, palladium, and platinum exhibit strong positive serial dependence, especially across lower and upper quantile combinations. This suggests that these minerals mirror the performance of clean energy stocks, particularly during market extremes when either market experiences sharp losses or gains. For lithium, the strongest link appears between the lower quantiles (0.2–0.4), whereas palladium and platinum show heightened dependence around the median quantiles when clean energy markets are booming (e.g., 0.5–0.6 to 0.9).

Conversely, zinc displays a predominantly negative response, especially when the clean energy market is underperforming. This counter-cyclical behavior highlights zinc’s potential as a hedging instrument against downside risks in clean energy portfolios. The implication for investors and portfolio managers is that zinc can serve as a diversification asset, buffering losses from exposure to lithium and precious metals (palladium and platinum) in clean energy-focused investments. The results thus highlight the portfolio optimization benefit of including zinc in clean energy investments and the need for caution in including lithium, palladium, and platinum in a similar portfolio. The findings also reinforce those of Yahya et al. (2020), underscoring directional negative

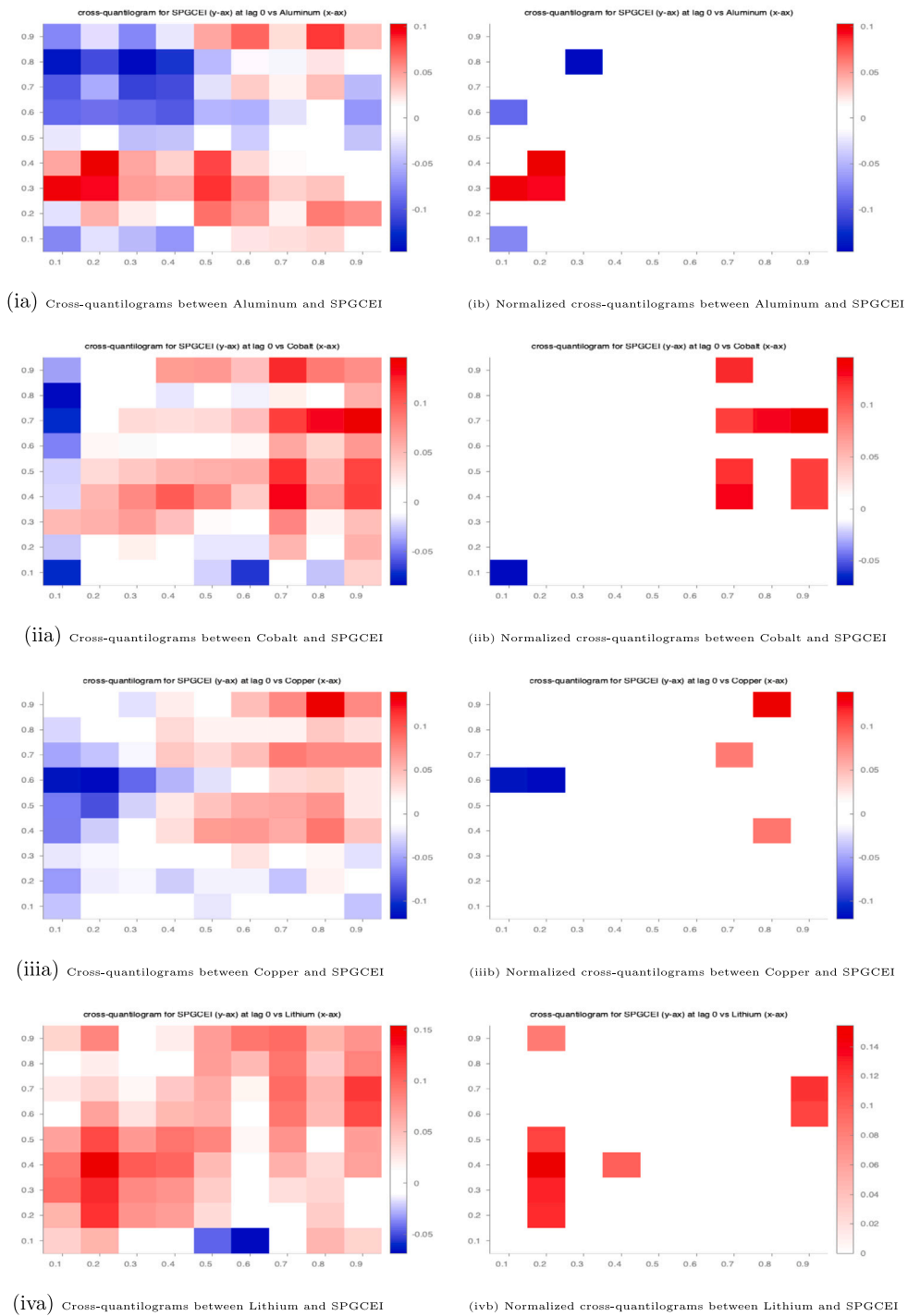
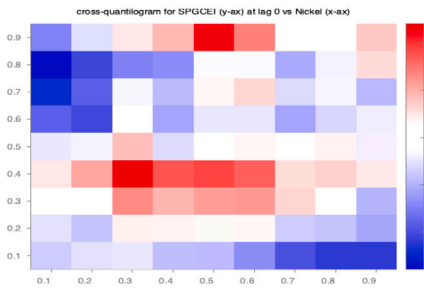
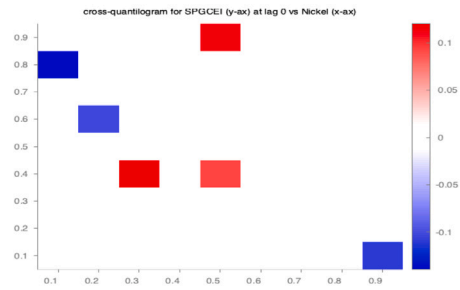


Fig. 3. Heatmap plots of cross-quantilograms and normalized cross-quantilograms between transition minerals and global clean energy index, considering all deciles combinations between each pair of series.

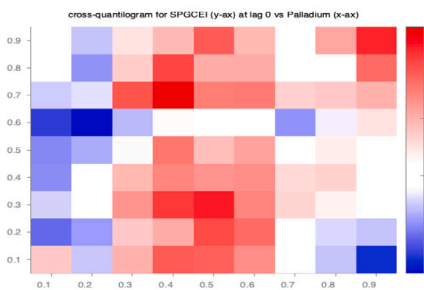
Note: Right and left figures represent cross-quantilograms and normalized cross-quantilograms between series pairs, respectively. SPGCEI denotes S & P Global Clean Energy Index. Each heatmap comprises 9×9 grids, corresponding to quantile combinations ranging from 0.1 to 0.9, with a step size of 0.1 based on 12-weeks lag, corresponding to quarterly memory length. The heatmaps color scale ranges from blue to red, denoting the magnitude and direction of dependence between each transition mineral on global clean energy as well as technology stocks. Specifically, blue indicates areas of negative dependence while red indicates a positive/negative relationship. The magnitude of dependence is shown by the saturation of the colors. We report heatmaps for both cross-quantilograms (Figure a) and normalized cross-quantilograms (Figure b).



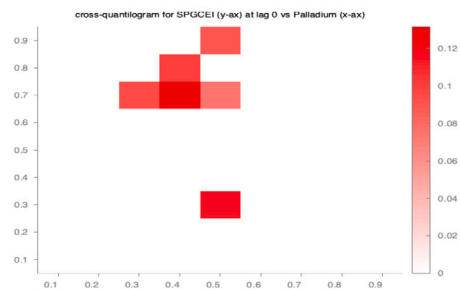
(va) Cross-quantilograms between Nickel and SPGCEI



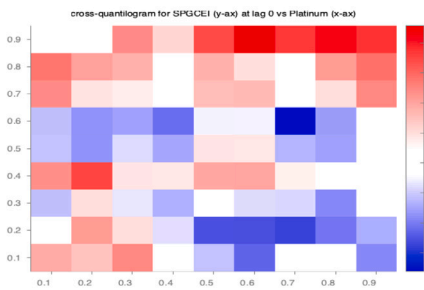
(vb) Normalized cross-quantilograms between Nickel and SPGCEI



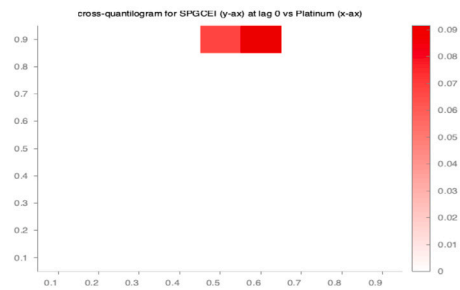
(via) Cross-quantilograms between Palladium m and SPGCEI



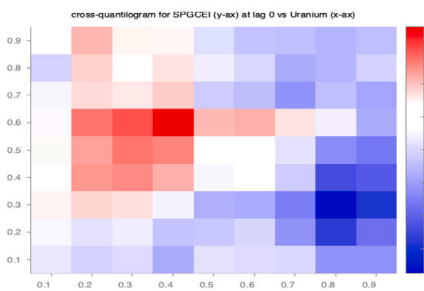
(vib) Normalized cross-quantilograms between Palladium and SPGCEI



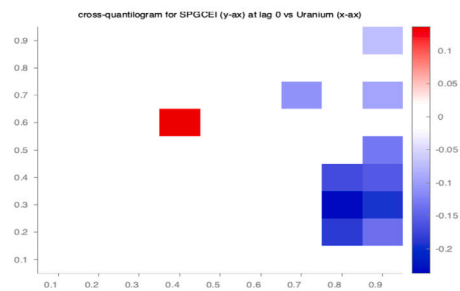
(viiia) Cross-quantilograms between Platinum and SPGCEI



(viiib) Normalized cross-quantilograms between Platinum and SPGCEI



(viiiia) Cross-quantilograms between Uranium and SPGCEI



(viiiib) Normalized cross-quantilograms between Uranium and SPGCEI

Fig. 3. (continued).

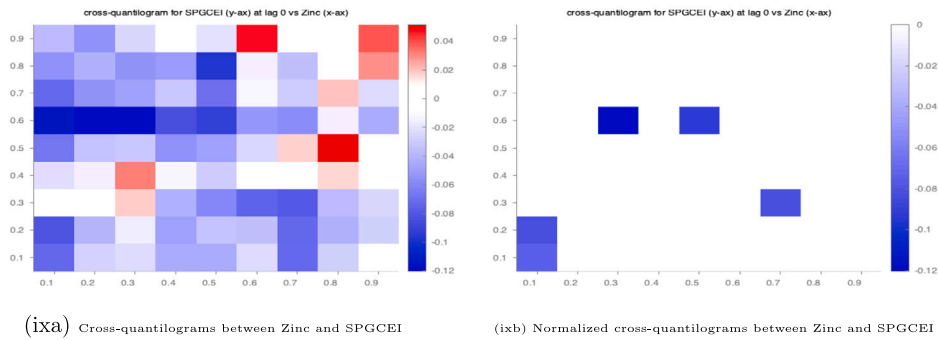


Fig. 3. (continued).

predictability from clean energy to certain non-ferrous metals. However, our result further emphasizes that the magnitude and direction of influence are quantile-dependent, a critical consideration for dynamic asset allocation strategies.

The results are mixed for the remaining transition minerals. For aluminum, cobalt, copper, and nickel, the results show positive and negative serial dependence across varying quantiles. Typically, these minerals exhibit negative responses in lower quantiles (bearish conditions), suggesting that clean energy downturns could amplify losses in already weak markets. However, the relationships in the upper quantiles (bullish conditions) are mostly positive, indicating potential procyclical gains. Interestingly, nickel stands out for its potential contrarian behavior: it may experience gains (positive shocks) following losses in clean energy markets, especially when both are in opposite market states. This makes nickel particularly valuable for speculative trading strategies or market-neutral portfolios. In this case, policymakers in resource-exporting countries should also note that volatility in global clean energy demand could spill over into domestic earnings from these minerals, amplifying macroeconomic vulnerability.

Lastly, uranium is negatively dependent across most quantile pairs, suggesting an overall decoupling or even inverse relationship with clean energy stocks. This nuanced behavior underscores uranium's distinct role in the energy transition, perhaps reflecting the unique nature of nuclear power in clean energy narratives and regulatory frameworks.

Fig. 4 presents the results on how transition minerals respond to changes in the returns of global technology. The figure generally reveals a stronger positive dependence between transition minerals and the global technology market than with clean energy stocks. Aluminum, cobalt, copper, and zinc show synchronous movements, especially during downturns. This implies that technology sector shocks transmit directly into these mineral markets, exacerbating losses during global tech pullbacks. For investors, this means that diversification benefits from combining tech stocks with transition metals are limited, especially during periods of tech-sector stress. Zinc, in particular, illustrates an intriguing shift: while it moves against clean energy returns, it moves in tandem with technology stocks, especially at middle-to-upper quantiles. This suggests a differentiated utility depending on portfolio composition and macroeconomic exposure.

Minerals such as nickel, palladium, platinum, and uranium exhibit mixed responses to changes in the return of global technology stocks, showing both potential comovement and divergence depending on market conditions. In which case, there are periods of joint losses and gains with the technology market and potential for diversification benefits depending on market conditions. For example, platinum and uranium respond negatively to tech market booms (upper quantiles) but positively during neutral or bearish tech market conditions, highlighting situational diversification potential. Lastly, lithium also exhibits this trend as it responds positively across most pairs of quantiles, except at the uppermost global technology index's and Lithium's lower quantile, during which the response is negative. The findings on lithium, broadly positive across quantiles, underscores its increasingly strategic alignment with tech-sector dynamics. At the same time, the evidence that the relationship turns negative at the uppermost quantile of the global tech index and lower quantile of lithium highlights tail risk concerns when market extremes collide, a scenario that investors need to be aware of.

3.2. Causality from global clean energy and technology markets to transition minerals

Fig. 5 reports the test results for Granger-causality in-mean and in-quantiles from the clean energy market to transition minerals. The dotted lines represent significance at 5%. Across all quantiles, changes in the clean energy market returns Granger-cause variations in the returns of transition minerals such as cobalt, copper, lithium, and zinc. These results hold under the null hypothesis of Granger non-causality at 5% significance level. This finding aligns with our earlier argument that developments in the clean energy sector are not only contemporaneously linked, but also predictive of the future performance of transition minerals. Nevertheless, this predictive influence weakens at the uppermost quantiles for minerals like aluminum, nickel, palladium, and platinum. Specifically, whereas we find statistically significant predictive effects at the lower and middle quantiles, there is no evidence of causality at the uppermost quantile (0.90), indicating that clean energy booms may not uniformly forecast gains in all mineral markets. Strikingly, we find no evidence of causality from the clean energy market to uranium across all quantiles, reinforcing earlier insights about its relative independence from clean energy market behavior.

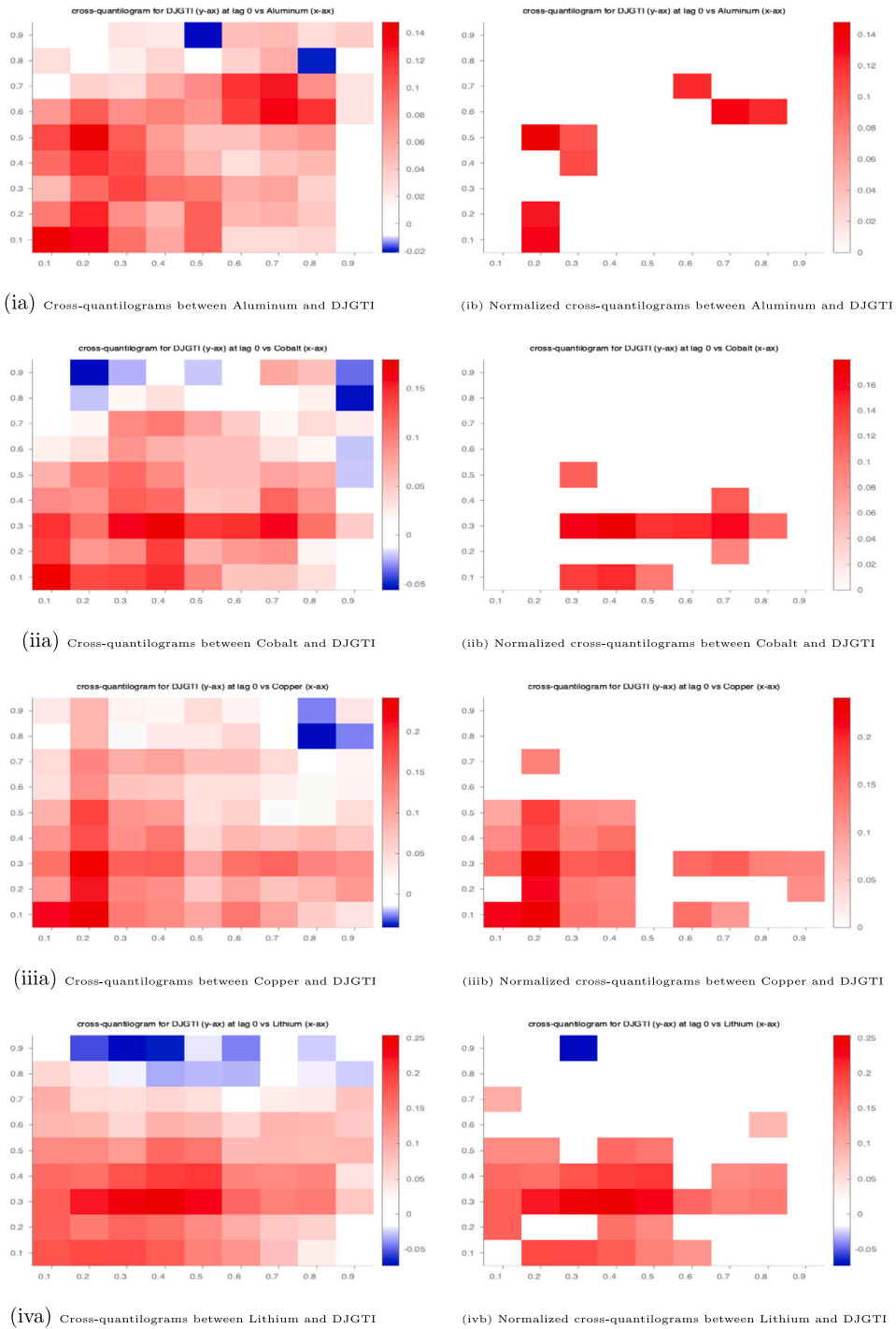
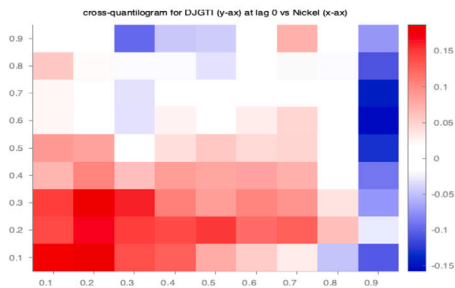
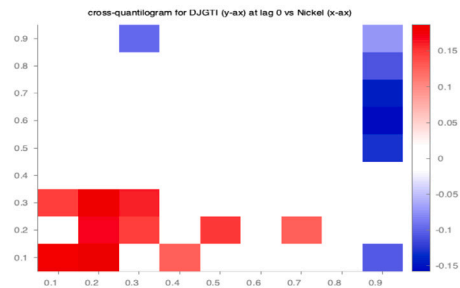


Fig. 4. Heatmap plots of cross-quantilograms and normalized cross-quantilograms between transition minerals and global technology index, considering all deciles combinations between each pair of series.

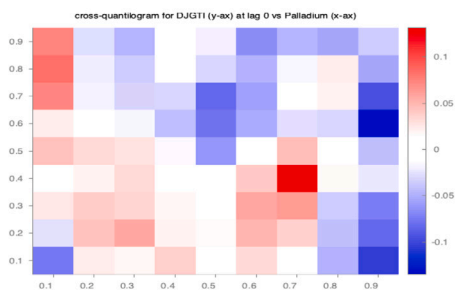
Note: Right and left figures represent cross-quantilograms and normalized cross-quantilograms between series pairs, respectively. DJGTI denotes Dow Jows Global Technology Index. Each heatmap comprises 9×9 grids, corresponding to quantile combinations ranging from 0.1 to 0.9, with a step size of 0.1 based on 12-weeks lag, corresponding to quarterly memory length. The heatmaps color scale ranges from blue to red, denoting the magnitude and direction of dependence between each transition mineral on global clean energy as well as technology stocks. Specifically, blue indicates areas of negative dependence while red indicates a positive/negative relationship. The magnitude of dependence is shown by the saturation of the colors. We report heatmaps for both cross-quantilograms (Figure a) and normalized cross-quantilograms (Figure b).



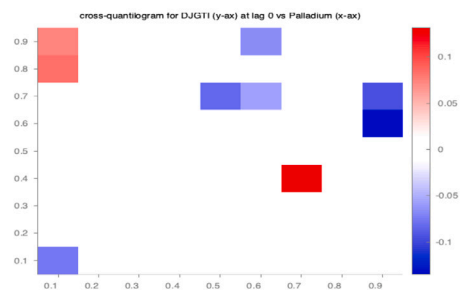
(v*a*) Cross-quantilograms between Nickel and DJGTI



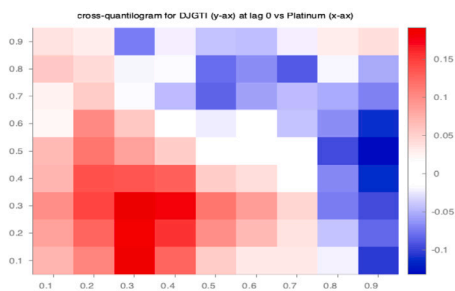
(v*b*) Normalized cross-quantilograms between Nickel and DJGTI



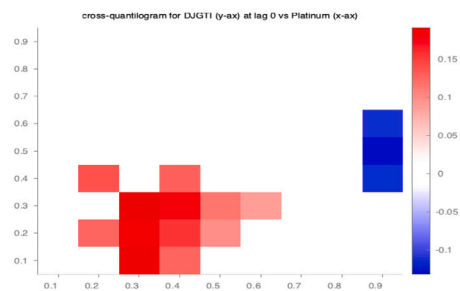
(v*i**a*) Cross-quantilograms between Palladium and DJGTI



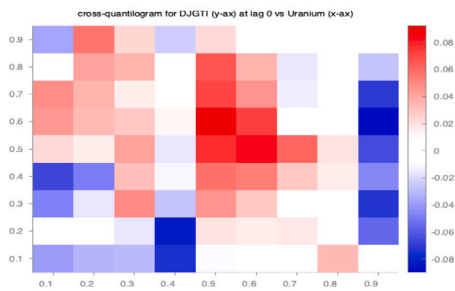
(v*i**b*) Normalized cross-quantilograms between Palladium and DJGTI



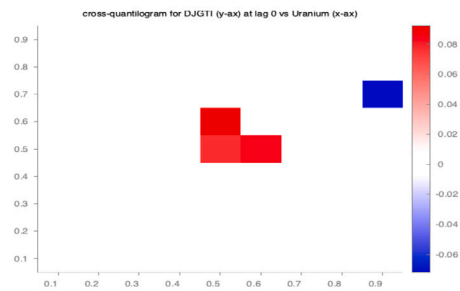
(v*i**i**a*) Cross-quantilograms between Platinum and DJGTI



(v*i**i**b*) Normalized cross-quantilograms between Platinum and DJGTI



(v*i**i**i**a*) Cross-quantilograms between Uranium and DJGTI



(v*i**i**i**b*) Normalized cross-quantilograms between Uranium and DJGTI

Fig. 4. (continued).

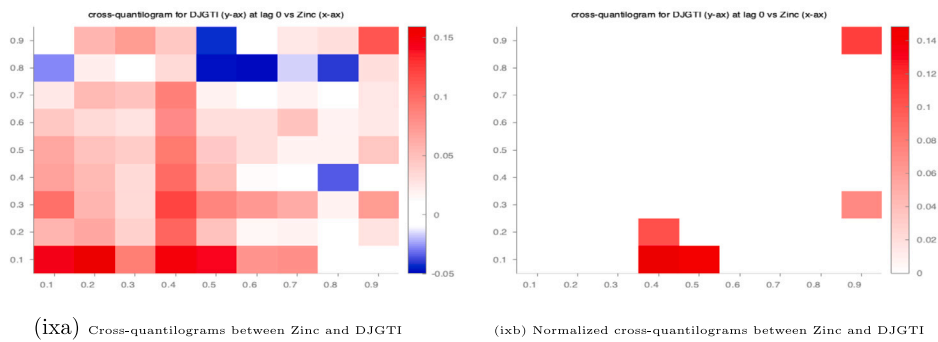


Fig. 4. (continued).

Taken together, these results show that positive or negative fluctuations in the global clean energy market lead to changes in the market for transition minerals, except for uranium. For investors and commodity traders, the results suggest a forward-looking informational edge in using clean energy market signals to anticipate price movements in specific mineral markets, particularly in hedging or timing strategies. For policymakers, especially in mineral-rich economies, this highlights the importance of tracking global clean energy demand trends as an early warning signal for revenue volatility and macroeconomic planning.

Fig. 6 reports the test results for the Granger-causality in-mean and in-quantiles from global technology market to transition minerals. As may be seen, there is more limited evidence of causality from the technology market to the transition minerals market than we found in the case of the clean energy market. Notably, there is no evidence of Granger causality to aluminum, platinum, zinc, or copper across all the considered quantiles. Results are mixed for the remaining transition minerals. For instance, we find evidence of causality from the technology market at lower quantiles to cobalt, lithium, nickel, and uranium. There is also evidence of causality from the technology market to palladium at the uppermost quantile (0.9).

Overall, these findings imply that the technology market lacks strong systemic causality, except for a few transition minerals during stress periods. This diminishes its usefulness for investors as a leading indicator for transition metal prices. Nevertheless, during market downturns, close attention to tech trends could help anticipate movements in minerals like nickel, lithium, and cobalt, which are heavily integrated into electronics and battery supply chains.

4. Conclusion

The accelerating global shift towards clean energy and advanced manufacturing technologies has significantly increased the demand for the so-called transition minerals—such as lithium, cobalt, rare earth elements, and graphite. In response, these minerals are increasingly recognized and evolving as strategic assets, highlighting the need to understand their behavior, risk-return profiles, and diversification potential within complex and dynamic financial systems. This paper contends that the strategic value of these minerals is inherently derived from the technologies such as clean energy and advanced manufacturing technologies that depend on them. Accordingly, it investigates the dynamic dependence of transition minerals on global clean energy and technology markets. The analysis relies on cross-quantilogram and Granger causality tests in mean and quantiles, which it applies to data spanning from December 28, 2018, to October 4, 2024.

The findings highlight asymmetric relationships that vary across different quantiles of the return distributions. Specifically, the results show that lithium, palladium, and platinum exhibit significant positive dependence on the clean energy market, particularly during extreme market conditions, while zinc shows negative dependence, offering diversification potential. The behavior of aluminum, cobalt, copper, and nickel is more nuanced, with both positive and negative dependencies across different market regimes. Similarly, uranium responds negatively to clean energy shocks across most quantiles, with limited diversification potential.

Conversely, the global technology market reveals generally stronger and more positive associations with transition minerals such as aluminum, cobalt, copper, and zinc, suggesting tighter linkages between technological innovation and industrial metal demand. However, except for a few cases, evidence of causality from the technology market is weaker than from the clean energy market. This suggests that while transition minerals may track the direction of the technology sector more closely, clean energy markets play a more determinative role in driving mineral price dynamics over time.

These results have important implications for investors, portfolio managers and policymakers. The asymmetric and quantile-dependent nature of the dependencies we document implies that risk management strategies and investment decisions should consider varying market regimes. For example, investors seeking exposure to transition minerals must factor in the conditional co-movements with clean energy and technology stocks, especially during market downturns. Minerals like zinc may serve as strategic hedges in portfolios sensitive to clean energy shocks, while lithium and palladium demand careful monitoring due to their heightened exposure to tail risks in the clean energy sector. For commodity traders, the presence of quantile-based serial dependence suggests that returns in transition mineral markets can be, to some extent, predicted based on the behavior of clean energy and technology indices. Traders thus may exploit this information to anticipate directional price movements, especially during extreme market conditions when such dependencies are most pronounced.

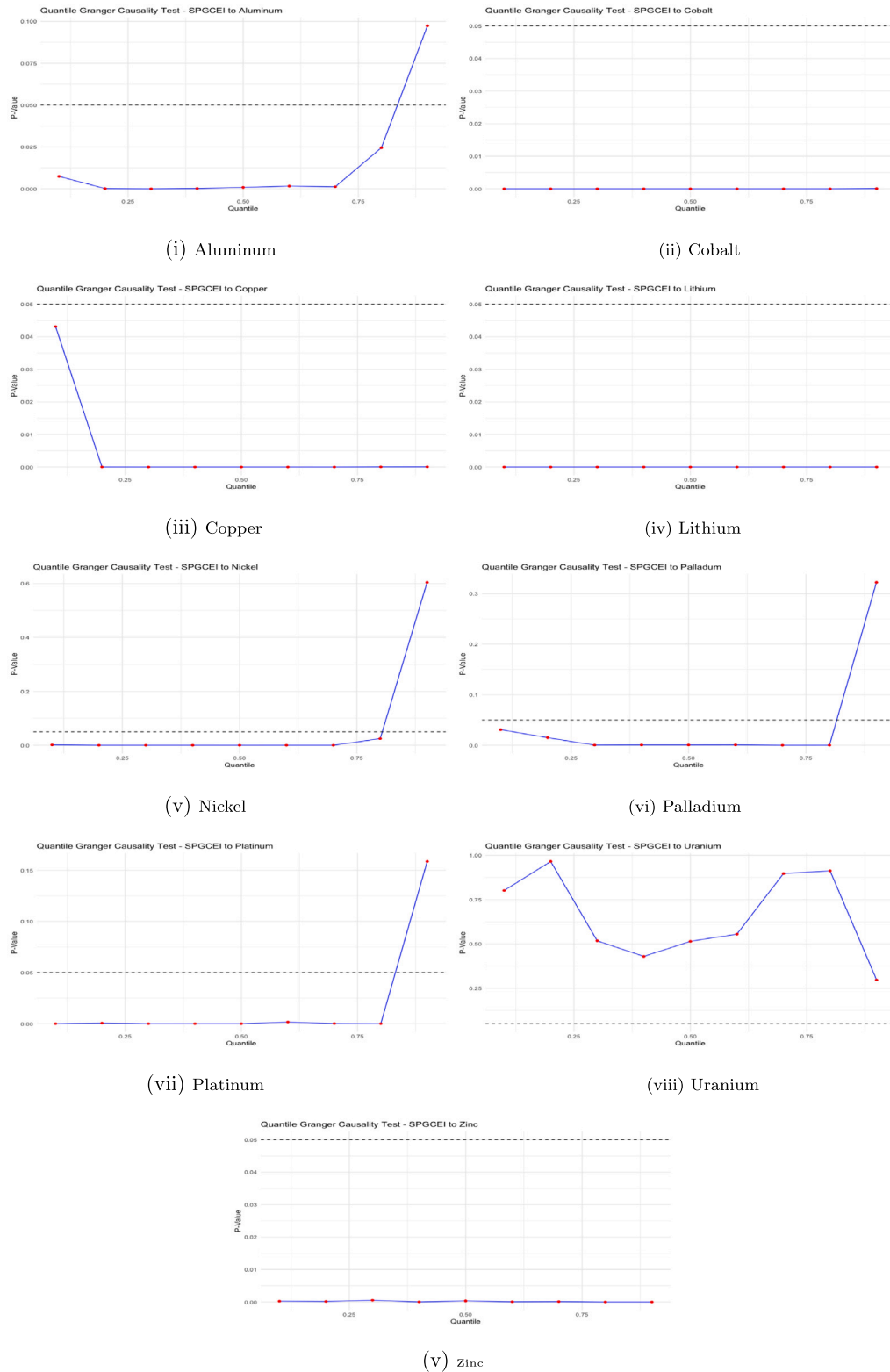


Fig. 5. Plots of p-values of quantile Granger causality from global clean energy to transition minerals. Note: Quantile-based p-values of for the null hypothesis of Granger non-causality at 5% significance level for the 0.1 to 0.9 quantiles. SPGCEI denotes S&P Global Clean Energy Index.

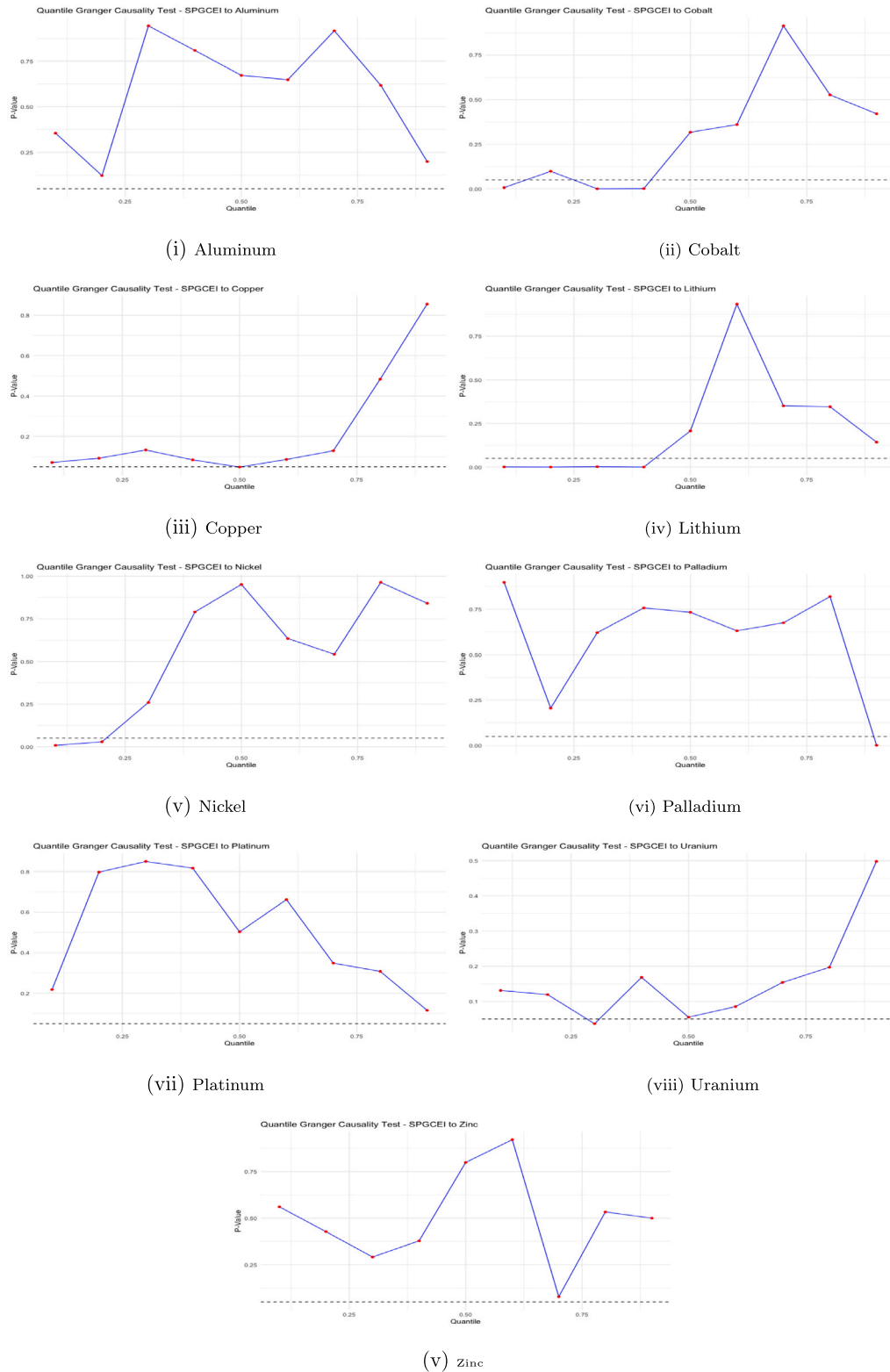


Fig. 6. Plots of p-values of quantile Granger-causality from global technology market to transition minerals. Note: Quantile-based p-values of for the null hypothesis of Granger non-causality at 5% significance level for the 0.1 to 0.9 quantiles. DJGTI represents the Dow Jones Global Technology Index.

From a policy standpoint, the strong interdependence between transition minerals and clean energy markets reinforces the importance of integrating commodity market insights into climate and energy policy frameworks. Moreover, dependence across markets, which we document, is indicative of the increasing entanglement between mineral markets and high-technology and transition-oriented technologies, signaling potential mineral supply chain vulnerabilities. Policymakers should consider stockpiling and diversifying supply sources to enhance resilience. Finally, the asymmetry and causality patterns highlight the importance of cross-sectoral policy coordination—linking mineral resource governance, industrial policy, energy transition planning, and trade policy in a more integrated manner. Future studies may consider exploring the interplay between environmental policy stringency and transition minerals prices. Such studies should shed light on how increasing climate policy stringency impact on the prices of these transition minerals, which are critical to development of renewable energies that facilitate energy transition.

CRedit authorship contribution statement

Gideon Ndubuisi: Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Christian Urom:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

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