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# A dynamic connectedness analysis between rare earth prices and renewable energy

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ABSTRACT

Current world environmental challenges put pressure on clean energy produced mostly through renewables. There is an undeniably important role of rare earth minerals in renewable energy technologies. This study aims to infer the relationship between rare earth, clean energy, renewable energy technologies, and carbon emissions, focusing on daily stock price index data and applying the novel quantile time-frequency connectedness model, and the cross-quantilogram dependence approach during 2012–2022. Results show that spillovers among rare earth minerals and renewable energy are dependent on market conditions, time horizons, and analyzed quantiles. They also highlight the net receiver role of rare earth, especially in the short term. Findings might help investors understand diversification benefits and support policymakers in developing strategies for lessening import dependence on rare earth metals, as important as they are for renewable technology adoption to ensure green growth.

## 1. Introduction

The negative externalities of environmental damage to climate and environment expose significant effects on human health, precipitation, agriculture, employment, and migration, which necessitates taking urgent steps to slow down these negative impacts (Dogan et al., 2022). To tackle the negative impacts of hazardous emissions, supranational authorities, such as the Conference of the Parties (COP) postulate quantifiable aims to aid countries to take necessary actions. By the end of 2021, about 200 countries attended the COP26 and most declared the willingness to decarbonize the global economy, which requires significant shifts from traditional energy means like fossil fuel to renewable energy (Arora and Mishra, 2021). Very recently, with COP27 some countries, led by India, intended to go further and suggested a commitment to phase down all fossil fuels. Even though this suggestion received lots of disputes and was refused eventually, the phase-down of all fossil fuels might always come to the stage. The inevitable shift to renewable energy production required consideration of the factors of production in this industry.

Rare earth minerals are one of the most significant ingredients of renewable energy technologies, as they are essential in the production of solar cells, wind turbines, and electric vehicles (Buchholz and Brandenburg, 2018). There exist no substitutes for rare earth in clean energy and clean technology production, besides they are also very critical in other areas of technological products like electronics, aerospace, healthcare, military, and other high-tech strategic applications (Müller et al., 2015). Therefore, rare earth is an important resource in economies, not available for all, and expensive turning necessary to define strict policies to accomplish the necessary goals.

Regardless of the necessity of rare earth in clean energy and clean technology production, their availability remains a big puzzle for many countries. Rare earth minerals are traded in a distorted market structure and there is regional incongruence in the distribution of the minerals (Haque et al., 2014, Bagdonas et al., 2022). China remains the domineering supplier of rare earth by providing 80% of the world (Fergus et al., 2016), and this type of monopoly is harmful since changes in foreign policy and export decisions can cause significant instabilities of the global market (Dutta et al., 2016). Increasing price pressures of rare

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earth minerals associated with increased demand and stiffened export quotas in China create distress regarding the presence. Moreover, the immense significance of rare earth minerals not only in clean production but also in many critical industries makes these minerals vulnerable to supply shocks and risks, with risk magnified once their production is dependent on finite ore sources (Opare et al., 2021). The carbon neutrality goal of many countries will drive and accelerate the transformation to clean energy and renewable energy technology production and adoption and these developments are a precursor to fierce industrial competition for rare earth (Zhang et al., 2022) and the significant issue is whether the current supply base of rare earth can attune to the projected clean energy and technologies.

To mitigate carbon emissions, technological advancements, and innovations are necessary. Renewable energy or clean technologies are known to be a standard means of coping with the detrimental impacts of climate change by diminishing carbon emissions (Suman, 2021). The literature notes several barriers to renewable energy adoption; the most significant two prevailing are the financial barriers and technological barriers (Luthra et al., 2015). As Olabi and Abdelkareem (2022) highlight, the means to reduce carbon emissions demand the increased efficiency of the current technologies, and efficient and environmental-friendly new devices must be developed to transition into renewable energy and clean energy sources. Renewable energy sources must be converted into electricity most efficiently and cost-effectively. Renewable energy delivers not only environmental and health benefits but also displays positive spillovers to technological improvements. To improve renewable energy technologies and mitigate carbon emissions, investments in these technologies should be enhanced (Ganda, 2019; Danish and Ulucak, 2021). Moreover, improvements in renewable energy technologies facilitate the reduction of technological costs which causes an increase in renewable energy technologies and increased penetration of clean energy sources.

Rare earth minerals could impact the stock prices of firms that are operating in sustainable industries with the concerns like renewable energy technologies, clean energies, carbon efficiency, and renewable energy production. Financial markets reflect the expectations of investors related to the concerns about shortages in the performance and valuation of clean energy stock prices (Baldi et al., 2014). Thus, these rare earth minerals have the potential to determine the performance of firms in environmentally sustainable indices. Also, the incidents in these firms might impact the performance of the companies that extract rare earth, as a result of increasing or decreasing demand for their products. As a result, there might exist bidirectional relationships between these companies.

Given these dynamic connections, this paper aims to understand the association between rare earth, clean energy, renewable energy technologies, and carbon emissions. Since these relationships can actively be investigated by focusing on the firms in these areas, the paper specifically considers MVIS Global Rare Earth/Strategic Metals Index, S&P Global Clean Energy Index, S&P/TSX Renewable Energy, and Clean Technology Index, and S&P 500 Carbon Efficient Index. The data covers the period of September 28, 2012, to October 7, 2022, by adopting the novel quantile time–frequency connectedness model of Chatziantoniou et al. (2022) and the cross-quantilogram dependence approach by Han et al. (2016).

The contribution of this paper to the literature is fourfold. First, given the promises of many countries to net zero emissions, a rapid transition to renewable energy and renewable energy technologies is essential. Since rare earth minerals are indispensable for these technologies, their prices stay a dominant factor in diminishing carbon emissions. Thus, the investigation of the performances of the rare earth companies to other related industries is of crucial significance both from a global perspective to mitigate emissions and from the investors' perspective as a significant asset class. Second, the paper adopts a very recent methodology of Chatziantoniou et al. (2022) quantile time–frequency connectedness model, which is superior to previous approaches in the sense that it does not necessitate an arbitrary window size, is less sensitive to outliers, examines the dynamics of parameters more accurately and precludes the loss of observations (Apergis et al., 2022). Thirdly, the paper considers a long daily data set that includes the COVID-19 pandemic, which had significant impacts on renewable energy technology, renewable energy investments, and financial markets. Fourth, to the best of the authors' knowledge, this is the first paper that considers the associations between the investments of rare earth and strategic minerals and the sustainability-related indices. Rare earth minerals became an attractive investment instrument with increasing attention due to their volatile and increasing prices. Thus, the nature of the connectedness with the other indices in sustainable industries is significant for both the investors and the policymakers that focus on environmental degradation.

The study also has significant policy importance in several aspects. Firstly, given the increasing shift to transition to clean energy to mitigate carbon emissions, ensuring a stable and sustainable supply of rare earth minerals is of significant importance. Policymakers need to recognize the importance of rare earth minerals to mitigate carbon emissions and improve strategies to reduce the risks associated with their limited availability and regional disparities in distribution. Secondly, the study stresses the necessity of designing policies to support the technological advancements in renewable energy, to come up with the creation of more efficient green technologies and wider adoption of renewable energy sources. Third, the study highlights the connectedness between rare earth minerals with the performance of firms in sustainable industries. Thus, policymakers should recognize the impact of rare earth mineral prices and their availability on the performance of these industries. The outcomes call for fostering international collaborations to support these clean firms. Moreover, financial markets have significant roles to attract investors to these sustainable industries. Thus, policymakers have to monitor and regulate these markets to ensure transparency and encourage clean energy sectors.

The paper proceeds as follows. Section 2 provides the literature review, Section 3 presents the data and methodology, Section 4 discusses the empirical findings and Section 5 concludes.

## 2. Literature review

The necessity of shifting to renewable energy or phasing down fossil fuels is known to diminish carbon dioxide emissions or other detrimental impacts on human health. But, relatively few papers focus on the necessity of rare earth minerals in renewable energy production or renewable energy technologies. Some literature defined the dependency on rare earth elements as a barrier to a broader adaptation of renewable energy technology or clean technology (Habib and Wenzel, 2014; Zhou et al., 2017). Some papers note that potential supply shortages of rare earth-like dysprosium could have hamper effects on green energy technologies (Hoenderdaal et al., 2013).

Some lines of literature focus on the price properties of rare earth minerals. Fernandez (2017) estimates the market capitalization and systematic risk of leading rare earth extracting and production companies and, by investigating the co-movement of prices of rare earth minerals and commodity prices. The results point to generally positive correlations of the price of these firms with commodity indices returns and the risk of these firms are higher than average S&P 500 firms. Proelss et al. (2020) investigate the volatility of rare earth minerals and evaluate the suitability of short (ARMA) and long-memory models (ARFIMA), and a GARCH model and evidence the presence of long-memory effects. In a similar vein, Riesgo García et al. (2018) improve transgenic time series using ARIMA models to improve price forecast accuracy for rare earth oxide prices.

Another stream of literature investigates the dynamics of rare earth minerals with other financial asset classes. Baldi et al. (2014) consider the impact of skyrocketing rare earth prices on the clean industry stocks' performance and conclude a detrimental impact of rare earth prices on these stocks. Apergis and Apergis (2017) present a pioneering study investigating the long-run relationship between rare earth prices and renewable energy consumption by adopting standard time series econometrics for the 2004–2016 period. They point to the existence of unidirectional long-run relationships from certain rare earth minerals to renewable energy consumption. They focus on the price transmission between rare earth stocks and the base metals, gold, clean energy, oil, and global MSCI stock markets. Reboredo and Ugolini (2020) analyze the price transmission mechanisms between rare earth stocks and the base metals, gold, clean energy, oil, and global MSCI stock markets by adopting a Markov switching vector autoregressive model. Rare earth stocks relate to base metals as a receiver and transmitters of volatility during low regimes, but they display low connections with clean energy, gold, oil, and general stock markets.

Zheng et al. (2021) connectedness study between new energy and rare earth markets at the firm level, using the Diebold and Yılmaz framework, and the results show indications of moderate volatility spillovers. Zheng et al. (2022) examine the crude oil, renewable energy, high-technology, and rare earth markets volatility spillovers relationship by adopting wavelet analysis and the BEKK-GARCH model. The results indicate significant volatility spillovers between renewable energy and high-tech markets and rare earths also show significant control in this system. Zhou et al. (2022) highlight that political risks are a dominant factor in time and frequency spillovers, with remarkable dominance in short-term dynamic connectedness. Song et al. (2021) apply a time-varying parameter vector autoregression model to detect connectedness between the rare earth index and clean energy world equity and oil indices and reveal the rare earth index to be a receiver of return and volatility shocks over the 2010–2020 period. Chen et al. (2020) also probe the volatility spillover relationship between the rare earth industry index, mainland new energy index, and Brent oil price using the asymmetric VAR-BEKK (DCC)-GARCH approach. Their results also unearth high volatility spillover between the rare earth index and the new energy index.

Apergis and Apergis (2017) were the first authors to explore the long-run relationship between rare earth prices and the consumption of renewable energy. However, they use monthly time series data for the period 2004–2016, concluding its existence but only for certain rare earth and regions. They call attention to the need to establish a global green energy environment. Investigating volatility spillovers and dynamic correlations, Chen et al. (2020) used daily data (2012–2018) to conclude that the strong evidenced relationship found between rare earth and new energy markets in China justifies their strong use in these new energy applications. More recently, Song et al. (2021) examined return and volatility connectedness between rare earth stock markets, clean energy markets, world equity, base metals, gold, and crude oil. The authors use a time-varying parameter vector autoregression approach using daily data from September 2010 to August 2020 to include the COVID-19 outbreak effects. The authors highlight the superior volatility connectedness as compared to that of returns, identifying a significant spike in February–March 2020. Moreover, the rare earth index evidenced higher interdependence with clean energy during the pandemic, being a return and volatility receiver over the entire period. Hanif et al. (2023) investigate the relationship between rare earth and renewable energy stocks by analyzing their time-frequency co-movements, return spillovers, and volatility spillovers using wavelet analysis and the spillover index methodology. The findings indicate that the COVID-19 pandemic leads to a significant increase in co-movements and spillovers in returns and volatility between rare earth and renewable energy stocks, with rare earth acting as net recipients and clean energy stocks as net transmitters of spillovers. In their study, Bouri et al. (2021) investigate the relationship between the rare earth stock index and indexes of clean energy, consumer electronics, telecommunications, healthcare equipment, and aerospace and defense by analyzing the dynamics of return and volatility connectedness between these indexes. The study finds that during the pandemic, the consumer electronics and clean technology indexes transition from being net receivers to net transmitters of return and volatility, while the rare earth index consistently remains on the recipient's side.

Most of the literature concentrates on the rare earth volatility spillover relationship with other asset classes and considers their impact on a portfolio. However, this paper aims to center the rare earth and sustainability indices relationship like clean energy, renewable energy technology, and carbon efficiency and conclude about the potential connections between rare earth minerals and clean energy firms and understanding the mechanisms that will determine the possibility to meet zero carbon goals. The paper also adopts very novel econometric approaches that would produce more robust outcomes. Moreover, the outcomes of the analyses have significant policy implications in terms of identifying the importance of rare earth minerals in clean energy sectors, promoting technological developments in renewable energy, supporting sustainable industries, and regulating and monitoring financial markets to promote investments in clean energy firms.

## 3. Data and methodology

### 3.1. Data

In this paper, quantile approaches are employed to explore the association among four variables. We especially used the quantile time–frequency connectedness proposed by Chatziantoniou et al. (2022) and the cross-quantilogram dependence established by Han et al. (2016). The four variables implemented are the following: MVIS Global Rare Earth/Strategic Metals Index (MVREMX) which measures the performance of the largest and most liquid companies in the global rare earth and strategic metals industry, S&P Global Clean Energy Index which measures the performance of companies in global clean energy-related businesses from both developed and emerging markets, S&P/TSX Renewable Energy and Clean Technology Index which measures the performance of companies listed on the TSX whose core business is the development of green technologies and sustainable infrastructure solutions and S&P 500 Carbon Efficient Index which measures the performance of companies in the S&P 500, while overweighting those companies that lower or higher levels of carbon emissions per unit of revenue. All the data are obtained from DataStream[1] and the daily datasets are for September 28, 2012, to October 7, 2022.

### 3.2. Quantile time–frequency connectedness methods

Chatziantoniou et al. (2022) established the quantile time–frequency connectedness based on the Chatziantoniou et al. (2021) quantile connectedness model and the frequency-domain measures of Baruník and Křehlík (2018). Initially, we calculate a quantile vector autoregression (QVAR) model by the below function:

$$l_t = s_t(z) + w_1(z)l_{t-1} + w_2(z)l_{t-2} + \ldots + w_v(z)l_{t-v} + q_t(z) \quad (1)$$

where $l_t$ shows the endogenous covariates of the estimated model and $z$ takes values $0-1$ and denotes the quantile level. The lag length is shown by $v$ and $w_i(z)$ is an estimated QVAR coefficient matrix while $q_t(z)$ is an error vector. Next, we can estimate the connectedness through the generalized forecast error variance decomposition (GFEVD). Briefly, we can calculate the five connectedness: the (overall) net pairwise connectedness (NPDC), the (overall) total directional connectedness TO others, the (overall) total directional connectedness FROM others, the (overall) NET total directional connectedness and the (overall) total connectedness index (TCI):

$$NPDC_{ij}(H) = \widetilde{b}_{ij}(H) - \widetilde{b}_{ji}(H) \quad (2)$$

[1] https://www.refinitiv.com/en/.

$$TO_i(H) = \sum_{i=1, i\neq j}^{N} \widetilde{b}_{ji}(H) \tag{3}$$

$$FROM_i(H) = \sum_{i=1, i\neq j}^{N} \widetilde{b}_{ij}(H) \tag{4}$$

$$NET_i(H) = TO_i(H) - FROM_i(H) \tag{5}$$

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H) \tag{6}$$

Including the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Yılmaz (2012, 2014), now the time-domain measures can be estimated as:

$$NPDC_{ij}(H) = \sum_{d} NPDC_{ij}(d) \tag{7}$$

$$TO_i(H) = \sum_{d} TO_i(d) \tag{8}$$

$$FROM_i(H) = \sum_{d} FROM_i(d) \tag{10}$$

$$NET_i(H) = \sum_{d} NET_i(d) \tag{11}$$

$$TCI(H) = \sum_{d} TCI(d) \tag{12}$$

In our study, we measure two frequency bands depicting short-term and long-term dynamics ranging from 1 to 5 days, $d1 = (\pi/5, \pi)$, and from 6 to infinite days, $d2 = (0, \pi/5]$.

### 3.3. Cross-quantilogram dependence

Initially, we estimate the quantile time–frequency connectedness to measure the average directional spillover level of our variables. After that, we want to study the fluctuation trend of our sample. Thus, we employ the cross-quantilogram (CQ) framework proposed by Han et al. (2016). A CQ model for two occurrences $\{k_{1t} \leq p_{1t}(r_1)\}$ and $\{k_{2t-s} \leq p_{2t-s}(r_2)\}$ for a pair of $r_1$ and $r_2$:

$$d_r(s) = \frac{E[\theta_{s1}(k_{1t} \leq p_{1t}(r_1))\theta_{s2}(k_{2t-s} \leq p_{2t-s}(r_2))]}{\sqrt{E\left[\theta_{s1}^2(k_{1t} \leq p_{1t}(r_1))\right]}\sqrt{E\left[\theta_{s2}^2(k_{2t-s} \leq p_{2t-s}(r_2))\right]}} \tag{13}$$

in equation (13) $k_t$ denotes the quantile-hit procedure while $s$ shows the lag length and $p_t$ displays the correlation of the quantile-hit procedure. Moreover, we can apply the partial cross-quantilogram (PCQ) model by the following equation:

$$R_{\bar{\tau}} = E\left[h_t(\bar{\tau})h_t(\bar{\tau})^T\right]; P_{\bar{\tau}} = R_{\bar{\tau}}^{-1} \tag{14}$$

All in all, we can estimate the CQ as $\frac{r_{\bar{\tau}12}}{\sqrt{r_{\bar{\tau}11} r_{\bar{\tau}22}}}$ and the PCQ as:

$$p_{\bar{\tau}/z} = -\frac{p_{\bar{\tau}12}}{\sqrt{p_{\bar{\tau}11} p_{\bar{\tau}22}}} \tag{15}$$

## 4. Empirical findings

Fig. 1 plots the four variable's returns under study. Returns were

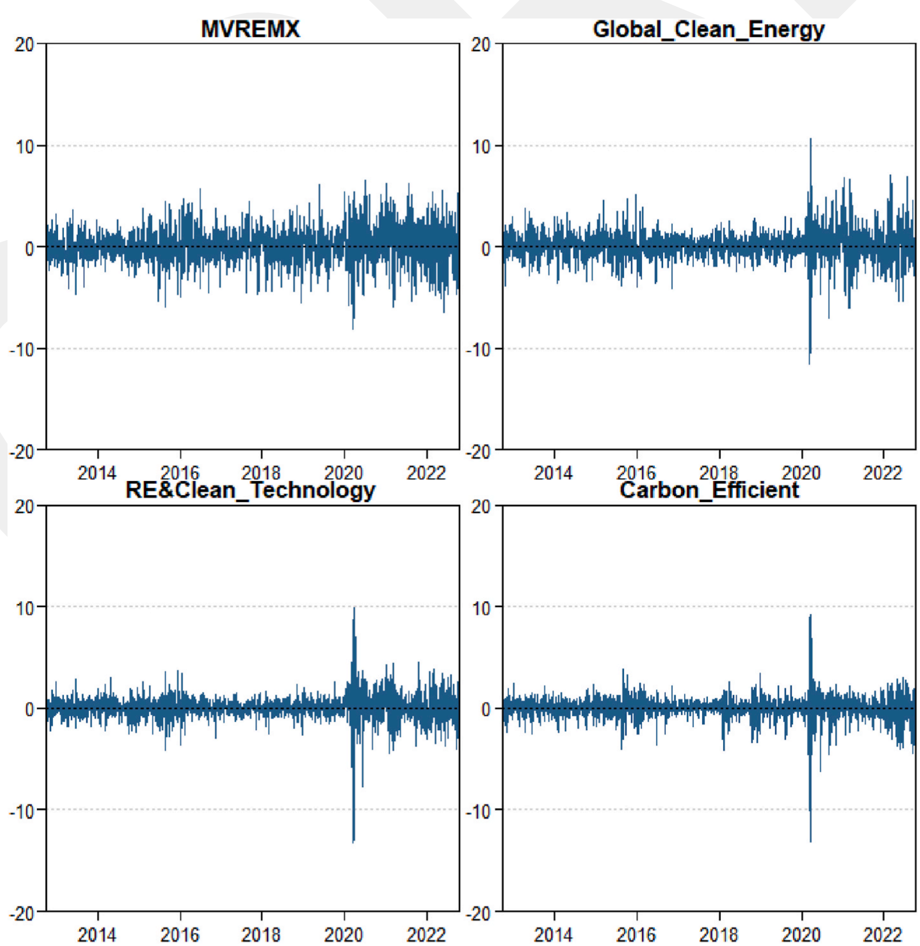


**Fig. 1.** Returns plot of the variables.

computed in the traditional way using the natural logarithm of price differences among consecutive periods. Except for the MVIS Global Rare Earth/Strategic Metals Index revealing huge volatility for the entire period analyzed, the other three series (clean energy, renewable energy and clean technology, and carbon-efficient indexes) evidence a huge spike at the beginning of the year 2020 due to the pandemic followed by high instability onwards revealed by higher volatility. The dynamics among all indexes appear to be synchronous even though some upward and downward movements are stronger in ones as compared to others. This first evidence seems to contradict what was pointed out by Song et al. (2021) where the authors found mixed patterns among the series under study (clean energy index, world equity index, global base metals index, gold index, and the oil index).

Considering the series of descriptive statistics and correlations presented in Table 1, is observed higher variance in the global rare earth minerals index representative, followed by the Global Clean Energy Index, as measured through variance and as expected provided Fig. 1 plots presented and discussed previously. The average returns are positive except that of the rare earth. Excess kurtosis and negative skewness are a reality and neither is equal to zero indicating that each series has typical characteristics of leptokurtosis and fat-tail. The Jarque-Bera statistics results rebut the normality of the unconditional distribution.

The Elliott et al. (1996) unit root test (ERS) shows that all series of index returns are stationary at the 1% level of significance. Fisher and Gallagher (2012) weighted portmanteau tests evidence significant autocorrelation of the series returns, suggesting significant conditional heteroscedasticity effects. In other words, series are left-skewed and exhibit ARCH/GARCH errors. Finally, all non-parametric Kendall rank correlation coefficients presented are positive and significant, being the highest correlation between the Global Clean Energy Index and the Renewable Energy and Clean Technology Index. If the performance of firms whose core business is on the development of green technologies and sustainable infrastructure solutions increases, that will enhance the performance of companies in the global clean-energy-related business.

### 4.1. Quantile time-frequency spillovers findings

In this sub-section, we present the results of the study and discuss pertinent issues which emerge from our analysis. We will focus on dynamic results under frequency and quantiles. By doing so we can analyze the connectedness by various frequencies allowing a more in-depth analysis of the time-domain connectedness approach. We present results by quantiles providing additional information regarding the tail dependencies, namely at the 5th, 50th, and 95th quantiles. This approach enables us to analyze whether the short-term and long-term connectedness changes across quantiles.

We start by presenting average median results at the 5th quantile (Table 2), at the 50th quantile (Table 3), and the 95th quantile (Table 4), as such considering results at specific points in time. All mentioned tables contain the time-domain values, more concretely the short and long-term connectedness values. The highest own-variance share spillovers occur in the case of the Renewable Energy and Clean Technology Index in the short term and the Global Rare Earth/Strategic Metals Index in the long term at the 5th quantile (Table 2). The same happens in the long term for the 50th quantile (Table 3), but in the short term, 50.35% are considered as short-term own-variance spillovers in the Carbon Efficient Index, the highest value reported. At the 95th quantile, the same is true for the long-term, but in the short term, the Carbon Efficient Index is still (similar to the 50th) the one with the highest own-variance share spillovers (Table 4).

Considering solely the Global Rare Earth/Strategic Metals Index we verify that at the 5th quantile own-variance share spillovers are 31.38%, and all others account for 68.62% of the MVREMX index forecast error variance. At the 50th quantile, own-share spillovers are 64.86% (Table 3, summing short and long-term values) and the other indexes

**Table 2**
Averaged dynamic connectedness (at the 5th quantile).

| Panel A: Short-term frequency connectedness measures | | | | | |
|---|---|---|---|---|---|
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 19.43 | 13.42 | 13.06 | 13.73 | 40.22 |
| Global Clean Energy | 13.82 | 20.83 | 15.61 | 15.62 | 45.05 |
| RE&Clean Technology | 14.98 | 17.23 | 23.39 | 17.34 | 49.55 |
| Carbon Efficient | 14.77 | 16.33 | 16.58 | 22.33 | 47.68 |
| TO | 43.56 | 46.98 | 45.26 | 46.69 | TCI |
| Net | 3.35 | 1.93 | −4.29 | −0.99 | 45.62 |
| **Panel B: Long-term frequency connectedness measures** | | | | | |
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 11.95 | 9.63 | 8.89 | 9.88 | 28.41 |
| Global Clean Energy | 7.40 | 10.42 | 8.20 | 8.09 | 23.70 |
| RE&Clean Technology | 5.77 | 6.59 | 8.25 | 6.45 | 18.81 |
| Carbon Efficient | 6.58 | 7.35 | 7.00 | 9.06 | 20.92 |
| TO | 19.75 | 23.57 | 24.09 | 24.42 | TCI |
| Net | −8.66 | −0.12 | 5.28 | 3.50 | 22.96 |

Notes: Findings are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead GFEVD.

**Table 1**
Summary statistics and preliminary tests.

| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient |
|---|---|---|---|---|
| Mean | −0.018 | 0.055 | 0.017 | 0.038 |
| Variance | 2.954 | 2.095 | 1.505 | 1.238 |
| Skewness | −0.075 | −0.253*** | −1.015*** | −0.991*** |
| Ex.Kurtosis | 1.394*** | 7.835*** | 19.215*** | 18.062*** |
| JB | 199.544*** | 6258.833*** | 37909.715*** | 33525.728*** |
| ERS | −20.224*** | −20.382*** | −19.800*** | −19.851*** |
| Q(20) | 114.678*** | 68.181*** | 85.440*** | 245.170*** |
| $Q^2(20)$ | 518.959*** | 1467.506*** | 3094.742*** | 2834.744*** |
| kendall | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient |
| MVREMX | 1.000*** | 0.242*** | 0.214*** | 0.230*** |
| Global Clean Energy | 0.242*** | 1.000*** | 0.378*** | 0.337*** |
| RE&Clean Technology | 0.214*** | 0.378*** | 1.000*** | 0.360*** |
| Carbon Efficient | 0.230*** | 0.337*** | 0.360*** | 1.000*** |

Notes: ***, **, and * show significance at 1%, 5%, and 10%, respectively; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test with constant; Q(20) and $Q^2(20)$: Fisher and Gallagher (2012) weighted portmanteau test.

**Table 3**
Averaged dynamic connectedness (at the 50th quantile).

| Panel A: Short-term frequency connectedness measures | | | | | |
|---|---|---|---|---|---|
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 47.96 | 7.03 | 6.25 | 9.61 | 22.88 |
| Global Clean Energy | 6.18 | 46.74 | 12.61 | 12.35 | 31.14 |
| RE&Clean Technology | 5.57 | 12.80 | 47.94 | 13.36 | 31.74 |
| Carbon Efficient | 6.75 | 12.63 | 13.57 | 50.35 | 32.95 |
| TO | 18.51 | 32.45 | 32.43 | 35.33 | TCI |
| Net | −4.37 | 1.31 | 0.69 | 2.38 | 39.57 |
| **Panel B: Long-term frequency connectedness measures** | | | | | |
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 16.90 | 3.73 | 3.31 | 5.23 | 12.27 |
| Global Clean Energy | 1.55 | 13.04 | 3.78 | 3.74 | 9.08 |
| RE&Clean Technology | 0.96 | 3.34 | 12.84 | 3.18 | 7.49 |
| Carbon Efficient | 1.31 | 2.75 | 2.69 | 9.95 | 6.75 |
| TO | 3.83 | 9.82 | 9.78 | 12.15 | TCI |
| Net | −8.44 | 0.74 | 2.30 | 5.40 | 11.86 |

Notes: Findings are based on a 200-day rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead GFEVD.

**Table 4**
Averaged dynamic connectedness (at the 95th quantile).

| Panel A: Short-term frequency connectedness measures | | | | | |
|---|---|---|---|---|---|
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 23.99 | 16.10 | 15.69 | 16.23 | 48.01 |
| Global Clean Energy | 17.45 | 25.31 | 18.30 | 18.63 | 54.38 |
| RE&Clean Technology | 17.09 | 18.88 | 26.46 | 19.32 | 55.30 |
| Carbon Efficient | 18.58 | 19.91 | 20.22 | 27.69 | 58.71 |
| TO | 53.13 | 54.88 | 54.21 | 54.18 | TCI |
| Net | 5.12 | 0.50 | −1.09 | −4.54 | 54.10 |
| **Panel B: Long-term frequency connectedness measures** | | | | | |
| | MVREMX | Global Clean Energy | RE&Clean Technology | Carbon Efficient | FROM |
| MVREMX | 8.90 | 6.18 | 6.26 | 6.65 | 19.09 |
| Global Clean Energy | 3.83 | 6.94 | 4.92 | 4.61 | 13.36 |
| RE&Clean Technology | 3.54 | 4.36 | 6.13 | 4.22 | 12.12 |
| Carbon Efficient | 2.73 | 3.23 | 3.27 | 4.37 | 9.23 |
| TO | 10.10 | 13.78 | 14.45 | 15.48 | TCI |
| Net | −8.99 | 0.42 | 2.33 | 6.25 | 13.45 |

Notes: Findings are based on a 200-days rolling-window QVAR model with a lag length of order 1 (BIC) and a 100-step-ahead GFEVD.

account for 35.14% of its forecast error variance. At the 95th quantile (Table 4), own-variance share spillovers are 32.89%, and all other indexes account for 67.11% of its forecast error variance.

As can be inferred from the results, each stock can be decomposed into short-term and long-term spillovers. In the event of the Carbon Efficient Index, which has the largest impact, in all considered quantiles and for both the short and long term, on the Global Rare Earth/Strategic Metals Index, we find that 13.73%, 9.61%, and 16.23% are caused by short-term spillovers, whereas 9.88%, 5.23%, and 6.65% originate from long term Carbon Efficient Index, at the 5th, 50th, and 95th quantiles, respectively.

In total and considering the short-term and 5th quantile (Table 2), we see that the Global Rare Earth/Strategic Metals Index influences the market by 43.56% and is influenced by 46.91% indicating that it is a net transmitter (3.35%) of shocks in the short-term. This is also true at the 95th quantile (5.12%) as exposed in Table 4, but the MVREMX Index reveals to be a net receiver of shocks (−4.37%) in the short-term at the 50th quantile (Table 3). In the long-term, the MVREMX results point out that it is always a net receiver of shocks (−8.66%, −8.44%, −8.99%, Tables 2–4, respectively). These results confirm those of Hanif et al. (2023) detecting that rare earth act as net recipients of spillovers.

Both the Renewable Energy and Clean Technology Index and the Carbon Efficient Index reveal to be net receivers of shocks in the short term at the extreme quantiles (5 and 95), being net transmitters of shocks in the long term at the mentioned extreme quantiles. However, for both the short-term and long-term and considering the 50th quantile, results point out that both have been net transmitters of shocks (0.69% and 2.38% in the short-term; 2.30% and 5.40% in the long-term). Finally, the Global Clean Energy Index seems to have been a net transmitter of shocks in both the short and long term at the 50th and 95th quantiles, but a net transmitter in the short term at the 5th quantile (1.93%) and a net receiver (−0.12%) in the long-term. These results contradict those of Hanif et al. (2023) which point out that clean energy stocks act as net transmitters of spillovers. However, these authors' conclusions respect solely the COVID pandemic period. Also, Bouri et al. (2021) find that during the pandemic, the consumer electronics and clean technology indexes transitioned from being net receivers to net transmitters of return and volatility, confirming our present results.

To sum up, in the short term, among the investigated series, and the 5th quantile (Table 2), the highest net transmitter is the MVREMX Index, and the highest net receiver is the RE&Clean Technology. For the 50th quantile, the highest net receiver of shocks is the MVREMX, and the net transmitter is the Carbon Efficient Index. Considering the 95th quantile, the Carbon Efficient Index turns out to be the highest net receiver (−4.54%) and the highest net transmitter the MVREMX (5.12%). For the long term, we have that at the 5, 50, and 95th quantiles the highest net receiver of shocks is the Global Rare Earth/Strategic Metals Index, whereas the highest net transmitter of shocks, in the 5th quantile, is the Renewable Energy and Clean Technology, and as quantiles increase (50 and 95), the Carbon Efficient Index turns to be the highest net transmitter of shocks. Thus, we do not validate completely the results of Bouri et al. (2021) considering the rare earth index, whose authors stated it consistently remained on the recipient's side. Our results suggest that its net transmitter and/or recipient role depends on the analyzed quantile.

Rare earth's emergence as net receivers in the long term in the entire system is not surprising since these are the basic minerals of renewables technologies innovations and broad low-carbon economic activities (Apergis and Apergis, 2017). Therefore, these are crucial in determining future renewable diffusion, and future consumption, considering that lower production costs associated with renewable energy sources will work as a stimulus for investors (Apergis and Apergis, 2017; Chen et al., 2020; Song et al., 2021). Moreover, rare earth minerals are likely to receive shocks from firms that use these for their environmentally friendly projects. Having the Carbon Efficient Index as the main net transmitter of shocks as quantiles increase and in the long term may suggest the intensification of the usage of clean technologies and clean energy. However, these values only demonstrate the average connectedness measures which might mask time-specific and time-varying effects, and for that, we continue by focusing on the dynamic connectedness plots by quantiles (Figs. 2–4, respectively for the 5th, 50th, and 95th quantiles).

Figs. 2–4 depict the median short-term, long-term, and total dynamic

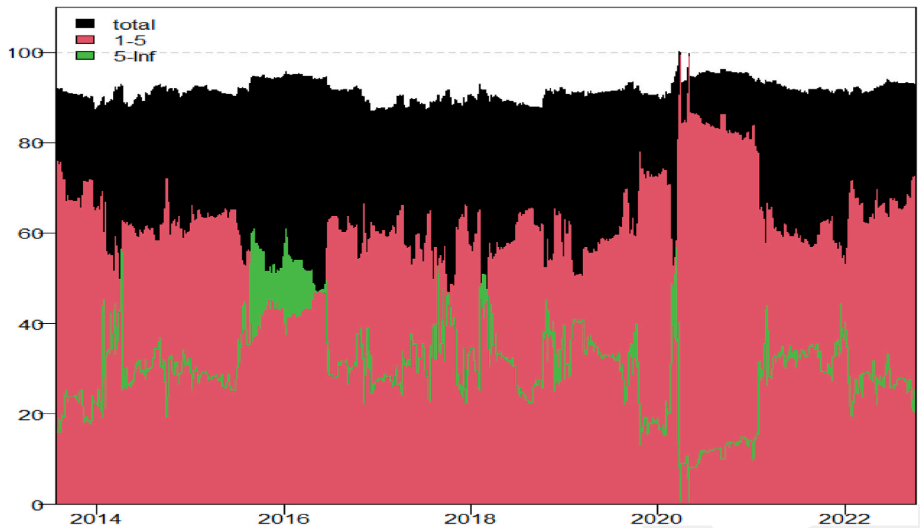


**Fig. 2.** Short- and long-term and overall dynamic total connectedness (at the 5th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

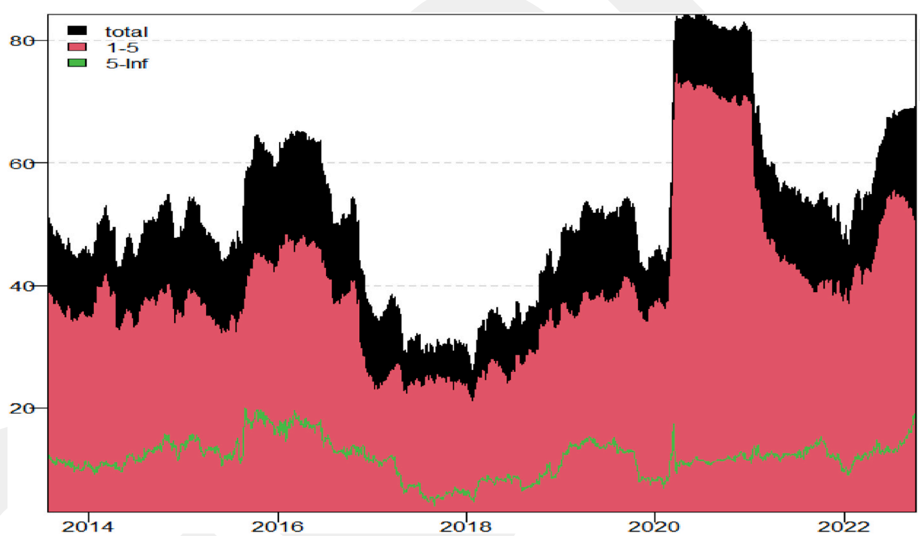


**Fig. 3.** Short- and long-term and overall dynamic total connectedness (at the 50th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

connectedness among series for the three considered quantiles, respectively. As stated by other authors the QVAR approach leads to more accurate and reliable results (see Chatziantoniou et al., 2022, and references therein). Overall, we see substantially high market spillovers among the four indices, similar in magnitude throughout the entire period when considered the 5th quantile (Fig. 2). However, in the short term, we have peaks and drops in different directions as compared to those in the long term. The same is true when we consider the 95th quantile (Fig. 4), where a huge peak, reaching values of 100% in the short term, is observed at the beginning of the pandemic period (2020). Considering the 50th quantile the results change regarding the overall dynamic connectedness.

The total connectedness index measures the degree of network interconnectedness and we observe from Fig. 3 that in 2016 we have a peak reaching a plateau of around 60%. The subsequent drop until 2018 is observed in all the areas, meaning in the time dynamic connectedness, and the long and short-term representatives. From all figures, we observe that presenting solely the total overall dynamic connectedness is very restrictive, considering that short-term and long-term dynamics are important and should be considered separately. This is true considering that looking only at the total dynamic connectedness would mask the origin of the index movements. Additionally, it is inferred from the results that the importance of considering the overall, short, and long-term dynamics changes depending on the quantiles analyzed, which have not been accounted for in the market index analysis of green indexes conducted by Chatziantoniou et al. (2022).

Concentrating our analysis now on the short and long-term and overall net total directional connectedness by quantiles presented in Figs. 5–7, we may infer the net transmission power of each series. In these figures, positive values correspond to net transmitters of shocks into the system and negative values to net receivers of shocks. With the considered indexes both long-term and short-term dynamics are responsible for each of the four series being a net receiver or transmitter, being that in these figures it is observed a distributed responsibility for that in both terms. Being the green areas associated with long-term dynamics, in the RE&Clean Technology index long-term dynamics

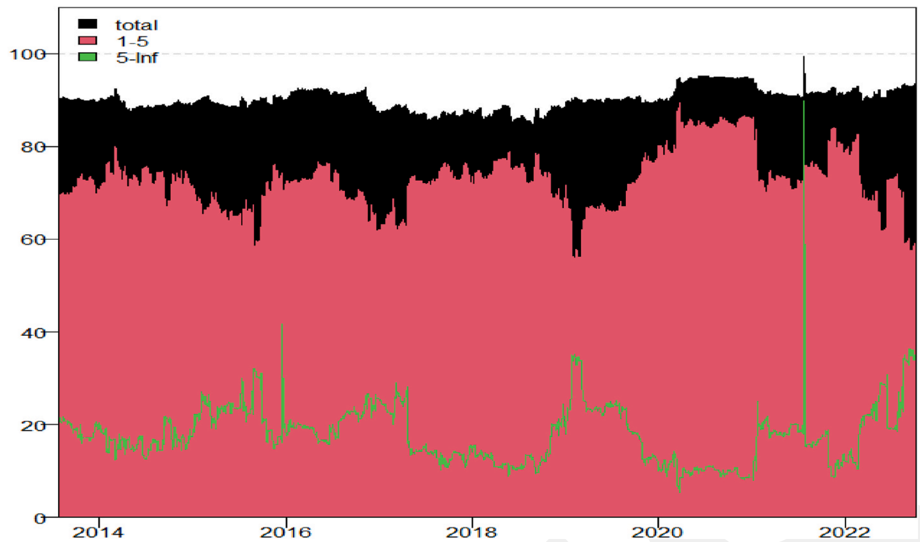


**Fig. 4.** Short- and long-term and overall dynamic total connectedness (at the 95th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

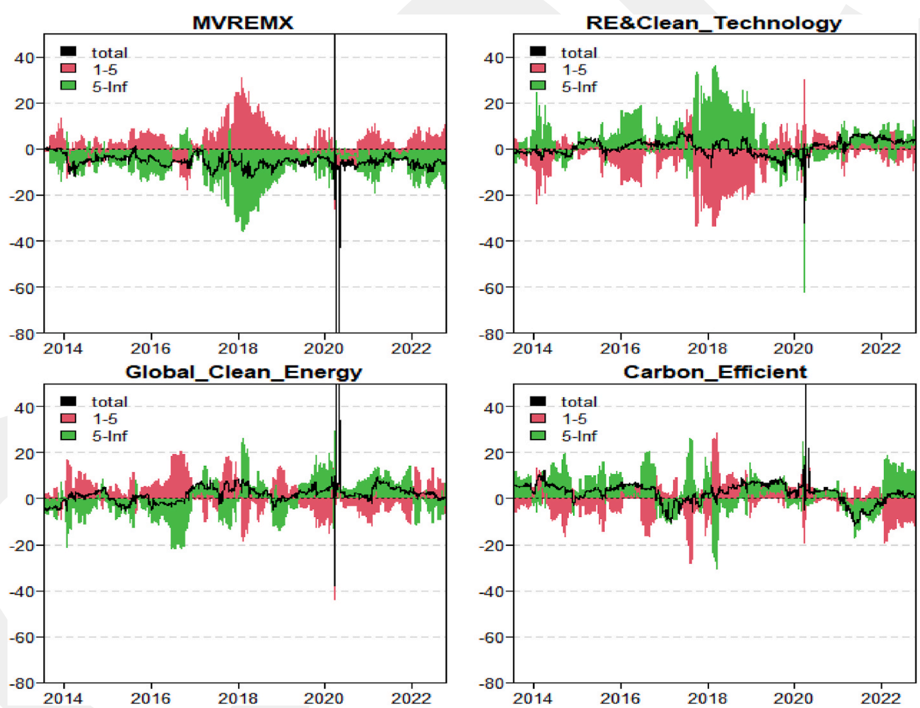


**Fig. 5.** Short- and long-term and overall net total directional connectedness (at the 5th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

dictate this index is a net transmitter of shocks, at least up to 2019, being the short-term dynamics responsible for MVREMX being a net transmitter of shocks at the 5th quantile. Results are mixed when we observe the behavior of the Global Clean Energy and that of the Carbon Efficient Indexes.

Fig. 6 for the 50th quantile turns even more evident the role of net transmitters and receivers of shocks being that in this situation the Global Rare Earth/Strategic Metals Index is a net receiver of shocks during the entire period mostly due to short-term dynamics. Overall, the Global Clean Energy Index, the Renewable Energy and Clean Index, and the Carbon Efficient Index are net transmitters of shocks, and still, the red areas dominate, meaning that the short-term dynamics are the highest contributor to that. It is important to note that the short-term net transmitter role at the 50th quantile of the series is more present, while long-term dynamics are less regular. Our results contradict those of Chatziantoniou et al. (2022) considering the Global Clean Energy Index, considering that in the author's article, it is pointed out that this index has turned a net receiver of shocks during the outbreak, where it turns evident that we may attribute a net transmitter of shocks role to this index from 2019 onwards. Furthermore, Hanif et al. (2023) findings indicate that the COVID-19 pandemic leads to a significant increase in co-movements and spillovers in returns and volatility between rare earth

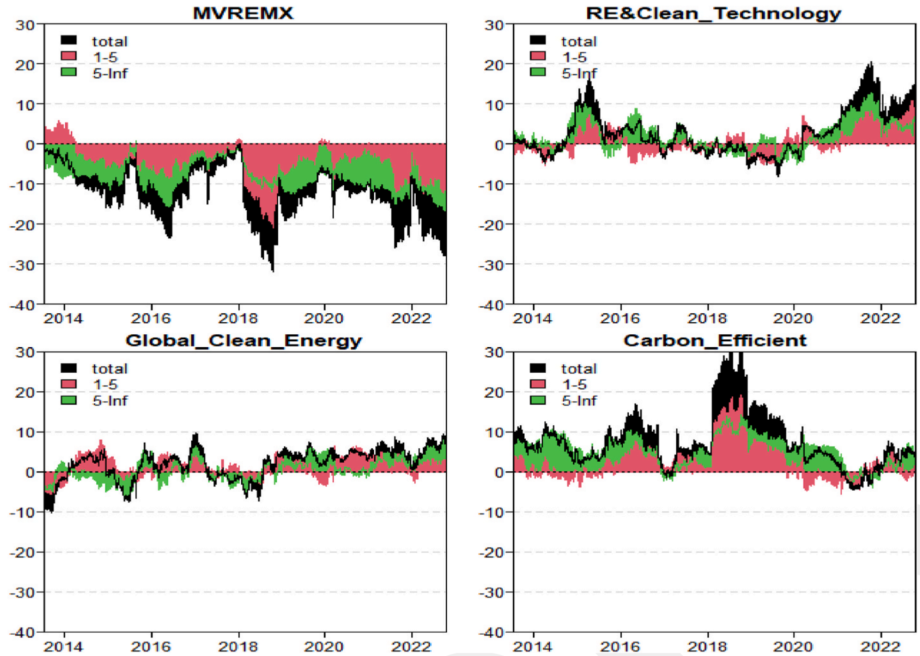


**Fig. 6.** Short- and long-term and overall net total directional connectedness (at the 50th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

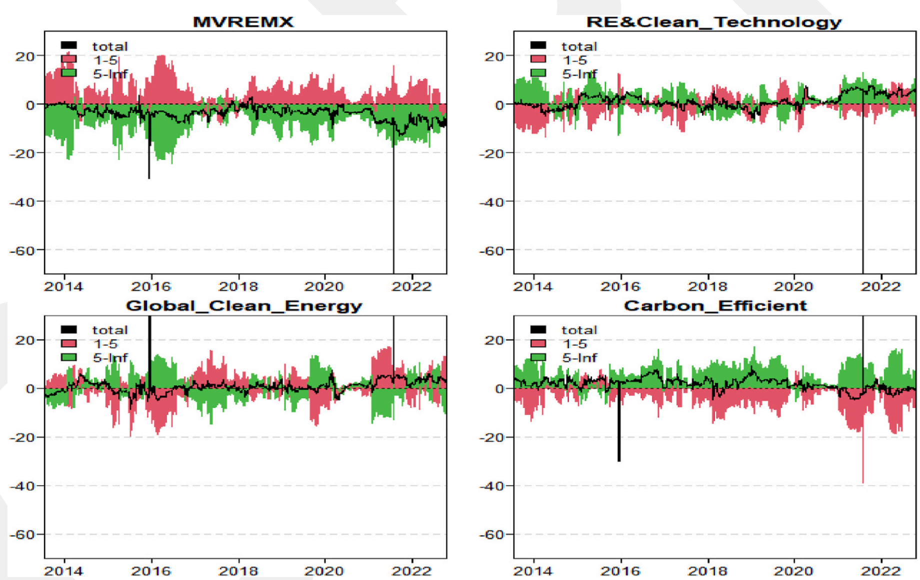


**Fig. 7.** Short- and long-term and overall net total directional connectedness (at the 95th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

and renewable energy stocks, with rare earth acting as net recipients and clean energy stocks as net transmitters of spillovers, confirming our findings. Moreover, Bouri et al. (2021) study finds that during the pandemic, the consumer electronics and clean technology indexes changed from being net receivers to net transmitters of return and volatility, while the rare earth index consistently remains on the recipient's side, partially validating our findings. Also, Chen et al. (2020) results unearth high volatility spillover between the rare earth index and the new energy index. Finally, whereas Zheng et al. (2021) evidence moderate volatility spillovers, Zheng et al. (2022) results indicate significant volatility spillovers between renewable energy and high-tech markets, with rare earth showing significant control in this system.

In Fig. 7 the net transmitter or receiver role of the series at the 95th quantile is not as evident as in the previously considered quantiles, since short and long-term dynamics are not so stable. Even so, the conclusions taken for Fig. 5 may be adapted in this context and apparently, the MVREMX continues a short-term net transmitter of shocks and a long-term net receiver of shocks, whereas the Carbon Efficient Index reveals the opposite (long-term net transmitter and short-term net receiver of shocks). In both the RE&Clean Technology and the Global Clean Energy Indexes we have instability in the short and long-term roles of net receivers and net transmitters of shocks during the entire period under analysis, and it seems that in the COVID-19 pandemic start in 2020, nor short nor long-term effects are evidenced.

Our results seem to point in the direction of those of Zhou et al. (2022), which highlight that political risks are a dominant factor in time and frequency spillovers, with remarkable dominance in short-term dynamic connectedness. Song et al. (2021) also reveal the rare earth index to be a receiver of return and volatility shocks over the 2010–2020 period, whose results we can validate but only in the long run. As for the COVID-19 pandemic period, authors such as Hanif et al. (2023) point to higher comovements and spillovers, Chen et al. (2020) for stronger relationships, and Song et al. (2021) for superior volatility connectedness and higher interdependence, which cannot be fully validated by this article presented results.

Moving one step forward, Figs. 8–10 depict the bilateral dynamics for us to understand in detail the dynamics of the rare earth in depth. These figures present the median net pairwise directional connectedness measures among the four series and take into account the different quantiles, respectively. As previously in the total directional connectedness measures, the positive values are associated with the role of a net transmitter of shocks and the negative ones with that of a net receiver of shocks of the four series. Once more, the green shaded area corresponds to long-term connectedness dynamics while the red shaded areas to short-term connectedness dynamics. What the pairwise connectedness analysis provides is the opportunity to consider pairs of variables and explore the interrelation evolution of these through time.

At the 5th, and mostly at the 95th quantiles, the pairwise connectedness varies in magnitude and the short-long-term net-transmitter-receiver roles of the series. Due to this, we will concentrate our analysis on the 50th quantile whose results are presented in Fig. 9. At almost every point in time, the short-term net pairwise connectedness highlights the domination of the Global Rare Earth/Strategic Metals Index. Therefore, the plots indicate that even though the MVREMX index obtains the lowest correlations with all others, being the most independent from the perspective of simultaneous dependence, its value is heavily driven by shocks in all other series, being a short-term net receiver of shocks.

In turn, a shock in one of the other considered series in the analysis will cause a net change in the Global Rare Earth/Strategic Metals Index not being the opposite true. This result points to the need to consider clean energy investment, renewable energy investment, and clean technologies investments as important drivers of the price of rare earth that might condition future investments in carbon efficient measures. Investments in these technologies should therefore be increased to advance renewable energy technologies and reduce carbon emissions (Ganda, 2019; Danish and Ulucak, 2021). Additionally, advancements in renewable energy technologies make it easier for technological costs to be reduced, which leads to an increase in renewable energy technologies and increased uptake of clean energy sources. According to some academic research (Habib and Wenzel, 2014; Zhou et al., 2017), the dependency on rare earth elements works as a barrier to a broader adaptation of renewable energy technology or clean technology. In some papers (Hoenderdaal et al., 2013, for example), it is noted that possible dysprosium shortages, which are similar to rare earth, could have negative effects on green energy technologies.

These results are in line with those of Apergis and Apergis (2017), Chen et al. (2020), and Song et al. (2021) regarding what respect the strong use of rare earth in renewable energy markets, volatility spillovers, and strong positive relationships found. We partially agree with Reboredo and Ugolini (2020) provided we are only able to denote the net receiver of the volatility role of rare earth, contradicting the author's finding of rare earth's low connections with clean energy. Zheng et al. (2021) results show indications of moderate volatility spillovers of rare earth, whereas we find a short-term strong dynamic connectedness of rare earth. But we strongly validate the Zheng et al. (2022) results which indicate significant volatility spillovers between renewable energy and high-tech markets, being that rare earths show significant control in this system. Finally, we also support Zhou et al. (2022) findings of remarkable dominance in short-term dynamic connectedness.

Considering Fig. 9 as well, none of the other indexes is constantly dominated by the other, but we may argue that the red areas dominate, meaning that short-term dynamics seem to lead. Curiously, results seem to point that from the outbreak of the COVID-19 pandemic the Global Clean Energy Index is a net transmitter of shocks to the Renewable Energy and Clean Technology Index as it is a net transmitter of shocks to the Carbon Efficient Index. As well, the RE&Clean Technology Index works as a net transmitter of shocks to the Carbon Efficient Index. These

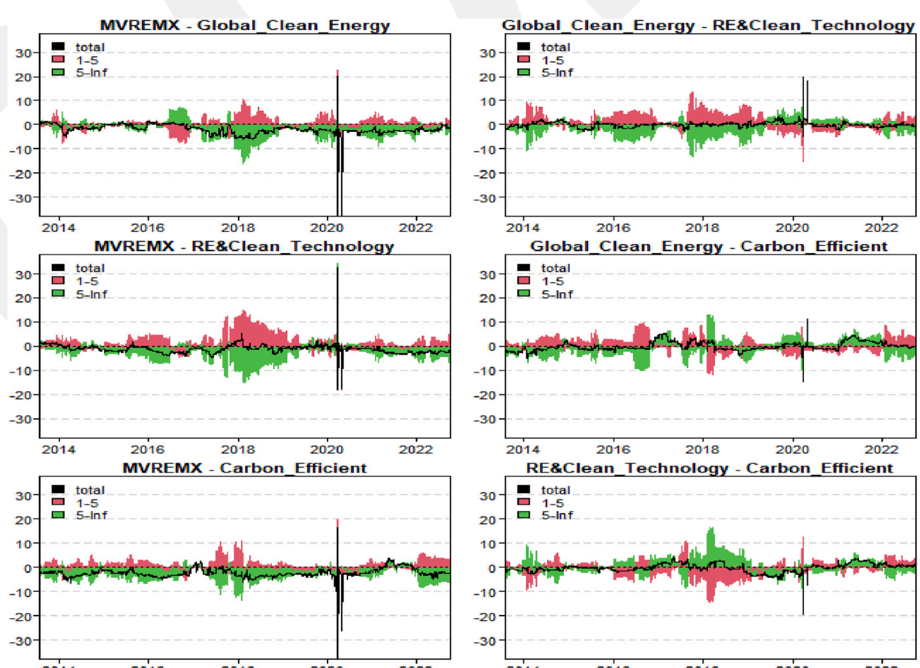


**Fig. 8.** Short-and-long-term and overall net pairwise directional connectedness (5th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

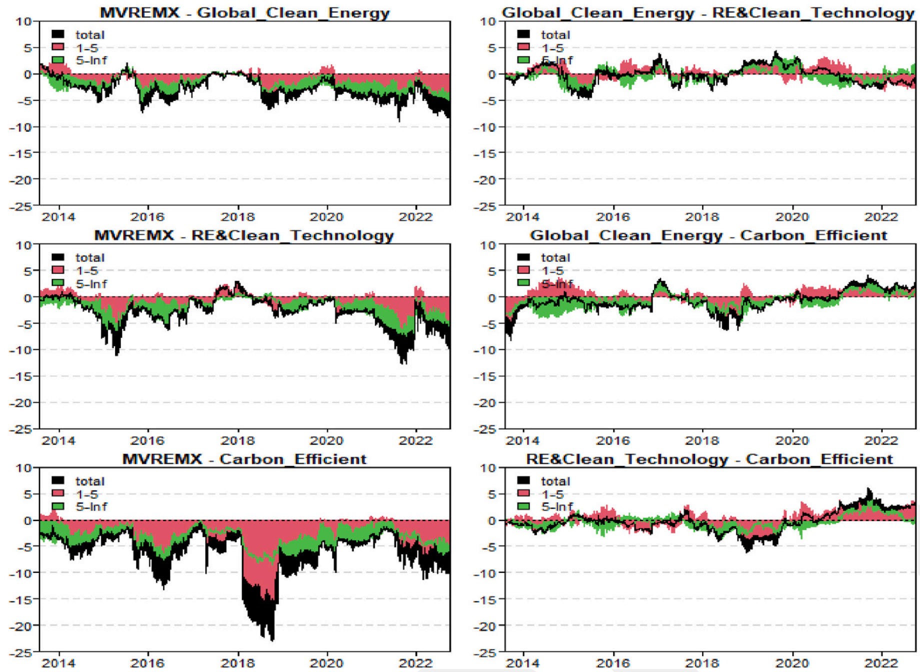


**Fig. 9.** Short- and long-term and overall net pairwise directional connectedness (50th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

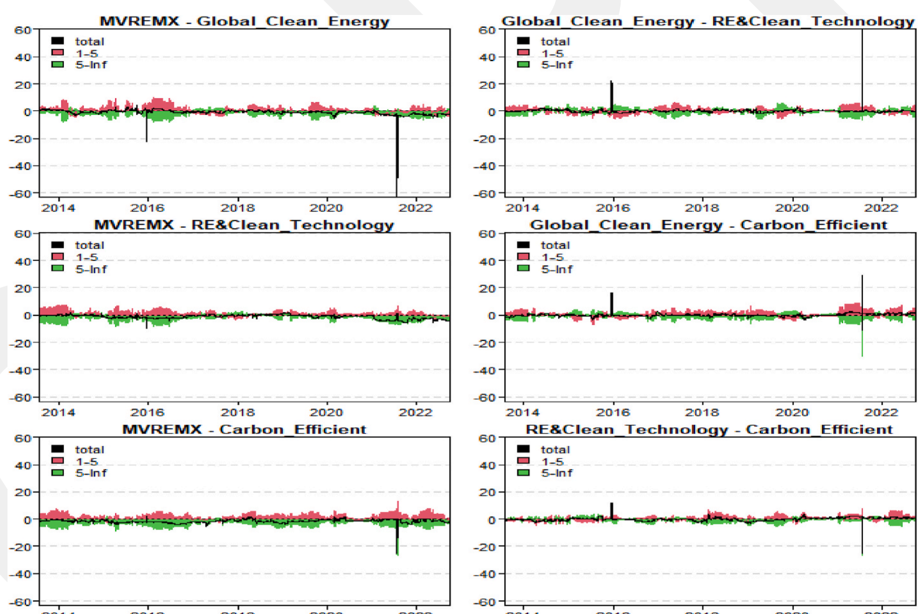


**Fig. 10.** Short-and-long-term and overall net pairwise directional connectedness (95th quantile).
Notes: Findings are based on a QVAR model with a 200-day rolling window size, a lag length of order one (BIC), and a 100-step-ahead GFEVD. The black area represents the time dynamic connectedness values while the green and red areas depict the long and short-term findings.

three relationships change in the short-term as well as in the long-term net transmission and net receiver positions through time.

### *4.2. Cross-quantilogram findings*

The cross-quantilogram framework allows investigating the cross-quantile dependence between the MVREMX index, the Carbon Efficient, the Global Clean Energy, and the RE&Clean Technology indexes, to capture the spillovers between these markets across a wide range of market conditions (Figs. 11 and 12).

Fig. 11 displays the mutual directionality, that is, the cross-quantile correlation between MVREMX to Carbon Efficient Index, Global Clean Energy Index, and RE&Clean Technology Index for four different lags. In each heatmap, the vertical axis presents the quantiles of MVREMX, while the horizontal axis represents other indices. In the case of one lag, MVREMX has a positive influence on Carbon Efficient Index at lower quantiles, when the markets are in a bearish state. However, the relationship is reversed when the returns of the Carbon Efficient Index are high and MVREMX returns are low and it is seen that MVREMX impacts Carbon Efficient Index negatively. At the same time, lower quantiles of

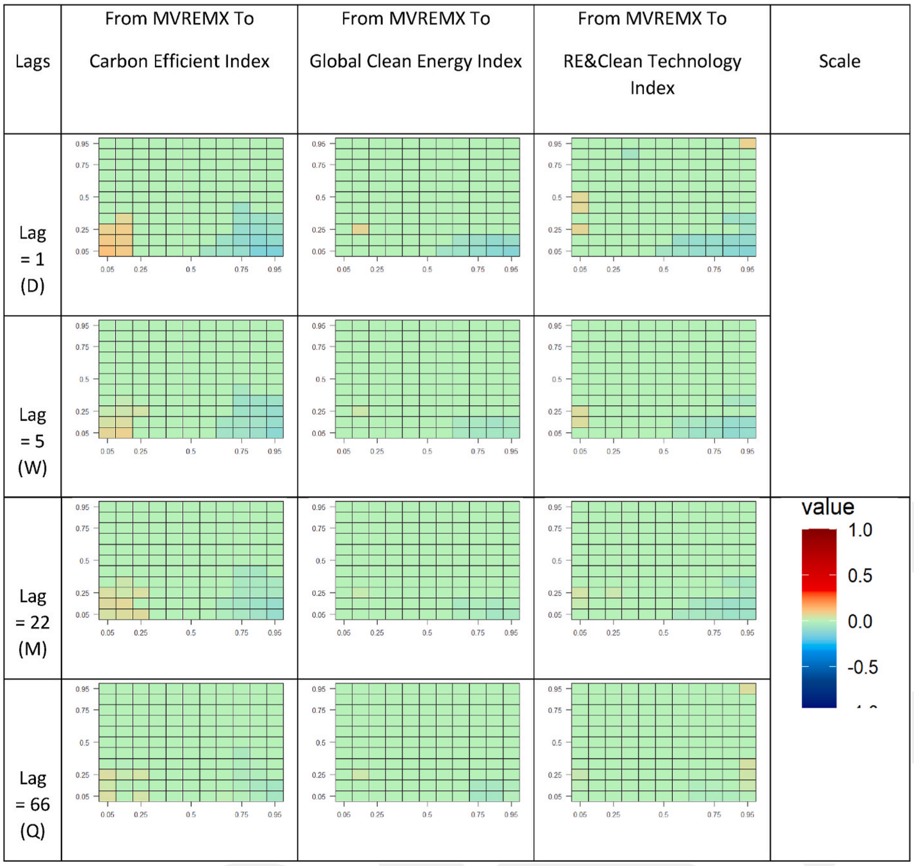


**Fig. 11.** Cross-quantilogram correlation from MVREMX to covariates.
Notes: D, W, M, and Q respectively stand for daily (1 day), weekly (5 days), monthly (22 days), and quarterly (66 days) lags. The Colour scale introduced on the right shows the direction of linkage.

MVREMX returns are predicting upper quantiles of Carbon Efficient Index returns. Despite that these results might seem opposing, they are an indication that the causality from rare earth firms to carbon-efficient firms has a varying structure. There are times when lower (or negative) returns of MVREMX are coupled to lower (or negative) returns of the Carbon Efficient Index, whereas there are times higher quantiles (higher positive returns) of MVREMX are followed by higher quantiles (higher positive returns) of Carbon Efficient Index. At longer lags, the negative impact disappears suggesting that the dependence structure fades over time. MVREMX and Carbon Efficient Index do not show any dependence at medium quantiles in all lengths.

When we investigate the cross-quantilogram correlation from MVREMX to the Clean Energy Index, we observe a dominant and negative influence of MVREMX when they are in opposite quantiles when its returns are low and Clean Energy returns are high. This finding suggests that the decline in rare earth stock prices is likely to have adverse effects on the prices of clean energy firms. This is probably due to the substitution effect that investors consider these firms as substitutes of each other while considering them in their portfolio and we may also propose that lower returns of rare earth stocks will be reflected shortly to the returns of clean energy firms. But the different (upper-lower) quantiles of both indices remind us that the crash and boom of these firms' prices are not simultaneous. The dependence structure is almost non-existent at longer lengths. A similar relationship is spotted for the MVREMX to RE&Clean Technology Index. At lower to medium returns of the rare earth minerals index, there is a positive dependence when the clean technology index is at lower returns. The dependence structure turns to negative impacts at higher returns of clean technology and lower returns of MVREMX. The negative impacts vanish at a quarter lag, while the impact twists to positive at higher quantiles of the clean technology index.

Fig. 12 depicts the cross-quantilogram correlations from Carbon Efficient Index, Global Clean Energy Index, and RE& Clean Technolgy Index to MVREMX. At a daily lag, MVREMX shows a strong dependence on all three indices almost at all quantiles. For the carbon-efficient index, the impact is even stronger especially at matching quantiles (e.g. 0.05:0.05, 0.95:0.95), while the effects are more profound at lower quantiles. This finding implies the strong dependence of return structures on boom and crush, but particularly negative returns display more dependence for these two indices. The dependence diminished at longer lags, but the dependence structure remains at lower to lower and higher to higher return quantiles. The findings are almost the same for the clean energy index and clean technology index but with lower scales. The results suggest that the dependence of the rare earth index on carbon efficiency, clean energy index, and clean technology is more intense. Investors consider these three indices as a determinant of rare earth mineral companies' success. Therefore, if these businesses are in boom states, they will demand more rare earth, which will directly influence the prices of these companies' common stocks.

We further examine the time-varying cross-quantile dependence through Fig. 13 by estimating a recursive estimation of the cross-quantilograms with the first window length of 245 days (a trading year), when all indices are in the 5%, 50%, and 95% quantiles. The blue line indicates the time-varying cross-quantilograms or correlations and the red lines correspond to a 95% confidence interval for the no-predictability null hypothesis.

We find that when both markets are in the 0.95 quantiles, the cross-quantilogram correlations increased at the end of 2021. The cross-quantilogram correlations between these markets in the middle quantile (0.50) are highly significant evidencing increases from 2016

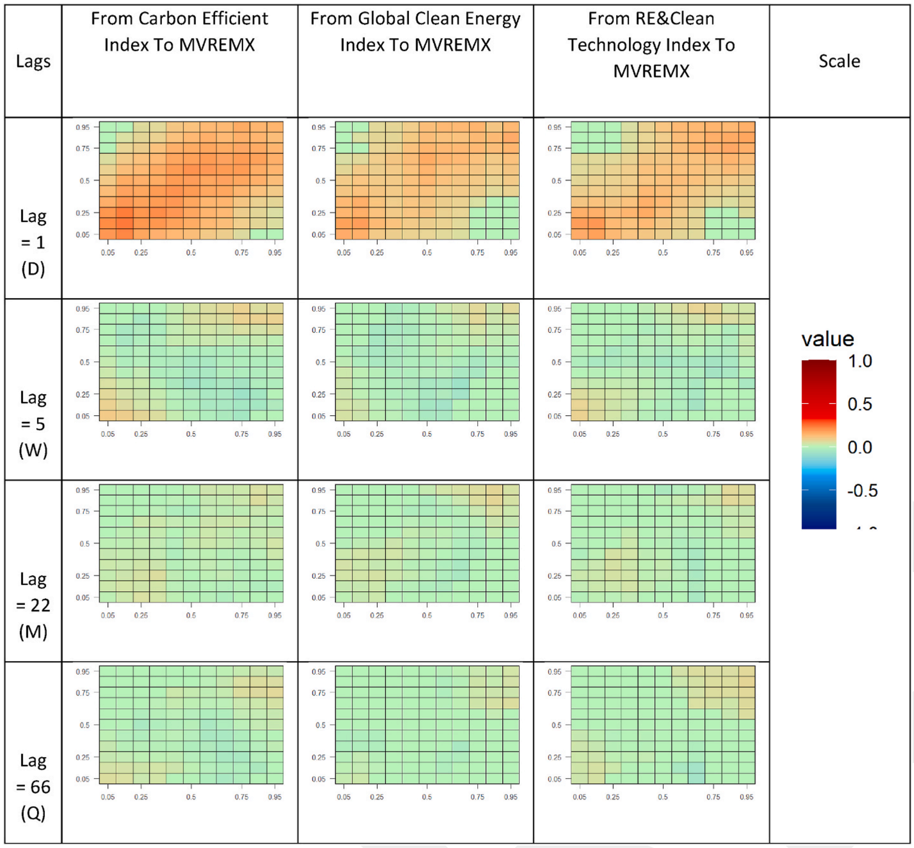


**Fig. 12.** Cross-quantilogram correlation from covariates to MVREMX.
Notes: D, W, M, and Q respectively stand for daily (1 day), weekly (5 days), monthly (22 days), and quarterly (66 days) lags. The Colour scale introduced on the right shows the direction of linkage.

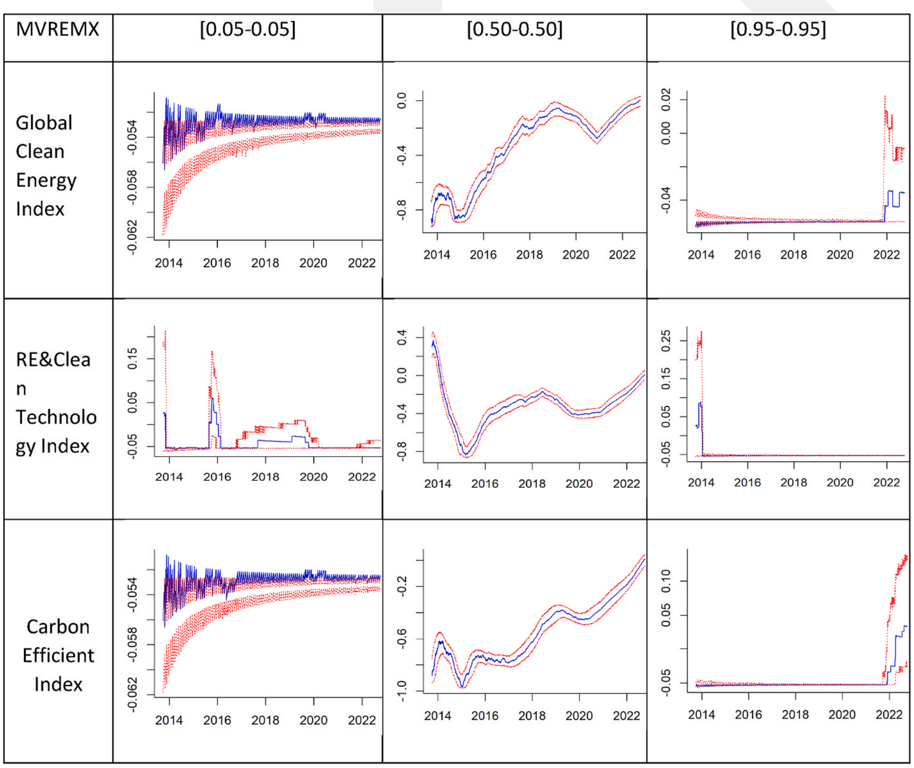


**Fig. 13.** Cross-quantilogram correlation between MVREMX and covariates in recursive subsamples.
Notes: This figure demonstrates CQ correlation for recursive subsamples. The length of the first window period is 245 days which advances daily. The first, second, and third columns respectively divulge the findings when both return distributions are at the 5%, 50%, and 95% quantiles. The horizontal axis represents starting year of the recursive subsamples. The blue lines are time-varying CQ correlations in the recursive subsamples whilst the red lines indicate a 95% confidence interval for the no-predictability null hypothesis. The confidence interval is the yield from the bootstrap procedure (1000 bootstrap iterations are applied).

onwards for all markets, with a decreasing jump verified at the beginning of 2020, coinciding with the outbreak of the COVID-19 pandemic. Considering that the indexes analyzed are part of the financial market, movements are influenced by the increasing contagion during financial crisis periods as also pointed out by Pham (2021), notably at the middle quantiles. It may also be inferred from the results of the short-lived nature of shocks in these markets. Or else, volatility spillovers between these markets are short-lived at lower and higher quantiles, as cross-quantilograms become insignificant after the initial lags.

The downward jump among all series in the cross-quantilogram at the middle quantile in 2015 denotes a negative correlation between the Global Rare Earth/Strategic Metals Index and the other considered indexes, which enter an upward positive correlation movement until 2020, with a sudden drop again, smaller than the one previously verified, and followed by a period of a considerable upward pattern until the end of the data period studied. Only the middle quantile presents a significant cross-quantilogram correlation among the returns which is significant throughout the entire period. Thus, results are sensitive to the quantiles analyzed as they are in specific periods in time, allowing investors to take advantage of investment opportunities, or at least to try to decrease the investment risk in their investment portfolios. Weak dependence evidenced among normal periods at the lowest and highest quantiles also offer good investment opportunities and should work as an alert to policymakers about the fact that rare earths work mostly as net receiver of shocks from the other markets as already discussed previously.

## 5. Conclusions and policy implications

This work emerged from the scarce evidence and literature discussion of rare earth minerals' important role over renewable technologies as an enhancer of environmental improvements and promoter of the desirable and needed green technologies. For that, we resorted to a relatively novel econometric framework, namely the quantile frequency connectedness approach, allowing the analysis of the network transmission mechanism by frequency and quantiles, and to the cross-quantilogram correlation approach. The studied series were, daily from September 28, 2012, to October 7, 2022, the MVIS Global Rare Earth/Strategic Metals Index, the S&P Global Clean Energy Index, the S&P/TSX Renewable Energy and Clean Technology Index, and the S&P 500 Carbon Efficient Index.

Overall results suggest that being a net transmitter or receiver of shocks depends on the fact that we are analyzing the short or long-term averaged dynamic connectedness, and changes considering the different quantiles. We may say that in the long term, the highest net receiver of shocks has always been the Global Rare Earth/Strategic Metals Index but the percentage varies among quantiles (−8.66%, −8.44%, −8.99%, respectively for the 5th, 50th, and 95th quantiles). Being a short-term or long-term net receiver or net transmitter of shocks depends on the considered quantiles as evidenced by the median net total directional connectedness measures. However, at the middle quantile, we may argue that the Global Rare Earth/Strategic Metals Index is both a short and long-term net receiver of shocks, whereas the Carbon Efficient Index is a net transmitter of shocks, independently of the period considered, being thus unchangeable even in the presence of extreme events as the COVID-19 pandemic.

Considering the median net pairwise directional connectedness measures results, it was inferred that a shock in one of the other considered series in the analysis will cause a net change in the Global Rare Earth/Strategic Metals Index not being the opposite true. This result points to the need to consider clean energy investment, renewable energy investment, and clean technologies investments as important drivers of the price of rare earths that might condition future investments in carbon efficient measures, impeding us to reach the desired environmental goals, reduce emissions, and decrease the high fossil energy dependence.

Energy demand explosion, rare earth import dependency, rapid increases in technology development and innovations, renewable technology dependence over rare earth minerals, fossil fuel energy dependence, economic growth, and population increase and consumption demanding patterns dictate the future of global energy demand patterns, that might only be met by renewable energy, dictate the importance to control for rare earth price and scarcity. If policymakers concentrate their attention on the COP decisions and agreements, satisfying the consumption demand patterns can only be done by ensuring security levels, decreasing import dependence, and betting on renewable energy to comply with climate change goals.

The results of the paper have significant sustainability implications. The high volatility of the Rare Earth Index highlights potential challenges for clean energy production. It is evident from the results discussed previously that the price of rare earth minerals, so important in building renewable energy equipment, is crucial in determining future renewable diffusion and consumption. As a net receiver of shocks, rare earth energy-related policy-making could account for a global agreement in the control of these minerals provided that only some countries detain their domain. Substitution options, recycling, and reuse of these minerals lead to higher efficiency, decrease the strong effect on their prices, diminish the possibility of shortages and conditions any type of monopolistic power that might emerge. To ensure the long-term viability of clean energy technologies it will be necessary to ensure a stable and sustainable supply of rare earth minerals (Hoenderdaal et al., 2013), which are fundamental for the long-term sustainability of clean energy technologies (Habib and Wenzel, 2014; Zhou et al., 2017; Ganda, 2019; Danish and Ulucak, 2021). Moreover, given the role of the renewable energy industry in creating green jobs, the fluctuations in these indices might impact investor confidence and can have implications for the workforce and social sustainability (Lehr et al., 2012). Increased volatility of the indices under scrutiny also might have effects on investor decision-making and green industries. Accordingly, a resilient financial ecosystem is important for the long-term economic sustainability of the clean energy industry (Apergis and Apergis, 2017; Zheng et al., 2021, 2022).

Furthermore, the interconnectedness among the rare earth index and the other clean energy sectors stresses the need to design a holistic approach to sustainability, where the developments in renewable energy, clean technology, and carbon efficiency are interconnected. In line with Baldi et al. (2014), our findings suggest the dependence of the clean industry performance on rare earth minerals. The results of the paper extend the standard time series analysis of Apergis and Apergis (2017) and note the dependence on the performance of both sectors. Thus, the results point to the need for coordinated efforts and collaboration among these industries to ensure the accomplishment of environmental sustainability goals.

This study's main limitation is the number of considered series in the dynamic analysis of connectedness, which leads us to suggest the inclusion of other series in the analysis such as the Green Bonds Index which might work as a financing strategy for renewable technologies investments and induce production cost reduction. To come up with a comprehensive understanding of the overall dynamics and interconnections in clean energy markets, other related indices might be investigated. Moreover, the used indexes are global indexes and a deep analysis could be performed in the future considering different markets. The results of the paper might be limited in terms of generalizability to different periods and different contexts, which could be surpassed through geographical comparative analysis.

## CRediT authorship contribution statement

**Mara Madaleno:** Conceptualization, Writing – original draft, discussion, Supervision, policy contribution. **Dilvin Taskin:** literature review, discussion, implications, Writing – review & editing, Writing – original draft. **Eyup Dogan:** Methodology, Software, Validation, Resources, Formal analysis, Investigation, Writing – original draft. **Panayiotis Tzeremes:** Methodology, Software, Validation, Resources.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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