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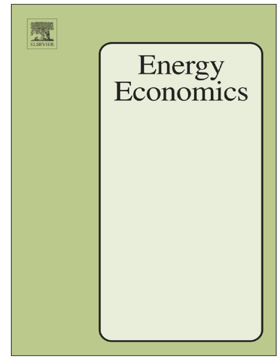

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PII: S0140-9883(25)00073-8

DOI: https://doi.org/10.1016/j.eneco.2025.108250

Reference: ENEECO 108250

To appear in: *Energy Economics*

Received date: 30 March 2024

Revised date: 18 January 2025

Accepted date: 23 January 2025

Please cite this article as: N. Arfaoui, D. Roubaud and M. Naeem, Energy transition metals, clean and dirty energy markets: A quantile-on-quantile risk transmission analysis of market dynamics, *Energy Economics* (2024), https://doi.org/10.1016/j.eneco.2025.108250

Energy Transition Metals, Clean and Dirty Energy Markets: A Quantile-on-Quantile Risk transmission Analysis of Market Dynamics

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Abstract

Amidst the imperative to address environmental degradation and realize sustainable development, energy transition metals have emerged as focal points for practitioners and scholars. This study delves into the role of these energy metals and clean energy markets in advancing environmental sustainability against dirty energy markets. Employing quantile-on-quantile risk transmission, the research scrutinizes asymmetric trends, unveiling crucial insights. Intriguingly, while markets exhibit intra-class risk transmission, energy metals appear notably detached. Dynamic analysis unravels time-varying spillovers, accentuating heightened connectivity during pivotal events like the shale oil crisis, COVID-19 pandemic, and Russia-Ukraine conflict. Notably, time-varying net spillovers highlight diversification benefits in energy metals and clean energy markets, urging stakeholders—ranging from policymakers to investors—to consider integrating energy metals into mainstream assets for risk reduction. In essence, this study underscores the pivotal role of energy metals and clean energy markets in fostering environmental sustainability.

Keywords: *Energy Metals; Clean Energy; Quantile-on-Quantile Connectedness; Static and Dynamic Spillovers*

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1. Introduction

Over many years, the issue of climate change has been somewhat neglected as an urgent and pressing global concern, prompting a concerted effort worldwide to address grave environmental challenges. (Stern et al., 2022). Encouraging the transition towards renewable energy sources, reducing the reliance on fossil fuels, by coordinated efforts at national and international levels emerge as an effective strategy to achieve environmental sustainability (Kabeyi and Olanrewaju, 2022). Environmental changes are intensifying and becoming increasingly unpredictable due to the extensive use of non-renewable energy sources, resulting in driving up global carbon emissions (Batten, 2018; Nguyen et al., 2021; Ugochukwu et al., 2022). Specifically, fossil fuels are the main source of carbon dioxide emissions coming especially from burning oil, natural gas and coal (Naeem and Arfaoui, 2023). For instance, in 2023, global emissions of carbon dioxide exceed 40 bn tones, including 37 bn tones coming from burning fossil fuels (EIA, 2023[1]). The transition towards clean energy sources while also reducing reliance on fossil fuels are crucial to addressing climate change and environmental degradation (Arfaoui et al., 2024).

Although investors' and policy makers' interests rising drastically towards clean energy source, fossil fuel market still occupied a central role in the global economy. The extensive emission of greenhouse gases coming from burning fossil fuels and their adverse effect on the environment, posing significant challenges to achieving environmental sustainability (Bazmi et al., 2011; Chen et al., 2018; Gielen et al., 2019; Elsayed et al., 2020). While eliminating fossil fuel market is unfeasible, sustained efforts can accelerate and facilitate the transition towards sustainable energy (Arfaoui et al., 2024; Naeem & Arfaoui, 2023; Nguyen et al., 2021). The increased environmental awareness and commitment to the 2015 Paris Agreement have driven investments in clean energy and developing green finance, with the aim to addressing climate change (Zhang et al. 2022; Tolliver et al. 2020). As such, clean energy investments are emerging as key avenues for responsible investing with potential long-term climate benefits.

The widespread adoption of clean energy is heavily depends on energy metals. Energy metals are characterized by their recyclability, energy efficiency, and renewable properties. More precisely, energy metals such as cobalt gallium and indium among others serve as a main tool

[1] https://www.eia.gov/

to produce clean energy technologies such as batteries, wind turbines, and solar panels. For instance, indium and gallium metals are widely used in solar photovoltaics (Li et al. 2023). The value of global thin film solar cells based on Copper, Indium, and Gallium was estimated to be USD 2809 million in 2022 and is estimated to reach USD 3537.7 million by 2029[2]. Cobalt is also considered as a clean energy source used as a key component of the lithium-ion batteries that power electric vehicles (Zhu and Chen, 2020). Energy metals are crucial to enhancing the efficiency and the performance of clean energy systems, highlighting its significant role in addressing environmental challenges, as they support the shift towards greener, low-carbon alternatives, helping to mitigate climate change and promote long-term sustainability (Wang et al., 2019). Therefore, these sustainable metals offer a pathway to sustainable development by replacing traditional materials. The growing demand for energy metals emphasizes their pivotal role in driving clean energy technologies and reinforcing its sustainable growth. In this spirit, according to the World Trade Organization, energy metals trades rise drastically over the last 20 years and move from USD 53 billion in 2020 to USD 378 billion in 2023[3]. We notice also that the dedication toward the 2025 COP25 (Climate Change Conference in Madrid) goals occurred in Madrid, to rise renewable energy production and electric vehicle market in order to align and reinforce the objectives of the Paris Agreement (2015) to curb global warming and reduce the level of greenhouse gas emissions, led to rising the international demand for energy metals.

While some studies in the literature have explored the connectedness across energy metals, clean energy and dirty energy market (e.g., oil, natural gas), to our knowledge the dynamic risk spillover across these markets under varying market conditions (bearish, normal, bullish) are not yet explored. To address this gap, this study explore the quantile-on-quantile risk transmission mechanism across these markets during recent and consecutive episodes of market crises including the shale oil revolution, the COVID-19 crisis, and the Russia-Ukraine war. Interestingly, this study raises several research questions regarding the relationship between energy metals, clean energy markets, and traditional energy markets, specifically focusing on the asymmetries and spillover effects among these markets at different quantiles. It explores how these markets interact and the impact of global events on these interactions across different market states. Understanding these dynamics can guide policymakers and

[2] https://www.conference-board.org/
[3] https://www.wto.org/

regulators in developing effective strategies and provide investors with insights into the benefits of focusing on energy metals for resource stabilization.

In light of the discussion above, the current work contributes to the existing literature in several ways. Firstly, to our knowledge, this study fill the void in the literature by exploring the connectedness across both clean (i.e., energy metals and clean energy) and traditional energy markets during different market states (Bearish, normal, Bullish), over the period spanning from June 2012 to December 2023. Secondly, the majority of the existing studies in the field explore the connectedness across financial markets during specific crisis events. Nevertheless, the current work seek to investigate the quantile-on-quantile risk transmission mechanism during distinct episodes of market turmoil such as the shale oil revolution, the COVID-19 crisis, and the Russia-Ukraine war. Interestingly, these recent episodes of market crises accelerate the transition towards sustainable energy solutions and heightened the demand for energy metals, which are crucial in addressing climate change. Thirdly, methodologically, this study investigates the quantile-on-quantile risk transmission mechanism across clean energy, energy metals and dirty energy markets, with a focus on the intricacies of connectedness among directly and reversely related quantiles, to understand their dynamic and intricate interplay. Precisely, in this work we employ the Quantile on Quantile connectedness technique advanced recently by Gabauer and Stenfors (2024), which extends the original quantile connectedness framework by capturing the intricate dynamics between various quantiles of financial series. Unlike the traditional approach, which suggest a uniform positive correlation across variables at a single quantile, the quantile-on-quantile connectedness approach provides a detailed analysis of spillover effects by capturing both the direction and intensity of spillover effects across different quantiles. Further, by capturing asymmetries and non-linarites, this approach provides richer and more accurate depiction of market dynamics (Wang et al., 2024). Finally, this study provides valuable insights for policymakers, environmental advocates, and investors, based on my findings.

Findings of this study Identify significant risk spillovers among markets, particularly at extreme lower and median quantiles, with complex interactions at higher quantiles due to increased uncertainty and volatility. The study also points out the impact of major events like the shale oil crisis, COVID-19 pandemic, and Russia-Ukraine conflict on market dynamics. Furthermore, we demonstrate the diversification benefits of energy metals and clean energy markets, which exhibit lower risk profiles compared to traditional energy markets. Overall, the analysis of risk spillovers across different quantiles and time periods highlights the fluctuating roles of energy metals and energy markets in managing risk, offering strategic insights for diversification.

The remainder of the paper is structured as follows: Section 2 outlines the methodology, Section 3 describes the data and statistical analysis, Section 4 presents the empirical findings, and Section 5 concludes the study.

2. Methodology

We conducted the methodological operations in a series of structured steps to achieve the desired outcomes from the study. Initially, we applied the GARCH (1,1) model to estimate the conditional volatilities of energy metals, as well as dirty and clean energy markets. This approach is extensively recognized and utilized in existing research (Byun and Cho, 2013; Liang et al., 2022; Wei et al., 2010). Subsequently, we examined the quantile-on-quantile (QQ) risk transmission across these markets. This analysis enabled us to explore spillover effects at the median, extreme lower and upper quantiles, and various combinations of different quantiles.

2.1 Volatility Estimation

The return series vector $ret_t = [ret_{1,t}, \ldots\ldots, ret_{n,t}]$ is estimated, and the corresponding equation is expressed as:

$$ret_t = \mu_t + \delta ret_{t-1} + \varepsilon_t. \quad (1)$$

In this formulation, μ_t represents the vector of returns captured through a constant term, while the error terms are denoted as $\varepsilon_t = [\varepsilon_{1,t}, \ldots\ldots, \varepsilon_{n,t}]$. Following this, the conditional volatilities for each series, denoted as $\sigma^2_{i,t}$, are calculated using the equation:

$$\sigma^2_{i,t} = c + \alpha\varepsilon^2_{i,t-1} + \beta h^2_{i,t-1}. \quad (2)$$

In this model, $c > 0, \alpha \geq 0, and\ \beta \geq 0$, with the additional constraint that $\alpha + \beta < 1$. These conditions ensure the non-negativity of the variance and the stationarity of the process, which are fundamental for accurate modeling of conditional volatility dynamics. The parameters

$c, \alpha, and\ \beta$ capture the long-term variance, the impact of past shocks, and the persistence of volatility, respectively.

2.2 Quantile-on-Quantile Risk transmission Estimates

The quantile-on-quantile risk transmission analysis approach is a generalization of the Ando et al. (2021) quantile risk transmission method using variable cross-quantile interdependencies. The technique involves the computation of the quantile level dependencies using a Quantile Vector Autoregressive model (1) of order p or QVAR(p):

$$\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B}_j(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) \quad (1)$$

where, $\boldsymbol{x}_t$ and $\boldsymbol{x}_{i-j}$ denote $K \times 1$ vectors incorporating endogenous variables, $\boldsymbol{\tau}$ denotes the quantiles vector taking values within the range $[0,1]$, p denotes the QVAR's lag order, $\boldsymbol{\mu}(\boldsymbol{\tau})$ denotes a $K \times 1$ vector incorporating conditional means, $\boldsymbol{B}_j(\tau)$ denotes a $K \times K$ matrix containing the coefficients of the QVAR model, and $\boldsymbol{u}_t(\boldsymbol{\tau})$ denotes a $K \times 1$ error vector incorporating a $K \times K$ variance-covariance matrix. The QVAR model is transformed into a Quantile Vector Moving Average (QVMA)—to estimate the Koop et al. (1996) Generalized Forecast Error Variance Decomposition (GFEVD)—by way of Wold's Decomposition Theorem: $\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B}_j(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{i=0}^{\infty} \boldsymbol{A}_i(\boldsymbol{\tau})\boldsymbol{u}_{t-i}(\boldsymbol{\tau})$. How a shock experienced by series j affects series i is accounted for by the F-step ahead GFEVD—as identified in equation (2):

$$\phi^{g}_{i\leftarrow j,\boldsymbol{\tau}}(F) = \frac{\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\boldsymbol{e}_j\right)^2}{\boldsymbol{H}_{ii}(\boldsymbol{\tau})\sum_{f=0}^{F-1}\left(\boldsymbol{e}_i'\boldsymbol{A}_f(\boldsymbol{\tau})\boldsymbol{H}(\boldsymbol{\tau})\boldsymbol{A}_f(\boldsymbol{\tau})'\boldsymbol{e}_i\right)}, \qquad gSOT_{i\leftarrow j,\boldsymbol{\tau}}(F) = \frac{\phi^{g}_{i\leftarrow j,\boldsymbol{\tau}}(F)}{\sum_{j=1}^{k}\phi^{g}_{i\leftarrow j,\boldsymbol{\tau}}(F)} \quad (2)$$

here, e_i denotes a $K \times 1$ zero vector incorporating unity as the ith element. The row sum of $\phi^{gen}_{i\leftarrow j,\boldsymbol{\tau}}$ requires a normalization—as Diebold & Yilmaz (2012) argue since it is unequal to unity. The normalization involves a division of $\phi^{gen}_{i\leftarrow j,\boldsymbol{\tau}}(H)$ using the row sum, culminating in the 'scaled GFEVD': $gSOT_{i\leftarrow j,\boldsymbol{\tau}}(F)$. The scaled GFEVD estimates the total directional risk transmission TO (FROM) others and is the bedrock of the risk transmission analysis. The

"TO" total directional risk transmission accounts for the impact of series i on other markets (in the sample)—i.e., equation (3). In contrast, the FROM total directional risk transmission calculates the impact of the other markets on series i—i.e., equation (4).

$$S_{i\rightarrow\cdot,\boldsymbol{\tau}}^{\text{gen, to}} = \sum_{k=1, i\neq j}^{K} gSOT_{k\leftarrow i,\boldsymbol{\tau}} \quad (3)$$

$$S_{i\leftarrow\cdot,\boldsymbol{\tau}}^{\text{gen, from}} = \sum_{k=1, i\neq j}^{K} gSOT_{i\leftarrow k,\boldsymbol{\tau}} \quad (4)$$

The series i's NET total directional risk transmission is computed as the difference between its TO and FROM total directional risk transmission, as identified in equation (5):

$$S_{i,\boldsymbol{\tau}}^{\text{gen, net}} = S_{i\rightarrow\cdot,\boldsymbol{\tau}}^{\text{gen, to}} - S_{i\leftarrow\cdot,\boldsymbol{\tau}}^{\text{gen, from}} \quad (5)$$

here, a positive magnitude of $S_{i,\boldsymbol{\tau}}^{\text{gen, net}}$ implies that series i imparts more influence on all remaining series in the sample than the influence it receives from them. As such, series i can be identified as a 'net transmitter of shocks.' By contrast, a negative $S_{i,\boldsymbol{\tau}}^{\text{gen, net}}$ reveals that series i receives more influence from others (in the sample) that it imparts to them. In such a situation, it is a 'NET receiver of shocks.'

Ultimately, equation (6) estimates the Total Risk transmission Index (TCI). The (adjusted) TCI measures the extent of the interconnectedness of the network system—with magnitudes representing greater market risk.

$$TCI_{\tau}(F) = \frac{K}{K-1} \sum_{k=1}^{K} S_{i\leftarrow\cdot,\boldsymbol{\tau}}^{\text{gen, from}} \equiv \sum_{k=1}^{K} S_{i\rightarrow\cdot,\boldsymbol{\tau}}^{\text{gen, to}} \quad (6)$$

Additionally, the computed quantile-on-quantile risk transmission measures are used in assessing the pairwise risk transmission networks and time-varying NET risk spillovers across the seven sample markets. The Diebold & Yilmaz (2014) method incorporates a pth order generalized Vector Autoregressive model or VAR(p) that is covariance stationary and contains N number of variables. $x_t = \sum_{i=1}^{p} \Phi_i \, x_{t-i} + \varepsilon_t$ specifies such a VAR(p), where $\varepsilon \sim (0, \Sigma)$ denotes a disturbance term which is identically and independently distributed (i.i.d.).

The Diebold & Yilmaz (2014) risk transmission approach also allows us to gauge the TO and FROM as well as NET total directional spillovers, over time, of series i vis-à-vis all remaining series (of the sample).

2.3. Data and preliminary analysis

This study explores the quantile-on-quantile risk transmission mechanism across energy metals, clean and dirty energy markets during several episodes of market turmoil. In this spirit, we analyze weekly prices of three categories of energy assets over the period ranging from 1 June 2012 to 29 December 2023. The dataset have sourced from Refinitiv DataStream with weekly frequency and include: (i) for energy metals, we employ the closing prices of Germanium (GER); Gallium (GAL); Indium (IND); Cobalt (COB); and Vanadium (VAN); (ii) for clean energy, we use the closing price of Wilder Hill Clean Energy (WCE), S&P Clean Energy (SPCE), and Renixx Clean Energy (REN); (iii) and for dirty energy, we consider the closing prices of Crude Oil WTI (WTI); Natural Gas (NTS); Coal (COAL); Fuel Oil (FOL); Gas Oil (GOL); and Gasoline (GSL).

[Insert Table 1 here]

Table 1 reports the descriptive statistics of the variables considered in the analysis. Results show that Renixx Clean Energy yields the highest mean value (32.6%) followed by S&P Clean Energy (13.7%). Nevertheless, Indium acts as the lowest mean value (-11.4%), followed by Gas oil (-3.1%). Natural gas (Gasoline) appears as the most (least) risky as they exhibit the highest (lowest) volatility. Findings also indicate that all return series show skewness different from zero and kurtosis greater than the value of 3. Based on Jarque-Bera test, all return series reject the hypothesis of normality at the 1% of significance level. Further, results of the unit root test based on Stock et al. (1996) indicate that all series are stationary at the 1% level. Meanwhile findings related to ARCH and Q-stat values report the existence of ARCH effect and non-randomness at lag 10 in all considered series, respectively.

[Insert Table 2 here]

Table 2 illustrates the correlation matrix across the considered markets in the current study. Firstly, the findings denote that all significant pairwise correlations are positive. Specifically, results indicate that the highest pairwise correlations are identified between SPCE-REN, followed by SPCE-WCE and WCE-REN. This empirical finding indicates that assets belonging to the clean energy market provide weak hedging and diversification benefits for portfolio managers and international investors seeking to alleviate the risk related to their portfolio. On the other hand, we find that the weakest pairwise correlations are reported between GSL-WTI and GSL-IND with 8% and 8.1%, respectively.

[Insert Figure 1 here]

Figure 1 depicts the evolution of returns series for the energy metals, clean and dirty energy markets over the period ranging from 1 June 2012 to 29 December 2023. At first glance, we find that the majority of variables showed a similar trend over time. Specifically, a stable trend is shown across GER, INP, VAN, and GSL, variables over the whole sample period. Such evidence highlights the resilience of these assets to various market conditions and economic fluctuations. Nevertheless, we see that the considered variables shown stable trends since the start of the sample period until the end of 2019, after which they report significant spikes around the COVID-19 outbreak and the ongoing Russia-Ukraine war, especially for NTS, WTI, and COAL. This finding highlights the sensitivity of dirty energy assets to exogenous shocks and underlines the importance of monitoring and managing risks during periods of high uncertainty. We notice that the rise of volatility during periods of market turmoil could be the results of the spectacular rising of uncertainty regarding disruption of energy supply chains and the excessive speculative activity in commodity market (Hau et al. 2020; Naeem and Arfaoui, 2023).

3. Empirical findings

3.1. Connectedness network

Figure 2 illustrates the connectedness network across the considered markets in the current work over the full sample period. For clarity, darker and wider arrows denote higher connectedness between markets. Starting with the median quantiles, results reported in Figure (2) show that some markets in the network exhibit stronger connections with each other than with others. Results indicate that assets belonging to the same category show strong connectedness among themselves and leading in the formation of a cluster. Specifically, we see that the strongest connectedness appears across clean energy markets (WCE, SPC, REN) during normal market conditions. This evidence could be due to the fact that green assets offer an effective potential for financial performance and resilience and provide a long-term sustainability to address challenges related to climate change and global warming, making them valuable tools for investors seeking to build robust portfolios (Yuan et al. 2023; Chatziantoniou et al. 2022). Results also show the presence of strong connectedness across dirty energy markets (WTI, GOL, and FOL) under normal market conditions. This finding indicates that changes in supply and demand related to dirty energy markets could swiftly propagate and therefore influence prices and market dynamics (Johnsson et al. 2017). Consequently, understanding the connections across these markets allows investors to foresee changes in prices and therefore establish well-informed strategies regarding their investments. We also find a weak connectedness across markets belonging to different energy markets class at the median quantile, suggesting that portfolio including these assets provide effective diversification benefits for investors and portfolio managers.

[Insert Figure 2 here]

When focusing the attention on the extreme lower quantiles, results reported in Figure 2(b) show a similar pattern compared to the results related to the median quantile with a slight weakening in the degree of connectedness. Specifically, the strongest connectedness is maintained across clean energy assets. One possible explanation for this finding could be attributed to the fact that with the occurrence of negative shocks, investors may shift their attention to green and eco-friendly assets, leading promptly to increasing demand for this class of assets. As a result, this heightened demand promptly boosts green assets prices as investors run to safer or more sustainable options. Further, we also document the presence of strong connectedness across dirty energy markets (WTI, GOL, and FOL). Dirty energy markets share common underlying factors affecting their prices, such as global demand for energy, supply chain, and regulatory policies (Heffron et al. 2020). During extreme market downturns, these common factors could have a pronounced effect on dirty energy assets, leading to a high degree of connectedness among them.

On the extreme higher quantiles front, results visualized in Figure 2(c) report a spectacular rise in the degree of connectedness across all assets considered in the current work, and even across markets belonging to different assets class. Such empirical findings could be due to the fact that the occurrence of positive shock is associated with an increase in market activity and volatility, which might lead to a pronounced connectedness across energy sectors including traditional energy, green energy and energy metals. During periods of rising market activity, investors tend to show greater sensitivity to factors influencing energy supply and demand, leading to closer connectedness among various energy-related assets.

3.2. Sub-sample analysis of connectedness:

Figure 3(a) highlights the pairwise connectedness across the examined markets during shale oil revolution, the COVID-19 outbreak and the ongoing Russia-Ukraine war at the median quantiles. Under normal market circumstances, we find that the whole network is more interconnected during the shale oil revolution. Specifically, the strongest connection is found across dirty energy markets (WTI, GOL, FOL). This empirical evidence is in line with the findings reported by Umar et al. (2022). The technological innovation and investments in the energy sector during the shale oil revolution have transformed the USA into the main supplier of oil and gas worldwide, as well as a leading exporter of fuels (Naeem and Arfaoui, 2023). Consequently, the shale boom has lowered energy costs and increased the demand for fossil fuels, leading the USA to extensively exploit these fuels and to shifting its strategy from a mind-set of scarcity to one seeking to maximize the advantages of energy abundance (Liu and Li, 2018). Further, we report a strong connectedness between energy metals (GAL-GER). Results also indicate the presence of a strong connection from energy metal to clean energy and especially from GAL to SPC. This empirical finding could be the result of the evolving nature of the supply chain dynamics and production processes during the shale oil boom. Particularly, industries have adjusted their manufacturing practices and material sourcing strategies with the aim to respond to the evolving energy environment landscape. For instance, the advancements recorded in shale oil extraction technology can have prompted shifts on the production processes for electronic devices and renewable energy technologies. This could in turn increase the demand for energy metals like Germanium and Gallium, which are considered as the main components in new manufacturing processes or product designs (Arvidsson and Sandén, 2017). We also report a strong dependency across clean energy assets during normal markets. The extensive production of oil and natural gas during the shale oil boom led to significant implications on the greenhouse gas emissions and the landscape of clean energy, resulting in increasing. Such situation raises awareness among policymakers about the importance of accelerating the transition to low-carbon economies through reinforcing investments in eco-friendly projects (Liu et al. 2023). Further, the weakest connectedness is identified across assets belonging to different assets classes. When focusing attention on the COVID-19 outbreak, we report different patterns compared to the Shale oil revolution. At first glance, we see that the degree of connectedness across the considered markets weakened compared to the shale oil revolution. Results show that the strongest connectedness appears in energy metals market especially between (IND-GER). During periods of market turmoil, investors focus their attention on energy metals, crucial for technologies and renewable industries, as resilient assets. This increased interest could in turn heightened demand for energy metals, and strengthening their market connectedness. Results also show that clean energy markets become more interconnected where each market receives and transmits spillovers to the other. Such result is in line with the findings reported in the study by Mirza et al. (2022). Specifically, investors seek to shift their attention towards green assets during periods of market turmoil with the aim to prevent downside risk and maximize gains. During the Russia-Ukraine war, results show similar patterns compared to the COVID-19 outbreak with a slight increase in the degree of connectedness. Specifically, we find that the connectedness across dirty energy markets strength during the Russia-Ukraine conflict. This finding could be the result of uncertainties regarding future fossil fuels supply especially after the western sanctions and boycotts targeting Russian fossil fuels, and the dramatic rise of energy prices (Chen et al. 2023; Martínez-García et al. 2023). We also report a strength in the degree of connectedness between clean energy indices during the Russia-Ukraine war. This finding could be the result of the spectacular rising of hydrocarbon prices, which has enhanced the competitiveness of clean energy compared to other hydrocarbons (Naeem and Arfaoui, 2023).

The results of extreme lower quantiles depicted in Figure 3(b) indicate that market behavior exhibits consistent patterns with slight variations during the shale oil revolution compared to the same period in a normal market state. Specifically, under the bear market, we see that the connectedness across the considered markets weakened especially across dirty energy assets. The shale oil revolution introduced significant technological innovation in oil and natural gas extraction, leading to boosting production and reshaping market dynamics. During the bear market, investors may reassess their investments in traditional fossil fuel, shifting capital towards investments in shale oil and gas (Guo et al. 2023). Such situation leading promptly to decreasing the level of connectedness across clean energy, energy metals, and dirty energy. Nevertheless, we find that the connectedness across clean energy markets is stronger compared to the median quantiles of the same period. Investors consider clean energy markets as safer or more resilient during bear markets due to their heightened sustainability and potential for long-term growth and performance (Dutta et al. 2020). When moving our attention to the COVID-19 outbreak, we see that the connectedness across the considered markets weakened compared to the shale oil revolution. The COVID-19 outbreak was associated with widespread economic uncertainty, resulting in heightened market turbulence in the financial market as a whole and raising the level of risk aversion among investors (Karanasos et al. 2022). Specifically, we report a decrease in the connectedness among assets belonging to the same markets. Such empirical evidence reveals the effectiveness of combining assets belonging to different class in the same portfolio. Further, findings show a weakness of connectedness across clean energy markets. This empirical evidence indicates that fear and uncertainty surrounding the pandemic could lead investors to move their investments into more stable and traditional assets such as bonds or defensive stocks. Nevertheless, results show strength of connectedness across dirty energy and clean energy markets compared to the shale oil revolution. When shifting our attention to the Russia-Ukraine war, results reveal the same patterns compared to the COVID-19 outbreak. Notably, in bear market, findings reveal that the connectedness across dirty energy markets record a quite strength during the Russia-Ukraine war. The uncertainty related to the war leads investors to adopt more aggressive hedging strategies, often involving derivatives or futures contracts related to dirty energy markets. Thus, rising hedging activity could exacerbate price fluctuations and enhance the interconnectedness among these markets. Moreover, we notice that the strongest connectedness appears between clean energy indices (REN-SPC) and energy metals indices (GAL-GER), with each relationship acting in the form of a feedback mechanism. The Russia-Ukraine war spurs a rapid transition towards renewable energy sources including solar and wind power and reinforce the use of energy metals, which encompass metals that are recyclable, energy-efficient, and renewable in nature (Karkowska and Urjasz, 2023). It is important to notice that under normal and bear market states, the connectedness across the markets exhibits the same patterns during the different episodes of market tension.

[Insert Figure 3 here]

Shifting our attention to the bull market, results depicted in Figure 3(c) demonstrate a significant and remarkable increase in connectedness across the examined markets during different market episodes, compared to the bear and normal market states. Specifically, during the shale oil revolution we see that the markets considered in the current work become more interconnected compared to the same period during bearish and normal market states. The shale boom brought new technologies for extracting oil and gas from shale formations, resulting in heightened levels of production and exploration endeavors (Reynolds and Pascal Umekwe, 2019). This technological advancement not only influenced the dynamics of the fossil fuel markets but also had a significant impact on associated industries, including energy metals crucial for manufacturing drilling equipment and renewable energy technologies. When moving to the COVID-19 outbreak, we report a spectacular rise of connectedness across the considered market compared to the shale oil boom. Bullish market during the COVID-19 period coincided with economic recovery, spurred technological innovation and technological progress especially in digitalization, automation, and clean energy, resulting in increased investments in energy technologies and infrastructure (Gribkova and Milshina, 2020). This innovation enhance the interdependence among energy markets, as companies collaborate, invest, and form partnerships to address evolving market needs. When shifting our focus on the ongoing Russia-Ukraine war, results show strength of connectedness compared to the shale oil boom and the COVID-19 outbreak. The Russia–Ukraine war has exacerbated an energy crisis, which directly leads to fossil fuels supply disruption and reinforce therefore the shifts toward global clean energy and energy metals. The transition to clean energy has sparked a surge in demand for energy metals, which is considered as a main component in renewable energy technologies and electric vehicles (Zhang et al. 2023; He et al. 2021). This growing demand highlights the interconnectedness of the energy landscape, as the shift towards clean energy relies not only on technological advancements but also on secure and sustainable access to energy metals.

3.3. Averaged total connectedness:

Figure 4 illustrates the averaged total connectedness across the considered markets, over the bivariate quantile spectrum. From this figure we see that the connectedness between reversely related quantiles is higher, rather than directly related quantiles. Precisely, the findings show that the strong average TCI are identified between extreme lower and extreme upper quantiles. This empirical evidence suggests that assets moved in opposite directions exhibit a more prominent impact on each other's performance. We notice that the strong connectedness reported between reverse quantiles could be the result of the existence of arbitrage opportunities and the hedging strategies adopted by investors. Surprisingly, the findings indicate that the strongest average TCI is shown between directly related quantiles, especially under extreme higher quantiles (($\tau_1 = 95\%$; $\tau_2 = 95\%$). This finding indicates that the considered markets in this study respond in tandem to market volatility, which makes it hard for investors to find effective diversification opportunities across these assets to alleviate risk. We notice also that the strongest connectedness across markets during extreme upper quantile could be the result of several combined factors including technological advancements, regulatory policies, and the spectacular shift toward clean and renewable energy. Results also show that the weakest average TCI are shown across assets during bearish market state ($\tau_1 = 30\%$; $\tau_2 = 30\%$). This finding reveals that the considered markets in this study showed relatively independent movements during market downturns, which is mostly the result of several underlying factors driving each market in this study. Consequently, this weak dependency provides investors effective opportunities for diversification and hedging against market-specific risks.

[Insert Figure 4]

3.4. Averaged NET connectedness:

Figure 5 displays the average Net Quantile-on-Quantile connectedness. From this Figure we see that the dependencies across quantiles are mostly positive for energy metals except for cobalt. Specifically, results show that the connectedness is more pronounced in directly related quantiles especially in bull market ($\tau_1 = 75\%$; $\tau_2 = 75\%$). Bull market is mostly dominated by the presence of optimistic investor behavior, heightened volatility, and speculative behavior. Such behaviors could exacerbate price fluctuation and dependence among energy metals assets as investors tend always to seek opportunity of investment in markets that have a growth potential especially with the rising of awareness about climate change and global warming (Wei et al. 2023). Furthermore, we report that among energy metals, Indium exhibits the highest connectedness under upper quantiles. Such findings could be the result of the rising interest of investors in sustainability and clean energy. To be precise, indium metal is extensively used in the energy sector and especially for the installation of solar photovoltaic. In this spirit, by 2050, approximately 97% of indium is estimated to be allocated for solar PV and the construction of solar cells[4]. Nevertheless, we notice the dominance of negative connectedness for cobalt across almost quantiles. Notably, the highest negative dependence is reported around reversely related quantiles ($\tau_1 = 75\%$; $\tau_2 = 5\%$). This empirical result underlines the effectiveness of cobalt in providing effective diversification and hedging opportunities for portfolio managers. When shifting our focus on clean energy indices results show that the highest connectedness is shown in Renixx Clean Energy and Wilderhill Clean Energy under direct related quantiles ($\tau_1 = 95\%$; $\tau_2 = 75\%$) with about 85.7% and 70.6%, respectively. During bull market states, governments might establish supportive policies and measures to promote and reinforce the adoption of clean energy in financial market by for instance, imposing carbon tax and reducing

[4]https://www.statista.com

progressively the dependence on fossil fuels toward clean energy sources (Zhu et al. 2023). As a result, this situation might boost the demand for cleaner and sustainable energy sources and therefore reinforce the connectedness among them. Moreover, findings indicate that the highest negative dependence appears at the S&P Global Clean Energy index especially at upper quantiles ($\tau_1 = 95\%; \tau_2 = 75\%$) with about 67.9%. Such result underlines the effectiveness of this index in providing diversification benefit for portfolio managers.

[Insert Figure 5]

Moving our attention to the dirty energy markets, results show that the strongest positive connectedness appear in WTI crude oil market around the directly related quantiles ($\tau_1 = 75\%; \tau_2 = 75\%$). Oil is considered as the main energy source for the global economy and always shows strong dependence on the financial market. A strong positive dependence is also shown in Gas oil market and especially around the reversely related quantiles ($\tau_1 = 75\%; \tau_2 = 5\%/\ 25\%$). This finding underscores the strong sensitivity of Gas oil to extreme market circumstances. More precisely, periods of heightened uncertainty are often characterized by the domination of herding behavior among investors, resulting in higher fluctuations in financial asset prices including energy (Chang et al. 2020). Thereby, this behavior could be reflected in gas oil prices, which can deviate considerably from their intrinsic values, especially in extreme market states. For instance, the imbalances resulting from the speculative behavior of buying or selling by traders or their response to geopolitical tensions could reinforce price swings, pushing gas oil prices towards extreme quantiles. Another interesting finding reported in Figure 5 shows that for Gasoline, the connectedness is negative across almost all market states. This finding underlines the ability of Gasoline in providing hedging and diversification benefits for portfolio managers across different market circumstances.

3.5. Dynamic connectedness:

Figure 6 illustrates the evolution of total connectedness over time and at different market quantiles. At first glance, we see that the connectedness across the considered markets ranges from 40% to 110% over the whole sample period. Results show that the connectedness across markets are much higher for the upper tail rather than for both lower and median tails, across time. Periods characterized by the occurrence of extreme positive shocks frequently push investors to seek shelter assets for their capital. In this regard, flight capital toward safer energy markets especially energy metals and clean energy assets reinforce in turn the level of connectedness across the considered markets. Moreover, this finding could be attributed to the occurrence of liquidity crisis, which is more pronounced during extreme positive shocks. Specifically, the occurrence of extreme positive shocks can trigger swiftly a liquidity crisis prompting heightened trading activity as investors reassess and adjust continuously their positions across different markets to alleviate potential portfolio losses. As a result, this lead promptly to tighter the interactions across markets, ultimately increasing their overall level of connectedness. Results also show that the level of dependence across the considered markets during upper tail appears stable and moves around 100% over the sample periods. On the other hand, results show that the connectedness across markets during median and lower quantiles show the same trend over the whole sample period. Particularly, the total connectedness follows an upward trend and reaches its maximum with about 63% and 57% respectively for the median and lower tails during the shale oil boom. The cheaper fossil fuels prices and their abundance during the shale oil revolution leading to boosting the demand and therefore increasing the level of carbon emissions resulting from burning fossil fuels (Liu and Li, 2018). This situation accompanied with the commitment to the 2015 Paris Agreement to promote the adoption of cleaner energy sources might explain the rising of connectedness across the examined markets (Middleton et al. 2017).

[Insert Figure 6]

Afterward, we see that the connectedness drops slightly and reaches about 42% and 48% in 2018, for median and lower tail, respectively, before increasing again during the COVID-19 outbreak. Notably, the total connectedness rises and reaches a high level with almost 58% and 55% for both median and lower tail during the recent health crisis. Such evidence could be attributed to the fact that environmental assets show strong resilience and high performance to the heightened uncertainty during the COVID-19 pandemic, leading investors to shift their focus from conventional assets to cleaner energy sources (Zhang et al. 2023). Then, the level of connectedness decreases and reaches a low level around mid-2021 with about 41% and 45% at the median and lower tail, respectively and followed later by a surge during the ongoing Russia-Ukraine war. The rising of connectedness could be the result of energy supply disruption and the western sanctions imposed on Russia which include a ban on Russia refined oil products, freezing assets of Russian banks. Consequently, this war leads to a remarkable bum in energy markets accompanied by soaring prices and high volatility especially in oil and gas prices (Balsalobre-Lorente et al. 2023). We also notice that from early 2020 until the end of sample period, the connectedness for lower tail is higher than median. Such evidence underlines the sensitivity of extreme market states to unexpected events.

Figure 7 (a) depicts the time-varying net dependency across the markets at median quantiles. For clarity, we notice that the Bleu (yellow) color in the heat-plot reveals that market acts as net risk receivers (transmitters) with negative (positive) values. Results show that gasoline 'GSL' appears as net risk receivers over the whole sample period. This evidence highlights the sensitivity of gasoline, which is the result of its inelastic demand. This finding also indicates the inappropriateness of considering gasoline as a shelter during normal market circumstance. Further, Cobalt 'COB' acts also as net risk receivers over the whole sample period, which is characterized by several episodes of crises. Despite the rising interest towards sustainability and climate risk, cobalt which is considers as one of clean source of energy, used as a component of battery materials that power electric vehicles, this market still at an emerging stage of its development, making it very sensitive comparing to other cleaner energy sources. Further, Indium 'IND' and Germanium 'GER' appear as net risk transmitter over the whole sample period. Indium and germanium are widely shown as pivotal components for various industries such as renewable energy, electronic and telecommunication. Their application in different sectors such as solar cells and optical fibers underlines their importance. In this spirit, any disruption in the supply chain or demand related to these sectors affecting promptly indium and germanium prices, which in turn propagate to other financial assets especially those linked to clean, metals and mineral energy sources.

[Insert Figure 7]

When focusing on extreme lower quantiles, results depicted in Figure 7(b), show that Cobalt 'COB' maintains its role as net risk receiver over the whole sample period. Such empirical evidence could be because despite the success of Cobalt as an alternative metal to conventional energy over the last years, this market still not yet sufficiently mature and the occurrence of negative shocks could disrupt promptly the cobalt supply chain and therefore exacerbating their price fluctuations (Manberger and Stenqvist, 2018). We notice also that Natural Gas 'NTS', Gasoline 'GSL' are shown as net receiver of shocks with negative values. This could be due to the inelastic demand of gasoline and natural gas, where price fluctuation exerts a limited effects on their consumption (Arzaghi and Squalli, 2015; Burke and Yang, 2016). This rigidity, particularly in the short-term arises from their essential roles in heating, transportation, and electricity generation. Consequently, during stressful periods, gasoline and natural gas exhibit lower sensitivity compared to other fossil fuels, thereby acting as net receivers of risk. Results also show that Crude Oil WTI 'WTI', Gas Oil 'GOL', Wilderhill Clean Energy 'WCE', S&P Clean Energy 'SPCE', Renixx Clean Energy 'REN' are shown as net risk transmitters. This could be due to the presence of speculative behavior in these markets during economic downturn, as investors pursuing high-risk trading strategies to seek potential profit. Such behavior could increase market sensitivity to liquidity crises, thereby accelerating the transmission of shocks across markets.

During the extreme higher quantiles, we report different results compared to the median and the extreme lower quantiles. More precisely, results illustrated in Figure 7(c) show that all considered markets shown mixed behavior between transmitter and receiver over the whole sample period. For instance, we see that Cobalt ‘COB’ appears as receiver of shocks from June 2012 until the end of 2020, then shift to risk transmitter during the mid of COVID-19 outbreak and the ongoing Russia-Ukraine war. Another interesting finding reported in this study shows that WTI, NTS, GOL and FOL show mixed behavior between transmitter and receiver during the period ranging from 2012 to 2020. This finding indicates that these markets could provide diversification benefit for investors as their behavior is not perfectly correlated with the rest of assets considered in the current work. Consequently, by including WTI, NTS, GOL and FOL in the same portfolio, investors can potentially alleviate the risk related to their portfolio through diversification. Later, from 2021 until 2023, these markets (e.g., WTI, NTS, GOL and FOL) appear as net transmitters of shocks. Under bull market, the shift in markets behavior during the COVID-19 outbreak and the ongoing Russia-Ukraine war could be the result of the high dependence of the global economy on fossil fuels, especially during periods of fear regarding energy supply disruption.

[Insert Figure 8]

Figure 8 depicts the averaged directly related and the averaged reversely related dynamic total connectedness as well as their difference. From this Figure, we see that reverse TCI and direct TCI show closer values over the whole sample period. For most cases reverse TCI exceeds direct TCI. Specifically, there are two short episodes when the direct TCI overshoots the reverse TCI with a narrow margin. The first episode is reported during the second quarter of 2018 which might be the result of the Katowice Climate Package hold in Poland in 2018 which represent a significant step for the implementation of the commitments made under the Paris Agreement in 2015 (Pyka and Nocoń, 2021). The second episode is reported in mid-2023, which could be the repercussion of the ongoing Russia-Ukraine war. Another interesting finding reported in Figure 8 shows that the reverse TCI exceeds the direct TCI by a substantial margin from early 2020 until the end of 2022. This is mostly due to the repercussion of COVID-19 outbreak and the ongoing Russia Ukraine war, which have disrupted the global energy markets and especially fossil fuels and rising the focus of investors towards cleaner energy sources (Tian et al. 2022; Gui et al. 2023; Naeem and Arfaoui, 2023).

4. Conclusion

This study explores the quantile-on-quantile risk transmission mechanism across clean energy, energy metals and dirty energy markets over the period ranging from 1 June 2012 to 29 December 2023. Specifically, in this study we employ the novel quantile on quantile connectedness approach to investigate the reversely related and directly related quantile spillover across the considered markets. Results show that in normal and bear market states, the connectedness across the examined markets exhibit the same patterns during the shale oil boom, the COVID-19 outbreak, and the ongoing Russia Ukraine war. Specifically, the strongest connectedness appears across clean energy assets (i.e., clean energy and energy metals). Nevertheless, when shifting our attention to the bull market, findings reveal the connectedness across markets strength during the different episodes of crises considered in this study.

Results of the averaged total connectedness across the considered markets indicate that the strongest averaged TCI is shown between directly related quantiles especially under extreme higher quantiles (τ_1=95%; τ_2=95%). Such evidence indicates that the considered markets in this study respond in tandem to market volatility, which makes it hard for investors to found effective diversification opportunities across these assets to alleviate risk. Nevertheless, the weakest averaged TCI are shown across assets during bearish market state (τ_1=30%; τ_2=30%). Results also show that the average quantile-based total connectedness is time varying and intensify during episodes of market tensions. Another interesting finding shows that under extreme lower quantiles, Cobalt acts as net risk receiver over the whole sample period. Nevertheless, Natural Gas and Gasoline are shown as net receivers of shocks with negative values. Under extreme higher quantiles, Cobalt appears as receiver of shocks from June 2012 until the end of 2020, then shift to risk transmitter during the mid COVID-19 outbreak and the Russia-Ukraine war. We notice also that these markets (e.g., WTI, NTS, GOL and FOL) react as net transmitters of shocks only from 2021 until 2023.

Results of this study provide valuable implications for policymakers, portfolio managers and international investors. Policymakers are invited to develop and formulate clear and consistent strategies to make it easy and support the establishment and development of cleaner technologies. This involves the development of investment in renewable energy infrastructures; promote energy efficiency and reducing the level of carbon emission to achieve zero CO2 emissions by 2050. Moreover, the transition towards clean energy requires ensuring a steady and reliable source of energy metals, which are crucial for the production of clean energy technologies. Policymakers such as governments are invited to enhance trade agreements and international collaboration to secure the stability of energy metals supply chains. This may include developing strategic reserves of critical materials, optimizing logistic systems, and incentivizing private sector investment in mineral exploration and production of these essential resources. Further, encouraging initiatives to enhancing the recycling of energy metals is essential to establishing a sustainable and circular economy within the renewable energy sector.

Portfolio managers and international investors' are also invited to include both clean energy and energy metals in their portfolio to mitigate risks related to exposure to fossil fuels. Specifically, portfolio managers and international investors could actively seek investment opportunities in assets related to sectors (e.g., solar panels, wind turbines, smart grid, and electric vehicle) driving the transition towards cleaner energy sources. Such situation leading portfolio managers and international investors to align their strategies with the global clean energy transition goals, enhancing performance while minimizing the risks associated with fossil fuel assets. Moreover, the rising demand for energy metals and rare earth elements provides substantial investments opportunities for portfolio managers' to invest in recycling technologies, mining, and specialized investment funds focusing on these critical materials. The swift shift towards clean energy increase the need for these metals that is mostly due to their critical applications in electric vehicle and the development of renewable energy technologies. Nevertheless, portfolio managers' should actively manage risks related to these investments such as supply chain vulnerabilities, ethical concerns, and geopolitical risks. Mitigating these risks involved diversifying their portfolios, investing in recycling technologies, and choosing companies that uphold responsible mining practices. Monitoring political instability and prioritizing regions with supportive regulatory frameworks can effectively mitigate geopolitical risks, allowing informed decisions and enhance long-term sustainable returns.

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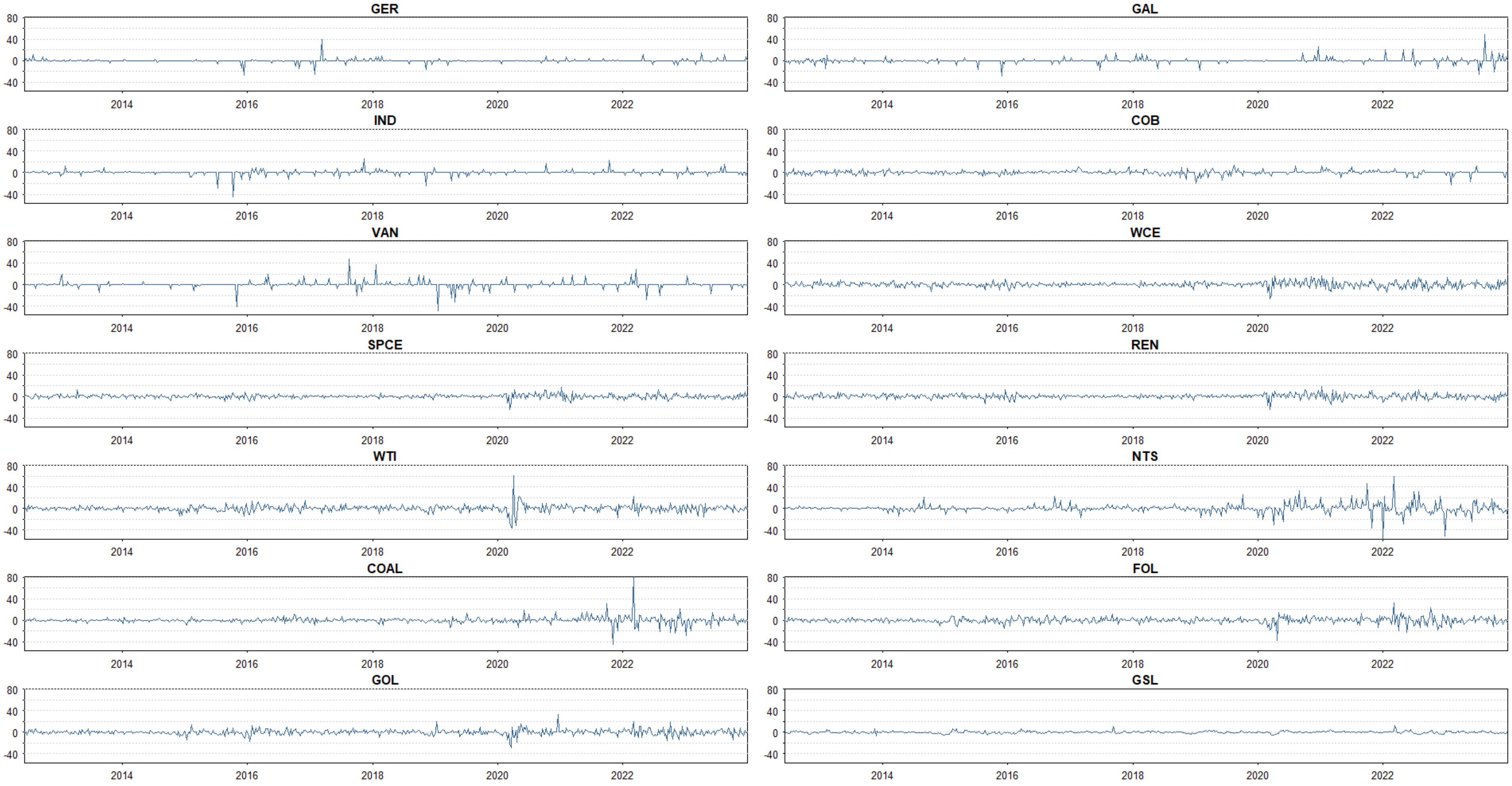
Table 1: Descriptive statistics of energy metals, clean and dirty energy markets

Group	Market	Symbol	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS	Q(10)	$Q^2(10)$
Energy Metals	Germanium	GER	0.048	10.002	1.002***	58.963***	87596.518***	-9.841	16.911***	22.843***
	Gallium	GAL	0.081	20.393	1.840***	30.822***	24248.875***	-7.512	9.744*	14.070***
	Indium	IND	-0.114	15.401	-2.572***	39.863***	40656.632***	-9.517	2.479	1.339
	Cobalt	COB	-0.002	13.427	-0.765***	6.112***	999.107***	-6.801	46.549***	8.655
	Vanadium	VAN	0.003	32.841	-0.522***	27.673***	19299.944***	-9.44	5.093	1.467
Clean Energy	Wilder Hill Clean Energy	WCE	0.065	23.804	-0.287***	2.296***	141.007***	-6.994	10.358*	169.497***
	S&P Clean Energy	SPCE	0.137	13.496	-0.332***	4.807***	592.690***	-7.26	11.540**	102.060***
	Renixx Clean Energy	REN	0.326*	17.449	-0.375***	3.378***	301.410***	-10.441	7.44	76.994***
Dirty Energy	Crude Oil WTI	WTI	-0.024	37.883	0.611***	20.129***	10234.560***	-9.443	14.258***	335.702***
	Natural Gas	NTS	0.066	63.177	0.156	16.500***	6854.389***	-9.226	15.146***	35.783***
	Coal	COAL	0.048	36.82	2.985***	58.694***	87594.702***	-9.132	7.97	5.962
	Fuel Oil	FOL	-0.013	28.038	-0.465***	7.119***	1297.127***	-8.973	4.63	51.994***
	Gas Oil	GOL	-0.031	24.861	0.193*	6.758***	1153.203***	-6.668	8.759	41.945***
	Gasoline	GSL	-0.023	3.682	0.780***	4.918***	669.948***	-5.769	277.083***	26.436***

Note: *, **, and *** indicates 10, 5, and 1% level of significance

Fig. 1. Time series of returns



Notes: This figure represents the time evolution of returns series for the energy metals, clean and dirty energy markets.

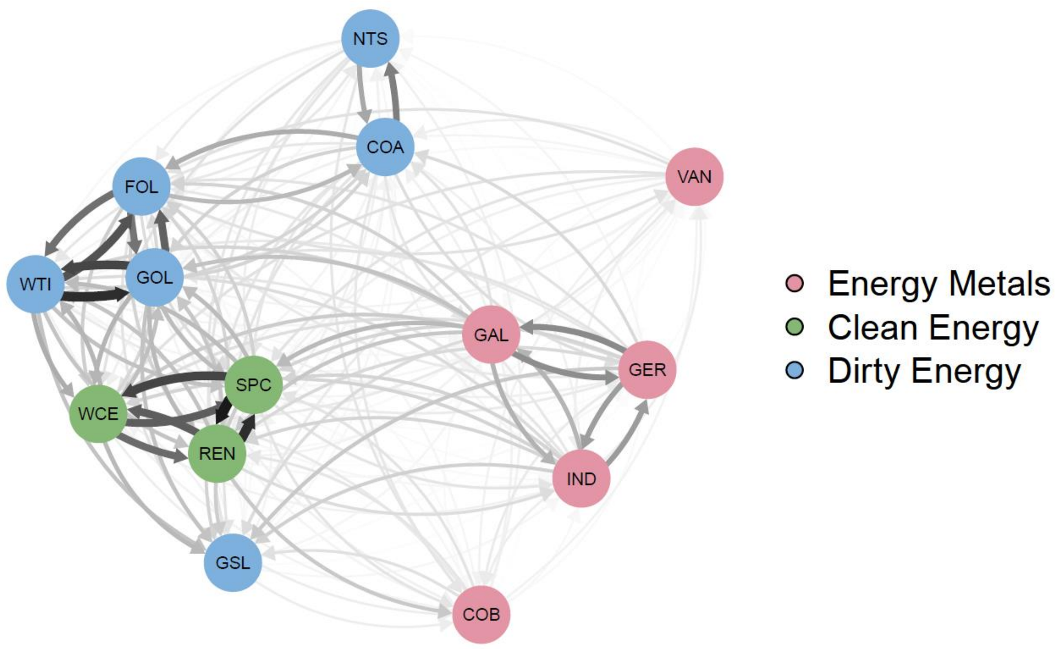
Table 2: Correlation matrix of the selected markets

	GER	GAL	IND	COB	VAN	WCE	SPCE	REN	WTI	NTS	COAL	FOL	GOL	GSL
GER	1.000***	0.195***	0.262***	0.091**	0.031	-0.027	-0.029	-0.032	0.031	-0.025	0.006	0.074	0.031	0.053
GAL	0.195***	1.000***	0.176***	0.053	0.073	-0.017	-0.013	-0.022	0.062	-0.018	0.014	0.123***	0.116***	0.049
IND	0.262***	0.176***	1.000***	0.077	0.044	0.025	0.002	0.011	0.052	0.038	0.05	0.074	0.084**	0.081**
COB	0.091**	0.053	0.077	1.000***	0.098**	0.034	0.046	0.036	0.078	0.055	0.04	0.105**	0.110***	0.062
VAN	0.031	0.073	0.044	0.098**	1.000***	0.01	-0.004	0.008	0.013	0.013	0.051	0.07	0.045	0.04
WCE	-0.027	-0.017	0.025	0.034	0.01	1.000***	0.857***	0.827***	0.255***	0.022	-0.037	0.187***	0.280***	0.032
SPCE	-0.029	-0.013	0.002	0.046	-0.004	0.857***	1.000***	0.891***	0.251***	0.047	0.001	0.162***	0.283***	0.015
REN	-0.032	-0.022	0.011	0.036	0.008	0.827***	0.891***	1.000***	0.204***	0.065	0.013	0.141***	0.244***	0.009
WTI	0.031	0.062	0.052	0.078	0.013	0.255***	0.251***	0.204***	1.000***	-0.024	0.155***	0.642***	0.525***	0.080**
NTS	-0.025	-0.018	0.038	0.055	0.013	0.022	0.047	0.065	-0.024	1.000***	0.411***	0.093**	0.093**	-0.007
COAL	0.006	0.014	0.05	0.04	0.051	-0.037	0.001	0.013	0.155***	0.411***	1.000***	0.255***	0.174***	0.006
FOL	0.074	0.123***	0.074	0.105**	0.07	0.187***	0.162***	0.141***	0.642***	0.093**	0.255***	1.000***	0.716***	0.069
GOL	0.031	0.116***	0.084**	0.110***	0.045	0.280***	0.283***	0.244***	0.525***	0.093**	0.174***	0.716***	1.000***	0.146***
GSL	0.053	0.049	0.081**	0.062	0.04	0.032	0.015	0.009	0.080**	-0.007	0.006	0.069	0.146***	1.000***

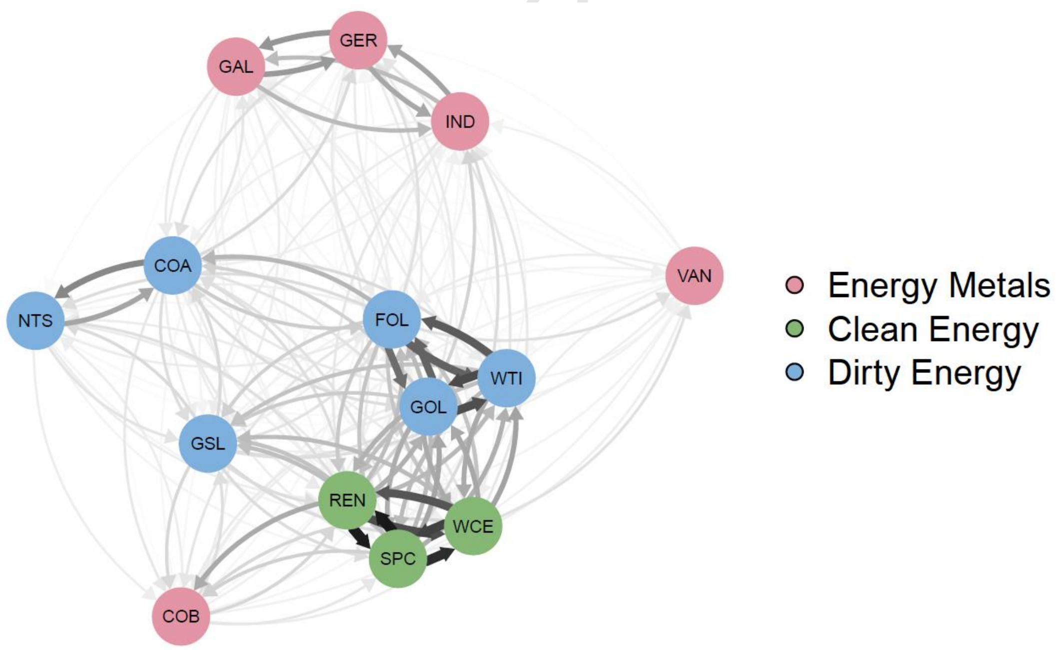
Note: This table showcases the Pearson correlation for the selected markets. *** represents significance at 1%.

Fig. 2. Pairwise risk transmission networks of markets – Full sample

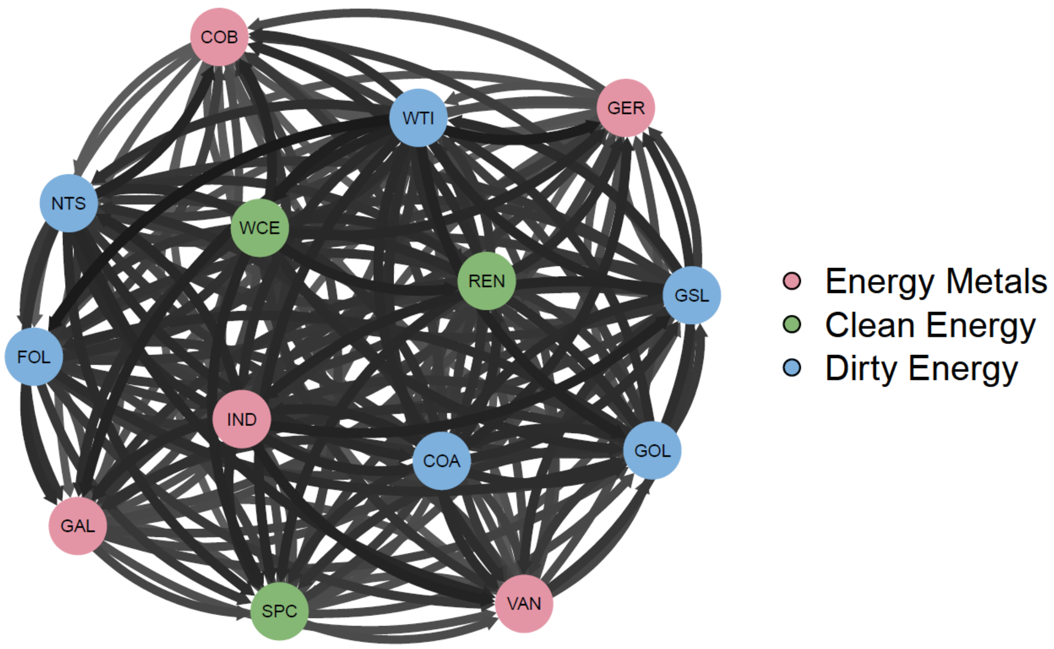
a) Median (50-50) quantiles



b) Extreme lower (5-5) quantiles



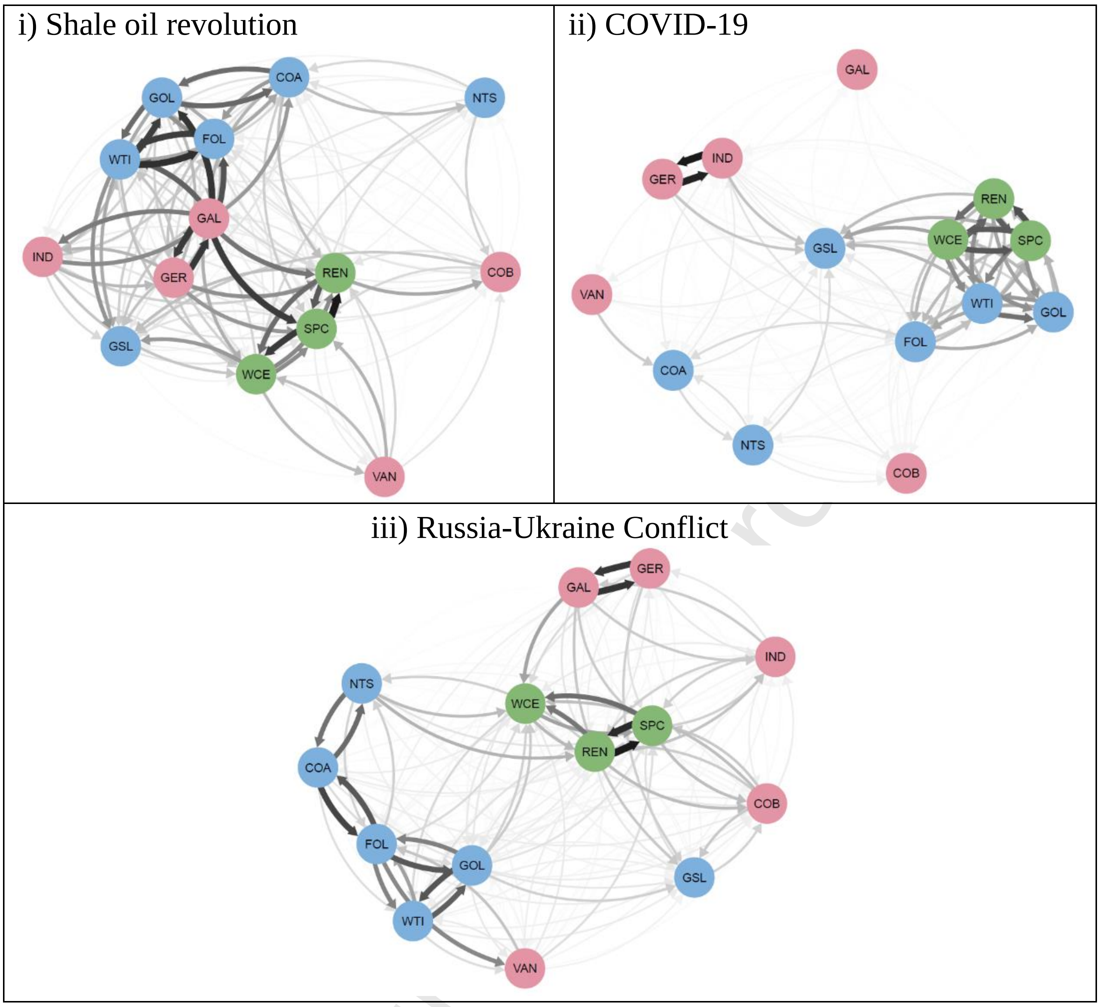
c) Extreme higher (95-95) quantiles



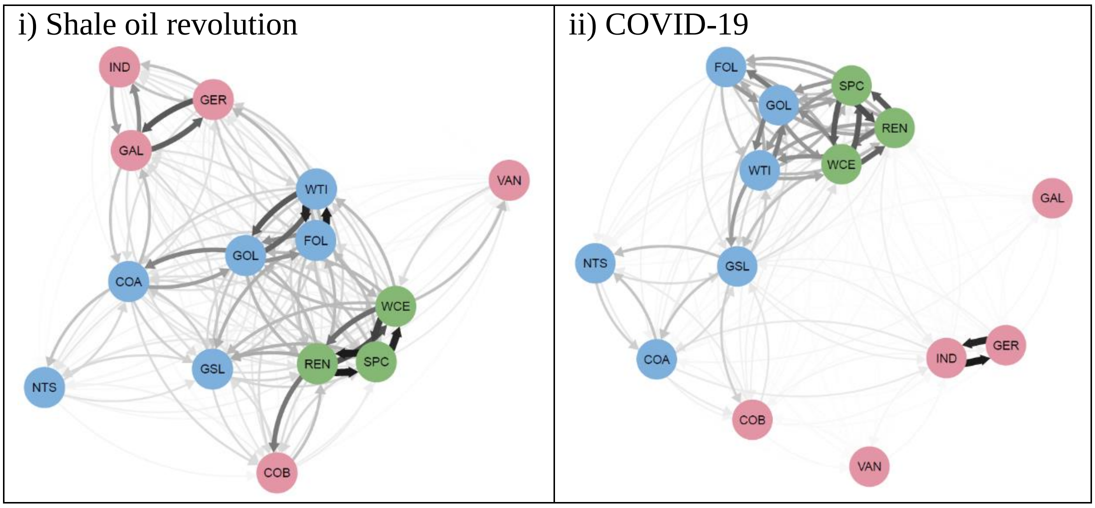
Note: This figure showcases the network spillovers of energy metals, clean and dirty energy markets using a Quantile-on-Quantile risk transmission model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

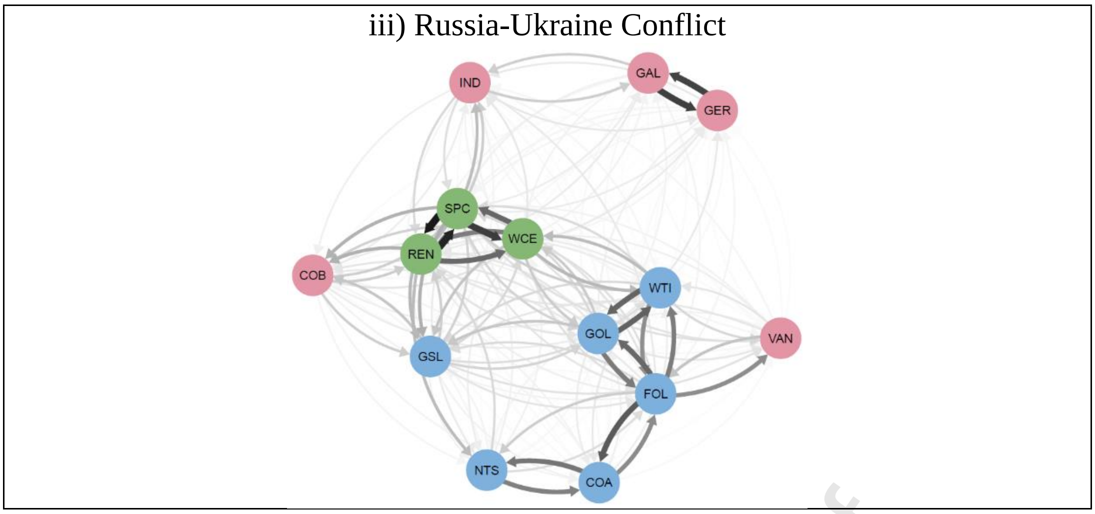
Fig. 3. Pairwise risk transmission networks of markets – Sub-sample

a) Median (50-50) quantiles

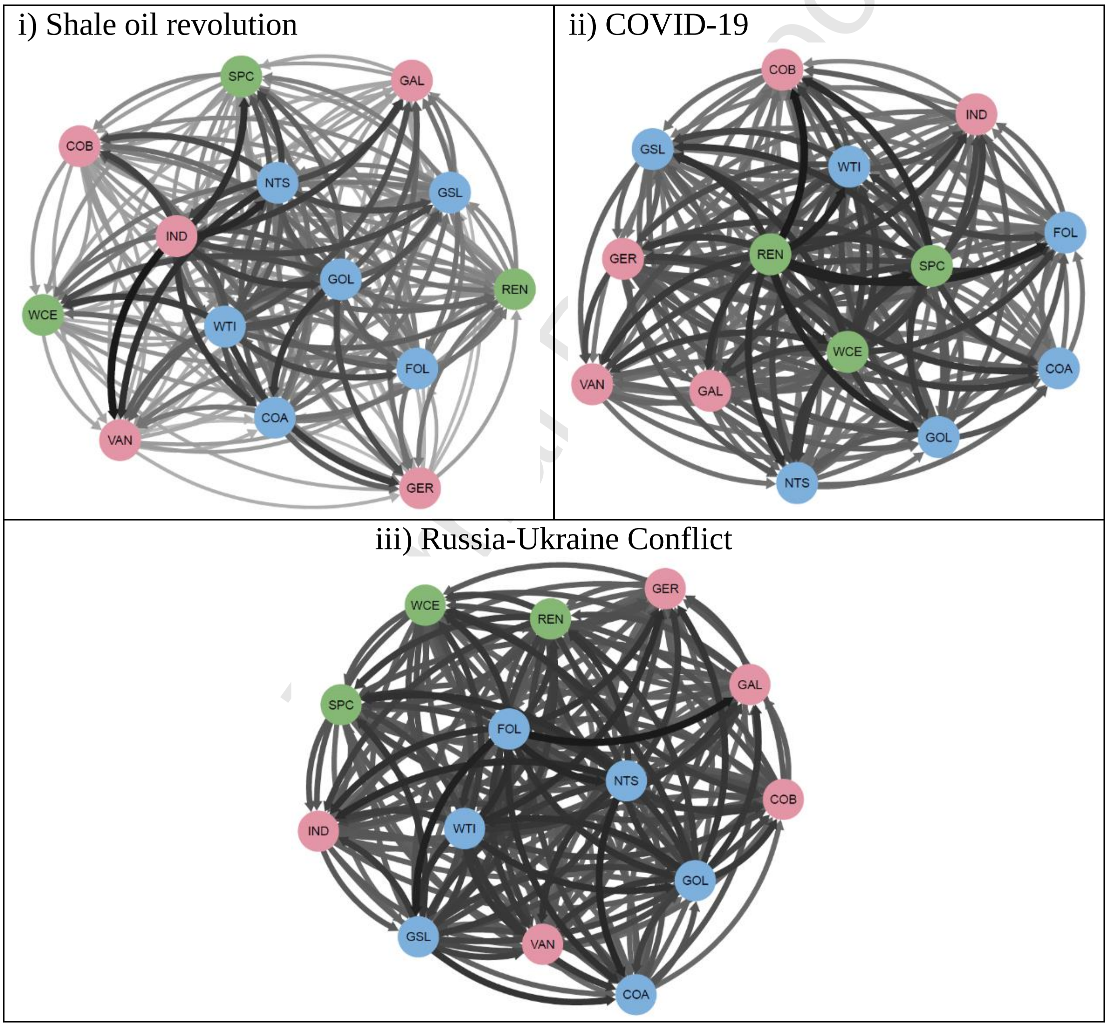


b) Extreme lower (5-5) quantiles



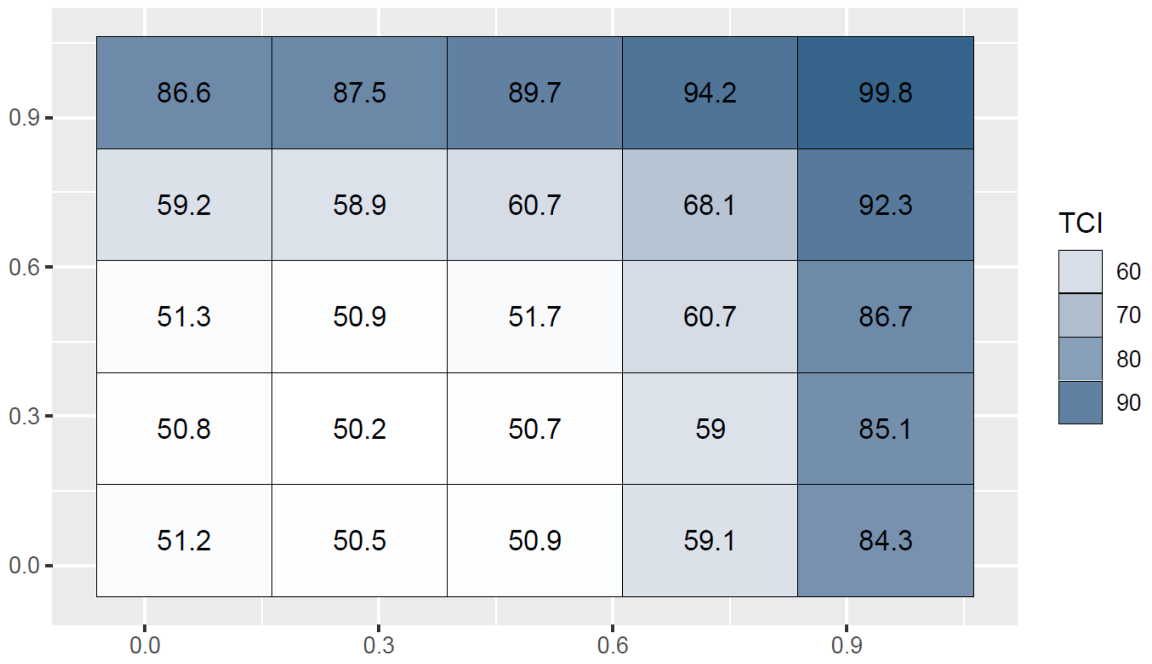


c) Extreme higher (95-95) quantiles



Note: This figure showcases the risk transmission networks of energy metals, clean and dirty energy markets for crises periods, i.e., shale oil revolution, COVID-19, and Russia-Ukraine conflict using a Quantile-on-Quantile risk transmission model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

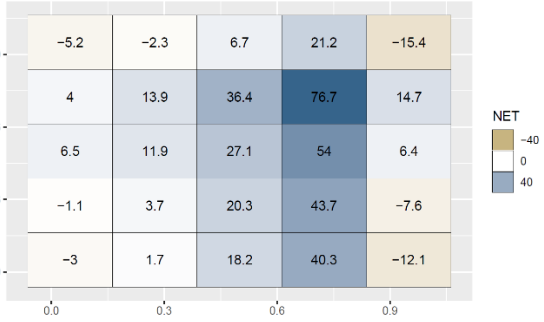
Fig. 4. Averaged TOTAL Quantile-on-Quantile risk transmission of markets.



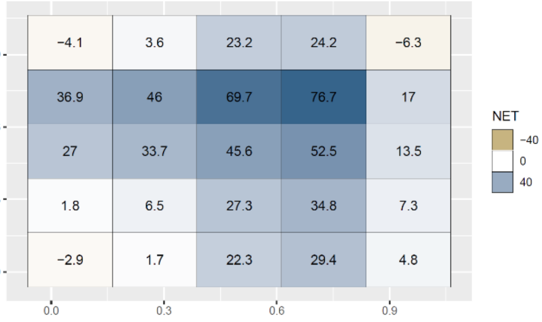
Notes: Results are based on a Quantile-on-Quantile risk transmission model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

Fig. 5. Averaged NET Quantile-on-Quantile risk transmission of markets.

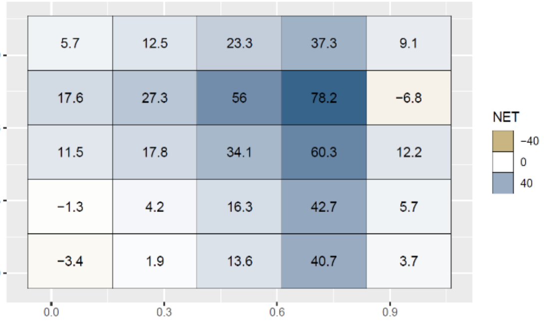
a) Germanium



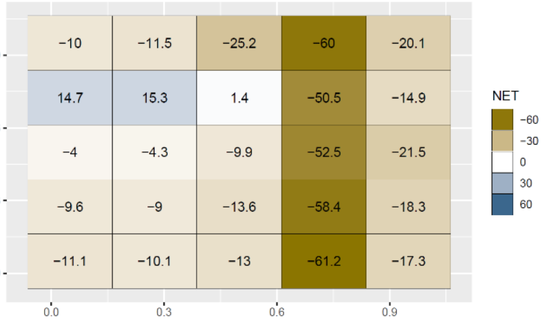
b) Gallium



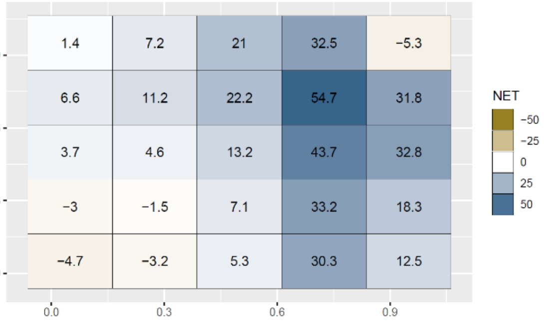
c) Indium



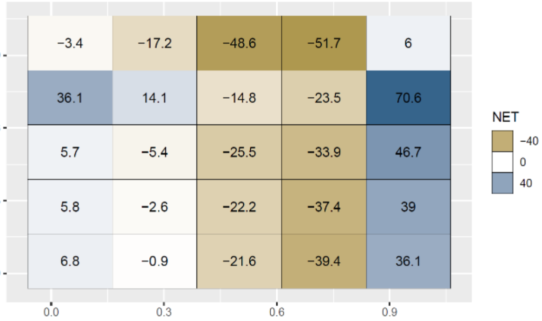
d) Cobalt



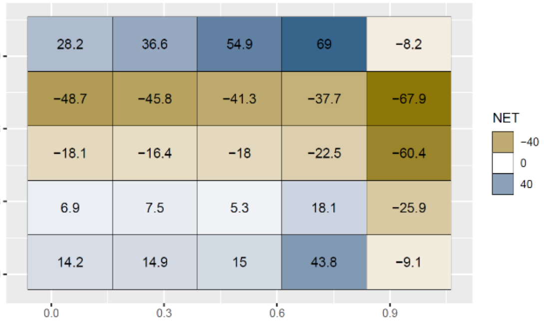
e) Vanadium



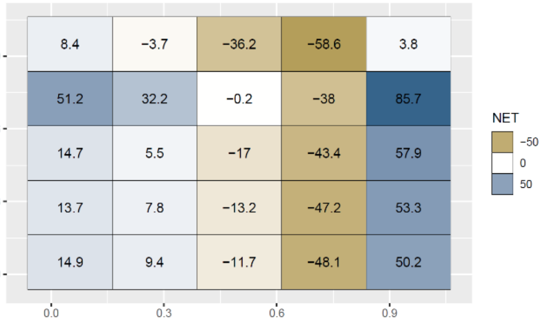
f) Wilderhill Clean Energy



g) S&P Global Clean Energy

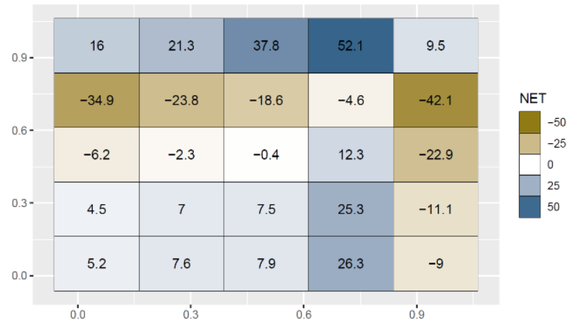


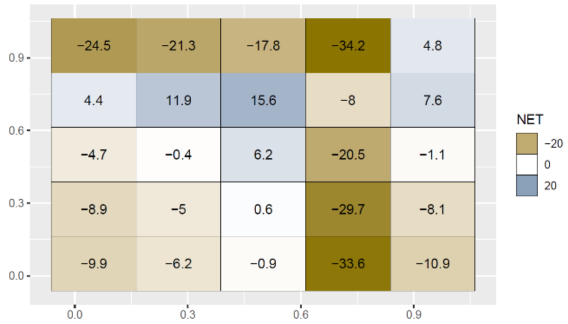
h) Renixx Clean Energy



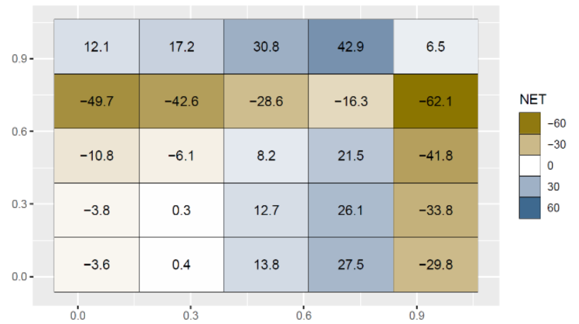
i) WTI Crude Oil

j) Natural Gas

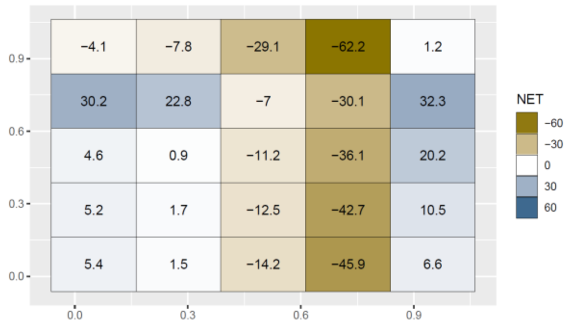




k) Coal

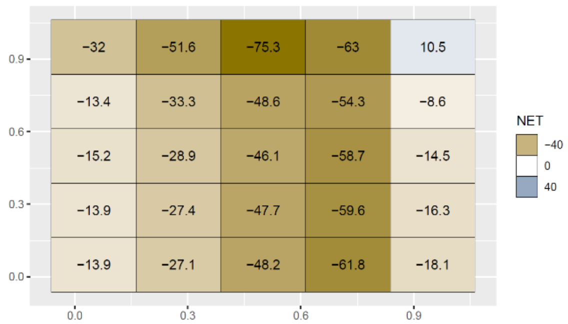


l) Fuel Oil



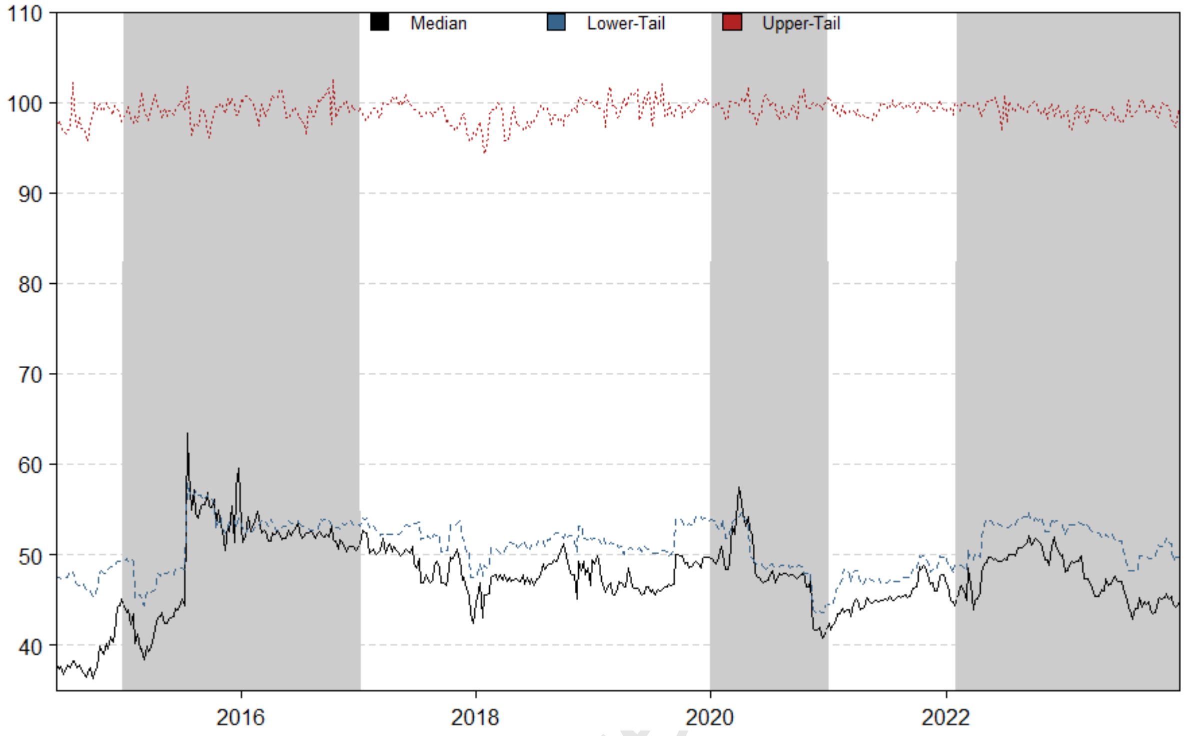
m) Gas Oil

n) Gasoline



Notes: Results are based on a Quantile-on-Quantile risk transmission model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

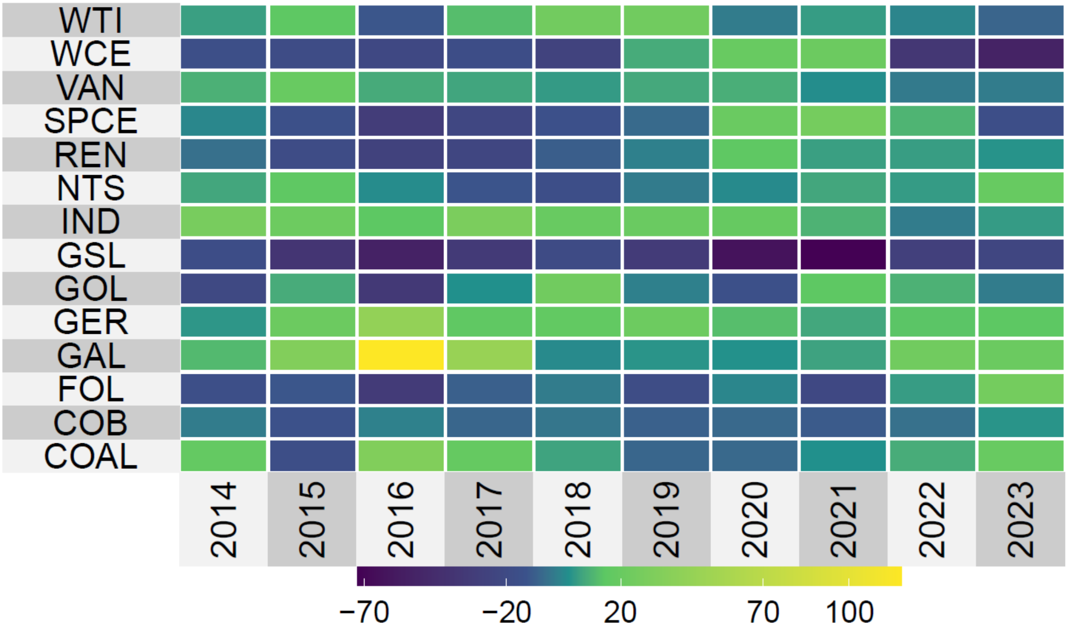
Fig. 6. Time-varying TOTAL risk transmission of markets.



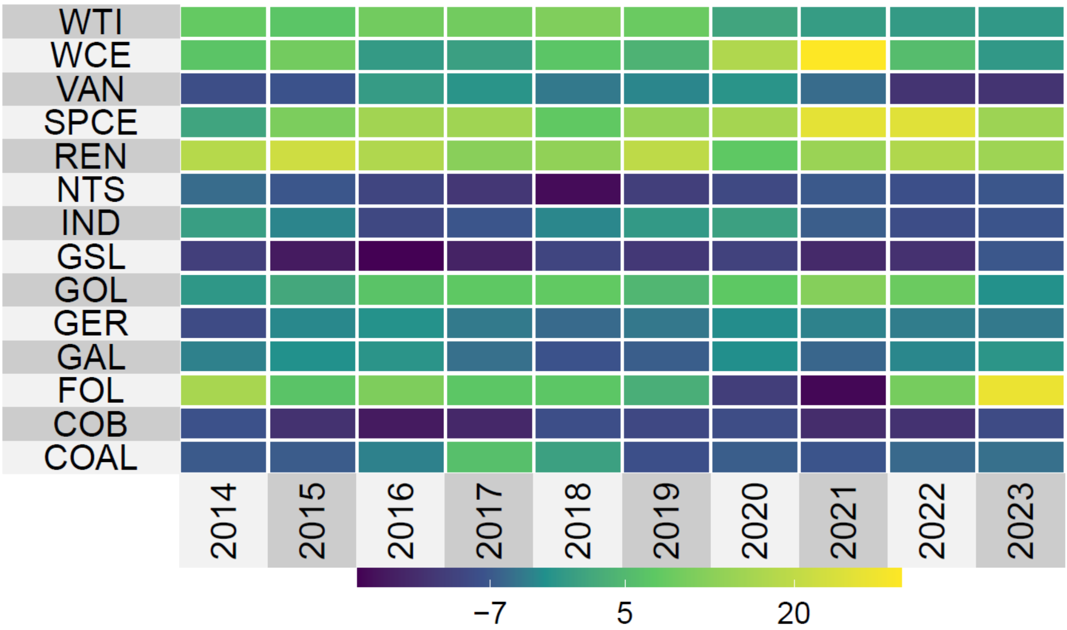
Notes: Results are based on a 106-day Rolling Window Quantile-on-Quantile risk transmission model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition. Black line represents risk transmission at 50-50 quantiles, while the blue (dashed) and the red (dotted) lines represent the results of the 5-5 and 95-95 quantiles, respectively. Grey shaded areas represent crises periods.

Fig. 7. Time-varying NET risk transmission of markets.

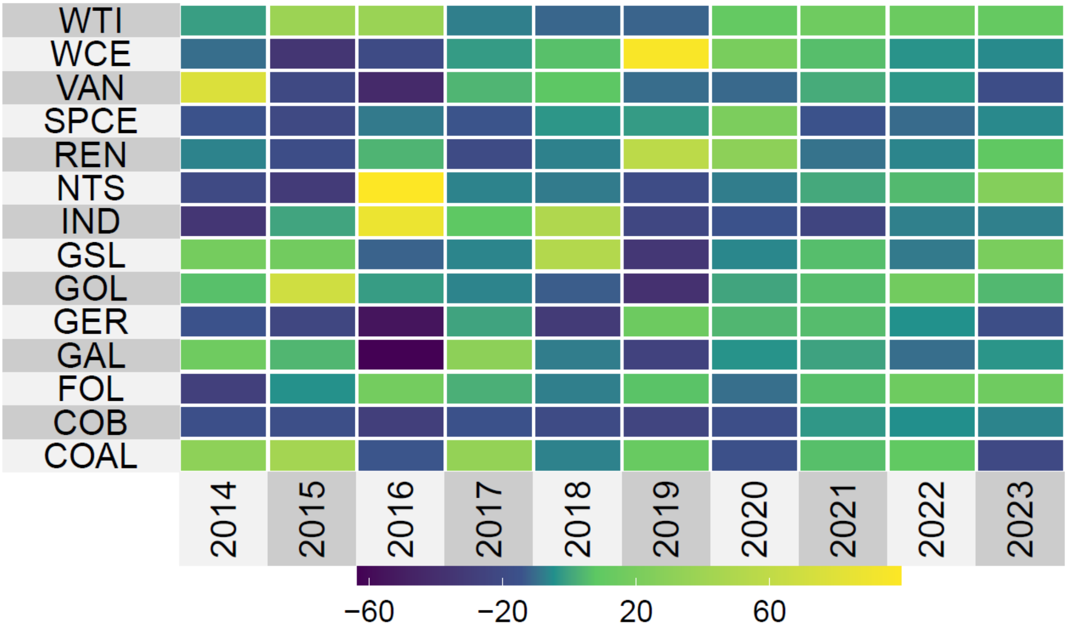
a) Median (50-50) quantiles



b) Extreme lower (5-5) quantiles



c) Extreme higher (95-95) quantiles



Notes: Results are based on a 106-day rolling-window Quantile-on-Quantile risk transmission with a lag length of order 1 (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Fig. 8. Dynamic directly related and reversely related quantiles risk transmission.

Notes: Results are based on a 106-day rolling-window Quantile-on-Quantile risk transmission with a lag length of order 1 (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Energy Transition Metals, Clean and Dirty Energy Markets: A Quantile-on-Quantile Risk transmission Analysis of Market Dynamics

Highlights

Energy transition metals have emerged as focal points for practitioners and scholars.

We employ quantile-on-quantile risk transmission to scrutinize asymmetric trends.

Time-varying net spillovers highlight diversification benefits in energy metals.

Stakeholders need to integrate energy metals into mainstream assets for risk reduction.

Energy metals and clean energy markets can foster environmental sustainability.