Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes

Author(s): Yahya, Muhammad; Ghosh, Sajal; Kanjilal, Kakali; Dutta, Anupam; Uddin, Gazi Salah

Title: Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes

Year: 2020

Version: Final draft (post print, aam, accepted manuscript)

Please cite the original version:

Yahya, M., Ghosh, S., Kanjilal, K., Dutta, A., & Uddin, G.S., (2020). Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes. Energy 202. https://doi.org/10.1016/j.energy.2020.117777

Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes

Muhammad Yahya
Department of Safety, Economics and Planning
University of Stavanger, Norway
Email: muhammad.yahya@uis.no

Sajal Ghosh
Management Development Institute Gurgaon, Room No C-10, Scholar Building, Mehrauli Road,
Sukhrali Gurgaon 122001, India
Email: sghosh@mdi.ac.in

Kakali Kanjilal
International Management Institute New Delhi
B-10, Qutub Institutional Area, Tara Crescent, New Delhi – 110016, India
E-mail: kakali@imi.edu

Anupam Dutta
School of Accounting and Finance
University of Vaasa, Finland
Email: adutta@uwasa.fi

Gazi Salah Uddin
Department of Management and Engineering,
Linköping University, Linköping, Sweden
E-mail: gazi.salah.uddin@liu.se

Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes

Abstract

This paper analyzes the cross-quantile dependence and causality between non-ferrous metals and clean energy indices by employing data from November 2003 to May 2019. Specifically, we utilize the time-varying copulas to examine the asymmetric connectedness among the assets. Based on the assessed dependence, we utilize the time-static and time-varying cross-quantilogram approach to evaluate the asymmetric dependence across different quantiles. Finally, we employ a Granger-causality in quantiles analysis to assess the causal relationship across different quantiles of the return distributions of the underlying assets. By utilizing time-varying copulas, we report that the conditional dependence between the assets is time-varying and asymmetric with the potential for tail dependence. Our results from the cross-quantilogram analysis provide further evidence that the interconnectedness is asymmetric across quantiles, and it increases with the increase in lags. In addition, we report that extreme market conditions positively influence the dependence structure. Finally, our findings from Granger-causality in quantiles indicate bidirectional causality among assets that intensifies with the increase in lag order. These findings are important for governmental policies that aim at mitigating the impact of climate change by transforming the global energy landscape towards clean and renewable energy sources.

1. Introduction

Climate change and energy security issues have emerged as the primary driving forces to transform the landscape of the global energy sector towards renewables or clean energy sources [1]. Climate risks intensified by global warming have also started manifesting its importance in energy portfolio diversification towards de-carbonization. Globally, the agreed goal is to limit the anthropogenic Green House Gas (GHG) emission to restrain the disasters of climate change. The anthropogenic CO_2 emission, one of the major GHGs, is responsible for an increase in global warming, which is expected to be higher towards the mid of the current century if the emission is left uncontrolled for [2,3]. The global energy-related CO_2 emission reached a peaked level of 33.1 giga-ton (gt) in 2018 [4]. The fallout of these events is observed in the energy sector with the dominance of clean energy like renewables towards the energy supply portfolio. The global energy sector is expected to witness a gradual shift towards clean energy sources [1]. According to [5], numerous institutional investors have dedicated to divesting their investment from the traditional energy sectors. As per Renewables Information 2018 [6], the share of renewable energy, which contributed 24% of the world's power demand in 2017, is expected to increase by 30% by 2023. An upsurge of investments in renewables to a level of $279.8 billion in 2017 makes the cumulative investments in the sector to $2.9 trillion since 2004 [7], providing an additional thrust to the renewables in the global energy sector.

A similar clean energy thrust is also observed in the transportation sector. Sales of electric vehicles (EVs) are gaining momentum at an unprecedented rate. In 2018, the global electric car population witnessed a staggering growth of 155% as compared to the previous year triggered by significant cost reduction and improved performance of car batteries. High penetration of EVs

has the potential to cut oil demand by 2.5 to 4.3 million barrels per day [mb/d] by 2030 under different policy scenarios as projected by [8].

The growth momentum also continues in the financial market performance of clean energy stocks, where both clean energy and clean technology stocks have frequently outperformed the MSCI Global and S&P 500 index. The inception of clean energy shares as a new asset class has attracted both the investors and the academic world [9] to a great extent. Both clean energy and clean technology stocks are closely linked [10,11] and are considered to be risky assets [12–14], compelling the need to identify a safe-haven asset for itself. So, do the traditional strategic commodities, crude-oil and gold, uphold the glory of safe asset classes even after the global financial crisis (GFC)? [15] have rightly pointed out that the identification of a safe-haven asset has become a challenge post the GFC as "many studies have questioned the safe-haven ability of gold during that period; when the interest-rate bound reached zero, and the financialization of gold investing intensified." Also, [16] has shown that the traditional strategic safe-haven commodities, crude oil, and gold may act as a weak safe-haven for clean energy stocks. This indicates that the search for safe-haven asset class for clean energy stocks may go beyond crude oil and gold as they cannot possibly unwind the embedded risks of clean energy indices anymore [17–19].

The emergence of clean energy stocks as an attractive asset class triggers the demand for ceratin non-ferrous metals, which are the basic building blocks for the development of clean energy technologies [1], thereby creating a new market for those metals.[1] The consumption of some of these non-ferrous metals has already witnessed an exponential growth. For instance, Gallium

---

[1]For example, solar photovoltaic (SPV) and wind energy require elements like Silicon, Copper, Silver, Tin, Cobalt, Manganese, Chromium, Molybdenum, Nickel, BariumIndium, Gallium, Selenium, Cadmium, Tellurium and rare earth metals like Dysprosium, Neodymium, Praseodymium, Yttrium, Terbium while energy storage and electrical grids needs Alluminium, Copper, Germanium, steel, Zinc, Tin, Lithium, Cobalt, Nickel, Manganese, Vanadium, Chromium among others.

consumption has increased by 1800% for the period 1971-2011, while consumption for Tellurium, Lithium, and Cobalt has increased by 900%, 800%, and 400%, respectively [20]. The experts believe that there may be a prerequisite of 3200 million tonnes (mt) of Steel, 310 mt of Aluminum, and 40 mt of Copper [21] to support the uprising of clean energy. In addition, Lithium is expected to increase by over 1000% over the long-run [22,23] along with gallium (400–600%), neodymium (150–380%) and indium (300%) [20]. Therefore, the supply of these strategic metals shall greatly influence the clean energy transition.

The investors have sensed the importance of these metals as soon as they become tradable assets as the non-ferrous metal index. This index appears to be comparable to the other conventional asset classes like bonds and equities, as established by [24]. Several studies have reported the importance of non-ferrous metals for the transition of clean energy. Still, the non-ferrous metal index, as a separate asset class, has received less attention from both the academic world and investors in terms of its connectedness, portfolio diversification, and hedging potential with clean energy stocks [24]. The safe-haven properties of the non-ferrous metals as established by [25–27] can open up a window of opportunity to diversify and hedge against clean energy stocks.

Our study addresses these knowledge gaps by examining the nonlinear and tail dependence of non-ferrous metal index, 'Dow Jones Non-ferrous price index', with two clean energy indices, 'Wilderhill clean energy' and 'S&P Global clean energy', and with one clean technology index, 'ARCA Tech index'. The literature, focusing on clean energy asset returns primarily concentrated on examining the connectedness dynamics between conventional fossil fuels, financial markets, and commodities with that of clean energy stocks.[2] However, the interconnectedness between non-ferrous metals and clean energy assets remains uncharted. So,

---

[2] See, for example, [11,17,19], among others.

as long as clean energy and non-ferrous metals are fundamentally related, the outcomes of this study will be useful to the investors for their strategic investment decisions at different time scales [16].

We fill the pivotal rift in several ways. First, we evaluate the less-explored non-ferrous metals interdependence in mean and quantiles to explore the possibility of non-ferrous metal stock as a safe asset class for clean indices and clean technology stocks. To the best of our knowledge, this is the first paper in this strand of literature examining the temporal dependence and causality in mean and quantiles of non-ferrous metals and clean energy and technology indices.

Second, we contribute to the literature by employing a time-varying copula approach, cross-quantilogram correlation (CQC), and Granger-causality in quantiles to explore the possibility of non-ferrous metal stock as a safe asset class for clean energy. A copula approach is preferred over conventional correlations and multivariate GARCH models[3] as it captures dependence both on average and during extreme co-movements [16,19]. However, due to its inability to incorporate lags, it assumes the connectedness dynamics as time-invariant. Therefore, we employ the CQC approach to estimate the dependence in the tails of the distributions and to include lags of variables. The employment of the CQC approach helps to evaluate (i) whether the series tend to exhibit extreme co-movement and tail dependence behavior and (ii) whether extremely low and high returns across various assets are symmetrically dependent.

Third, we analyze the mean and quantile causal relationships between non-ferrous metals and clean energy assets. This is naturally the next step in our analysis to evaluate whether the observed dependence in quantiles is resulted due to a causal link between the assets.

---

[3]The conventional cointegration approaches also fail to capture the co-movements and connectedness of different asset classes in an average (a normal) and extreme market conditions [52,75].

Furthermore, in order to capture the investor trading behavior, we consider different lag specification and also look at the sensitiveness between quantile dependence and quantile causality at different lags. There is a difference between directionality and dependence. In our study, we consider the correlation structure among the investigated variables under the different states (normal vs downward and upward market) by utilizing quantile dependence approach. Whereas we look at the directionality at the different states (normal vs downward and upward market) by incorporating quantile causality approach. We utilize the test proposed by [28] to evaluate the flow of Granger cause across various quantiles of distribution.

Our empirical analysis based on the time-varying dynamic conditional correlation (DCC)-Student-t copula reveals asymmetric connectedness dynamics that vary over time. Although the mean dependence between assets is characterized by moderate linkage, the time-varying connectedness indicates significant fluctuation. Furthermore, based on the analysis from cross-quantile correlation (CQC) for four different lags, we find that non-ferrous metals positively affect clean energy stocks when both are in extreme lower tails (turmoil period) of the return distribution. On the contrary, the CQC from the clean energy assets to non-ferrous metals indicates a relatively weaker positive influence from these assets to non-ferrous metals. In addition, the time-varying CQC shows asymmetric behavior across lower, median, and upper quantiles of distribution. The estimates of Granger-causality in mean and quantiles indicate that the changes in clean energy assets (non-ferrous metals) do not Granger-cause variations in non-ferrous metals (clean energy assets) at the 1% significance level for lag 1. However, for the higher lag orders, we report bidirectional causality among assets across nearly all quantiles.

Our results indicate that non-ferrous metals are essential for the development of clean energy assets. These results are crucial as clean assets are vital for minimizing the impact of climate

risks. The tail dependence between the variables suggests that positive assurance and stability of the non-ferrous metals are crucial to mitigate the uncertainty in clean energy markets.

This paper is ordered in the following sections. Section 2 provides a review of the literature on the linkages between clean energy stocks and strategic commodities. Section 3 focuses on data. Section 4 provides the methodology. The empirical findings are discussed in Section 5.

2. Literature Review

The clean energy stocks, as an instrument in the equity market, have exhibited systematic co-movement with other asset classes [29]. Although no theoretical explanations can be provided regarding linkages among clean energy index (clean technology stocks) and crude oil [13], the empirical researches on clean energy and oil nexus are found in plenty. Studies linking the clean energy (clean technology) stocks to crude oil [17,19,30–39] advocate mixed findings on how clean energy stocks are related to oil. Majority of these works contend that crude oil price plays a dominant role in determining clean energy stock prices barring a few [9,11,17,34].

The last decade has also witnessed precious metals as an emerging asset class for investors [40]. Studies pertaining to the risk spillover and hedging effectiveness of precious metals with stock markets are well documented in the literature [41–47]. In addition to that, numerous studies explore the connectedness between precious metals and oil prices [13,34,48–53]. While investigating the link between precious metals and clean energy stocks, [9] concludes that gold is not the preeminent risk management instrument for these stocks. [54] establishes that the silver market uncertainty would create a negative impact on the global solar energy stock indexes. [16] establish that gold is a superior asset class for clean energy indices in case of extreme market movements. [29] find that gold returns positively affect clean energy stocks during periods of

turmoil. In another strand of research, [15] investigate the safe-haven properties of Bitcoin for stock markets during extreme market situations and if bitcoin reveals similar safe-haven characteristics as gold or general commodity index. The study defines a novel approach of identifying weak and strong safe-haven properties[4] of assets using a bivariate cross-quantilogram approach for developed and emerging economies. Their findings support time-varying but weak safe-haven roles of Bitcoin, gold, and other commodities.

[55] investigate the volatility spillover among some of the key non-ferrous metals and report strong evidence of spillover among the assets over the post-crisis period. The key rationale offered for strong spillovers is related to the increased utilization of these metals in industrial production. For instance, the automobile industry is highly reliant on nickel and aluminum and the increased utilization of lead and copper in the electrical sector and electronics. [56] find persistency and asymmetric effect in volatilities of the non-ferrous metals' spot and futures price series using TGARCH and EGARCH frameworks. [57,58] utilize the HAR and LHAR model to forecast the volatility of the futures prices of Chinese non-ferrous metals, respectively. [59] report the time-varying effects of non-ferrous metals on the industrial economy of China.

Surprisingly, in this plethora of empirical research, studies on the nexus between clean energy stocks and/or technology and non-ferrous metals are nonexistent despite its widespread application in the industry and importance in the commodity markets [60–62].

3. Methodology

---

[4] A strong safe-haven property of an asset exists when there is evidence of causality from a stock to that asset in the low quantiles of both the stock and the asset returns, and the sign of causality is negative. In contrast, the asset has a weak safe-haven characteristic when there exists no evidence of causality from a stock index to that asset in the low quantiles of both the stock and the asset returns (refer to[15]).

3.1. Time-varying copula

The copula frameworks are flexible and effective in characterizing and modelling connectedness. We utilize a DCC-Student-t copula to assess the extreme nonlinear tail dependence, which generally characterize the financial and commodity returns. According to [63] theorem, the joint distribution function for a copula may be defined:

$$F_{XY}(x, y) = C(u, v) \qquad\qquad 1$$

where $u = F_X(x)$ and $v = F_Y(y)$ represent the univariate functions for X and Y and $F_{XY}(x, y)$ corresponds to the joint distribution function. We may define the Student-t copula as:

$$C_{d,\rho}(u, v) = t_{d,\rho}\left(t_d^{-1}(u), t_d^{-1}(v)\right),$$

where ρ represents the time-invariant correlation matrix, and d represents the degrees of freedom. Similarly, we can generalize Student-t from the bivariate to multivariate case as:

$$C_{d,\rho}(u_1, \dots, u_n) = t_{d,\rho}\left(t_d^{-1}(u_1), \dots, t_d^{-1}(u_n)\right)$$

$$= \int_{-\infty}^{t_d^{-1}(u_1)}, \dots, \int_{-\infty}^{t_d^{-1}(u_n)} \frac{\Gamma\left(\frac{d+n}{2}\right)|\rho|^{-\frac{1}{2}}}{\Gamma\left(\frac{d}{2}\right)(\pi v)^{\frac{n}{2}}} \left(1 + \frac{1}{d}z^T \rho^{-1} z\right)^{\frac{d+n}{2}} dz_1, \dots, dz_n, \qquad 2$$

where t_d^{-1} refers to the inverse univariate t distribution with d representing the symmetric tail dependence and $t_{d,\rho}$ corresponds to multivariate t distribution. We substitute the linear correlation matrix with the DCC matrix of [64] that is defined as:

$$R_t = \operatorname{diag}(\tilde{Q}_t)^{-\frac{1}{2}} Q_t \operatorname{diag}(\tilde{Q}_t)^{-\frac{1}{2}},$$

$$Q_t = \Delta\bar{R} + \alpha\, \epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1},$$

where $\Delta = 1 - \alpha - \beta$, $\bar{Q}$ is the sample covariance of ϵ_t, $\tilde{Q}_t$ represents the square root of diagonal components of Q_t. Estimation of the marginal distribution model is an essential precursor to estimate copula. Based on AIC, we determine an ARMA(1,0)-EGARCH(1,1) to best capture the dynamics in the evaluated series.[5] We may specify the generalize form EGARCH(P, Q) as:

$$\log\sigma_t^2 = \kappa + \sum_{i=1}^{P}\beta_i\log\sigma_{t-i}^2 + \sum_{j=1}^{Q}\alpha_j\left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right\}\right] + \sum_{j=1}^{Q}\xi_j\left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right), \qquad 3$$

where α_j and β_i corresponds to the ARCH and GARCH parameters, correspondingly, and ξ_j reflects the asymmetric effect in the underlying series.

3.2. Cross-quantilogram

To evaluate the variations in dependence across different quantiles of the return distributions, we utilize a cross-quantilogram correlation (CQC) approach of [65]. The CQC approach is superior to copulas as it provides a detailed overview to examine whether extreme returns among the assets are symmetrically connected. The CQC approach is model-free, and the primary condition for its application necessitates that the underlying series should be a stochastic stationary process.

We provide the outputs of CQC in terms of the heatmap for various lags. Heatmaps enable us to provide an estimate of entire connectedness dynamics across various quantiles $[q = (0.05, 0.1, 0.2, ..., 0.95)]$ of the return distribution. The statistically significant cross-quantile dependence parameter is presented by the color scale, and the insignificant parameter is set as zero.

---

[5] The best GARCH model is chosen from various marginal distributional models (GARCH, EGARCH, GJR-GARCH). However, for brevity, we only report the estimates from the best-suited model.

Let x_t and y_t represents the two-underlying series. Based on the following assumption that $x_t = (x_{1t}, x_{2t})^T \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$ and $y_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^{2}$,[6] we can define the conditional distribution and a quantile function as $F_{(y_i|x_i)}(\cdot |x_{it})$ and $q_{i,t}(\tau_i) = \inf\{v : F_{(y_i|x_i)}(v|x_{it}) \geq \tau_i\}$ for any $\tau_i \in (0,1)$. We can then define the cross-quantilogram as the cross-connectedness of various quantiles that is expressed as:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(y_{1,t} - q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(y_{1,t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}} \qquad 4$$

where k represents the lead-lag to time t. We follow [65] and evaluate the null-hypothesis of no conditional dependence $(H_0: \rho_\tau(1) = \cdots = \rho_\tau(p) = 0)$ against an alternative representing different from zero $(H_1: \rho_\tau(k) \neq 0, \forall\, k \in \{1 \dots \dots \dots p\})$ by employing a Box-Ljung test for statistical inference, which can be expressed as:

$$\hat{Q}_\tau(p) = T(T+2)\sum_{k=1}^{p}\frac{\hat{\rho}^2(k)}{T-k}. \qquad 5$$

3.3. Mean and quantile Granger-causality

We deploy the quantile Granger-causality test by [28] to examine the causality among underlying assets. Given two underlying series X_t and Y_t, [66] shows that X_t do not cause Y_t if the historic X_t values do not forecast future Y_t values. Assuming an explanatory vector $I_t \equiv (I_t^Y, I_t^X)' \in \mathbb{R}^d$, $\mathrm{d} = \mathrm{s} + \mathrm{q}$, where I_t^X represents the historic values of X_t, $I_t^X := (X_{t-1}, \dots, X_{t-q})' \in \mathbb{R}^q$, then the no-cause from X_t to Y_t null hypothesis may be defined as follows:

$$H_0^{X \nrightarrow Y}: F_Y(y|I_t^Y, I_t^X) = F_Y(y|I_t^Y), \quad \forall \quad y \in \mathbb{R},$$

---

[6] Here, $x_{it} = \left[x_{it}^1, \dots, x_{it}^{d_i}\right]^T \in R^{d_i}$

where $F_Y(\cdot \,|I_t^Y, I_t^X)$ is the function for the conditional distribution of Y_t given (I_t^Y, I_t^X). Let $Q_\tau^{Y,X}(\cdot \,|I_t^Y, I_t^X)$ be the τ-quantile of $F_Y(\cdot \,|I_t^Y, I_t^X)$, we can specify the above function for quantiles as follows:

$$H_0^{QC:X \nrightarrow Y}: Q_\tau^{Y,X}(Y_t|I_t^Y, I_t^X) = Q_\tau^Y(Y_t|I_t^Y), \text{a. s.} \quad \forall \quad \tau \in \mathrm{T},$$

where $\mathrm{T} \subset [0,1]$, and the τ-quantiles of Y_t must fulfill the following limitations:

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

Given an independent vector I_t, then $\Pr\{Y_t \leq Q\_\tau(Y_t|I_t)|I_t\} = E\{1[Y_t \leq Q_\tau(Y_t|I_t)]|I_t\}$, where $1[Y_t \leq y]$ represents that $Y_t \leq y$. Thus, we may define the null hypothesis for no-causality as:

$$E\{1[Y_t \leq Q_\tau^{Y,X}(Y_t|I_t^Y, I_t^X)]|I_t^Y, I_t^X\} = E\{1[Y_t \leq Q_\tau^Y(Y_t|I_t^Y)]|I_t^Y\}, \quad \text{a.s.} \quad \forall \quad \tau \in \mathrm{T},$$

where, by definition, the left-hand side is equal to the τ-quantile of $F_Y(\cdot \,|I_t^Y, I_t^X)$. The τ-conditional quantile, $Q_\tau^Y(\cdot \,|I_t^Y)$, is defined using a quantile parametric model $m(I_t^Y, \theta_0(\tau))$ that relies only on the restricted information set I_t^Y. The null hypothesis of non-causality may be restated as:

$$H_0^{X \nrightarrow Y}: E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))]|I_t^Y, I_t^X\} = \tau, \quad \text{a.s.} \quad \forall \quad \tau \in \mathrm{T}, \qquad\qquad 6$$

where $m(I_t^Y, \theta_0(\tau))$ refers to conditional quantile $Q_\tau^Y(\cdot \,|I_t^Y)$, for all $\tau \in \mathrm{T}$. Let Ψ be a matrix of $T \times n$ with components $\psi_{i,j} = \Psi_{\tau_j}\left(Y_i - m\left(I_i^Y, \theta_T(\tau_j)\right)\right)$, where $\Psi_{\tau_j}(\varepsilon) := 1(\varepsilon \leq 0) - \tau_j$. Then, following [28], we utilize the test statistics as follows:

$$S_T = \frac{1}{Tn}\sum_{j=1}^{n}|\psi_{\cdot j}' \boldsymbol{W} \psi_{\cdot j}|, \qquad\qquad 7$$

where $\boldsymbol{W}$ represents $T \times T$ matrix with components $w_{t,s} = \exp[-0.5(I_t - I_s)^2]$, $\psi_{\cdot j}'$ represents j-the respective column of Ψ. We utilize the S_T test by specifying three alternative quantile

autoregressive (QAR) frameworks $m(\cdot)$, for all $\tau \in \mathrm{T} \subset [0,1]$, under the null of no-causality as follows:

$$\text{QAR(1): } m^1\big(I_t^Y, \theta(\tau)\big) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \sigma_t \Phi_u^{-1}(\tau),$$
$$\text{QAR(2): } m^2\big(I_t^Y, \theta(\tau)\big) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \sigma_t \Phi_u^{-1}(\tau),$$
$$\text{QAR(3): } m^3\big(I_t^Y, \theta(\tau)\big) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \mu_3(\tau)Y_{t-2} + \mu_4(\tau)Y_{t-3} + \sigma_t \Phi_u^{-1}(\tau), \qquad 8$$

where we estimate parameter $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \mu_4(\tau), \sigma_t)'$ by maximum likelihood using an equally spaced quantile grid.

4. Data and descriptive statistics

We utilize the daily data spanning from November 2003 to May 2019. The sample span is selected based on the availability of the data. For example, the S&P global clean energy index (CEI) data is only available from November 2003. The CEI is a global weighted index based on the market capitalization of 30 large firms affiliated with CE-related business, for instance, CE production and CE equipment and technologies. In addition to CEI, we consider non-ferrous metals (NFM), Wilderhill clean energy (WHCE), and NYSE ARCA Technology index (NAT). The NFM index comprises of several industrial metals, for instance, aluminum, copper, lead, nickel, tin, and zinc, among others.[7] These metals represent a significant proportion of the Dow Jones non-ferrous metals index and LME non-ferrous metal index, which are widely accepted instruments to evaluate the investment performance of industrial metals, and as economic indicators [24,67]. NFM, which mainly represents global commodity markets, is largely employed in the CE production over recent years. WHCE tracks the clean energy sector, especially the businesses that signify technological innovation, CE, and importance to prevent

---

[7] For a robustness check, we have examined the disagreggate level analysis for some of the key metals in the non-ferrous metals index. The obtained outputs for individual metals are qualitatively similar to the estimates obtained between non-ferrous metals and clean energy indexes. However, the intensity of individual metals are relatively weaker than the aggregate non-ferrous metals index. For the sake of brevity, we chose not to report these estimates. However, these estimates are available from the corresponding author upon request.

global warming. NAT provides a benchmark to measure the relevance of technology-related firms over a comprehensive spectrum of businesses. We collected the data from Thomson Reuters DataStream. The logarithmic returns for each series at time t and $t-1$ as $r_{i,t} = \ln(P_{i,t}) - \ln(p_{i,t-1})$.

Figure 1 presents the progress of the price and returns series in our sample. Interestingly, all the assets exhibit an increasingly upward trend from 2004 to 2008 period and exhibit a swift decline over the global financial crisis of 2007-08 (GFC). Some key observations can be made for the post-GFC period. First, the NFM price increases significantly to the pre-GFC price level with simultaneous periods of rising and falling trends and eventually returning to the 2004 price levels towards the end of the sample. Second, WHCE and CEI further declined and remained persistently low till the end of our sample. Interestingly, NAT increased steadily over the post-GFC period and peaked towards the end of the sample.

Table 1. Preliminary statistics and stochastic properties.

	NFM	WHCE	CEI	NAT
Mean(%)	-1.504	-5.680	-2.940	10.237
SD	0.502	0.313	0.286	0.191
SR	-0.110	-0.470	-0.303	1.064
Max	0.252	0.145	0.181	0.101
Min	-0.227	-0.145	-0.150	-0.081
Skew	-0.162	-0.359	-0.539	-0.245
Kurt	9.050	8.325	17.052	8.302
J—B	5970.2***	4696.7***	32308.5***	4612.3***
Q(15)	20.1	27.2**	113.0***	38.7***
$Q^2(15)$	2427.3***	5857.6***	6695.9***	3999.3***
ARCH(15)	716.2***	1230.4***	1355.6***	1089.2***
ADF	-61.251***	-59.474***	-53.679***	-65.778***
PP	-61.237***	-59.450***	-53.363***	-66.125***
Pearson	1.000	0.619	0.573	0.576
Kendall	1.000	0.409	0.372	0.368
Spearman	1.000	0.571	0.523	0.518

Notes. We report annualized values of mean and standard deviation(SD). SR corresponds to the reward-to-risk measure [68], and J—B shows the test-statistics from the Jarque-Bera normality test. Q(15) and $Q^2(15)$ represent the test-statistics from the Ljung-Box test for serial correlation in returns and squared returns with 15 lags. ARCH(15) corresponds to the statistics from [69] test for homoscedasticity with 15 lags. The notations ***, **, and * show that the null hypothesis of normality, no autocorrelation, and homoscedasticity is rejected at 1%, 5%, and 10% threshold level, respectively.

Table 1 provides preliminary statistics. The average annualized return is negative for NFM (-1.50%), WHCE (-5.68%), and CEI (-2.94%), while it is positive for NAT (10.24%). The annualized SD ranges from 0.19 for NAT to 0.50 for NFM. Regarding reward-risk measure, NAT generates the highest return compared to the uncertainty of 1.06, while CEI gives the least reward of -0.47. All the series exhibit negative skewness, and the value of kurtosis is higher than 4, suggesting deviation from normality. The null-hypothesis of normality, independence, and homoscedasticity is rejected at a 1% significance level by the Jarque-Bera, Ljung-Box, and ARCH-LM test, respectively. This illustrates the importance and relevance of utilizing the quantile analysis that provides robust estimates to non-normal skewness.
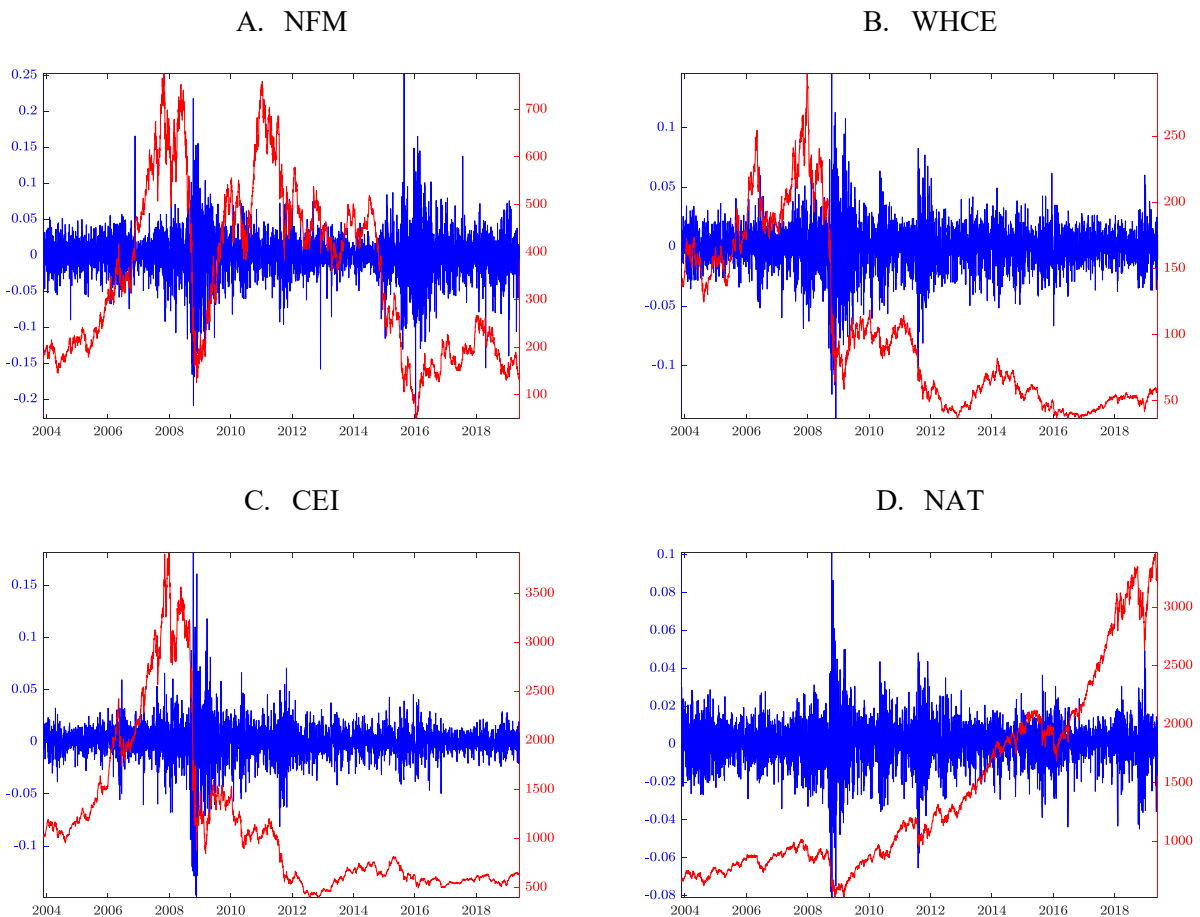

Figure 1. Development of price and return series.

Since the primary requirement for utilizing the CQC framework necessitates that the time series should be stationary, we test the stationarity by employing the augmented Dickey-Fuller [70] and Phillips-Perron (PP)[71] tests. The estimates from these tests indicate that the logarithmic difference is stationary.

5. Empirical analysis

5.1. Estimations of copula functions

To estimate the DCC-Student-t copula function, we follow a two-step method. The first step of this procedure comprises of estimation of the marginal model for returns. Table 2 shows the coefficients of the ARMA(1,0)-EGARCH(1,1). The lagged autoregressive coefficient is significant for all the clean energy assets, indicating previous returns are instantly manifested in current returns. The ARCH (α), GARCH (β), and leverage effect (ξ) components are highly significant, indicating that lagged squared shocks, persistency, and asymmetric shocks in conditional volatilities, respectively. The tail dependence, DoF, is highly significant, suggesting strong potential for connectedness in upper and lower quantiles. The results from diagnostic tests on residuals reveal no serial correlation or ARCH effects, suggesting the adequacy of the applied framework.

Table 2. Marginal distribution model

	NFM	WHCE	CEI	NAT
Panel A: Mean				
Ω	0.000	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	0.012	0.069***	0.145***	-0.035**
	(0.016)	(0.016)	(0.016)	(0.017)
Panel B: Variance				
κ	-0.043***	-0.154***	-0.096***	-0.218***
	(0.013)	(0.030)	(0.022)	(0.032)
β	0.994***	0.981***	0.989***	0.977***
	(0.002)	(0.004)	(0.002)	(0.004)
α	0.093***	0.158***	0.153***	0.120***
	(0.012)	(0.016)	(0.016)	(0.016)
ξ	-0.052***	-0.049***	-0.047***	-0.131***
	(0.007)	(0.009)	(0.009)	(0.012)
DoF	6.846***	12.406***	8.792***	8.216***
	(0.584)	(2.245)	(1.240)	(1.048)
Log(L)	8724.1	10486.3	11374.4	12401.9
AIC	-17434.1	-20958.6	-22734.9	-24789.8
Skewness	-0.267	-0.284	-0.169	-0.525
Kurtosis	7.009	3.670	3.981	4.239
J—B	2660.3	125.3	175.2	429.3
Q(15)	18.795	15.983	8.448	13.974
Q^2(15)	9.555	23.648*	21.897	14.433
ARCH(15)	9.430	21.696	21.012	13.432

Notes. This table presents the outcomes of the ARMA(1,0)-EGARCH(1,1) specification. Standard errors are presented in parenthesis. The significance level is indicated by ***, **, and * for 1%, 5%, and 10% level, respectively. The signs***, **, and * on diagnostics reflect the null-hypothesis rejection of normality, no serial correlation, and conditional homoscedasticity at the 1%, 5%, and 10% significance level respectively.

Based on marginal distribution estimates, we examine the connectedness dynamics among assets by utilizing copula. Table 3 presents the estimated parameters of the DCC-Student-t copula framework. The connectedness is moderate and highly significant among the assets. The dependence between NFM and assets stands at 0.486 (CEI), 0.502 (NAT), and 0.546 (WHCE). The DoF parameter is strongly significant, reflecting extreme comovements. The parameter α and β capturing the asymmetric effect and time-varying connectedness structure of conditional connectedness between assets are strongly significant.

Figure 2 presents the time-varying development of the connectedness parameter. It is worthwhile noting that extreme market conditions significantly impact the connectedness structure between assets peaking during the GFC and later during the European debt crisis of 2011-2012. This is in accordance with several studies in the field, examining the connectedness structure among commodities and clean energy assets [for example, 9,11,16,18,36,39,72]. However, the copulas consider the dependence structure between the assets as time-static, as it cannot include lags and measure only a general connectedness between the assets. Therefore, we utilize the CQC and quantile-based Granger-causality approaches, which provide an estimation of variations in dependence and causality across different quantiles and enable us to incorporate lag orders.

Table 3. Copula parameters

	WHCE	CEI	NAT
ρ	0.546***	0.486***	0.502***
	(0.002)	(0.003)	(0.002)
DoF	10.356***	10.300***	11.661***
	(1.722)	(1.938)	(2.223)
α	0.036***	0.028***	0.050***
	(0.006)	(0.004)	(0.008)
β	0.955***	0.965***	0.930***
	(0.009)	(0.006)	(0.013)
Log(L)	864.369	684.235	699.470
AIC	-1722.739	-1362.470	-1392.940

Notes. This table presents the parameters of time-varying DCC-Student-t copula parameters. Standard errors are presented in parenthesis. The significance level is indicated by ***, **, and * for 1%, 5%, and 10% level, respectively.
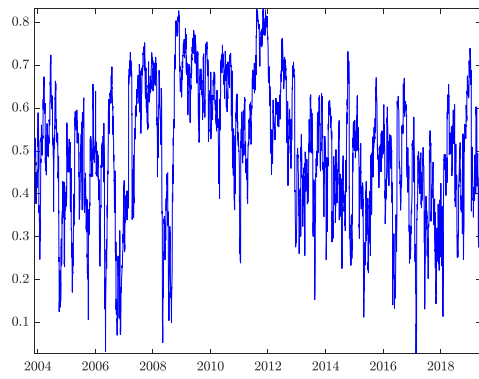
A.   WHCE   B.   CEI
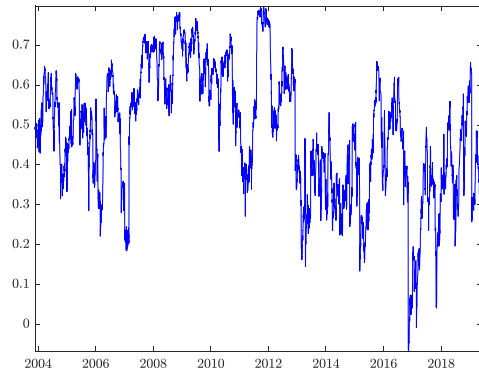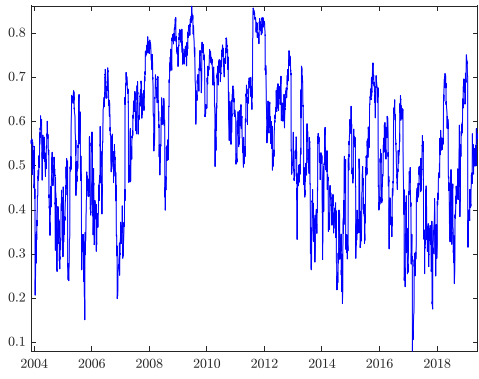
C. NAT

Figure 2. Development of connectedness parameter.

5.2. Cross-quantile correlation

In Figure 3 and Figure 4, we show the cross-quantile correlation (CQC) to/from clean energy from/to NFM for four different lags. To provide the statistical significance of predictability, we utilize the Box-Ljung test, and all the insignificant estimates are replaced as zeros. In each of the heatmap in Figure 3, the horizontal and vertical axis corresponds to the quantiles of NFM and clean assets, respectively. Similarly, for each heatmap in Figure 4, the horizontal and vertical axis corresponds to the quantiles of clean energy assets and NFM, respectively. The magnitude (positive/negative dependence) is displayed through the color scale from red (highly positive) through green (uncorrelated) to blue (highly negative).

In the case NFM and WHCE at lag 1 in Figure 3, we observe positive influence of NFM on WHCE when both series are in the lower quantiles. Specifically, we observe strong positive influence on WHCE from NFM when the NFM is in lower quantiles and WHCE is in the lower to middle quantile. This outcome indicates that when the return series of NFM exhibit downward movement (extreme market conditions), NFM positively influences the WHCE. In general, NFM represents the health of the global commodity market. A positive development in the NFM index suggests an expansion of the global economy, and good global economic health triggers investment in the clean energy sector. So, the positive link between NFM and WHCE during a bearish market condition indicates that both the stocks become less attractive to the investors. Also, during the downturn of the commodity market, CE firms reap the benefit most. Furthermore, NFM has a negative influence on WHCE when NFM is in the upper quantile, and WHCE is in the lower quantile. This result is expected as due to the intensive utilization of NFMs in CE production and CE technologies and equipment, an upward price shock in NFMs should negatively impact the clean energy indices. These effects between the two series

deteriorate but persist over the one week (lag 5), month (lag 22), and a quarter (lag 66). So, in the long-term, an upward price shock may have detrimental effects on clean energy firms. However, we do not detect significant spillover in median or upper quantiles among NFM and WHCE. This signifies the importance and relevance of utilizing the cross-quantilogram approach in evaluating the dependence among the NFM and the clean energy assets as the utilization of mean-based approaches only consider information in the means of the distribution. In this regard, these approaches ignores significant information linkage in the tails of the distribution or during extreme market conditions.

In the case of NFM and CEI, we observe strong positive dependence exhibiting from NFM on CEI. The directional predictability from NFM to CEI indicate that the NFM is influencing CEI throughout the entire distribution. Our findings indicate that the NFM impact on CEI is stronger at the same quantile level (for instance, $0.05{:}\,0.05, 0.25{:}\,0.25, 0.9{:}\,0.9$) but the interconnectedness is insignificant in opposite quantiles (for instance, $0.25{:}\,0.75, 0.75{:}\,0.25$). Furthermore, with the increase in lag length, although there is no median-to-median dependence, we report strong tail dependence between assets during the extreme market condition. The positive dependence between NFM and CEI could be due to smaller selection of focused energy stocks in the domain of clean energy production, equipment, and technology firms as opposed to WHCE comprising of 37 stocks in the areas of energy conversion (21% sectoral weight), power delivery and conservation (21% sectoral weight), greener utilities (11% sectoral weight), energy storage (21% sectoral weight) and cleaner fuels (5% sector weight).

For the CQC between NFM and NAT, we report strong tail dependence at lag 1. This indicates that the NFM positively influence the NAT when NFM is in the lower quantile of the distribution. However, the magnitude deteriorates over the one week (lag 5) and month (lag 22).

Furthermore, we observe relatively weak dependence over the quarter (lag 66). In addition, we find that the dependence between NFM and NAT is moderately negative when NFM is in the upper quantile of the return distribution. This outcome strengthens over the one-week period (lag 5). Nevertheless, over the increased lags (lag 22 and 66), this relationship weakens, suggesting a weakening of connectedness structure with time. This indicates that the upward price shocks in NFM have an adverse impact on the technology stocks due to the increase in input costs. These findings also suggest that we may expect a negative dependence structure and attain diversification benefits when the NFMs prices tend to exhibit an upward trend. These findings are in line with the [16] as they report gold and crude oil as weak safe-havens for clean energy stocks.

Figure 4 presents the mutual directionality from clean energy assets to NFM. Similar to the findings reported for CQC from NFM to clean energy assets, the estimates from Figure 4 indicate strong evidence of tail dependence and extreme co-movements characterize the series. However, the intensity of predictability is relatively weaker from clean energy asset to the NFM. This further suffice the flow of directionality from NFM to the clean energy assets. It is worthwhile noting that all the clean assets show negative dependence with NFM when the clean assets are in the lower tail, and NFM is in the upper tail (for example, $0.05: 0.95, 0.10: 0.90$). Furthermore, this effect tends to persist over one week (lag 5) and month (lag 22) but dissipate over the longer lag length (lag 66). This is in accordance with the findings of [38] as they report the asymmetric impact of positive and negative shocks on the clean energy assets. The finding suggests a possibility of a strong safe-haven [15] role of NFM for clean assets as there is evidence of predictability from clean energy stocks to NFM in the lower quantiles and the sign of predictability is negative.
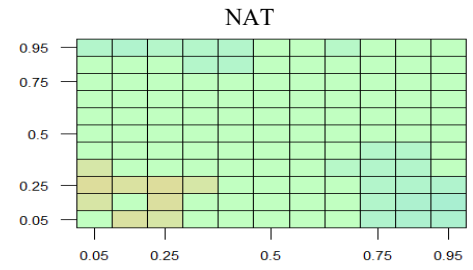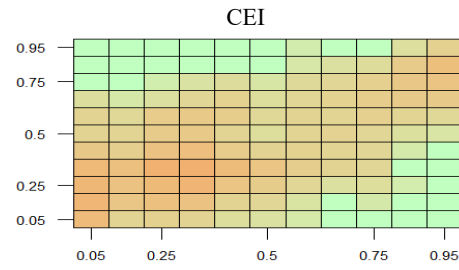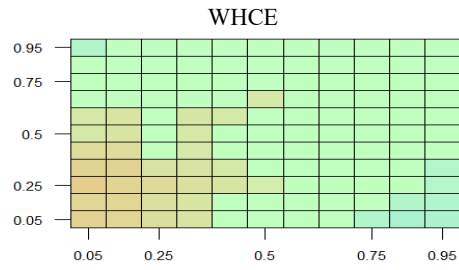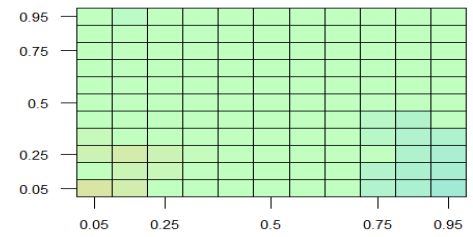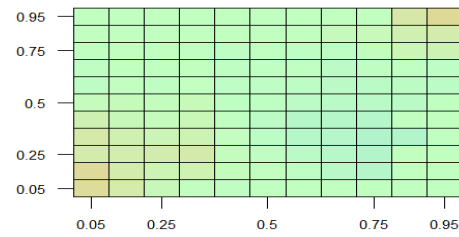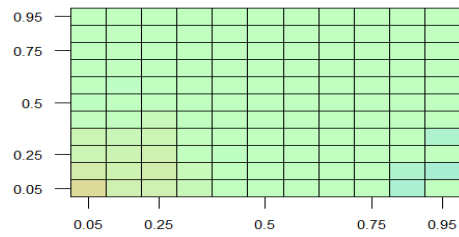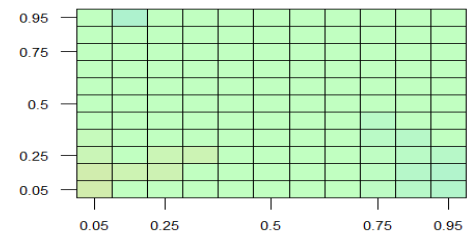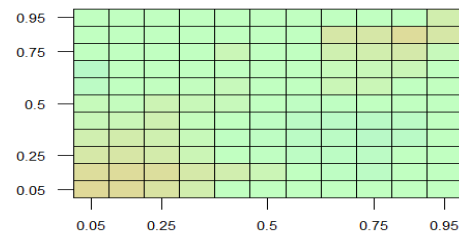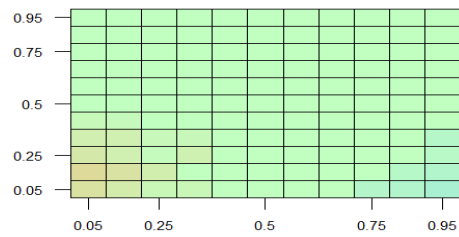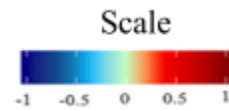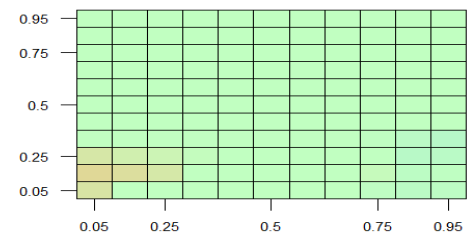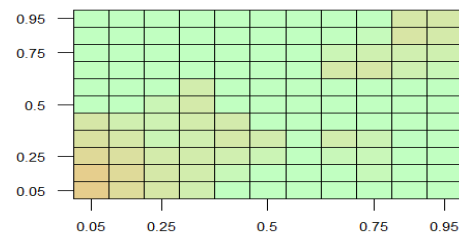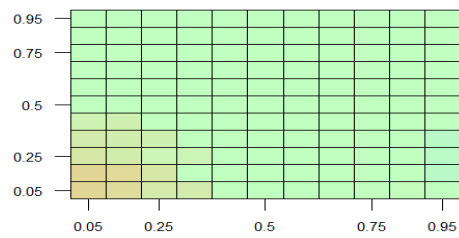
Figure 3. Cross-quantilogram plot from NFM to clean energy assets. Notes. The CQC is evaluated by utilizing Eq. (4) and the statistical significance is calculated by utilizing Ljung-Box test as specified in Eq.(5). We set the insignificant correlation to zero and report only the significant correlation. The lags correspond to daily, weekly, monthly, and quarterly lags, respectively. The scale represents the intensity and direction of relationship.

WHCE   CEI   NAT
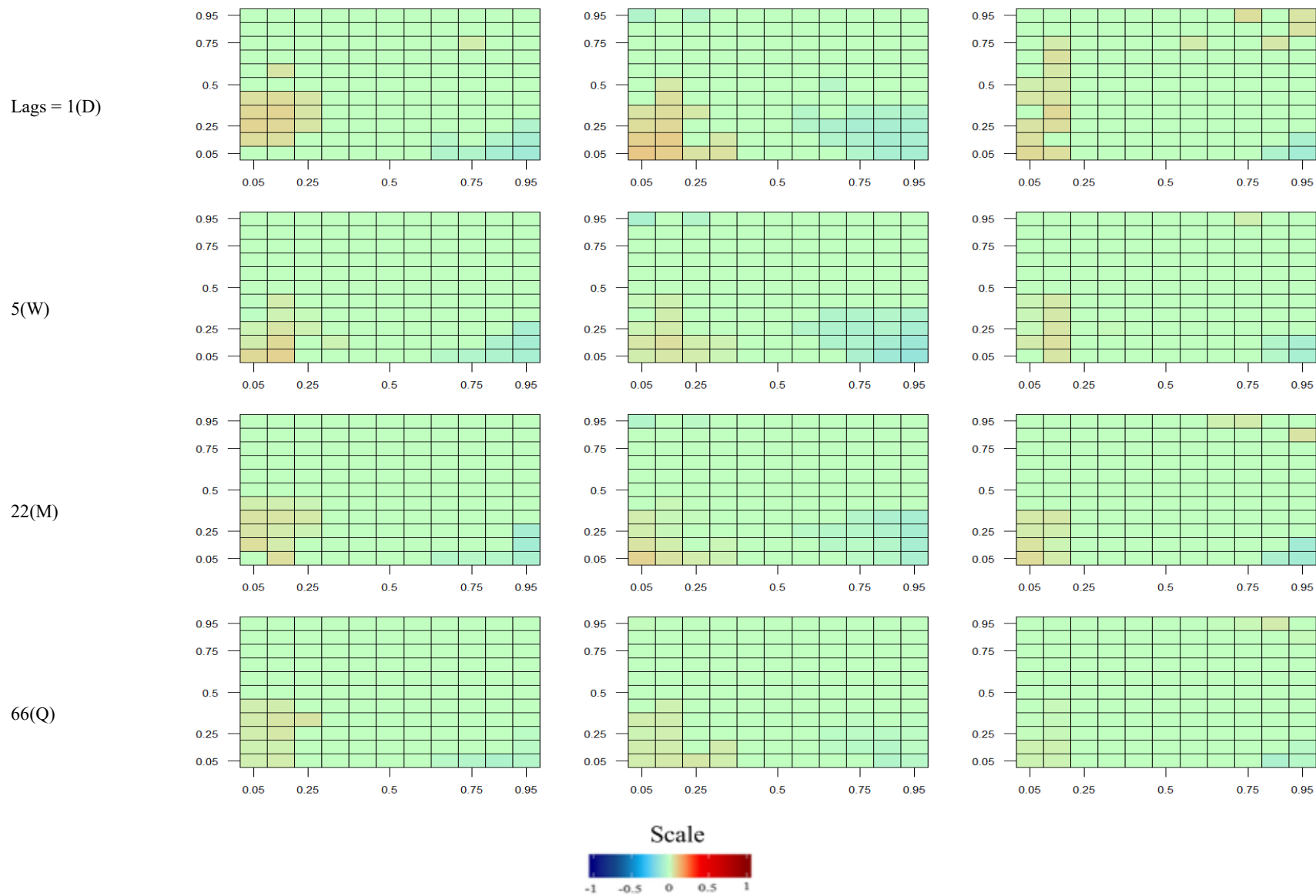
Figure 4. Cross-quantilogram plots from the clean energy assets to NFM. Also, see notes Figure 3.
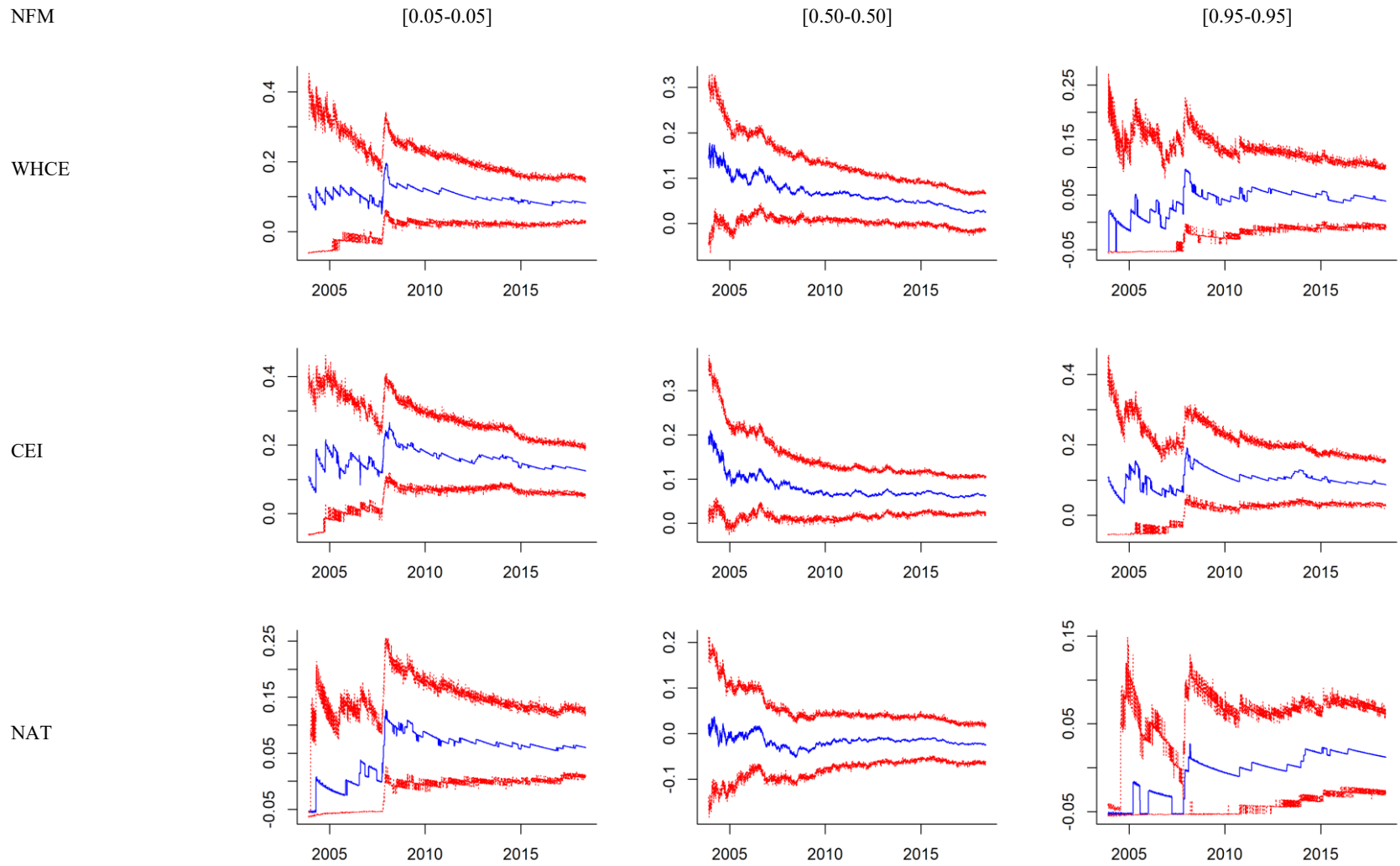
Figure 5. Cross-quantilogram correlation among NFM and CE stocks by utilizing the recursive subsampling technique. Notes. We set 252-days as the length of the first window that moves forward on a daily basis. The columns from left-to-right present recursive CQC estimates when both return distributions are at the 5% (lower quantile), 50% (median quantile), and 95% (upper quantile) threshold levels, respectively. The blue lines represent the time-varying CQCs in the recursive subsamples, while the red lines represent no-predictability of the null hypothesis at 95% confidence interval, which is derived from a bootstrap procedure of 1000 iterations at each point of the recursive subsample.

The CQC heatmaps provide an overview of quantile connectedness between the underlying assets in a time-invariant scenario. Therefore, we utilize the recursive approximations to evaluate any potential time-varying connectedness shifts across different cross-quantiles. In this study, we use 252-days length of the first window for the recursive subsample estimation process. Specifically, we evaluate the cross-quantile dependence for the first window period, then re-estimate the CQC by adding one day to the window-length and continued this procedure until the end of the sample. Figure 5 shows the estimates when both series are at 5% (lower quantile), 50% (median quantile), and 95% (upper quantile). The blue lines represent the time-varying cross-quantile correlations from recursive estimations, while the red lines represent the 95% interval for rejection of the null hypothesis, which is approximated from a 1000-bootstrap iteration technique at each point of the recursive subsample.

From the lower quantile (0.05-0.05) of recursive CQC plots, we can observe a sharp increase in the CQC during the GFC. The abrupt shift in dependence is indicative of a potential structural break in the connectedness structure. With the outbreak of GFC, we find an increase in the connectedness, which exhibits a declining spree over the post-GFC period. Regarding the NFM dependence with NAT, we find that the correlation is slightly negative but has an inclining spree until the advent of GFC. The level of connectedness increases during GFC and becomes relatively stable over time. Overall, these results indicate that financial turmoil contributes positively to the dependence over the lower quantiles. This increase may be attributed to the increased interdependence among the financial and commodity markets due to higher uncertainty perceived by the investors in the financial products alone over periods of crisis. The finding of increasing connectedness among NFM and other asset classes post-crisis is in line with the study by [73] demonstrating a higher degree of integration between commodity and financial market

after the GFC. Furthermore, the dependence among the NFM and clean energy indices did not decline significantly over the post-GFC period, which may be attributed to the increased investment in the clean energy sector [29].

In terms of median quantile (0.50-0.50) dependence of recursive subsamples, we find a lack of median-to-median interdependence indicative from the blue line is almost flat around zero for NAT. The recursive subsampling CQC plot of CEI indicates that the blue line flattened around 0.1, indicating a lower degree of interdependence, whereas the CQC is downward trended between NFM and WHCE, indicating that the dependence among these assets approximates to neutrality. These findings are in accordance with the time-static CQC reported in Figure 3 and Figure 4, which indicate no interdependence among the assets in the median quantiles, except for CEI.

For the upper quantile (0.95-0.95), we observe a structural break with the advent of GFC for the three clean energy assets. The CQC of NAT primarily fluctuates around zero, indicating neutrality hypothesis and a lack of upper quantile dependence, whereas the CQC of CEI significantly increases during the GFC and overtime decline to 0.1 over the post-GFC period. On the other hand, the recursive CQC of WHCE partially increased until the outbreak of GFC with a persistent decline in dependence over the post-crisis period. These findings are in accordance with the findings reported in [16,18] indicating asymmetric information connectedness of positive and negative shocks among NFM and clean energy assets.

5.3. Causality in quantiles

The copula and CQC approach provide an overview of static and time-varying connectedness structure. However, they do not provide an indication of a causal relationship. Therefore,

following [28], we utilize the quantile Granger-causality test to evaluate cause and effect relationships across various quantiles. By using this method, we can differentiate between causality impacting the tails and median of the distribution.

Table 4 and Table 5 provide the p-values from the quantile causality test in Eq.(7) to/from NF metals from/to clean energy assets by estimating three different specifications of QAR in Eq.(8) with the null of neutral quantile causality in Eq.(6). The S_T test is implemented over 19 equally spaced quantile grids T = [0.05; 0.95]. Following [28,74], we utilize a size of $b = [kT^{2/5}]$ for subsample, where $k = 5$ is a constant parameter, $T = 3902$, and $[\cdot]$ is the integer part of a number, which equals to 137.

Table 4. Quantile Granger-causality to NF metals

τ	$\Delta WHCE_t$ to ΔNFM_t			ΔCEI_t to ΔNFM_t			ΔNAT_t to ΔNFM_t		
$I_t^{\Delta NFM_t}$	1	2	3	1	2	3	1	2	3
[0.05;0.95]	0.093	**0.000**	**0.000**	0.892	**0.000**	**0.000**	0.922	**0.000**	**0.000**
0.05	0.526	0.022	0.022	0.574	0.022	0.022	0.579	0.022	0.022
0.10	0.564	**0.000**	**0.000**	0.769	**0.000**	**0.000**	0.768	**0.000**	**0.000**
0.15	0.642	**0.000**	**0.000**	0.874	**0.000**	**0.000**	0.875	**0.000**	**0.000**
0.20	0.485	**0.000**	**0.000**	0.911	**0.000**	**0.000**	0.916	**0.000**	**0.000**
0.25	0.250	**0.000**	**0.000**	0.901	**0.000**	**0.000**	0.918	**0.000**	**0.000**
0.30	0.108	**0.000**	**0.000**	0.911	**0.000**	**0.000**	0.920	**0.000**	**0.000**
0.35	0.126	**0.000**	**0.000**	0.789	**0.000**	**0.000**	0.852	**0.000**	**0.000**
0.40	0.109	**0.000**	**0.000**	0.617	**0.000**	**0.000**	0.674	**0.000**	**0.000**
0.45	0.407	**0.000**	**0.000**	0.489	**0.000**	**0.000**	0.513	**0.000**	**0.000**
0.50	0.357	**0.003**	0.011	0.343	**0.003**	0.011	0.359	**0.003**	0.011
0.55	0.239	**0.004**	**0.003**	0.461	**0.004**	**0.003**	0.538	**0.004**	**0.003**
0.60	0.131	**0.000**	**0.000**	0.638	**0.000**	**0.000**	0.852	**0.000**	**0.000**
0.65	0.084	**0.000**	**0.000**	0.698	**0.000**	**0.000**	0.943	**0.000**	**0.000**
0.70	0.078	**0.000**	**0.000**	0.808	**0.000**	**0.000**	0.894	**0.000**	**0.000**
0.75	0.084	**0.000**	**0.000**	0.857	**0.000**	**0.000**	0.907	**0.000**	**0.000**
0.80	0.147	**0.000**	**0.000**	0.883	**0.000**	**0.000**	0.904	**0.000**	**0.000**
0.85	0.450	**0.000**	**0.000**	0.889	**0.000**	**0.000**	0.907	**0.000**	**0.000**
0.90	0.454	**0.000**	**0.000**	0.771	**0.000**	**0.000**	0.758	**0.000**	**0.000**
0.95	0.323	**0.000**	**0.000**	0.320	**0.000**	**0.000**	0.320	**0.000**	**0.000**

Notes. The table reports the obtained p-values from the quantile causality test in Eq.(7). $\Delta WHCE_t$, ΔNFM_t, ΔCEI_t, and ΔNAT_t

are the logarithmic returns of WHCE, NFM, CEI, and NAT, respectively. $I_t^{\Delta NFM_t}$ represents the lags of the explained variable, ΔNFM_t, with the null of no causality in Eq.(6).

The p-values of the quantile causality test from clean energy assets to NFM are reported in Table 4. Considering all quantiles for $I_t^{\Delta NFM_t} = 1$, we find no Granger-causality from the clean energy assets to NFM at a 1% significance level. However, with the increase in the number of lags, $I_t^{\Delta NFM_t} = 2$ and $I_t^{\Delta NFM_t} = 3$, we find Granger-causality running from the clean energy assets to NFM at the 1% significance level. Two key observations can be made regarding these findings. First, the presence of dependence does not essentially indicate causality. Second, the causal relationship is sensitive to the selection of the lag length.

The p-values of the quantile causality test from NFM to clean energy assets are reported in Table 5. For the $I_t^{\Delta WHCE} = 1$, we find evidence that variations in NFM Granger-cause the changes in WHCE at the 1% threshold level when undertaking all quantiles $[0.05; 0.95]$ of the distribution. Furthermore, we find significant p-values around the median-level, $\tau = \{0.30, 0.35, 0.40\}$ and $\tau = \{0.60, 0.65, 0.70\}$, indicating that there is Granger-causality from ΔNFM_t to $\Delta WHCE_t$. However, the p-values of the test at lag 1 is insignificant for ΔCEI and ΔNAT, indicating no Granger-causality from NFM to these assets. In terms of higher lag orders, we observe the flow of causality from ΔNFM to the clean energy assets for nearly all the quantiles at the 1% threshold level. An increase in NFM, in general, represents a boom in the commodity market triggered by the expansion in the global economy. Investors who are looking forward to long-term sustainable growth with environmental responsibility would prefer to invest in clean energy stocks instead of sectors that have higher carbon footprints. The investment in fossil fuel companies is risky as global action on emissions is becoming tougher. With the global investment focus changing from fossil fuel to clean and renewables, an upsurge in clean energy

stock price necessitates the demand for metals and minerals used for clean energy production, which causes a growth in NFM. These findings are in-line with [13,18] as they report bidirectional and symmetric effect of clean energy assets with commodities.

Table 5.Granger-causality to clean energy assets

τ	ΔNFM_t to $\Delta WHCE_t$			ΔNFM_t to ΔCEI_t			ΔNFM_t to ΔNAT_t		
	$I_t^{\Delta WHCE}=1$	$I_t^{\Delta WHCE}=2$	$I_t^{\Delta WHCE}=3$	$I_t^{\Delta CEI}=1$	$I_t^{\Delta CEI}=2$	$I_t^{\Delta CEI}=3$	$I_t^{\Delta NAT}=1$	$I_t^{\Delta NAT}=2$	$I_t^{\Delta NAT}=3$
[0.05; 0.95]	**0.003**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.984	**0.000**	**0.000**
0.05	0.728	0.254	0.254	0.959	**0.000**	**0.000**	0.741	0.475	0.378
0.10	0.831	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.944	**0.000**	**0.000**
0.15	0.670	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.949	**0.000**	**0.000**
0.20	0.298	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.937	**0.000**	**0.000**
0.25	0.048	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.943	**0.000**	**0.000**
0.30	**0.001**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.951	**0.000**	**0.000**
0.35	**0.000**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.885	**0.000**	**0.000**
0.40	**0.002**	**0.000**	**0.000**	0.710	**0.000**	**0.000**	0.731	**0.000**	**0.000**
0.45	0.077	**0.000**	**0.000**	0.272	**0.000**	**0.000**	0.581	**0.000**	**0.000**
0.50	0.357	**0.000**	**0.000**	0.577	**0.000**	**0.000**	0.508	**0.000**	**0.000**
0.55	0.100	0.261	0.318	0.247	0.044	0.029	0.534	0.212	0.288
0.60	**0.005**	**0.001**	**0.001**	0.732	**0.000**	**0.000**	0.746	**0.007**	**0.001**
0.65	**0.001**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.935	**0.000**	**0.000**
0.70	**0.000**	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.980	**0.000**	**0.000**
0.75	0.041	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.986	**0.000**	**0.000**
0.80	0.314	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.978	**0.000**	**0.000**
0.85	0.548	**0.000**	**0.000**	1.000	**0.000**	**0.000**	0.961	**0.000**	**0.000**
0.90	0.597	**0.000**	**0.000**	0.967	**0.000**	**0.000**	0.881	**0.000**	**0.000**
0.95	0.285	**0.000**	**0.000**	0.822	**0.000**	**0.000**	0.501	**0.000**	**0.000**

Notes. The table reports the obtained p-values from the quantile causality test in Eq.(7). Also, see notes Table 4.

Conclusion and policy implication

Increased climate risk and energy security issues have emerged as the primary driving forces in transforming the landscape of the global energy sector towards clean energy or renewables sources. The transition towards clean energy depends on some technologies whose success relies on the availability of some strategic non-ferrous metals. In this paper, we evaluate cross-quantile dependence and causality between non-ferrous metals and clean energy assets. We assess the

time-varying asymmetric dependence among the assets using copulas. Based on the copula estimates, we employ the cross-quantilogram analysis to evaluate the time-invariant and time-varying asymmetric dependence across various quantiles. Finally, we utilize the Granger-causality in quantiles to examine the flow of causal relationships.

Our findings indicate that the dependence among non-ferrous metals and clean energy assets is time-varying and asymmetric with potential for extreme co-movements, indicating that the conditional dependence among the assets strengthens during the turmoil period but weakens over the periods of economic prosperity. The analysis from the CQC analysis indeed affirms this hypothesis. Furthermore, we find that the extreme market conditions tend to strengthen the spillover among the assets as reported by strong dependence in the lower quantiles of the return distributions; the connectedness structure deteriorates but persists in longer lags. In contrast, our findings indicate insignificant or weak dependence in the top quantile of the return distributions, indicating deterioration of connectedness structure during phases of financial and economic prosperity. Moreover, the recursive CQC affirms this asymmetric connectedness among the non-ferrous metals and clean energy assets as the lower quantiles exhibit a strong dependence as opposed to the connectedness in the median and top quantiles, indicating a strong safe-haven role of non-ferrous metals. Furthermore, the dependence among the assets significantly increased during the GFC, suggesting strong co-movement during periods of turmoil. The analysis from the Granger-causality in quantiles indicates the insignificant causal relationship among non-ferrous metals and clean energy assets, except for Wilderhill clean energy. However, we find evidence of bidirectional causality in higher lag orders among the assets over nearly all quantiles of the return distributions.

Our empirical findings are insightful and have pertinent implications for policymakers and market participants. The following phenomena can explain the bidirectional linkage between NFM and clean energy stock indices. The focus of global investors has now shifted towards non-fossil fuel because the investment in fossil fuel companies is becoming risky as global action on emissions gets tougher, which may create stranded assets in the coal, oil, and gas sector. Our findings have significant implications for market participants given that the growing concerns about energy security and climate change encourage financial institutions to invest in clean energy industries. Hence, the results are of paramount importance to investors who intend to decarbonize their portfolio and swap dirty assets (e.g., oil) for clean energy equities. It is also worth mentioning that proper knowledge on how investors participating in alternative energy markets can hedge their investment is essential for risk management. To this end, our analysis indicate that the linkage between stock and commodity prices would be useful for portfolio managers seeking to attain diversification benefits and investment protection against downside risk. As renewable energy stocks have emerged as a new asset class, these stocks can be highly volatile [16]. Thus, exact information on how the risk is linked to clean energy assets could play a pivotal role in outlining sustainable business strategies and designing optimal portfolios. This may further perturb the access to capital, impacting the share price of fossil fuel producers adversely. Given that investments in renewable energy have positive environmental and socio-economic impacts that potentially help ensure a certain degree of sustainability, the results of our empirical study have important implications for institutional investors who make attempts to precisely detect the clean energy market risk through proper financial modeling. Many institutional investors like sovereign wealth funds, pension funds, faith-based organizations, philanthropic foundations, and educational institutions have commitments to divest from

traditional fuel to clean energy sources. The magnitude of divestment has witnessed an exponential growth of 11,900 percent in the last four years. This increasing thrust of investment from fossil fuel to the clean energy sector explodes the demand for NFM encompassing certain strategic minerals and metals, which are highly critical for clean energy production. This means that NFM is certainly going to emerge as an attractive investment option in the investors' fraternity. However, there is a downside to an increase in demand for certain critical metals that are required for a clean energy transition. The majority of these metals are available in certain geographical locations in the world, which are highly politically sensitive. So, a physical withholding or a possible cartelization of these critical metals may increase the price of these strategic metals, which may dampen the prospect of clean energy projects entirely. Therefore, the investors should make a careful decision while selecting non-ferrous metals as the best safe haven creating their long-term investment portfolio. Apart from the investors, the outcomes of this study are of great interest to policymakers as it would help them to identify the window of opportunity for policy interventions and boost public investment to enhance the economic viability of clean energy projects. Additionally, the findings have implications to researchers and academics as well. For instance, researchers are always in search of precise asset pricing models and finding such processes often requires better understanding of how financial markets are interconnected. Therefore, the results could enable them to precisely model the time-varying volatility of clean energy stocks. Moreover, the presence of asymmetric linkage between nonferrous metals and stock markets would shift the academics from linear modeling to the adoption of non-linear approaches. Hence, this empirical work could be useful for researchers in estimating market risk associated with green assets.

References

[1]   Grandell L, Lehtilä A, Kivinen M, Koljonen T, Kihlman S, Lauri LS. Role of critical metals in the future markets of clean energy technologies. Renew Energy 2016;95:53–62. doi:10.1016/j.renene.2016.03.102.

[2]   Masson-Delmotte V, Zhai P, Pörtner H-O, Roberts D, Skea J, Shukla PR, et al. IPCC, 2018: Global warming of 1.5° C. World Meteorol Organ Geneva, Switzerland 2018:32.

[3]   Masson-Delmotte V, Zhai P, Pörtner H-O, Roberts D, Skea J, Shukla PR, et al. IPCC, 2018: Summary for Policymakers. World Meteorol Organ Geneva, Switzerland 2018:32.

[4]   IEA. Global Energy & CO2 Status Report. Int Energy Agency 2018. https://www.iea.org/geco/emissions/ (accessed October 10, 2019).

[5]   Advisors A. The Global Fossil Fuel Divestment and Clean Energy Investment Movement 2018 Report. 2018.

[6]   Birol F. Renewables 2018. Int Energy Agency 2018. https://www.iea.org/renewables2018/?utm_content=buffer0d761&utm_medium=social&utm_source=linkedin.com&utm_campaign=buffer&utm_content=buffer0d761&utm_medium=social&utm_source=linkedin.com&utm_campaign=buffer (accessed October 10, 2019).

[7]   McCrone A, Moslener U, D'Estais F. Global trends in renewable energy investment report 2018. 2018.

[8]   Global EV Outlook 2019. Global EV Outlook 2019. Int Energy Agency 2019. https://www.iea.org/publications/reports/globalevoutlook2019/ (accessed October 10, 2019).

[9]   Ahmad W, Sadorsky P, Sharma A. Optimal hedge ratios for clean energy equities. Econ Model 2018;72:278–95. doi:10.1016/j.econmod.2018.02.008.

[10]   Ortas E, Moneva JM. The Clean Techs equity indexes at stake: Risk and return dynamics analysis. Energy 2013;57:259–69. doi:10.1016/j.energy.2013.03.046.

[11]   Maghyereh AI, Awartani B, Abdoh H. The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. Energy 2019:895–913. doi:10.1016/j.energy.2018.12.039.

[12]   Ahmad W. On the dynamic dependence and investment performance of crude oil and clean energy stocks. Res Int Bus Financ 2017;42:376–89. doi:10.1016/j.ribaf.2017.07.140.

[13]   Dutta A, Bouri E, Roubaud D. Nonlinear relationships amongst the implied volatilities of crude oil and precious metals. Resour Policy 2019;61:473–8. doi:10.1016/j.resourpol.2018.04.009.

[14] Rezec M, Scholtens B. Financing energy transformation: The role of renewable energy equity indices. Int J Green Energy 2017;14:368–78. doi:10.1080/15435075.2016.1261704.

[15] Shahzad SJH, Bouri E, Roubaud D, Kristoufek L, Lucey B. Is Bitcoin a better safe-haven investment than gold and commodities? Int Rev Financ Anal 2019;63:322–30. doi:10.1016/j.irfa.2019.01.002.

[16] Elie B, Naji J, Dutta A, Uddin GS. Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. Energy 2019:544–53. doi:10.1016/j.energy.2019.04.155.

[17] Reboredo JC, Rivera-Castro MA, Ugolini A. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. Energy Econ 2017;61:241–52. doi:10.1016/j.eneco.2016.10.015.

[18] Reboredo JC, Ugolini A. The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach. Energy Econ 2018;76:136–52. doi:10.1016/j.eneco.2018.10.012.

[19] Reboredo JC. Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Econ 2015;48:32–45. doi:10.1016/j.eneco.2014.12.009.

[20] UKERC, Speirs J, Gross R, Contestabile M, Candelise C. Materials availability for low-carbon technologies : An assessment of the evidence 2014:1–48.

[21] Vidal O, Goffé B, Arndt N. Metals for a low-carbon society. Nat Geosci 2013;6:894–6. doi:10.1038/ngeo1993.

[22] Mohr SH, Mudd GM, Giurco D. Lithium resources and production: Critical assessment and global projections. Minerals 2012;2:65–84. doi:10.3390/min2010065.

[23] Teske S, Florin N, Dominish E, Giurco D. Renewable Energy and Deep-Sea Mining: Supply, Demand and Scenarios. 2016.

[24] Ciner C, Lucey B, Yarovaya L. Spillovers, integration and causality in LME non-ferrous metal markets. J Commod Mark 2018. doi:10.1016/j.jcomm.2018.10.001.

[25] Agyei-Ampomah S, Gounopoulos D, Mazouz K. Does gold offer a better protection against losses in sovereign debt bonds than other metals? vol. 40. 2014. doi:10.1016/j.jbankfin.2013.11.014.

[26] Delatte AL, Lopez C. Commodity and equity markets: Some stylized facts from a copula approach. vol. 37. 2013. doi:10.1016/j.jbankfin.2013.06.012.

[27] Jacobsen B, Marshall BR, Visaltanachoti N. Stock market predictability and industrial metal returns. Manage Sci 2019;65:3026–42. doi:10.1287/mnsc.2017.2933.

[28] Troster V. Testing for Granger-causality in quantiles. Econom Rev 2018;37:850–66.

doi:10.1080/07474938.2016.1172400.

[29]   Uddin GS, Rahman ML, Hedström A, Ahmed A. Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. Energy Econ 2019;80:743–59. doi:10.1016/j.eneco.2019.02.014.

[30]   Dutta A. Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. J Clean Prod 2017;164:1157–66. doi:10.1016/j.jclepro.2017.07.050.

[31]   Sun C, Ding D, Fang X, Zhang H, Li J. How do fossil energy prices affect the stock prices of new energy companies? Evidence from Divisia energy price index in China's market. Energy 2019:637–45. doi:10.1016/j.energy.2018.12.032.

[32]   Wen X, Guo Y, Wei Y, Huang D. How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Econ 2014;41:63–75. doi:10.1016/j.eneco.2013.10.018.

[33]   Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ 2012;34:248–55. doi:10.1016/j.eneco.2011.03.006.

[34]   Bondia R, Ghosh S, Kanjilal K. International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy 2016;101:558–65. doi:10.1016/j.energy.2016.02.031.

[35]   Broadstock DC, Cao H, Zhang D. Oil shocks and their impact on energy related stocks in China. Energy Econ 2012;34:1888–95. doi:10.1016/j.eneco.2012.08.008.

[36]   Managi S, Okimoto T. Does the price of oil interact with clean energy prices in the stock market? Japan World Econ 2013;27:1–9. doi:10.1016/j.japwor.2013.03.003.

[37]   Henriques I, Sadorsky P. Oil prices and the stock prices of alternative energy companies. Energy Econ 2008;30:998–1010. doi:10.1016/j.eneco.2007.11.001.

[38]   Kocaarslan B, Soytas U. Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis. Energy Reports 2019;5:117–25. doi:10.1016/j.egyr.2019.01.002.

[39]   Kumar SS, Managi S, Matsuda A. Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. Energy Econ 2012;34:215–26. doi:10.1016/j.eneco.2011.03.002.

[40]   Urom C, Anochiwa L, Yuni D, Idume G. Asymmetric linkages among precious metals, global equity and bond yields: The role of volatility and business cycle factors. J Econ Asymmetries 2019;20. doi:10.1016/j.jeca.2019.e00120.

[41]   Bams D, Blanchard G, Honarvar I, Lehnert T. Does oil and gold price uncertainty matter for the stock market? vol. 44. 2017. doi:10.1016/j.jempfin.2017.07.003.

[42] Baumöhl E, Lyócsa Š. Directional predictability from stock market sector indices to gold: A cross-quantilogram analysis. vol. 23. 2017. doi:10.1016/j.frl.2017.02.013.

[43] Shahzad SJH, Raza N, Shahbaz M, Ali A. Dependence of stock markets with gold and bonds under bullish and bearish market states. vol. 52. 2017. doi:10.1016/j.resourpol.2017.04.006.

[44] Iqbal J. Does gold hedge stock market, inflation and exchange rate risks? An econometric investigation. Int Rev Econ Financ 2017;48:1–17. doi:10.1016/j.iref.2016.11.005.

[45] Lucey BM, Li S. What precious metals act as safe havens, and when? Some US evidence. Appl Econ Lett 2015;22:35–45. doi:10.1080/13504851.2014.920471.

[46] Mensi W, Al-Yahyaee KH, Hoon Kang S. Time-varying volatility spillovers between stock and precious metal markets with portfolio implications. Resour Policy 2017;53:88–102. doi:10.1016/j.resourpol.2017.06.001.

[47] Nguyen C, Bhatti MI, Komorníková M, Komorník J. Gold price and stock markets nexus under mixed-copulas. Econ Model 2016;58:283–92. doi:10.1016/j.econmod.2016.05.024.

[48] Behmiri NB, Manera M. The role of outliers and oil price shocks on volatility of metal prices. vol. 46. 2015. doi:10.1016/j.resourpol.2015.09.004.

[49] Dutta A. Implied volatility linkages between the U.S. and emerging equity markets: A note. Glob Financ J 2018;35:138–46. doi:10.1016/j.gfj.2017.09.002.

[50] Dutta A. Impacts of oil volatility shocks on metal markets: A research note. Resour Policy 2018;55:9–19. doi:10.1016/j.resourpol.2017.09.003.

[51] Ewing BT, Malik F. Volatility transmission between gold and oil futures under structural breaks. vol. 25. 2013. doi:10.1016/j.iref.2012.06.008.

[52] Kanjilal K, Ghosh S. Dynamics of crude oil and gold price post 2008 global financial crisis – New evidence from threshold vector error-correction model. Resour Policy 2017;52:358–65. doi:10.1016/j.resourpol.2017.04.001.

[53] Kumar S. On the nonlinear relation between crude oil and gold. Resour Policy 2017;51:219–24. doi:10.1016/j.resourpol.2017.01.003.

[54] Dutta A. Impact of silver price uncertainty on solar energy firms. J Clean Prod 2019;225:1044–51. doi:10.1016/j.jclepro.2019.04.040.

[55] Todorova N, Worthington A, Souček M. Realized volatility spillovers in the non-ferrous metal futures market. Resour Policy 2014;39:21–31. doi:10.1016/j.resourpol.2013.10.008.

[56] Gil-Alana LA, Tripathy T. Modelling volatility persistence and asymmetry: A Study on selected Indian non-ferrous metals markets. Resour Policy 2014;41:31–9. doi:10.1016/j.resourpol.2014.02.004.

[57] Zhu X, Zhang H, Zhong M. Volatility forecasting in Chinese nonferrous metals futures market. Trans Nonferrous Met Soc China (English Ed 2017;27:1206–14. doi:10.1016/S1003-6326(17)60141-9.

[58] Zhu X, Zhang H, Zhong M. Volatility forecasting using high frequency data: The role of after-hours information and leverage effects. Resour Policy 2017;54:58–70. doi:10.1016/j.resourpol.2017.09.006.

[59] Zhong M, He R, Chen J, Huang J. Time-varying effects of international nonferrous metal price shocks on China's industrial economy. Phys A Stat Mech Its Appl 2019;528. doi:10.1016/j.physa.2019.121299.

[60] Beckmann J, Czudaj R. The forward pricing function of industrial metal futures - evidence from cointegration and smooth transition regression analysis. Int Rev Appl Econ 2013;27:472–90. doi:10.1080/02692171.2012.736480.

[61] Geman H, Scheiber M. Spot Price Modelling of Industrial Metals. Univ London 2014.

[62] Liu Q, Chng MT, Xu D. Hedging Industrial Metals With Stochastic Volatility Models. J Futur Mark 2014;34:704–30. doi:10.1002/fut.21671.

[63] Sklar A. Fonctions de Reparition a n Dimensions et Leurs Marges. Publ l'Institute Stat l'Universite Paris 1959;8:229–31.

[64] Engle R. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J Bus Econ Stat 2002;20:339–50. doi:10.1198/073500102288618487.

[65] Han H, Linton O, Oka T, Whang Y-J. The Cross-Quantilogram: Measuring Quantile Dependence and Testing Directional Predictability between Time Series. vol. 193. 2016.

[66] Granger CWJ. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. vol. 37. 1969. doi:10.2307/1912791.

[67] Boulamanti A, Moya JA. Production costs of the non-ferrous metals in the EU and other countries: Copper and zinc. Resour Policy 2016;49:112–8. doi:10.1016/j.resourpol.2016.04.011.

[68] Sharpe WF. The Sharpe Ratio. J Portf Manag 1994;21:49–58. doi:10.3905/jpm.1994.409501.

[69] Engle R. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica 1982;50:987. doi:10.2307/1912773.

[70] Dickey DA, Fuller WA. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. J Am Stat Assoc 1979;74:427. doi:10.2307/2286348.

[71] Phillips PCB, Perron P. Testing for a unit root in time series regression. Biometrika

1988;75:335–46. doi:10.1093/biomet/75.2.335.

[72]   Mejdoub H, Ghorbel A. The dynamic relationship between oil prices and returns on renewable energy companies. Am J Financ Account 2018;5:173. doi:10.1504/ajfa.2018.10011656.

[73]   Zhang D, Broadstock DC. Global financial crisis and rising connectedness in the international commodity markets. Int Rev Financ Anal 2018. doi:10.1016/j.irfa.2018.08.003.

[74]   Sakov A, Bickel PJ. An Edgeworth expansion for the m out of n bootstrapped median. Stat Probab Lett 2000;49:217–23.

[75]   Yahya M, Oglend A, Dahl RE. Temporal and spectral dependence between crude oil and agricultural commodities: A wavelet-based copula approach. Energy Econ 2019;80:277–96. doi:10.1016/j.eneco.2019.01.011.