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# Analyzing Crisis Dynamics: How metal-energy Markets influence green electricity investments

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## Abstract

The world continues to face major economic challenges due to crises that have a considerable impact on energy consumption. Since the global energy crisis, energy commodity costs have risen, and economic slowdowns in various regions continue to influence electricity market trends. Clean energy markets, propelled by the growing interest of economic entities and investors, are now interconnected with several commodity markets. In this context, energy metals play a crucial role in influencing the dynamics of the clean energy and particularly electricity markets. This study takes a close look at the complex interconnections between clean energy indices and the metals market, focusing on volatility dynamics. Drawing on advanced methodologies, including the Diebold and Yilmaz method, we unveil the complex relationships that link these markets. Our results reveal distinct patterns and interactions, highlighting the nuanced nature of the connection between clean energy indices and metal prices. The insights revealed have significant implications for policymakers and investors seeking to align their strategies with sustainable energy transitions and ensure financial stability. By enhancing our understanding of the interdependencies between clean energy indices and metals markets, this research provides valuable guidance for navigating the changing clean energy investment landscape.

**Keywords:** Clean energy; Electricity market; Energy metals; Stock market; spillover Connectedness; Energy transition.

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# 1 Introduction

The global electricity market has become a complex network of interconnected systems, where electricity is traded across borders and across diverse markets (Arshad and Beyer, 2023; Naeem et al., 2020). This interconnection has increased the vulnerability of electricity markets to external shocks, requiring a deeper understanding of spillover effects between markets. Recent economic and geopolitical shocks, including the global financial crisis, the COVID-19 pandemic and the Russian Ukrainian war, have underlined the importance of studying contagion dynamics in electricity markets in times of crisis.

In addition, Environmental concerns have led to significant changes in the energy sector. Two particularly important developments have arisen in response to these concerns: the introduction of emissions trading mechanisms, notably the Emissions Trading Scheme (ETS), and intensified exploration of existing and potential sources of renewable and clean energy. Rising emissions costs have prompted for-profit entities to turn to cleaner energy sources, with the aim of mitigating carbon emissions and rationalizing production costs. Consequently, fluctuations in carbon prices have dynamic effects on clean energy prices, influencing clean energy indices and in particular the electricity market (Mhadhbi, 2024).

This transition to clean energy is expected to be led by renewable energy companies, driving up demand for specific metals essential to their operations, including nickel, copper, and cobalt, as highlighted by the International Energy Agency (IEA, 2021). The expected demand increase for these metals will likely strengthen the links between clean energy initiatives and metal prices, further accentuating the existing interdependencies between metal prices and fossil fuels. This highlights the central role of energy as a fundamental input in metal production processes.

As clean energy technologies gain ground and their adoption accelerates, demand for metals such as nickel, copper, and cobalt is set to grow exponentially. These metals are essential to various renewable energy systems, including wind turbines, solar panels, and electric vehicle batteries. Nickel and cobalt, for example, are indispensable components of lithium-ion batteries, which play a central role in energy storage in electric vehicles and renewable energy storage systems. Copper, renowned for its superior electrical conductivity, is essential in the electrical wiring of renewable energy infrastructures, electric vehicle charging stations, and grid connections. Therefore, clean energies and electricity markets are favored by a greater number of economic entities and investors. The following table provides a comprehensive overview of the role of various metals in clean energy technologies and their link with the electricity market.

The interconnection between the clean energy, electricity, and energy metals markets can be explained by a number of factors. First, energy metals are essential raw materials for the clean energy and electricity sectors. Rising energy metal prices mean higher costs for these industries and higher prices in these sectors. This is due to the fact that advances in clean energy technologies, such as electric vehicles, solar power, and wind power generation, are driving the evolution of the electricity industry (Dominković et al., 2018; Yuan et al., 2021). Second, the clean energy and electricity sectors display significant dependence on energy metals (He et al., 2021), particularly for energy storage batteries, photovoltaic modules, wind turbines, and electrical infrastructure, all of which require metals such as copper, aluminum, silver, nickel and cobalt. Third, the clean energy and energy metals industries are mutually dependent on a constant supply of electricity (Schwarz, 2008; Sgouridis et al., 2021). For example, the manufacture of energy-efficient household appliances, the manufacture of solar panels, and the charging of electric vehicles all depend on a regular and abundant electricity supply.

From a theoretical point of view, the correlation between non-ferrous metals and the stock market for clean energy, especially electricity, can be understood from two key perspectives (Deng et al., 2023). Firstly, progress in the clean energy industry is closely linked to technological innovation, with non-ferrous metals serving as essential raw materials for clean energy technologies. These production links establish a close relationship between supply and demand for non-ferrous metals and clean energy, with prices and market dynamics influencing each other through production costs. This interdependence can impact clean energy installation costs and, consequently, the share prices of the clean energy companies concerned. Secondly, as the clean energy and non-ferrous metals markets increasingly become tradable financial assets, their financial markets become closely correlated. Investors are increasingly focusing on portfolio effects between non-

ferrous metals and clean energy assets, as non-ferrous metals can provide a safe haven for investors in clean energy stocks. However, external crises such as the COVID-19 pandemic and geopolitical crises have put considerable pressure on the global clean energy supply chain, leading to shortages and soaring prices of metals essential to the clean energy industry and increasing the connectivity between the electricity and metal markets (Zhang et al., 2023). This underlines the importance of studying the relationship between non-ferrous metals and clean energy supplies, particularly in the context of crises, in order to ensure market stability, promote energy transformation, and enhance energy security.

The conflict between Russia and Ukraine has had a significant impact on global financial markets, with negative returns observed on many stock markets (Boubaker et al., 2022). This situation highlighted the strong interconnection between the electricity market and metallic energies, particularly due to Europe’s dependence on Russian oil and gas (Deng et al., 2022). In addition, companies promoting renewable energy initiatives recorded gains in the midst of this crisis, reflecting investors’ growing interest in alternative energy sources (Umar et al., 2022).

Our study highlights the crucial importance of examining the complex economic and financial interconnections between the clean energy sectors, particularly electricity, and the dynamics of the energy metals market. Such in-depth analysis is imperative for investors and financial practitioners seeking to optimize diversification strategies and deploy advanced hedging techniques, particularly in the face of global crises.

In our study, we develop the dynamic connectedness measures proposed by Diebold and Yilmaz (2014) by implementing a time-varying parameter vector autoregressive (TVP-VAR) methodology. Our choice of a TVP-VAR-based connectivity methodology offers distinct advantages over traditional approaches, in particular those based on simple VAR models estimated using rolling windows. Firstly, our method avoids the loss of observations inherent in rolling window analyses, resulting in more complete dynamic measures of connectedness. Secondly, by eliminating the need for rolling window analysis, we avoid having to arbitrarily select sample sizes, which improves the robustness of our results. In addition, our methodology is less sensitive to outliers, resulting in refined and reliable measures of dynamic connectedness.

In addition, Diebold and Yilmaz (2009, 2012, 2014) developed a methodology to address the limitations of multivariate GARCH models in capturing the time-varying characteristics of the volatility spillover effect.

The DY method can describe the direction of volatility spillovers and the dynamics of volatility spillovers. Due to its ease of use, the DY method has been widely used to predict the direction of volatility spillovers between financial markets.

Our decision to use TVP-VAR models and Diebold and Yilmaz’s connectedness index is in line with our research objective, which focuses on exploring dynamic interconnections during crisis periods. Although other analysis such as wavelet analysis is a viable alternative, it does not fully capture the complexities of dynamic interconnectedness, especially given the focus on stationary variables. Therefore, the TVP-VAR approach better fits our research objectives.

We selected 2014 to 2023 as our study period, strategically encompassing critical global events, including the oil crisis, the COVID-19 pandemic, and the Russian-Ukrainian war. These unprecedented events have led to considerable volatility and uncertainty in the financial markets. It is, therefore, imperative to closely examine the dynamics between energy metals and clean energy indices to develop sound risk management strategies.

Our contribution to the literature is as follows. Firstly, it extends the current understanding of the interconnection between the electricity market and the energy metals market, using clean energy indices, namely the Global Clean Energy Index (GCEI) and the NASDAQ Clean Edge Green Energy Index (NAZDAQ), as proxies for the electricity market. By conducting a comprehensive analysis during major global events such as the oil crisis, the COVID-19 pandemic and the Russian-Ukrainian war, our study provides nuanced insights into the dynamics of these interconnected markets. In addition, few studies take several major events into account when examining the relationship between metals markets and the clean energy sector. This article fills this gap by analyzing the impact of various major events, including energy crises, the COVID-19 pandemic and geopolitical conflicts, on market connectivity. By examining these events and incorporating clean energy indices into the analysis to capture the impact on the electricity market, the study offers a more comprehensive understanding of how different factors influence interconnections between metals markets and clean energy investments.

Second, our research addresses the critical need for risk measurement and management in electricity, and metals markets, in line with the focus of Diebold et al. (2017). Through an in-depth exploration of relationships during periods of heightened volatility and uncertainty triggered by the events mentioned, we provide valuable insights that can contribute to the formulation of effective risk management strategies.

Thirdly, by focusing on the supply and demand channels between the metals and electricity markets, our article highlights the mutual dependency that characterizes these sectors. This understanding is crucial, particularly in times of global stress, and contributes to the broader literature by providing a nuanced perspective on how these markets interact and influence each other.

This study is organized as follows: Section 2 discusses the relevant literature, Section 3 describes the research methodology and data, Section 4 presents the empirical results and their implications, and Section 5 concludes the study.

Table 1: Role of Metals in Clean Energy Technologies

<b>Metal</b>	<b>Description</b>	<b>Role in Clean Energy</b>
Neodymium	A rare earth metal used in permanent magnets.	Critical component in wind turbine generators and electric vehicle motors.
Zinc	A bluish-white metal used in various applications.	Used in the production of rechargeable batteries for energy storage systems and in solar panel manufacturing.
Nickel	A silvery-white metal known for its corrosion resistance and conductivity.	Key component in lithium-ion batteries for electric vehicles and grid-scale energy storage.
Cobalt	A hard, lustrous, gray metal used in various industrial applications.	Essential in lithium-ion batteries for electric vehicles and renewable energy storage systems.
Aluminium	A lightweight, corrosion-resistant metal.	Widely used in the construction of solar panels, wind turbines, and transmission lines for renewable energy infrastructure.
Copper	A soft, malleable metal with excellent electrical conductivity.	Essential in electrical wiring for renewable energy systems, electric vehicle charging infrastructure, and grid connections.
Lithium	A soft, silvery-white metal with the lowest density of all metals.	Primary component in lithium-ion batteries used for energy storage in electric vehicles and renewable energy systems.
Manganese	A hard, gray-white metal with high tensile strength.	Used as an alloying element in steel production for wind turbine towers and in lithium-ion batteries for energy storage.
Dysprosium	A rare earth element used in various high-tech applications.	Critical for the production of high-strength magnets in wind turbines and electric vehicle motors.
Indium	A rare, soft, malleable metal with a bright luster.	Used in the production of thin-film solar cells, transparent conductive coatings, and semiconductors for clean energy technologies.
Lead	A heavy, soft, and malleable metal with a low melting point.	Used in lead-acid batteries for backup power systems, energy storage applications, and solar panel manufacturing.

## 2 Literature review

The extensive literature on the correlation between fossil fuels and metals markets has studied the link between fossil fuels and metals in depth, taking into account a wide range of metals and market conditions, including reliance on mean and tail. Given the growing interest in clean energy, recent research has begun to examine the association between metals and clean energy prices. However, existing studies have mainly focused on the relationship between precious metals and clean energy. More specifically, researchers have looked at the hedging and safe-haven characteristics of precious metals in relation to clean energy prices. The following table provides an exhaustive analysis of the literature on this subject:

Table 2: Literature Review Summary Table

<b>Authors</b>	<b>Focus of Study</b>	<b>Method</b>	<b>Major finding</b>
Chen et al. (2022)	Spillovers and hedging non-ferrous metals and sub-sectoral clean energy stocks	Diebold and Yilmaz spillover index, Barunik and Křehlí spillover index and DCC methods	Non-ferrous metals can be effective hedging asset for some clean energy stocks
He et al. (2021)	Dependence of clean energy and electricity industries on energy metals	Dynamic panel model	The technological progress of the electric power industry exhibits a strong metal consumption effect
Asl et al. (2021)	Importance of understanding linkages and characteristics for economic decision-makers	Asymmetric VAR BEKK-MGARCH model	Highlight the importance of understanding linkages and characteristics for economic decision-makers
Dominković et al. (2018)	Opportunities and barriers in a clean energy transition	Method for the transition of the transportation sector towards 100% renewable	Highlight the interdependence of clean energy and electricity industries on energy metals
Schwarz (2008)	Mutual dependence of clean energy and energy metals industries on the supply of electricity	Computer-based partial equilibrium model	Emphasize the mutual dependence of clean energy and energy metals industries on the supply of electricity
Sgouridis et al. (2021)	Importance of electricity supply for clean energy and energy metals industries	Linear optimization system	Indicate the importance of electricity supply for both clean energy and energy metals industries
Gustafsson et al. (2022)	Energy Metals and Clean Energy Stock Prices	Baur and McDermott 2010 and Baur and Lucey 2010 frameworks	Limited hedging capacity of energy metals against clean energy stock prices due to positive linkages between these markets
Naeem et al. (2020)	Return and volatility spillover relationships among electricity, clean energy, and carbon markets	Generalized forecast error variance decomposition (GFEVD) of VAR errors	Demonstrate return and volatility spillover relationships among electricity, clean energy, and carbon markets
Reboredo and Ugolini (2018)	Identification of electricity prices as a major contributor to the return dynamic of EU clean energy stocks	Multivariate vine-copula dependence setup	Identify electricity prices as a major contributor to the return dynamic of EU clean energy stocks
Bonato et al. (2020)	Higher-order moment spillovers in energy and metal markets	Linear, nonparametric, and time-varying (rolling) tests of causality	Extreme positive and negative returns of gold and oil tend to drive the volatilities in these markets
Cui et al. (2022)	Higher-order moment spillovers between international oil and Chinese futures markets	DCC-MVHAR-RS/RK model	Investigate higher-order moment spillovers between international oil and Chinese futures markets
Chen et al. (2022)	Extreme quantile spillovers between fossil energy, clean energy, metals, and carbon markets	Quantile VAR model and Diebold and Yilmaz (2012)	The relationship between the energy, metals and carbon markets varies over time, and volatility is relatively low under both extremely positive and negative conditions
Ahmad et al. (2018)	Gold and Clean Energy Stock Prices	Extreme value theory (EVT) approach	Gold is not an effective hedge for clean energy stocks
Dutta (2019)	Silver Volatility and Solar Energy Stocks	GARCH-jump process	Negative responses of solar energy stock prices to silver volatility
Dutta et al. (2020)	Gold, Silver, Oil Volatilities, and Clean Energy	DCC-GARCH process	Negative relationship between the volatilities of gold, silver, and oil, and clean energy stock prices. Suggests potential for gold, silver, and oil as hedges against clean energy stocks
Erdoğan et al. (2022)	Precious Metals and Clean Energy Stocks	Granger causality in distribution test	Precious metals may not effectively hedge the downside risk of clean energy stock investments.
Islam et al. (2022)	Mineral Import Demand and Clean Energy Transition	Cross-sectional autoregressive distributed lag (CS-ARDL) approach	Significant response of mineral import demand to increasing solar and wind energy capacities in 29 OECD countries

## 3 Data and Methodology

### 3.1 Data

This study focuses on a daily data set covering the period from January 2014 to November 2023. The choice of the period 2014-2023 is influenced by the availability of complete and reliable data during these years in both contexts. In addition, this period encompasses important events such as the COVID-19 pandemic, the renewable energy investment boom and the ongoing conflict in the Russian-Ukrainian war.

The selection of metals and indices in this study aims to represent and analyse the interconnection between the electricity and metals markets. Clean energy indices, such as the NASDAQ Clean Edge Green Energy Index and the S&P Global Clean Energy Index, serve as proxies for the electricity market and provide insight into the performance of companies involved in clean energy technologies. In addition, Table 1, which describes the role of metals in clean energy applications, provides a comprehensive overview of the importance of each metal in advancing renewable energy technologies.

This data set will provide us with comprehensive information on the link between the clean energy and metal markets. The definition of the data selected for this study is presented in Table 2. Table 3 gives a complete overview of the descriptive statistics of the logarithmic returns of the variables considered. The mean values of all variables remain approximately equal to 0, suggesting a balanced distribution around the mean. The clean energy indices, along with cobalt, copper, manganese and dysprosium, exhibit negative skewness. This means that the tails of their distributions are more pronounced on the left than on the right, implying a greater likelihood of extreme negative returns. In contrast, other metals, such as neodymium, nickel, lithium and indium, exhibit positive asymmetry, suggesting a greater probability of extreme positive returns in their distributions.

In particular, the neodymium, nickel, cobalt, lithium, manganese, dysprosium and indium series show broad-tailed distributions, indicating that extreme values or outliers are more likely to occur in these series. This implies a potential for significant fluctuations in yields for these variables. In contrast, the other variable yield series show relatively flat-tailed distributions, meaning that yields are more evenly distributed and do not exhibit significant tails. To assess the stationarity of the variables, Augmented Dickey-Fuller (ADF) tests were used. The results are conclusive, indicating that all variables are stationary at the 1% significance level. This means that the variables have stable and consistent behavior over time, providing a basis for reliable statistical analysis and prediction.



Table 3: Summary of Variable Definitions

Variable	Definition	Data Source
Neodymium	Spot price of neodymium metal	Datastream
Zinc	Spot price of zinc metal	Datastream
Nickel	Spot price of nickel metal	Datastream
Cobalt	Spot price of cobalt metal	Datastream
Aluminium	Spot price of aluminium metal	Datastream
Copper	Spot price of copper metal	Datastream
Lithium	Spot price of lithium metal	Datastream
Manganese	Spot price of manganese metal	Datastream
Dysprosium	Spot price of dysprosium metal	Datastream
Indium	Spot price of indium metal	Datastream
Lead	Spot price of lead metal	Datastream
NASDAQ Clean Edge Green Energy Index (NASDAQ)	The NASDAQ Clean Edge Green Energy Index is a modified market capitalization weighted index designed to track the performance of companies that are primarily manufacturers, developers, distributors, and/or installers of clean energy technologies, as defined by Clean Edge.	Datastream
S&P Global Clean Energy Index (GCEI)	The S&P Global Clean Energy Index is designed to measure the performance of companies in global clean energy-related businesses from both developed and emerging markets, with a target constituent count of 100.	Datastream

Table 4: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis	ADF
NeodymiumRe	2,833	0.0001	0.0105	-0.1522	0.1271	1.4910	50.7749	-36.8750***
ZincRe	2,833	0.0001	0.0154	-0.0719	0.0995	0.0448	4.8712	-46.1790***
NickelRe	2,833	0.0000	0.0221	-0.1615	0.4873	3.5804	89.5364	-53.0050***
CobaltRe	2,833	0.0001	0.0178	-0.2900	0.2819	-0.9708	64.1625	-61.4620***
AluminiumRe	2,833	0.0000	0.0128	-0.0783	0.0640	0.0745	5.5258	-47.0870***
CopperRe	2,833	0.0000	0.0127	-0.0810	0.0698	-0.0757	5.5169	-49.5810***
LithiumRe	2,833	0.0005	0.0080	-0.0889	0.1744	7.3941	149.3607	-30.9460***
ManganeseRe	2,833	-0.0001	0.0243	-0.7802	0.4261	-9.1494	450.1775	-43.0230***
DysprosiumRe	2,833	-0.0001	0.0126	-0.2007	0.1516	-3.2372	85.3500	-35.7800***
IndiuRe	2,833	-0.0002	0.0106	-0.0818	0.2383	5.3398	115.2330	-38.6320***
LeadRe	2,833	0.0000	0.0148	-0.0757	0.0723	0.1483	4.8385	-45.8200***
GCEIRe	2,833	0.0002	0.0145	-0.1250	0.1103	-0.3992	11.2039	-44.2340***
NASDAQRe	2,833	0.0004	0.0199	-0.1558	0.1314	-0.3610	8.0977	-51.2480***

Note: \*\*\* indicates the significance level of 1%.

## 3.2 Methodology

We employ a methodological approach using time-varying parameter vector autoregression (TVP-VAR) to explore interdependencies between markets. This methodology allows us to track the evolution of relationships between different market returns over time, offering valuable insights into their dynamic nature. In addition, we enhance our analysis by integrating the Diebold and Yilmaz (DY) approach with the TVP-VAR model, enabling a comprehensive examination of the interactions between different markets.

### 3.2.1 TVP-VAR approach and DY Framework

Our study employs a dynamic spillover analysis using a combined methodology that merges the DY framework (Diebold and Yilmaz, 2012; 2014) with a TVP-VAR model (Koop and Korobilis, 2014). While the DY framework traditionally uses a rolling window method to generate dynamic results, we adopt this mixed approach to overcome its inherent limitations. This approach has several advantages: it retains complete data observations, eliminates the need for arbitrary window length selection and improves robustness to outliers, as highlighted by Antonakakis and Gabauer (2017). To determine the optimal lag structure for the TVP-VAR model, we use the Akaike Information Criterion (AIC), setting the lag length to one for our two models. Through this methodology, we are able to study the evolution of interconnections between clean energy market indices and energy metal markets over time, capturing their dynamic interactions and potential spillover effects.

We initiate our analysis by employing a time-varying Vector Autoregressive (TVP-VAR) model, defined as follows:

$$z_t = B_t z_{t-1} + u_t, \quad u_t \sim N(0, S_t) \quad (1)$$

$$vec(B_t) = vec(B_{t-1}) + v_t, v_t \sim N(0, R_t) \quad (2)$$

Where  $z_t$  and  $z_{t-1}$  denote the error term,  $mu_t$  are vectors of dimension  $K$ . Matrices  $B_t$  and  $S_t$  have dimensions  $n \times n$ . The vectorized form of  $B_t$ , denoted as  $vec(B_t)$ , is a column vector with dimensions  $k^2$ . The information available up to time  $t-1$  is represented by  $rho_{t-1}$ . The error term  $\gamma_t$  is a column vector with dimensions  $k^2$ , while  $R_t$  is a square matrix with dimensions  $k^2 \times k^2$ . Both  $S_t$  and  $R_t$  are variance-covariance matrices that vary over time.

Diebold and Yilmaz (2009, 2012, 2014) introduce a connectedness measure based on the generalized forecasting error variance decomposition developed by Koop et al. (1996) and Pesaran and Shin (1998). This measure evaluates the interconnections between variables and represents a substantial enhancement of the original technique.

In line with Diebold and Yilmaz (2014), the generalized forecast error variance decomposition (GFEVD) is derived by converting the time-varying parameter vector autoregressive model (TVP-VAR) into its corresponding vector moving average representation (TVP-VMA) using Wold's theorem. This process follows the methodology outlined by Diebold and Yilmaz (2014) and involves the specific transformation detailed below:

$$z_t = \sum_{i=1}^p B_i z_{t-i} + u_t = \sum_{j=0}^{\infty} A_j u_{t-j} \quad (3)$$

The unscaled Generalized Forecast Error Variance Decomposition (GFEVD), denoted as  $\Phi_{ij,t}(H)$ , is rescaled to ensure that the summation in each row is equal to one. We obtain  $\Phi_{ij,t}(H)$ , which indicates the pairwise directional connectedness between variable  $j$  and variable  $i$ . It measures the effect of variable  $j$  on variable  $i$ , considering its contribution to the overall variance of the forecast error. The calculation of these terms involves the following steps:

$$\tilde{\phi}_{ij,t}^g(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (\iota_i' A_t S_t \iota_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} (\iota_i A_t S_t A_t' \iota_i)} \quad (4)$$

$$\phi_{ij,t}^g(H) = \frac{\tilde{\phi}_{ij,t}^g(H)}{\sum_{j=1}^k \tilde{\phi}_{ij,t}^g(H)} \quad (5)$$

The selection vector is defined as  $\iota_i$  where, for the index  $i$ , its value is 1 and 0 otherwise. The connectedness measures are then derived from the methodology introduced by Diebold and Yilmaz (2012, 2014), as outlined below:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ij,t}^g(H) \quad (6)$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\phi}_{ji,t}^g(H) \quad (7)$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (8)$$

$$TCI_t = k^{-1} \sum_{j=1}^k TO_{jt} \equiv k^{-1} \sum_{j=1}^k FROM_{jt} \quad (9)$$

Equation (6) provides a measure of the total directional connectedness from the variable  $j$  to all other variables in the network. Equation (7) calculates the total directional connectedness directed towards variable  $j$  from all other variables in the system. Equation (8) represents the disparity between equations (6) and (7), indicating the net directional connectedness associated with variable  $j$ . For instance, if  $NET_{jt} > 0$ , this would mean that  $j$  is a net driver of the network as it is primarily involved in transmitting shocks. Equation (10) provides an aggregate measure of the total connectedness of all network variables, to assess overall interconnectedness and potential market vulnerability. A higher total connectivity index (TIC) means that a shock to a specific variable has a significant impact on the whole network, thus increasing the associated market risk. Conversely, a lower total connectivity index indicates reduced connectivity, meaning that shocks to a particular variable have minimal effects on other variables in the network, thereby reducing overall market risk.

## 4 Results and recommendations

We see a first increasing of the connectness and so contagion of risk from metal markets to green electricity investments in middle of 2015 and during all year 2016 with a decreasing in 2017. In 2015 and 2016, several factors contributed to the dependence of the green and clean energy index on metal prices. First of all the global economic conditions. The world was recovering from the 2008 financial crisis, and economic conditions were still uncertain. The green energy sector, heavily reliant on investments and government support, felt the impact of economic instability. Metal prices, being sensitive to economic trends, influenced the overall performance of the green and clean energy index.

Then the China's economic slowdown. Indeed China, a major player in both metal production and renewable energy consumption, experienced an economic slowdown during this time. As a significant consumer of metals like copper and rare earth elements for renewable technologies, reduced demand from China affected metal prices, influencing the green energy index.

We can think about too the new trend on policy and regulatory environment. A major and crucial changes in government policies and regulations in 2015-2016 appeared which is the COP 21 agreement in Paris. It is a new policy and regulatory environment, particularly related to renewable energy subsidies and incentives, influenced investor confidence. Metal prices played a role in shaping these policies as they impacted the cost structure of renewable projects.

There are clearly then a COVID effect on green electricity investments since in both markets (i.e. NASDAQ and GCEI) we see an increase of contagion of prices in march 2020 and until beginning of 2021. The impact of COVID-19 on metal prices and the green and clean energy index can be attributed to several factors. The pandemic disrupted global supply chains, affecting the production and distribution of metals crucial for renewable energy technologies. Additionally, uncertainties surrounding economic recovery led to fluctuations in demand for these metals. As countries invested in green initiatives for post-pandemic recovery, there was an increased demand for metals like copper, lithium, and rare earth elements used in renewable energy infrastructure. This heightened demand, coupled with supply chain disruptions, contributed to price volatility. The green and clean energy index is sensitive to these fluctuations, as it reflects the performance of companies involved in sustainable energy solutions. The interplay of disrupted supply chains, changing demand dynamics, and the global focus on green recovery collectively amplified the impact of metal prices on the green and clean energy index during the COVID-19 pandemic.

The importance and impact of Rare earth elements on green electricity investments is also well captured since we see increasing of the connectness from Dysprosium and Neodymium after 2021. We know that this rare earth element is crucial in the process of construction of both battery storage and permanent magnet used in offshore wind (Depraeter and Goutte, 2023). Indeed, Rare earth elements, particularly neodymium and dysprosium, are vital for the production of powerful permanent magnets used in wind turbine generators. These magnets enable turbines to efficiently convert wind energy into electricity, improving turbine performance and reducing energy loss.

The importance of dysprosium in our research stems not only from its critical function in the physical construction of renewable energy infrastructure, but also from its identified role as the main transmitter of shocks across interconnected variables. This complex relationship highlights the central role played by certain rare earth elements in steering the trajectory of green electricity investment, making dysprosium a key influencer in the complex web of market interdependencies.

The oversupply of rare earth metals not only strengthens the links between the rare earth market and other clean energy and metals markets, it also amplifies this interdependence, particularly in times of crisis. Falling rare earth metal prices, a consequence of oversupply, take on added importance in times of crisis, as economic uncertainties and disruptions amplify market interdependence. In times of crisis, clean energy projects become even more dependent on profitable rare earth metals, reinforcing the links between the rare earth market and the clean energy sectors.

The impact of the Global Clean Energy Index (GCEI) on metals such as nickel, cobalt, copper, lithium and lead is of particular importance in the context of the transition to cleaner electricity production. Technological advances in renewable energies, notably solar and wind power, as well as the proliferation of electric vehicles, have led to increased demand for metals essential to electricity generation and storage. For example, the expansion of GCEI may mean an increased need for

metals in solar panels, wind turbines and electric vehicle batteries. At the same time, government policies to encourage the adoption of clean energy, such as tax incentives for electric vehicles, could amplify this trend by further stimulating demand for metals used in battery manufacture. As a result, fluctuations in the GCEI index can exert a substantial influence on demand for metals used in electricity generation and storage, impacting the prices and volatility of these metals on world markets.

Electricity plays a crucial role not only in the use of metals, but also in their extraction and processing, underscoring the importance of examining the transmission of electricity market shocks to metals. This underlines the importance of examining the transmission of shocks from the electricity market to metals. In this vein, fluctuations in electricity consumption and production can significantly influence demand for these metals, affecting their prices and volatility on world markets. In addition, during crises such as the COVID-19 pandemic, disruptions to global supply chains can lead to shortages and price rises for essential metals. Given the clean energy sector's heavy reliance on these metals, such supply disruptions can have a profound impact on clean energy deployment and metals markets, exacerbating difficulties in meeting clean energy targets and disrupting the stability of metals markets.

Investor reactions to crisis-induced market fluctuations further contribute to this increased connectivity, as perceptions of risk and opportunity influence decisions in interconnected markets. In addition, political responses to economic crises can shape regulatory landscapes, fostering new connections between the rare earths sector and the broader clean energy and metals markets. As a result, oversupply-induced connectivity takes on heightened importance during times of crisis, reflecting the complex interplay of market forces, investor behavior and regulatory responses that shape the sustainable energy investment landscape.

Metals used in electricity power grid to transfer electricity, make connection in the system or used in technology devices are the one which transmit the more with our two green/clean electricity investment markets. Indeed, both Aluminum, Zinc, Lead and Copper exhibit the largest connectness to GCEI and Nasdaq Green energy Index. They are all crucial for the electricity market due to several key characteristics that make them essential materials in various aspects of the electrical industry:

- Aluminum's combination of electrical conductivity, lightweight properties, corrosion resistance, and cost-effectiveness makes it a crucial material in the electricity market, particularly in applications such as power transmission and distribution.
- Copper's exceptional electrical conductivity, low resistance, malleability, corrosion resistance, and other properties make it indispensable in the electricity market. It is a primary material for electrical wiring, transmission lines, and a wide range of electrical components essential for power generation, distribution, and consumption.
- While zinc's role in the electricity market is more indirect compared to copper or aluminum, its significance lies in its contribution to the development and application of batteries, especially those designed for energy storage. As the demand for reliable and scalable energy storage solutions grows, the importance of zinc in supporting these technologies becomes increasingly relevant to the broader electricity landscape.
- Nickel plays a key role in the orientation of metals such as zinc, dysprosium, and copper towards electricity markets. Its unique properties contribute to the interconnectedness observed in our research, highlighting the nuanced dynamics of these markets.

To strengthen the electricity market within the global clean energy index, policymakers need to diversify supply chains for critical metals, particularly rare earths. Building up strategic stocks and encouraging recycling technologies for these metals guarantee the stability and sustainability of electricity production. The implementation of monitoring systems facilitates the development of proactive policies, reducing vulnerability to market fluctuations. The adoption of technology-neutral policies promotes diversity in the clean energy landscape, thus guarding against supply chain disruptions. Working with industry stakeholders to develop resilience plans for clean energy projects, particularly in the power sector, reinforces sector stability. These strategic measures collectively support a safe and sustainable electricity ecosystem, advancing the global transition to cleaner energy sources.

## 4.1 Additional test

In order to assess potential cointegrating relationships between the variables under consideration, a cointegration test was carried out using Johansen's methodology, which is particularly suited to the analysis of cointegrating relationships between several time series. Unlike the Engle-Granger test, which examines a single cointegrating relationship between two variables, the Johansen test allows us to examine several cointegrating relationships within the data set. In this paper the Johansen test was chosen because of its ability to explore complex relationships between several variables.

Tables 5 and 6 present the results of Johansen's cointegration test carried out for model 1, using the GCEI index, and for model 2, using the NASDAQ index. The analysis revealed that, for both models, there is no evidence of cointegration between the variables considered. This means that the variables in each model do not show a long-term relationship that can be represented by a linear combination, as indicated by the non-significance of the test statistics at the 5% significance level. Specifically, if the calculated trace statistic is below the critical value, the null hypothesis is rejected, suggesting the absence of cointegration. We can therefore conclude that, for both models, there was no evidence of cointegration between the variables under consideration. This confirms that differentiation does not lead to an unnecessary loss of information. We believe that this addition strengthens the robustness of our methodology and improves the accuracy of our results. In addition, to effectively navigate short-term dynamics, it is important to employ sound risk management strategies and prioritize diversification between different asset classes.

Table 5: Johansen Cointegration Test: Model 1

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.** Critical Value
None *	0.289512	8846.073	334.9837	0.0000
At most 1 *	0.284627	7878.770	285.1425	0.0000
At most 2 *	0.279656	6930.857	239.2354	0.0000
At most 3 *	0.262984	6002.541	197.3709	0.0000
At most 4 *	0.254465	5138.979	159.5297	0.0000
At most 5 *	0.251681	4307.941	125.6154	0.0000
At most 6 *	0.235577	3487.450	95.75366	0.0000
At most 7 *	0.229511	2727.218	69.81889	0.0000
At most 8 *	0.213966	1989.352	47.85613	0.0000
At most 9 *	0.158346	1308.014	29.79707	0.0000
At most 10 *	0.140945	820.1595	15.49471	0.0000
At most 11 *	0.128803	390.2208	3.841465	0.0000

Note: Trace test indicates 12 cointegrating equation(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

Table 6: Johansen Cointegration Test: Model 2

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.** Critical Value	
None *	0.289195	8910.382	334.9837	0.0000	
At most 1 *	0.284308	7944.343	285.1425	0.0000	
At most 2 *	0.278777	6997.694	239.2354	0.0000	
At most 3 *	0.268904	6072.832	197.3709	0.0000	
At most 4 *	0.254502	5186.446	159.5297	0.0000	[flushleft]
At most 5 *	0.251286	4355.266	125.6154	0.0000	
At most 6 *	0.244478	3536.269	95.75366	0.0000	
At most 7 *	0.229730	2742.890	69.81889	0.0000	
At most 8 *	0.217707	2004.219	47.85613	0.0000	
At most 9 *	0.158467	1309.380	29.79707	0.0000	
At most 10 *	0.141179	821.1200	15.49471	0.0000	
At most 11 *	0.128861	390.4088	3.841465	0.0000	

Note: Trace test indicates 12 cointegrating equation(s) at the 0.05 level

\* denotes rejection of the hypothesis at the 0.05 level

\*\*MacKinnon-Haug-Michelis (1999) p-values

## 5 Conclusion

The study of the relationship between metal markets and clean and green energy investments is a compelling and multidimensional area of research that intersects economic, environmental, and technological domains. Metal markets, characterized by the prices and availability of key elements like copper, lithium, and rare earth metals, significantly impact the feasibility and cost-effectiveness of renewable energy technologies. Understanding this relationship is essential for policymakers, investors, and industry stakeholders seeking sustainable energy solutions.

**These metals are essential for clean energy and power generation: copper in cables, lithium in batteries and rare earths in wind turbines and electric vehicles. Understanding their importance highlights the influence of metals markets on the sustainability of renewable energies.**

The fluctuations in metal prices directly influence the economic viability of clean energy projects, affecting investment decisions and project timelines. Furthermore, metals play a pivotal role in the development of critical technologies such as solar panels, wind turbines, and energy storage systems, shaping the trajectory of the renewable energy sector. Investigating these dynamics provides insights into the challenges and opportunities associated with the transition to a green economy. It also sheds light on the geopolitical implications of metal dependencies, as certain nations hold strategic positions in the global supply chain.

Chen et al (2022) and Deng et al., (2023) found a significant increase in spillovers between China's clean energy and non-ferrous metals markets during the COVID-19 crisis, suggesting increased risk transmission and market connectivity. However, only a few previous studies have explored the relationship between clean energy and metals markets during several major events, while taking into account global clean energy indices. This highlights the importance of investigating how events such as energy crises, pandemics and geopolitical conflicts affect market connectivity. Our study fills this gap by analysing how connectivity evolves during these critical periods, providing crucial insights for managing risk and promoting resilience in the clean energy and metals sectors

This research contributes to a holistic comprehension of the intricate interplay between metal markets and the advancement of clean energy, fostering informed decision-making and sustainable development practices in the pursuit of a low-carbon future. Furthermore, our research has important implications for investment portfolios in the clean energy and metals markets.

First, the time-varying analysis of our results indicates a significant increase in connectivity and risk contagion from metals markets to green electricity investments in mid-2015, with a peak in 2016, followed by a gradual decrease in 2017. During this period, several factors contributed to the interdependence of the green and clean energy index with metal prices.

Second, the aftermath of the 2008 financial crisis, combined with China's economic slowdown and major political changes such as the COP 21 agreement, created a landscape in which metal prices played a central role in shaping the Clean Energy Index. Therefore, investors in the electricity market should always pay attention to extreme risks in the energy metals markets, and optimize portfolio allocation according to energy metals market conditions, especially in times of crisis that impact energy use and economic activity. by Implement real-time monitoring systems to stay abreast of market developments, including fluctuations in metal prices, geopolitical events, and economic indicators.

Third, the study underlines the growing importance of rare earth elements, particularly dysprosium and neodymium, after 2021, highlighting their critical role in the construction of storage batteries and permanent magnets used in offshore wind power. These elements are essential for improving wind turbine performance and reducing energy losses, underlining their central role in the green electricity investment landscape. Consequently, investors are faced with strategic considerations, recognizing emerging markets and diversifying portfolios to include companies involved in rare earth technologies. Given the growing importance of these elements, investors are advised to conduct meticulous supply chain analyses, identify potential vulnerabilities and employ hedging strategies to mitigate risks. Focusing on sustainable practices and aligning with companies that promote long-term environmental goals can strengthen portfolio resilience. Industry stakeholders aiming for sustainable energy solutions must proactively address the implications of the growing importance of rare earth elements. By integrating these elements responsibly, diversifying supply chains, engaging in long-term planning, advocating for sustainable policies, and educating consumers, industry stakeholders can contribute to the development of resilient and environmentally conscious energy solutions.



Furthermore, Metals such as aluminum, zinc, lead and copper show substantial connectivity with the GCEI and the Nasdaq Green Energy Index, as they play an essential role in energy transmission and distribution, as well as in technological devices. Their characteristics make them indispensable in various aspects of the electrical industry, from power transmission to energy storage solutions. Recommendations include policy makers diversifying sources, supporting research, and implementing responsible regulations. Investors should diversify portfolios, manage risks, and prioritize sustainability. Industry stakeholders are advised to enhance supply chain resilience, adopt rare earth technologies, and engage transparently with consumers. Collaborative efforts aligned with sustainable goals are crucial for navigating the evolving landscape of these elements and metals in green electricity investments.

The results obtained in this paper have practical implications for policymakers and investors in the clean energy sector. Policymakers aiming to maintain the stability of sustainable financial markets are advised to flexibly supervise metals markets over different time periods, and to strengthen regulations in the event of shocks. Based on the empirical results, policymakers can identify risk transmission channels and prioritize critical markets for increased oversight.

Understanding the risk structure of markets is essential for environmentally friendly investors. They need to adapt their asset selection according to their maturity preferences, and take into account the results of the risk transmission path in order to effectively reduce investment risk and achieve diversification benefits. In addition, recommendations are made to companies operating in the clean energy sector to implement risk management strategies in the event of a crisis. These include diversifying sources of supply for critical metals, building up strategic stocks and adopting monitoring systems to detect market fluctuations and mitigate potential risks. Investors in the electricity market should always pay attention to extreme risks in the energy metals markets, and optimize portfolio allocation according to metals market conditions.

Finally, policymakers and regulators are encouraged to promote policies that strengthen the resilience of the clean energy sector and the electricity markets in the event of a crisis. This involves developing sector-specific resilience plans, promoting technology-neutral policies and working with industry stakeholders to strengthen the stability of the sector as a whole. Through concerted efforts, stakeholders can ensure a secure and sustainable energy supply, even in times of crisis.

While this study provides valuable insights into the relationship between metals markets and investment in green electricity as clean energy, certain limitations must be acknowledged. The reliance on historical data and the dynamic nature of the markets pose problems for predicting future conditions. The study does not offer a detailed analysis of country-specific policy implications, leaving room for future research to explore regional variations. In addition, a closer look at technological advances aimed at reducing dependence on specific metals in the green energy sector would enhance our understanding. These considerations highlight further avenues for research, contributing to a more comprehensive understanding of the complex interplay between metals markets and sustainable energy investments.

## Appendix

Table 7: Average dynamic total return connectedness for GCEI

	NeodymiumRe	ZincRe	NNickelRe	CobaltRe	AluminiumRe	CopperRe	LithiumRe	ManganeseRe	LeadRe	IndiuRe	DysprosiumRe	GCEIRe	FROM
NeodymiumRe	77.52	0.94	1.52	0.66	0.86	1.49	1.99	0.58	0.8	3.71	9.01	0.93	22.48
ZincRe	0.98	43.29	10.06	0.44	9.86	14.29	0.69	0.66	13.38	1.85	1.9	2.61	56.71
NNickelRe	1.34	11.28	51.45	0.61	7.56	11.85	0.8	0.59	7.21	2.23	1.51	3.57	48.55
CobaltRe	1.45	1.27	1.7	83.93	0.77	1.39	1.12	1.2	1.32	1.81	2.81	1.23	16.07
AluminiumRe	1.11	11.09	8.05	0.6	49.85	13.42	0.84	0.56	6.87	2.5	2.67	2.44	50.15
CopperRe	1.58	13.79	10.75	0.44	10.89	42.3	1.3	0.42	8.65	4.1	1.46	4.33	57.7
LithiumRe	3.2	1.1	1.28	0.64	0.61	1.68	82.89	0.7	0.8	3.14	2.58	1.39	17.11
ManganeseRe	0.89	0.72	0.74	0.76	0.57	0.74	0.64	89.52	0.86	1.32	2.43	0.81	10.48
LeadRe	0.96	15.24	7.33	0.7	7.06	10.3	0.62	0.82	51.2	1.89	1.68	2.21	48.8
IndiuRe	3.45	1.13	2.02	0.55	0.59	2.27	1.42	1.47	1.13	81.02	3.25	1.68	18.98
DysprosiumRe	9.73	0.64	0.62	0.91	0.63	0.84	0.54	0.9	0.53	2.32	81.49	0.85	18.51
GCEIRe	1.17	3.45	5.18	0.67	2.65	6.15	1.37	0.94	1.86	2.84	2.4	71.3	28.7
TO	25.87	60.66	49.25	6.99	42.04	64.43	11.33	8.84	43.41	27.7	31.69	22.05	394.26
Inc.Own	103.39	103.94	100.7	90.92	91.89	106.73	94.22	98.36	94.6	108.71	113.18	93.36	Total
NET	3.39	3.94	0.7	-9.08	-8.11	6.73	-5.78	-1.64	-5.4	8.71	13.18	-6.64	35.84/32.85

Table 8: Average dynamic total return connectedness for NASDAQ

	NeodymiumRe	ZincRe	NickelRe	CobaltRe	AluminiumRe	CopperRe	LithiumRe	ManganeseRe	LeadRe	IndiuRe	DysprosiumRe	NASDAQRe	FROM
NeodymiumRe	78	0.63	1.24	0.65	1.17	0.93	2.3	0.6	0.8	3.68	9.21	0.8	22
ZincRe	0.86	43.91	9.25	0.49	9.83	15.78	0.77	0.61	12.74	1.45	2.04	2.27	56.09
NickelRe	1.14	10.46	52.38	0.61	8.45	12.36	0.82	0.57	7.47	1.69	1.49	2.56	47.62
CobaltRe	1.4	1.26	1.48	84.86	0.95	1.07	1.3	1.09	1.27	1.78	2.51	1.05	15.14
AluminiumRe	1.1	10.9	8.5	0.61	50.62	12.49	0.86	0.52	7.5	2.17	2.79	1.95	49.38
CopperRe	1.18	15.23	10.95	0.43	10.88	42.93	1.17	0.43	9.29	2.93	1.03	3.55	57.07
LithiumRe	3.28	0.8	0.98	0.63	0.96	1.04	83.77	0.67	0.84	3.3	2.76	0.97	16.23
ManganeseRe	0.88	0.68	0.66	0.77	0.65	0.56	0.7	89.94	0.82	1.24	2.38	0.73	10.06
LeadRe	0.96	14.32	7.31	0.68	7.67	10.65	0.69	0.68	51.43	1.54	1.96	2.12	48.57
IndiuRe	3.69	0.63	1.55	0.58	1.31	1.14	2.14	1.46	1.21	82.02	3.31	0.98	17.98
DysprosiumRe	9.72	0.68	0.48	0.9	0.79	0.53	0.63	0.83	0.54	2.16	82.09	0.64	17.91
NASDAQRe	1.33	2.98	3.66	0.96	2.72	5.57	1.24	0.82	1.73	1.56	2.44	75	25
TO	25.54	58.57	46.05	7.31	45.37	62.12	12.61	8.28	44.21	23.49	31.91	17.61	383.06
Inc.Own	103.54	102.47	98.43	92.16	95.99	105.05	96.38	98.22	95.64	105.51	114.01	92.61	Total
NET	3.54	2.47	-1.57	-7.84	-4.01	5.05	-3.62	-1.78	-4.36	5.51	14.01	-7.39	34.82/31

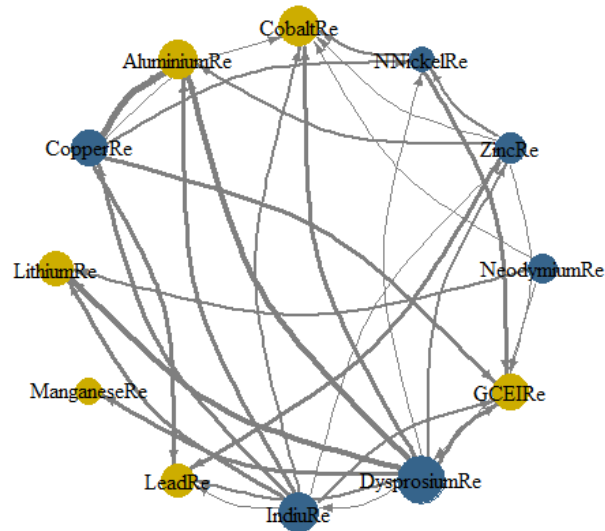


Figure 1: Net Pairwise Dynamic Connectedness with GCEI

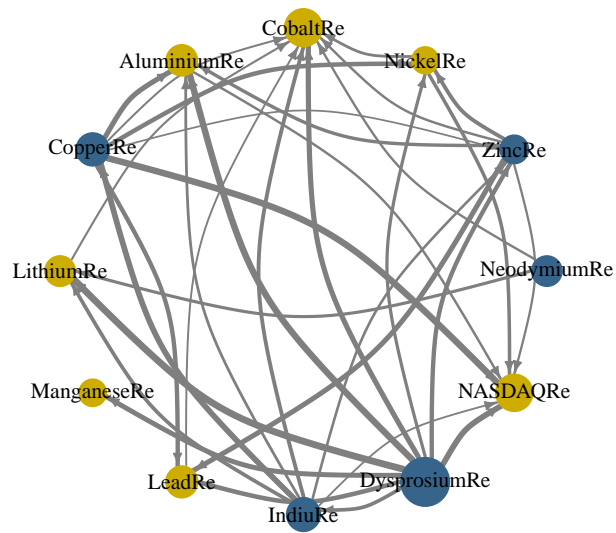


Figure 2: Net Pairwise Dynamic Connectedness With NASDAQ

Note: Blue nodes signify the senders of net shocks, while yellow nodes indicate the receivers. The size of the nodes is proportionate to the absolute values of the NET connectedness index. Arrows between nodes depict the direction of spillovers between variables, and the thickness of these arrows signifies the strength of the spillovers.

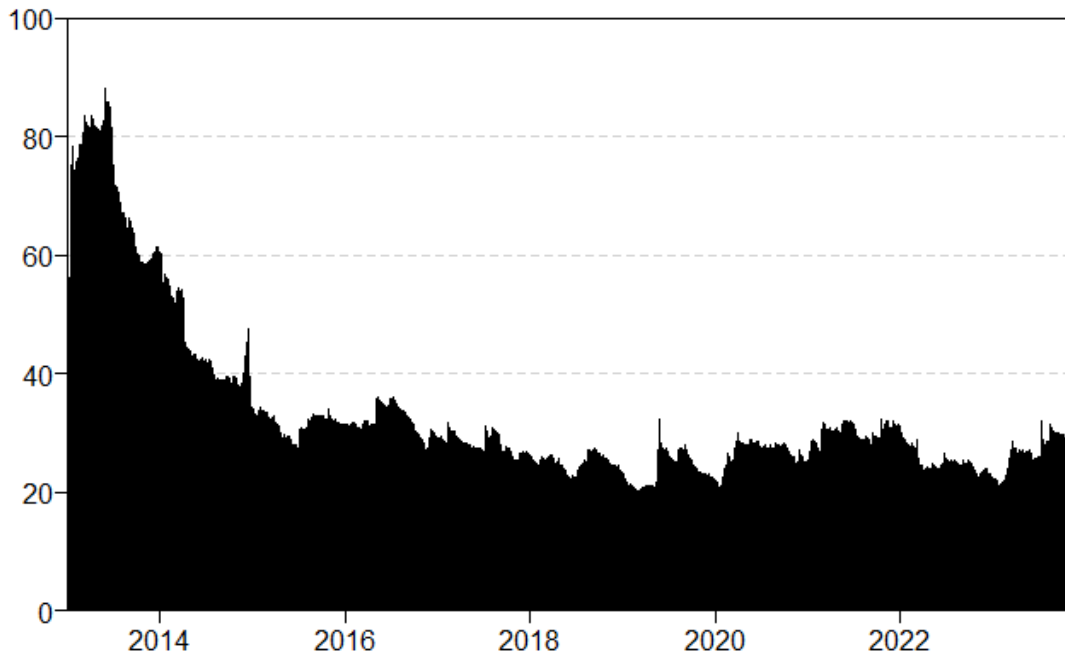


Figure 3: Total Connectedness Index with GCEI

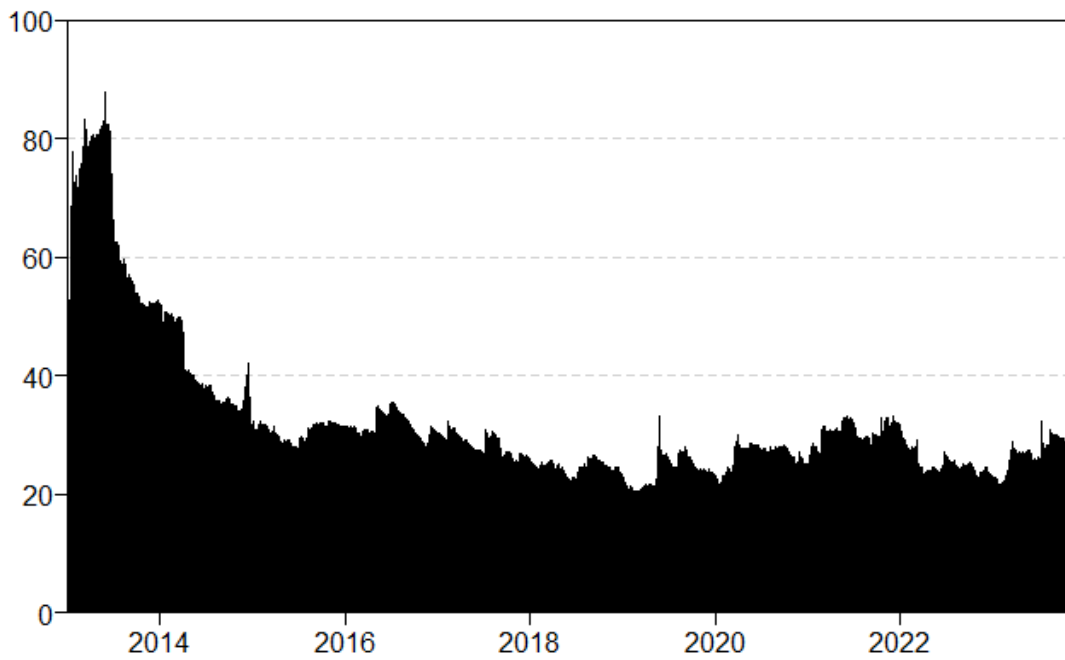


Figure 4: Total Connectedness Index with NASDAQ

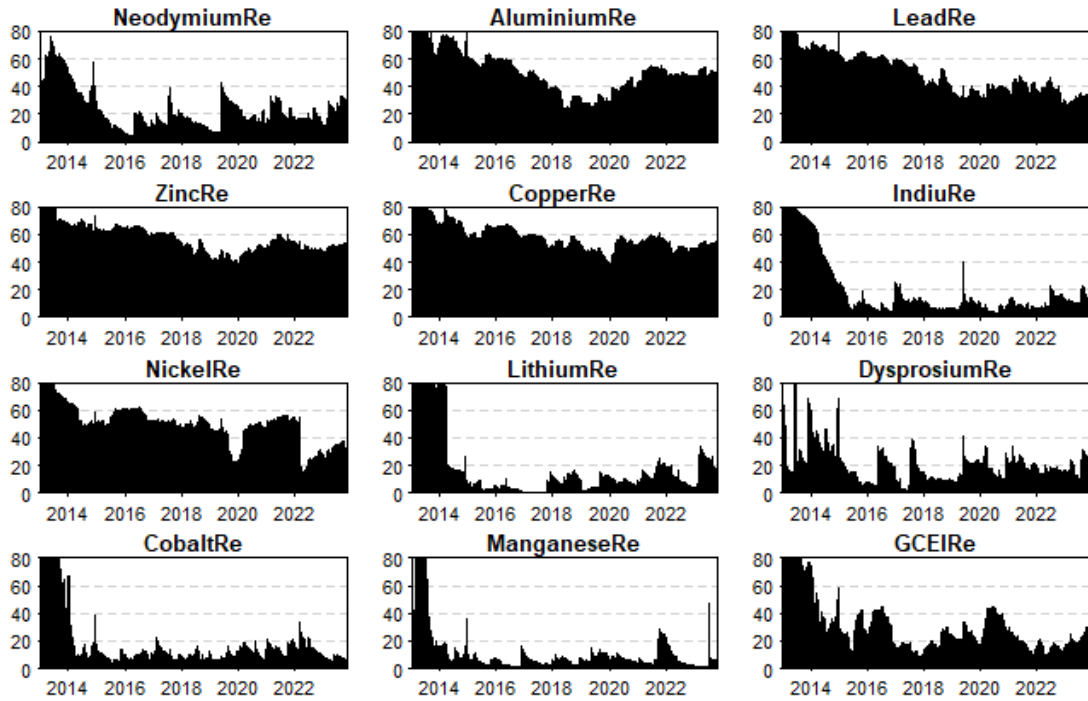


Figure 5: Dynamic directional return connectedness FROM others with GCEI

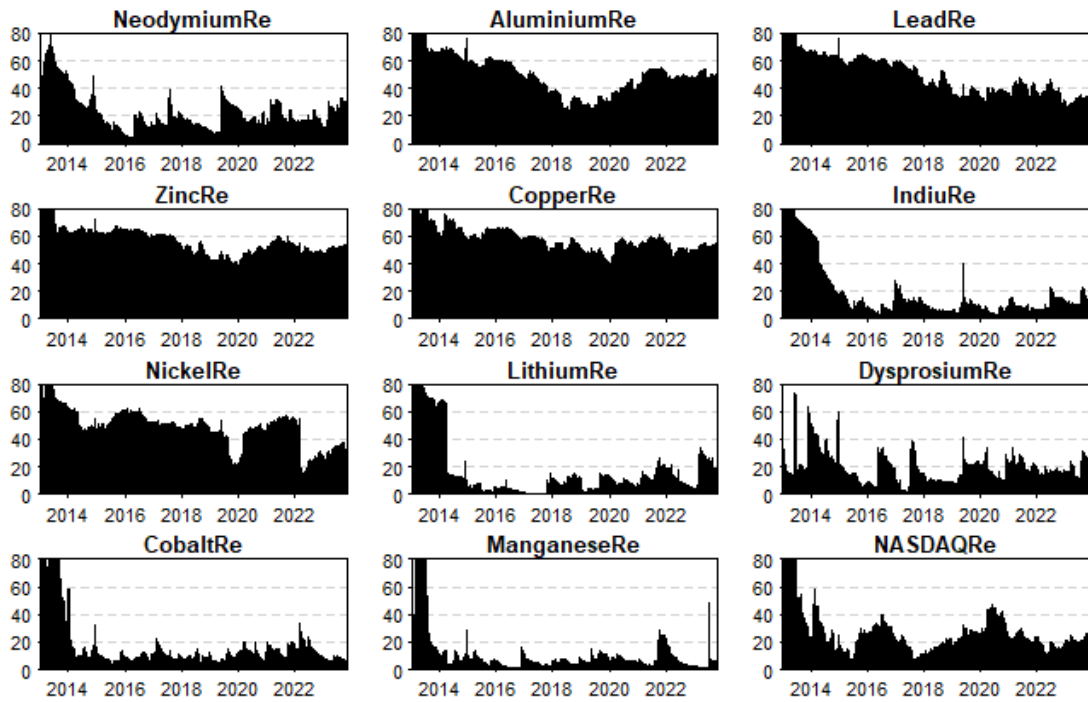


Figure 6: Dynamic directional return connectedness FROM others with NASDAQ

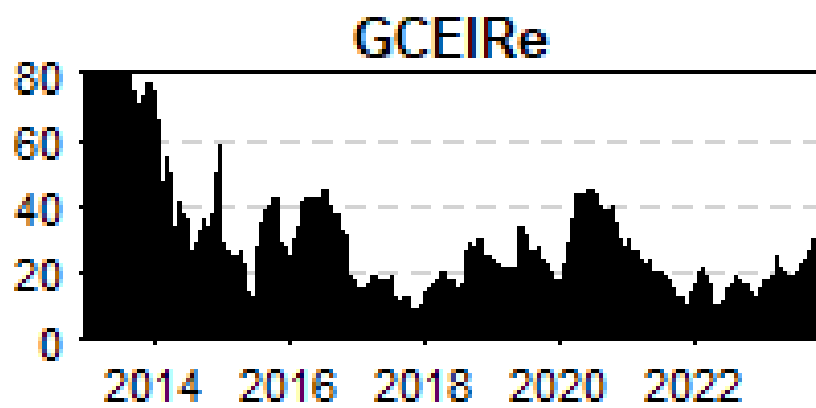


Figure 7: Dynamic directional return connectedness FROM others To GCEI

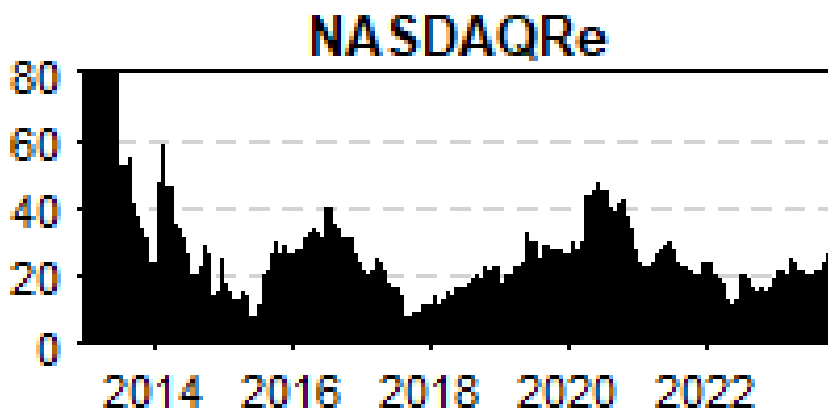


Figure 8: *Analyzing Crisis Dynamics*: Dynamic directional return connectedness FROM others To NASDAQ

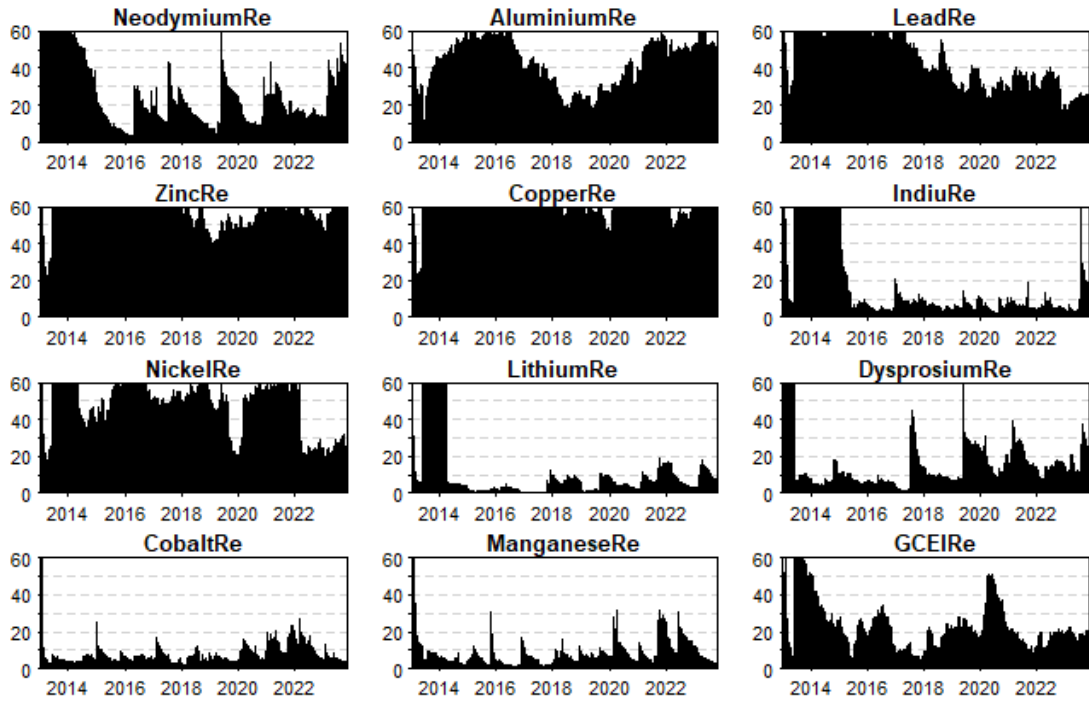


Figure 9: Dynamic directional return connectedness TO others with GCEI

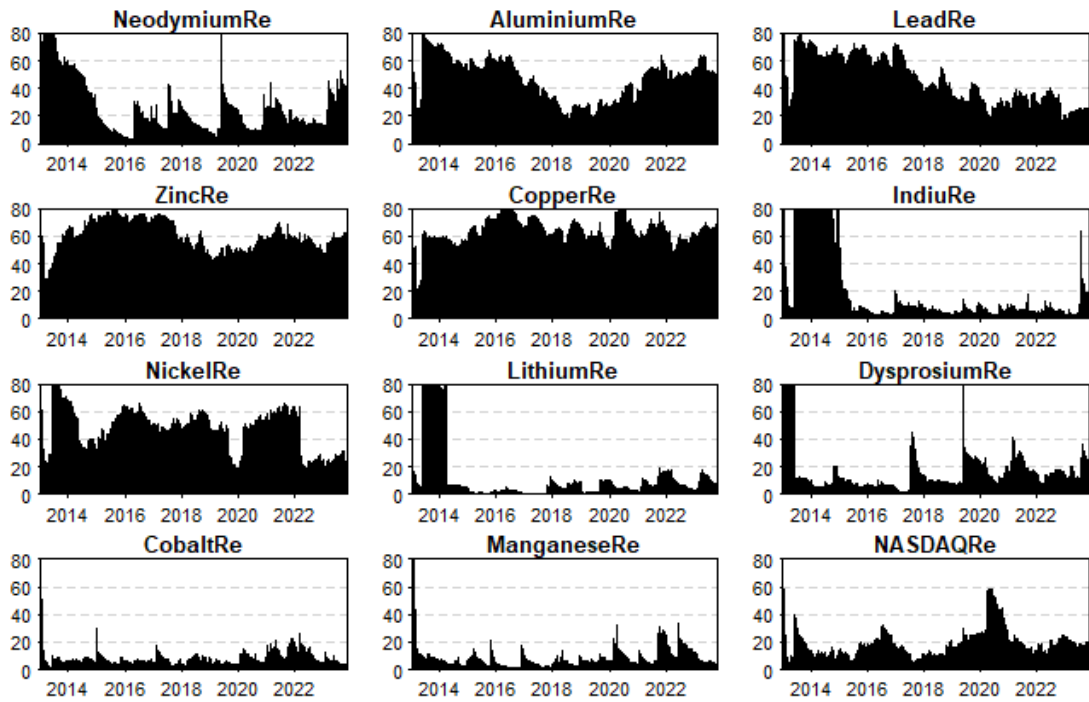


Figure 10: Dynamic directional return connectedness TO others with NASDAQ



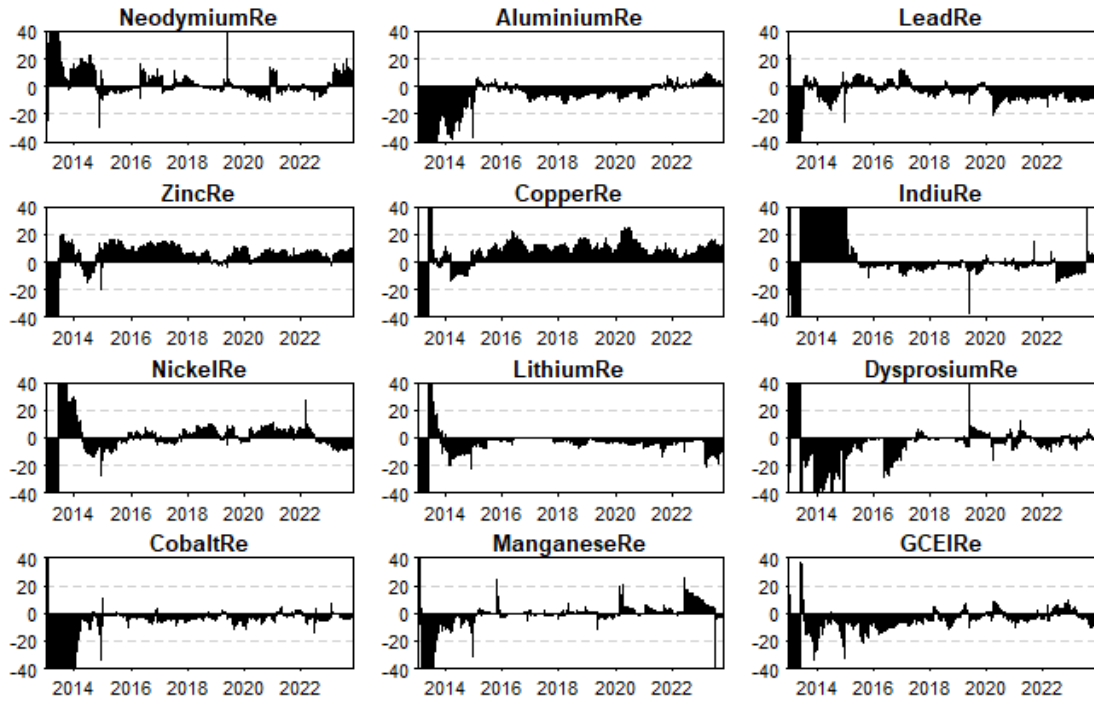


Figure 11: Total net return connectedness With GCEI

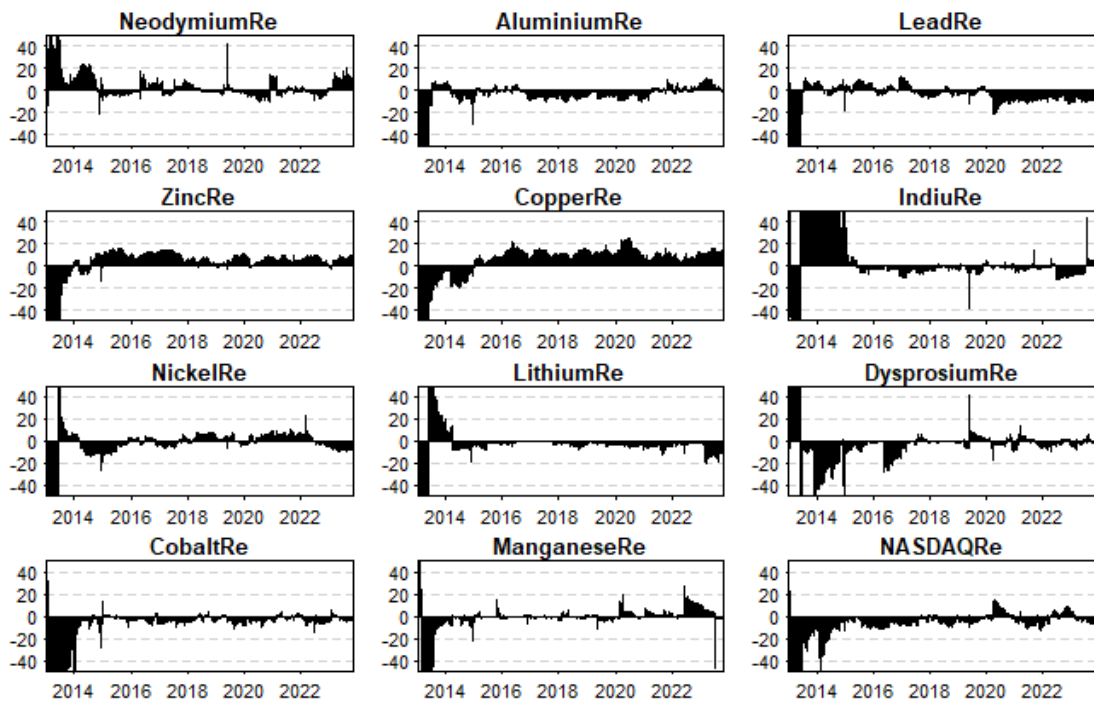


Figure 12: Total net return connectedness with NASDAQ

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