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Dependence and Spillover Dynamics Between Clean Energy, Non-Ferrous Metals, and Technological Innovation: Insights from a Global Stress Event

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Abstract

The rapid expansion of clean energy markets, coupled with the growing importance of non-ferrous metals and technological innovation, has created a highly interconnected financial and economic system. Understanding the dynamics of these interdependencies is essential for assessing market resilience, investment diversification, and the sustainability of the global energy transition. This paper investigates the dynamic dependence and connectedness between clean energy, non-ferrous metals, and technological innovation indices, with particular attention to the impact of the COVID-19 pandemic as a global stress event. Using daily data from December 2004 to July 2020, we employ a comprehensive empirical framework that combines copula-based dependence modeling with a dynamic connectedness approach. This methodology allows us to capture nonlinear relationships, tail dependencies, and volatility spillovers across markets. The results reveal that the dependence structure between clean energy and the other sectors is symmetric and time-varying, with stronger linkages observed between clean energy and technological innovation than with non-ferrous metals. The connectedness analysis indicates a moderate level of total spillovers, with clean energy acting as the main transmitter of shocks and technological innovation as the primary receiver. Focusing on the COVID-19 period, we find a significant increase in both dependence and connectedness, suggesting that these markets become more severely integrated during periods of extreme uncertainty. These findings support the presence of contagion effects and highlight the reduced effectiveness of diversification strategies during crisis episodes. The results offer forward-looking implications for investors and policymakers regarding risk transmission, portfolio management, and the resilience of markets supporting the global transition toward sustainable energy.

Keywords: clean energy; non-ferrous metals; connectedness

1. Introduction

Over the past two decades, global energy use has escalated dramatically, accompanied by a substantial increase in carbon emissions that has intensified environmental degradation and accelerated global warming. For instance, global energy demand rose by 2.3% in 2018, the highest growth rate of the decade, while CO_2 emissions increased by 1.7%, reaching a record level, according to the International Energy Agency (IEA). In this context, the

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transition toward clean energy has become essential not only to mitigate environmental risks but also to meet the growing global demand for energy in a sustainable manner.

The development of oil markets alongside advances in clean energy technologies has significantly supported the expansion of renewable energy production and consumption. In recent years, many countries have increasingly shifted toward renewable energy sources as part of broader sustainability strategies. This transition is reflected in the rapid growth of the renewable energy market, with global investment exceeding USD 272.9 billion in 2018 (Global Trends in Renewable Energy Investment, UN Environment). As a result, clean energy companies have experienced improved financial performance, attracting substantial attention from institutional investors seeking both sustainable and diversified investment opportunities.

Ref. [1] suggests that this transition to alternative energy resources can significantly improve environmental system efficiency and contribute to achieving climate targets, including limiting global warming to 1.5 °C without relying heavily on carbon dioxide removal technologies (CDR).

Importantly, the expansion of clean energy technologies has led to a parallel increase in demand for non-ferrous metals, which serve as critical inputs in renewable energy infrastructure. Metals such as copper, aluminum, and nickel are essential components in the production of solar panels, wind turbines, and energy storage systems. Consequently, the growth of clean energy markets has stimulated the emergence and development of non-ferrous metals as a strategic asset class (see, for instance, ref. [2]).

This growing importance has attracted institutional investors, leading to increased trading volumes and enhanced financial integration between clean energy and non-ferrous metal markets. As a result, these markets are expected to exhibit significant interactions, which may manifest through various channels, including causality, dependence structures, connectedness, and volatility spillovers.

Despite the economic and financial relevance of these linkages, the existing literature has largely focused on the relationship between clean energy and fossil fuel markets [3–6].

In contrast, relatively little attention has been devoted to examining the dynamic interactions between clean energy and non-ferrous metals. This gap is particularly important given the central role of critical materials in supporting the global energy transition and the increasing integration of these markets in both real and financial terms.

Building on these developments, technological innovation plays a crucial complementary role in influencing the evolution of clean energy markets. Advances in digital technologies, energy storage systems, and smart grid infrastructure have significantly improved the efficiency, scalability, and economic viability of renewable energy production. As a result, the performance of clean energy assets is increasingly connected not only with the availability of critical materials but also with the pace of technological progress. This creates a multi-dimensional nexus linking clean energy, non-ferrous metals, and technological innovation, where shocks affecting one sector may propagate to others through complex financial and economic channels.

Despite the growing importance of this interconnected system, existing empirical studies have largely explored these relationships in fragmented frameworks. Most studies focus either on the linkage between clean and fossil energy markets or on the hedging properties of traditional assets such as gold, while relatively few investigate the joint dynamics between clean energy, non-ferrous metals, and technology-driven sectors.

Moreover, prior investigations typically rely on linear relationships or volatility-based approaches. These approaches may fail to capture nonlinear dependencies, tail co-movements, and time-varying spillover effects, properties that are particularly important during periods of market stress. Consequently, the existing literature provides only a partial understanding of how these strategically important sectors interact under normal and extreme conditions.

In this perspective, the COVID-19 pandemic offers a unique natural context to investigate the behavior of these markets under conditions of intensified uncertainty and global disruption. The pandemic generated unprecedented volatility across financial and commodity markets, disrupted global supply chains, and altered investor behavior, thereby amplifying interdependencies across sectors. While the immediate effects of the pandemic have settled, analyzing this period provides valuable insights into how clean energy, critical materials, and technological innovation respond to systemic shocks. More importantly, it allows us to draw forward-looking implications regarding market resilience, risk transmission, and diversification opportunities in the face of future crises such as geopolitical tensions, climate-related shocks, or sharp financial instability.

Against this background, this paper examines the dynamic dependence and connectedness between clean energy, non-ferrous metals, and technological innovation indices, with a particular focus on the impact of the COVID-19 pandemic. By jointly analyzing dependence structures and spillover effects, the study aims to provide a comprehensive description of the interaction mechanisms linking these markets. The COVID-19 period is thus interpreted not merely as a historical episode, but as a stress-testing environment that reveals the underlying structure and fragility of these interconnections.

This study contributes to existing literature in several important ways. First, it extends prior research by simultaneously analyzing clean energy, non-ferrous metals, and technological innovation, thereby offering a more integrated perspective on the clean energy ecosystem. Second, it employs a comprehensive empirical framework that combines copula-based modeling with a dynamic connectedness approach, allowing for the identification of nonlinear dependence structures and volatility spillovers. Third, it introduces a hypothesis-testing procedure to assess structural changes in dependence and connectedness patterns before and during the COVID-19 pandemic. Finally, by interpreting the pandemic as a global stress event, the study provides forward-looking insights that are relevant for investors seeking diversification benefits and for policymakers aiming to improve the resilience of the energy transition.

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature. Section 3 introduces the methodology and the data, Section 4 presents the empirical results, and Section 5 provides policy implications. Section 6 closes with a conclusion.

2. Literature Review

Empirical studies on the dependence and spillovers between renewable energy and other commodity stock markets focus mainly on the examination of the association between renewable and fossil energy markets. A four-variable vector auto-regression model is employed to explore the linkage among several alternative energy stocks and oil prices, along with other variables [7]. A significant causal relationship from oil prices to the stock prices of the considered energy assets is found. A three-variable TVP-SV-VAR model is considered to assess the interrelationships among the stock prices of new energy, fossil energy, and a selected group of companies operating in high technology [8]. The outcomes of the study mainly show a significant linkage between the stock prices of new energy companies and the prices of most of the fossil energy. The wavelets technique is employed to investigate the returns and risk spillovers among oil and clean energy markets [9]. The results of the wavelets approach revealed significant co-movements between the studied markets. The effect of the variability of the prices of the main fossil energy on company stock prices operating in a new energy sector is investigated in [10]. The findings show that past stock prices of new energy companies had the strongest influence on the current level. Conversely, only a limited contribution of fossil energy prices in the stock price fluctuations of new energy companies is highlighted. Recently, a growing number of empirical studies have examined the patterns of relationships between energy stock and precious metals. A GARCH-jump process is employed to assess the impact of the uncertainties in the silver market on solar energy stock indices globally [11]. The results of the study reveal a significant negative effect of the silver volatility index on the considered equity indices. These findings suggest that an increase in silver market volatility may lead to significant uncertainty in the solar energy industry.

Because gold is mostly viewed as a safe haven for investors, the relationship in terms of dependence and spillovers between this precious metal and the Clean Energy Index has been widely investigated in different research papers. How several assets, including gold, can be used to hedge an investment in clean energy equities is examined in [12]. Using competing multivariate GARCH models, they find that VIX is the best asset to hedge clean energy equities. In addition, they find that crude oil outperforms gold in being a hedge asset for clean energy equities. The copula approach was employed [13] to examine the potential roles of gold as a safe-haven asset against extreme down movements in clean energy stock indices. The results reveal that gold is a weak safe-haven asset for clean energy indices. A cross-quantilogram approach is used to explore the dependence between renewable energy stock returns and gold prices amongst other financial assets, revealing that gold returns exert a positive influence on the renewable energy stock returns [14]. The study also reports that this positive influence is observed only during extreme market conditions.

Recently, increasing attention has been directed toward the role of non-ferrous and critical metals in determining the dynamics of clean energy markets, particularly during periods of global stress such as the COVID-19 pandemic and geopolitical crises. Ref. [15] analyzed the dynamic volatility spillovers between China's clean energy sub-sectors and non-ferrous metal futures, finding that the COVID-19 pandemic significantly amplified risk transmission, with clean energy acting as the primary net sender of risk. Using a combination of Diebold–Yilmaz spillover indices and Minimum Spanning Tree (MST) networks, the study shows how the crisis shifted contagion paths toward specific nodes such as smart grids and zinc, emphasizing the importance of targeted risk management in these sectors. Ref. [16] investigated the asymmetric impact of COVID-19 news on the connectedness among green energy, dirty energy, and non-ferrous metal markets. The study demonstrates that positive pandemic-related news exerts stronger effects on market connectedness than negative news, emphasizing the importance of investor sentiment and expectations in risk transmission mechanisms. Ref. [17] employed a Quantile Vector Autoregression (QVAR) framework to examine tail-risk connectedness between energy and metal markets during COVID-19. Their results indicate that dependence between the markets becomes considerably stronger during extreme bullish and bearish conditions, while energy metals increasingly emerge as net transmitters of shocks after 2021 due to supply chain disruptions.

Ref. [18] further extended the literature by examining frequency-domain spillover effects between critical metals and energy markets. The authors show that lithium and platinum play a dominant role in driving long-term market integration, whereas short-term spillovers are mainly associated with policy uncertainty and market sentiment. Ref. [19] explored the evolving role of clean energy metals as strategic financial assets during successive global crises. Their findings indicate that lithium has shifted from being a passive receiver of shocks to a dominant volatility transmitter during the Russia–Ukraine conflict, thereby challenging the traditional hedging role of gold and improving the resilience of portfolio allocation strategies based on clean energy metals. In addition, ref. [20] analyzed volatility spillovers between oil shocks, energy assets, stocks, and gold in emerging markets. The study highlights that oil supply shocks generate more persistent and long-term spillover effects than demand-side shocks, reducing diversification opportunities across financial and commodity markets. Ref. [21] investigated spillover effects between China's carbon market and energy-related industries through a dynamic spillover framework. Their findings suggest that external crises and renewable energy policy interventions significantly alter spillover structures, while the carbon market increasingly responds to fluctuations in both fossil-fuel and renewable-energy sectors.

Overall, the existing literature exploring the dependence between renewable energy stock returns and other commodity returns has several limitations. First, empirical studies aiming to explore movements between renewable energy stock prices and other commodities frequently concentrate on the first and second moments of the distribution of the returns, ignoring the possible dependence of the lower and upper tails.

Moreover, these studies do not study both the dependence and spillovers between renewable energy stock returns and other commodities. Although recent studies [22] have increasingly adopted advanced methodologies such as time-varying parameter vector autoregression (TVP-VAR), the quantile vector autoregressive (QVAR), and frequency-domain connectedness approaches, there remains limited evidence integrating clean energy, non-ferrous metals, and technological innovation within a single analytical framework. In addition, most studies in the field focus on the relationship between renewable energy stock and oil or precious metals prices. However, despite the importance of the non-ferrous metals as basic building blocks for the development of clean energy technologies, only Yahya et al. analyzed the dependence and causality between non-ferrous metals and clean energy indices in [2]. The finding shows that the conditional dependence between the assets is time-varying and asymmetric, with the potential for tail dependence. The volatility connectedness between oil prices and clean energy firms between 2011 and 2020 is explored in [23]. The findings reveal a significant variation in the volatility connectedness during the COVID-19 pandemic.

According to this review, despite the growing body of literature examining the relationship between clean energy markets and other financial or commodity assets, several important limitations remain. First, most existing studies focus primarily on the linkage between clean energy and fossil fuel markets or traditional safe-haven assets such as gold, while relatively little attention has been devoted to the interaction between clean energy and non-ferrous metals. This represents a significant gap, given that non-ferrous metals constitute essential inputs in renewable energy technologies and play a critical role in supporting the global energy transition.

Second, prior research typically examines dependence structures and spillover effects separately, relying either on correlation-based approaches or volatility transmission frameworks. Such approaches may provide only a partial view of market interactions, as they do not capture the joint dynamics between nonlinear dependence and connectedness. In particular, the presence of tail dependence and time-varying co-movements during periods of market stress remains largely unexplored.

Third, the role of technological innovation as a key driver of clean energy development is often overlooked in empirical analyses. Given the increasing importance of innovation in enhancing the efficiency and scalability of renewable energy systems, ignoring this dimension may lead to an incomplete understanding of the interactions within the clean energy ecosystem.

Finally, while recent studies have investigated the impact of the COVID-19 pandemic on financial markets, limited attention has been given to how this global shock has affected the joint dependence and connectedness between clean energy, non-ferrous metals, and

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technological innovation. In particular, there is a lack of formal statistical testing to assess whether the observed changes in these relationships are structurally significant.

To address these shortcomings, this paper makes several key contributions. First, it provides a comprehensive analysis of the interaction between clean energy, non-ferrous metals, and technological innovation, thereby offering a more integrated perspective on the clean energy ecosystem. Second, it introduces a unified empirical framework that combines copula-based dependence modeling with a dynamic connectedness approach, allowing for the identification of nonlinear relationships, tail dependencies, and volatility spillovers. Third, the study proposes a hypothesis-testing procedure to formally assess changes in dependence and connectedness patterns before and during the COVID-19 pandemic. Finally, by interpreting the pandemic as a global stress event, the paper aims to provide forward-looking insights into market resilience, risk transmission, and diversification strategies in the context of future economic and financial shocks.

3. Methodology and Data

3.1. Copula Models

In this paper, we propose to investigate the dependence structure between the returns of clean energy indices (ECO and SPGTCED), the DJUSNF, and the ARCA using the static copula approach proposed by Sklar [24]. In addition, to extract the series of time-varying dependence coefficients, we employ Patton's model [25], which is an extension of Sklar's theorem in ref. [24].

A p-dimensional copula $C(u_1, \ldots, u_p)$ is a multivariate distribution function in the unit hypercube $[0,1]^p$. The marginal distributions of this copula function are uniformly distributed $U(0,1)$. It is suggested in [26] that any joint distribution, $F(x_1, \ldots, x_p)$ with marginals $F_1(x_1), \ldots, F_p(x_p)$, can be expressed as

$$F(x_1, \ldots, x_p) = C(F_1(x_1), \ldots, F_p(x_p)) \quad (1)$$

for a function C called a copula of F. In addition, if the marginals are continuous, then there is a single copula associated with the joint distribution, F, constructed from

$$C(u_1, \ldots, u_p) = F\left(F_1^{-1}(u_1), \ldots, F_p^{-1}(u_p)\right) \quad (2)$$

In 2006, Patton developed an extension to the static copula construction by proposing copula constructions that evolve over time and assuming that the process that follows the time-varying copulas is an autoregressive moving average ($ARMA(p,q)$) process.

In the literature, there are large copula constructions used to identify the dependence between two or more random variables (see, for instance, ref. [27]).

In this paper, we estimated several copula constructions. The ranking of copulas based on several information criteria indicates that for most of the studied stock markets, Student's and Gaussian copulas fit the data well. Thus, we briefly present the static and time-varying versions of these copulas.

Most of the prior studies on the correlation among assets used the Gaussian copula, having as cdf

$$C_n^{\Phi}\left(u, \Omega^{\Phi}\right) = \Phi_n\left(\Phi^{-1}(u_1), \ldots, \Phi^{-1}(u_n); \Omega^{\Phi}\right) \quad (3)$$

where u is a vector of marginal probabilities, Φ_n represents the cdf for the n-variate standard normal distribution, Ω^{Φ} denotes the correlation matrix. The Gaussian copula implies tail independence when the random variables are imperfectly correlated.

The second competing copula construction is the Student's t-copula, having a cdf

$$C_n^{\Psi}\left(u,\Omega^{\Psi}\right) = \Psi_n\left(\Psi^{-1}(u_1;\nu),\ldots,\Psi^{-1}(u_n;\nu);\Omega^{\Psi},\nu\right) \tag{4}$$

where Ψ_n represents the cdf for the n-variate Student's t distribution, Ω^{Ψ} denotes the correlation matrix and ν is the number of degrees of freedom ($\nu > 2$).

A greater value for ν decreases the probability of occurrence of events at both tails. The Student's t-copula construction assigns higher probabilities to tail events than the Gaussian copula. In addition, the Student's t-copula displays tail dependence even though the correlation coefficients are equal to zero.

In addition to static copula investigation, to assess the time-varying dependence, we use the extension proposed by [25], assuming that the dynamic copula parameter is conditional on historical information following a $ARMA(p,q)$ process.

3.2. Connectedness Framework

The model proposed by Diebold and Yilmaz in 2012 is an extended version of the DY spillover index, see [28]. The approach is based on the technique of variance decomposition in relation to an N-variable vector autoregression. They proposed a method based on the forecast error variance decomposition. The forecast error variance of one variable is decomposed into parts attributed to the various variables in the system. Compared to the standard DY approach that focuses on the total spillovers in a model VAR construction, the novel approach allows assessing the directional spillovers in a generalized VAR framework. This helps to eliminate the impact of variable ordering on the levels of dependence between them.

The DY model considers a covariance stationary N-variable $VAR(p)$, $X_t = \sum_{i=1}^{p} \Phi_i X_{t-1} + \epsilon_t$, where ϵ_t is the disturbance term such as $\epsilon_t \sim (0,\Sigma)$. The moving average representation of the above equation is written as $X_t = \sum_{j=1}^{\infty} A_j \epsilon_t$, where A_j is an $N \times N$ coefficient matrix obeying the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots \Phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$.

The dynamic of the system can be analyzed based on several transformations, such as the impulse response functions and the variance decompositions. Specifically, in the innovative framework [29], the variance decompositions are used and allow for parsing the forecast error variances into parts that are attributable to the different system shocks. The variance decompositions allow the assessment of the fraction of the H-step-ahead forecast error variance in forecasting $\boldsymbol{x}_i$ that is due to $\boldsymbol{x}_j$, $\forall j \neq i$ for each i.

Accordingly, several measures of variance shares and spillovers are identified. Next, we briefly present and define the most useful measures.

Ref. [29] defined the own variance share to be the fraction of the H-step-ahead forecast error variances in forecasting $\boldsymbol{x}_i$ due to shocks to $\boldsymbol{x}_i$. The spillovers or cross variation shares represent the fraction of the H-step-ahead forecast error variance in forecasting $\boldsymbol{x}_i$ due to shocks to $\boldsymbol{x}_i$ for all $\forall j \neq i$, for each i. Using the H-step-ahead generalized forecast-error variance decomposition as suggested in [30,31] and after a series of mathematical transformations, the total connectedness can be expressed as

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \overset{\sim g}{\theta}_{ij}(H)}{N} \times 100 \tag{5}$$

This formula assesses the contribution of spillovers of volatility shocks across the investigated variable (Clean Energy Index) to the total forecast error variance.

To evaluate the directional volatility spillovers received by an index i from all indices j, it is possible to use Equation (6), which is commonly known as the directional connectedness $(i \leftarrow j)$:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \overset{\sim g}{\theta}_{ij}(H)}{N} \times 100 \quad (6)$$

A second directional connectedness is denoted $(i \longrightarrow j)$ and is defined to assess the directional volatility spillovers transmitted by the index i to all other indices j as presented by

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \overset{\sim g}{\theta}_{ji}(H)}{N} \times 100 \quad (7)$$

By calculating the difference between the two directionally connectedness $(i \leftarrow j)$ and $(i \longrightarrow j)$, we can assess the net volatility spillover from the index i to all other indices j. Explicitly, the net connectedness is calculated using Equation (8).

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{jg}(H) \quad (8)$$

Finally, to assess the difference between the gross volatility shocks transmitted from an index i to index j and those transmitted from j to i, we calculate the net-pairwise volatility connectedness presented in Equation (9):

$$S_{ij}^{g}(H) = \left(\frac{\overset{\sim g}{\theta}_{ji}(H) - \overset{\sim g}{\theta}_{ij}(H)}{N} \right) \times 100 \quad (9)$$

The combination of copula-based dependence modeling and the Diebold and Yilmaz (DY) connectedness framework provides a comprehensive empirical strategy to investigate the interrelationships between clean energy, non-ferrous metals, and technological innovation markets. While the copula approach allows us to capture nonlinear dependence structures and tail co-movements, particularly relevant during periods of extreme market conditions, the DY framework quantifies the magnitude and direction of volatility spillovers across these markets. By jointly analyzing dependence and spillovers, this framework enables a deeper understanding of how shocks are transmitted and amplified within the clean energy ecosystem. From an economic perspective, this approach is essential for identifying channels of risk propagation, assessing market integration, and evaluating the resilience of sectors that are critical to the energy transition. Building on this integrated methodology, we next formally test whether the dependence and connectedness structures have significantly changed in response to the COVID-19 pandemic.

3.3. Hypothesis Testing Framework

3.3.1. Timeline and Specification of Dummies

This hypothesis-testing framework has considerable contextual background. We focus on comparing the dynamic dependence and connectedness between the clean energy stock markets and the non-ferrous metal and the technology innovation indices before and during the COVID-19 pandemic.

The context of the COVID-19 pandemic and the resulting social, economic, and financial chaos is certainly relevant to our investigation into a wide set of potential ways. Ref. [32] suggests that compared to other disasters, such as terrorist attacks and natural calamities, the COVID-19 pandemic is expected to generate spillover effects between international financial markets. Ref. [33] also provides evidence of an upsurge of uncertainty and spillovers between financial and commodity markets during the period of the COVID-19 pandemic. However, due to the dramatic collapse in oil prices and conventional financial markets, coupled with the global spread of the COVID-19 pandemic, and following the theory on investor attention, investors will pay more attention to the potential to invest in clean energy stocks [34]. This suggestion is motivated by the implementation of green recovery plans. Hence, it is important to investigate the behavior of the renewable energy index and its dependence and spillover patterns with other financial and commodity markets during the COVID-19 pandemic.

Based on the recent literature [34,35], the current study sets 18 January 2020 as the official date for the declaration of the pandemic. To meet the main objective of this study, namely, to analyze the change in connectedness between the different indices before and during the pandemic, we propose a symmetrical window around the start of the COVID-19 pandemic. We consider a one-year period divided into two sub-periods of six months. The choice of period depends on the date when the data were retrieved from the Bloomberg database. We also believe that the period before the pandemic did not contain any particular shock that could have caused a change in the structure of volatility between the various indices in this study. It is important to understand whether the pandemic can be treated as a financial crisis and whether it can cause a contagion effect between clean energy stocks, non-ferrous metals, as a basic building block for the development of renewable energy, and the clean technology index [36].

3.3.2. Hypothesis

To test whether the COVID-19 pandemic induced variation in the structure of dependence and connectedness between the Clean Energy Index, the non-ferrous metals index, and the innovation technology index, we suggest these four hypotheses:

Hypothesis 1. *There is no significant variation in the level of dependence between the Clean Energy Index and the DJUSNF due to the COVID-19 pandemic.*

Hypothesis 2. *There is no significant variation in the level of dependence between the Clean Energy Index and the ARCA due to the COVID-19 pandemic.*

Hypothesis 3. *There is significant variation in the level of connectedness between the Clean Energy Index and the DJUSNF due to the COVID-19 pandemic.*

Hypothesis 4. *There is no specific change in the level of connectedness between the Clean Energy Index and the ARCA due to the COVID-19 pandemic.*

In this case, given that we have only two phases describing the COVID-19 pandemic periods (pre-COVID-19 and during the COVID-19 pandemic), we propose to test the hypotheses in the following way:

$$\begin{cases} H_0 : \overline{\rho}_{pre} = \overline{\rho}_{During} \\ H_1 : \overline{\rho}_{pre} \neq \overline{\rho}_{During} \end{cases}$$

where ρ_{pre} is the average level of dependence (connectedness) in the pre-COVID-19 outbreak period, and $\overline{\rho}_{During}$ is the average level of dependence (connectedness) during the period of the COVID-19 outbreak.

Under the null hypothesis, the degree of dependence (connectedness) is claimed to be unchanged in the two considered periods. Rejecting the null means that the level of dependence (connectedness) changes between the two periods. As we must compare the means of two populations, a Student's *t*-test is the most appropriate method.

3.4. Data

We use daily data covering the period from 30 December 2004 to 31 July 2020 of two clean energy indices, the WilderHill Clean Energy Index (ECO) and S&P Global Clean Energy Index (SPGTCED), as well as the NYSE Arca Tech 100 Index (ARCA), and the Dow Jones U.S. Non-ferrous Metals Index (DJUSNF). All data were extracted from Bloomberg. The ECO includes the publicly traded companies whose businesses stand to benefit substantially from societal transition towards the use of cleaner energy and conservation. The SPGCTCED provides liquid and tradable exposure to 30 companies from around the world that are involved in clean energy-related businesses. The ARCA is a price-weighted index of 100 tech-related companies. It is a multi-industry tech index of companies that deploy innovative technologies in their products. Finally, the DJUSNF comprises the main industrially used non-ferrous metals, namely aluminum, copper, lead, nickel, tin, and zinc.

4. Analysis Results

In this section, we first conduct a preliminary analysis of the data, followed by a correlation study. In addition, we present and discuss the results of the dependence and connectedness patterns across clean energy, non-ferrous metals, and the innovation technology index on the entire sample. Finally, we focus on the impact of the COVID-19 pandemic by comparing the patterns of dependence and connectedness before and during the pandemic.

4.1. Preliminary Analysis

Figure 1 illustrates the evolution of prices and returns for four indices. All indices show not only a progressively increasing trend during the period 2005–2007 but also a rapid decline compared to the global financial crisis (GFC) of 2007–2008. All previous indices show a second decline observed in March 2020, corresponding to the onset of the coronavirus pandemic. Compared to other indices, the ARCA was the least sensitive to the 2007–2008 global financial crisis and recorded a continuous increase during the period of 2005–2020. The DJUSNF exhibits large variability, and several peaks (a rise and fall) have been observed; the current level of the index is comparable to that of 2005. The other two indices, ECO and SPGTCED, show practically the same downward trend over the same time. Interestingly, the ARCA behaves differently in the post-financial crisis period as compared to the other indices. Figure 1 also shows that, overall, the return series of the ARCA, ECO, DJUSNF, and SPGTCED have three spikes in common over the sample period. The first spike occurred during the period 2007–2008 due to the GFC. The second unstable period return is observed from 2010 to 2012, representing the European sovereign debt crisis (ESDC) and the banking crisis, and the last strong spike, highlighted by the green circle, represents the COVID-19 pandemic, which has been observed since March 2020.

Table 1 reports the summary statistics for the studied series for the whole sample. On average, the daily return for the ARCA is positive and represents the highest average return, supporting the general upward trend of high-technology stock prices. In contrast, the average daily returns for ECO, SPGTCED, and DJUSNF are negative, mainly due to the global financial crisis (recently COVID-19), causing a slow pivot towards clean and renewable alternatives. Comparing the standard deviations of four indices, the ECO, SPGTCED, and DJUSNF are more volatile compared to the ARCA. The DJUSNF shows the highest spread between the minimum and maximum returns during the study period;

thus, it is more volatile than the clean energy and technology sectors. A negative average return of the ECO and a positive average return for the ARCA for the period from January 2003 to September 2017 are also documented in [37]. Statistics also show that the ECO is more volatile than the ARCA.

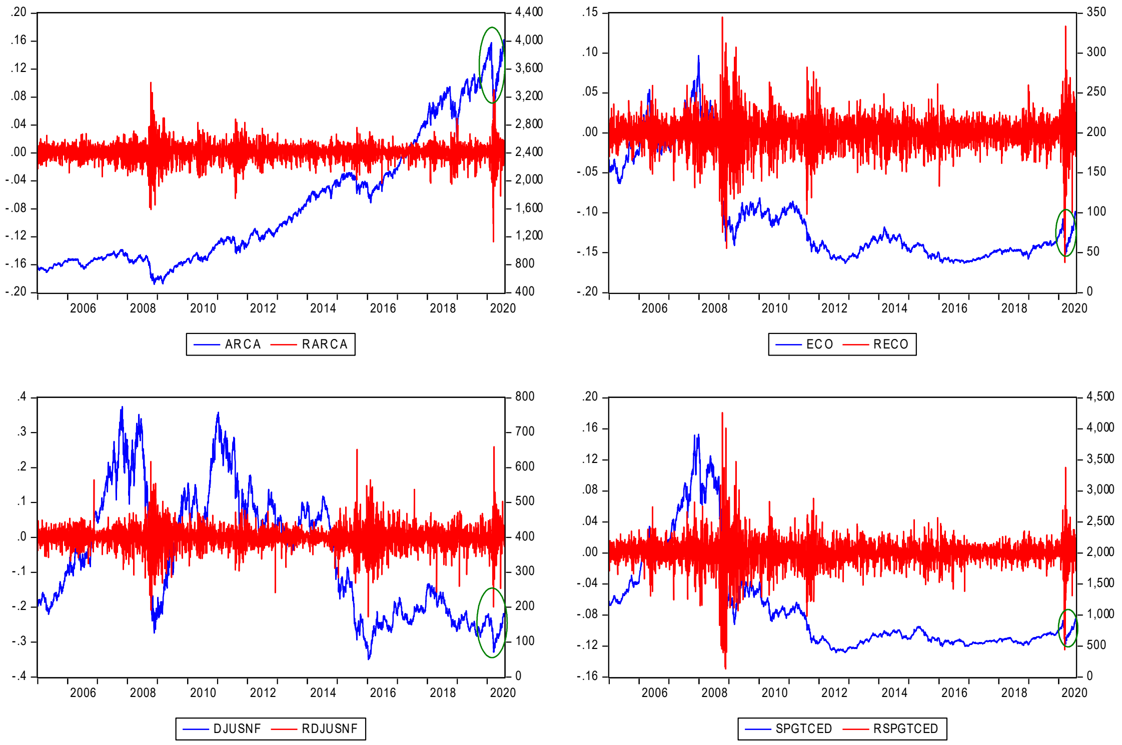

Figure 1. Time series plot of price and return. Notes: The graphs show the evolution of the four variables considered over the sample period from 31 December 2004 to 31 July 2020 (a total of 4066 daily observations). ECO denotes the WilderHill Clean Energy Index, and SPGTCED refers to the S&P Global Clean Energy Index. ARCA represents the NYSE Arca Tech 100 Index, and DJUSNF represents the Dow Jones U.S. Non-ferrous Metals Index.

Table 1. Descriptive statistics (on index returns).

	ARCA	ECO	DJUSNF	SPGTCED
Mean	0.040	−0.013	−0.006	−0.007
Median	0.062	0.0321	0.000	0.058
Maximum	10.09	14.5195	25.99	18.09
Minimum	−12.73	−16.239	−22.74	−14.97
Std. Dev.	1.269	2.0561	3.24	1.83
Skewness	−0.45	−0.56762	−0.14	−0.65
Kurtosis	12.66	10.03565	9.99	17.06
J-B	15,965.1 ***	8604.5 ***	8309.2 ***	33,808.6 ***
ADF	−70.80 ***	−42.20 ***	−63.06 ***	−55.62 ***
PP	−70.80 ***	−62.14 ***	−63.06 ***	−55.43 ***
Ljung–Box Q (15)	127.21 ***	37.63 ***	22.13 *	101.78 ***
Ljung–Box Q^2 (15)	4888.8 ***	5005.4 ***	2260.7 ***	6419.4 ***
ARCH (15)	1164.97 ***	1159.88 ***	687.02 ***	1357.92 ***

Note: The table presents descriptive statistics of daily returns for the NYSE Arca Tech 100 Index (ARCA), WilderHill Clean Energy Index (ECO), S&P Global Clean Energy Index (SPGTCED), and the Dow Jones U.S. Non-ferrous Metals Index (DJUSNF). Returns are calculated by taking the log difference in the price indices and then multiplying by 100, so the numbers are in percentage points. We report the annualized values of means and standard deviation (Std. Dev.); J-B and ADF denote the empirical statistics of the Jarque–Bera test for the normality and the Augmented Dickey and Fuller (ADF) unit root test. Q (15) and Q^2 (15) are the Ljung–Box statistics of serial correlation in returns and squared returns with 15 lags. Arch (15) tests the homoscedasticity with 15 lags. ***, and * indicate statistical significance at the 1%, and 10% levels, respectively.

The skewness coefficients of all indices are negative, indicating that returns are skewed left, and the kurtosis measure is always larger than three (the kurtosis of the normal distribution), showing that the series under investigation are heavy-tailed and are quite different from the normal shape. This non-normality is sustained by the Jarque–Bera test statistics, which reject normality for all the series at the 1% significance level. The results of the unit root test of the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) indicate that all the series are stationary processes at the 1% level. Finally, the hypotheses of independence and homoscedasticity are both rejected based on the Ljung–Box and ARCH-LM tests, respectively.

4.2. Correlation Analysis

Figure 2 illustrates the scatterplot of all selected index returns. The labels in the main diagonal report the indices. In the upper left box, the percentage of the ARCA return appears. Reading to the right, we see a scatter of points that relates to the correlation of the percent of the ARCA return with the percent of the ECO return. In this case, the return of the first index is considered the dependent variable, and the return of the second index is the independent variable. The scatter of points suggests a positive correlation between the two indices. The scatterplot matrix shows a positive correlation between all pairs of variables. It is interesting to study dependence and the marginal distribution functions by means of the copula.

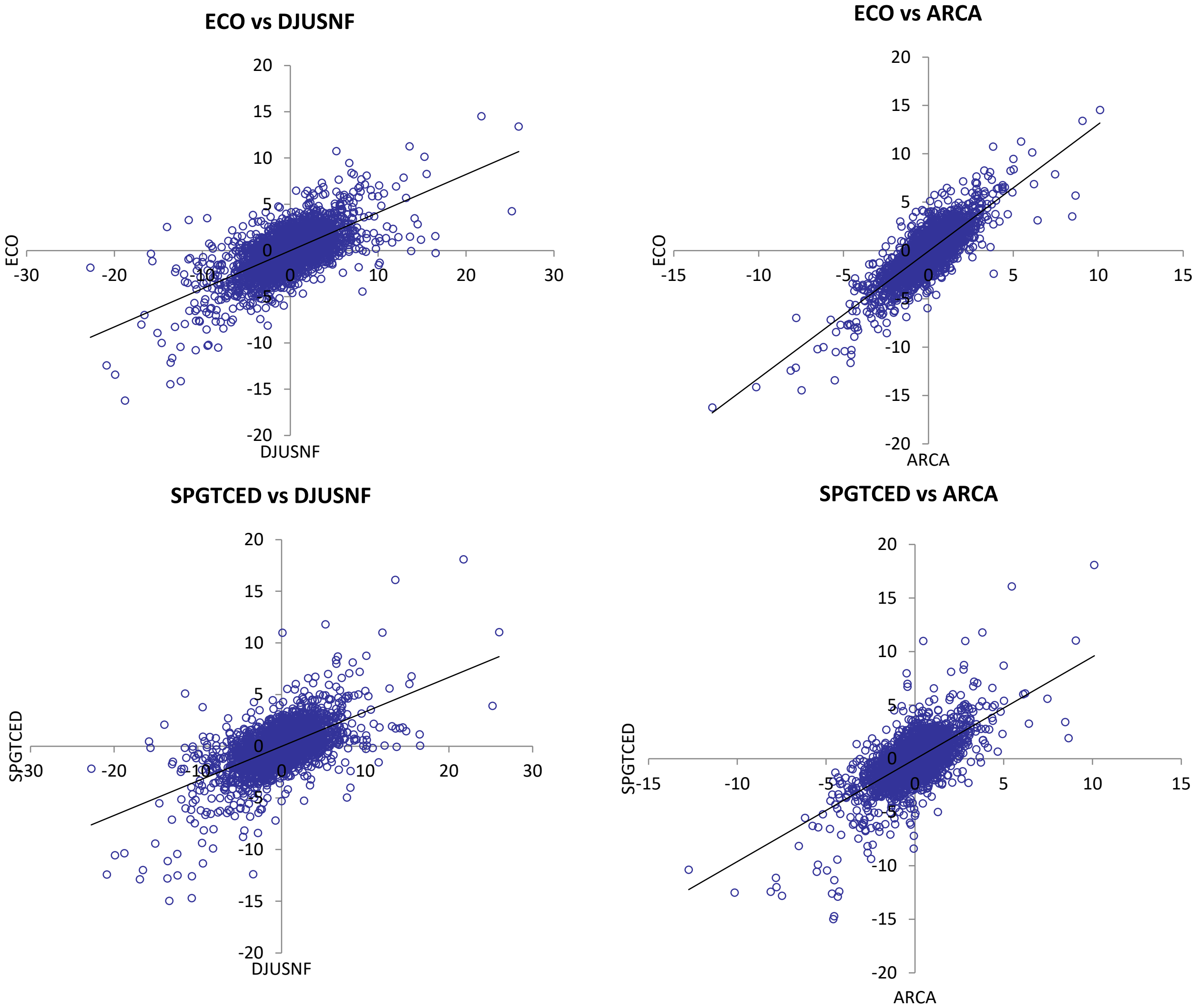

Figure 2. Scatter plots of renewable energy, non-ferrous metals, and ARCA returns.

Table 2 reports the correlations among the pairs of series under study. We find that all correlation coefficients are significantly positive at the 1% level, except for the negative correlation between the ARCA price and the other variables. Following the correlations between returns, the highest significant correlation is between ARCA and ECO with a coefficient of 0.81. Yet the lowest correlation is between SPGTCED and DJUSNF, with a coefficient of 0.59.

Table 2. Pairwise correlations between daily prices and returns.

	Correlations Between Prices				Correlations Between Returns			
	ARCA	**ECO**	**DJUSNF**	**SPGTCED**	**RARCA**	**RECO**	**RDJUSNF**	**RSPGTCED**
ARCA	1.00				1.00			
ECO	−0.56 ***	1.00			0.81 ***	1.00		
DJUSNF	−0.60 ***	0.48 ***	1.00		0.61 ***	0.65 ***	1.00	
SPGTCED	−0.52 ***	0.94 ***	0.53 ***	1.00	0.66 ***	0.82 ***	0.59 ***	1.00

Notes: This table reports the correlation coefficients between all possible pairs of the daily series (prices and returns) over the whole sample period (31 December 2004 to 31 July 2020). *** indicates statistical significance at 1%.

4.3. Analysis of the Entire Sample

4.3.1. The Pairwise Dependence Patterns

The static copula results show that the co-movement between the clean energy indices and the DJUSNF and the ARCA is best described by the Student *t* copula. To save space, we report only the results of the Student's *t*-copula in Table 3. All detailed copula results can be provided upon request. This finding is confirmed for the two used clean energy indices (ECO and SPGTCED). In addition, the results show that there is a strong positive association between the Clean Energy Index and the non-ferrous metals, with a dependence level exceeding 0.59 for the ECO/DJUSNF pair and more than 0.51 for the SPGTCED/DJUSNF pair. Moreover, the results show stronger positive co-movement across energy indices and the technology innovation index. The dependence level across the ECO and ARCA equals 0.74. These results support those obtained by non-conditional correlation measures reported in the correlation matrix (Table 2).

Table 3. Static Student's copula model results.

Copula	Dependence on ECO		Dependence on SPGTCED	
	DJUSNF	**ARCA**	**DJUSNF**	**ARCA**
τ	0.594	0.740	0.515	0.562
ν	6	5	7	7
BIC	−1796.35	−3296.76	−1265.95	−1600.16

Notes: This table reports the estimated copula parameters and the BIC information criteria.

Regarding the structure of dependence, since the data are best fitted by the Student's *t*-copula, the dependence between the clean energy indices and the non-ferrous metals is symmetric. Moreover, there are strong dependencies on the right and left tails of the distribution. In addition, the estimated number of degrees of freedom of the Student's *t*-copula is significantly low for all the considered pairs, indicating that it is not likely to proceed by normal approximation. Thus, tail dependencies must be considered when exploring the whole structure of co-movement patterns across clean energy and non-ferrous metals.

Concerning the co-movement patterns among the clean energy and innovation index, the results also reveal symmetric dependence patterns of both ECO/ARCA and SPGTCED/ARCA pairs. The results also indicate a significant departure from the Gaussian

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copula, since the Student's t-copula is significantly low with a small number of degrees of freedom.

In addition to the static copula, we estimated several time-varying copula constructions. Based on the information criteria, Student's t time-varying copula was selected. Table 4 and Figure 3 provide the most useful information for a complete description of the time paths of the dependence levels across the clean energy, the non-ferrous metals, and the technology innovation indices.

Table 4. Summary of the time-varying dependencies.

	ECO_DJUSNF	ECO_ARCA	SPGTCED_DJUSNF	SPGTCED_ARCA
Mean	0.3975	0.5696	0.4962	0.3763
Std. Dev.	0.2706	0.2332	0.1282	0.2734
Skewness	−0.2737	−0.7564	−2.2043	−0.2091
Kurtosis	3.0631	4.0277	12.8430	2.8729
Minimum	−0.7143	−0.5387	−0.3615	−0.6823
Maximum	0.9985	0.9986	0.8171	0.9957

Notes: This table includes the summary statistics and the deciles describing the time-varying dependence levels among the considered series.

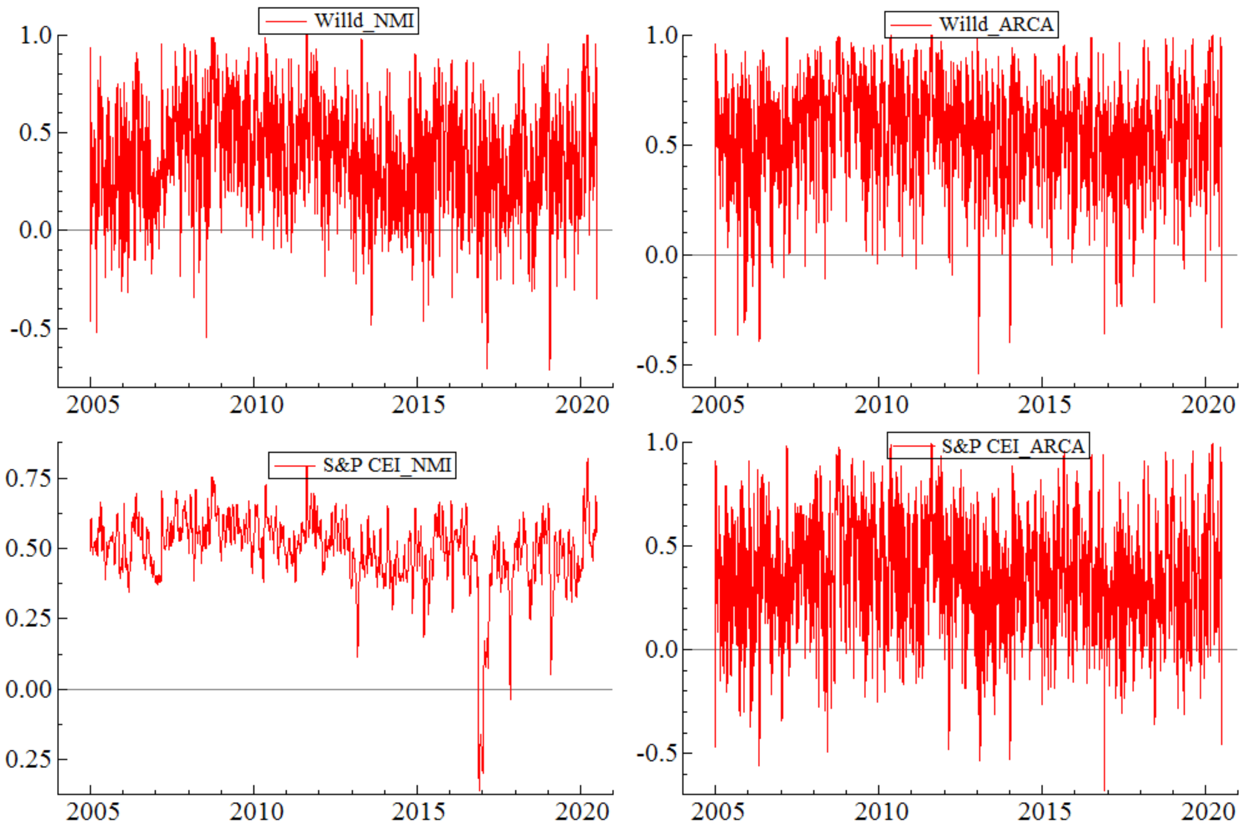

Figure 3. Dependence on time of the pairs ECO/DJUSNF, ECO/ARCA, SPGTCED/DJUSNF, and SPGTCED/ARCA.

Table 4 shows that, on average, the dependence of the energy index on the non-ferrous metal is relatively lower than that of the innovation technology index. In terms of variability, based on the unconditional measures, there are no significant differences between the considered pairs. In addition, the results show the presence of extreme positive dependence levels for all the pairs. For instance, the co-movement between the ECO/DJUSNF pair reaches its maximum at 0.99, indicating perfect correlation between them. Moreover, some extreme negative dependencies are highlighted mainly for the ECO/DJUSNF pair, reaching a value of −0.71.

In addition to the numerical description reported in Table 4, Figure 3 illustrates the time paths of dependence parameters for the pairs ECO/DJUSNF, ECO/ARCA, SPGTCED/DJUSNF, and SPGTCED/ARCA. Figure 3 shows that dependence evolves over time and is very volatile for all the studied pairs. The dependencies are mostly positive and reach extremely high levels in the three sub-periods. The first is from 28 February 2007 to 13 March, the second covers the period from 5 September 2008 to 27 October 2008, and the third runs from 3 March 2020 to 1 April 2020, with 16 observations exceeding 0.95 for the SPGTCED/DJUSNF pair and 19 observations exceeding 0.96 for the ECO/ARCA pair.

These periods of extreme dependence between the considered indices can be explained by specific events. Specifically, the first period can be explained by the impact of the GFC. The negative effects of the COVID-19 pandemic can explain the third period.

From the above analysis, the results indicate that the dependence structure between clean energy and the other sectors is symmetric and time-varying, with the strongest dependence observed between clean energy and technological innovation. This finding reflects the fundamental role of technological progress in driving the development and profitability of clean energy firms. Advances in innovation, such as improvements in energy storage, grid efficiency, and renewable technologies, directly influence the performance of clean energy companies, thereby increasing their financial co-movement.

In contrast, the significantly weaker dependence between clean energy and non-ferrous metals can be explained by the indirect nature of their relationship. While non-ferrous metals are essential inputs in renewable energy infrastructure, their prices are also influenced by broader industrial demand and global economic cycles. As a result, the linkage between these markets, although positive, is less immediate and more sensitive to external macroeconomic conditions.

Moreover, the presence of time-varying dependence suggests that the relationship between these markets is not stable but evolves in response to changing economic environments. In particular, periods of market stress tend to amplify co-movements, indicating that investors reevaluate the interconnectedness of these assets under uncertainty.

4.3.2. The Connectedness Behavior

Using the methodology developed by [29,38], we examined, in the first group, the dynamics of connectedness on return between ECO, ARCA, and DJUSNF, and, in the second group, we replaced only the ECO with SPGTCED. The results of the nature of connectedness in a dynamic environment are presented. Then, the pairwise connectedness among the above-cited group of indices is discussed. The primary results for the pairwise correlations between returns show a significant and positive correlation between the four indices used in this study, and they predict an indication of connectedness as well as a spillover effect between several variables. Tables 5 and 6 show the total and net connectedness between the indices of the two groups.

Table 5 (Panel A) exhibits the connectedness (the first group) of ECO, ARCA, and DJUSNFes using the entire sample. Percentages in diagonal represent the own connectedness of indices and are the greatest individual parameters of the table, fluctuating between 52% (the own connectedness of ECO) and 61% (the own connectedness of DJUSNF). The total directional connectedness “From” others (calculated as one minus the own share of the total variance of forecasting error) is also large, and the total connectedness is close to 45%. This result reveals a moderate level of total spillovers across the examined indices, suggesting that under normal market conditions, clean energy, non-ferrous metals, and technological innovation retain some degree of independence. This partial segmentation reflects differences in sector-specific fundamentals, including production structures, demand drivers, and investor behavior.

Table 5. Connectedness table of the ECO, DJUSNF, and ARCA.

	From (*j*)			
To (*i*)	**ECO**	**DJUSNF**	**ARCA**	**From**
Panel A: Total Spillover Index				
ECO	51.961	17.91	30.131	48.039
DJUSNF	20.427	61.27	18.304	38.731
ARCA	30.691	16.32	52.99	47.01
To others	51.118	34.23	48.434	133.78
All	103.079	95.5	101.425	TCI = 44.593
Panel B: Net-Pairwise Volatility Spillover Index				
ECO	0	−2.517	−0.56	
DJUSNF	2.517	0	1.984	
ARCA	0.56	−1.984	0	
Net	3.079	−4.504	1.425	
Conclusion	Net-transmitter	Net-recipient	Net-transmitter	

Table 6. Connectedness table of the SPGTCED, non-ferrous metals, and ARCA.

	From (*j*)			
To (*i*)	**SPGTCED**	**DJUSNF**	**ARCA**	**From**
Panel A: Total Spillover Index				
SPGTCED	59.895	16.53	23.575	40.105
DJUSNF	16.468	64.36	19.175	35.644
ARCA	22.04	18.21	59.747	40.253
To others	38.508	34.74	42.751	116
All	98.403	99.1	102.498	TCI = 38.667
Panel B: Net-Pairwise Volatility Spillover Index				
SPGTCED	0	0.062	1.535	
DJUSNF	−0.062	0	0.965	
ARCA	−1.535	−0.965	0	
Net	−1.597	−0.903	2.5	
Conclusion	Net-recipient	Net-recipient	Net-transmitter	

Table 6 (Panel A) exhibits the connectedness (the second group) of SPGTCED, ARCA, and DJUSNF. The own connectedness of indices appears to be also the dominant component, varying from 60% (as observed for SPGTCED and ARCA) to 64% (the own connectedness of DJUSNF). The total directional connectedness of the second group is close to 39% and less than that of the first group, indicating that the spillover is more important with the ECO.

Panel B (Tables 5 and 6) displays the contributions from variables i and j in Panel A, called the net-pairwise directional spillovers. This method offers more details if, in any case, a variable is a net-receiver or net-transmitter of the volatility shocks. The variable i can be a net-transmitter (net-receiver) of the spillover effects to (from) variable j, signifying the positive (negative) values of the net spillover index. The sum of the net-pairwise directional spillovers (see column "Net") can be positive or negative (net-transmitter or net-recipient, respectively).

Following Tables 5 and 6, the total connectedness indicates that the mutual influence of the first group is larger than that of the second group.

Consequently, when comparing the results of the two panels, the proportion of volatility of all indices explained by itself in Table 6 (Panel A) is obviously larger than that in Table 5 (Panel A). This means that the ECO is more subject to volatility spillover than the SPGTCED with DJUSNF and ARCA. We also find that the DJUSNF contributes the least to the volatility spillover relative to the other three indices. In fact, the self-volatility of DJUSNF is typically more than 60%, as shown in Tables 5 and 6.

As shown in Table 5 (Panel A), the total directional connectedness 'From' ranges between 38.73% and 48.04%. The ECO and ARCA are both highly affected compared to the DJUSNF, which is less affected by other indices, indicating a total directional connectedness 'From' of 38.73%. However, the total directional connectedness from each index to others represents its contribution to the forecast error variances of the remaining indices. Results display that the total directional connectedness in the 'To' column has great variation. The ECO has a larger impact on ARCA (30.69%) and DJUSNF (20.43%). We also observe the same impact of ARCA on ECO (30.13%).

Table 6 (Panel A) shows that the total directional connectedness 'From' ranges between 35.64% and 40.25%. The SPGTCED and ARCA are highly affected in both directions. The results also show a joint effect between DJUSNF and ARCA. Results show that the total directional connectedness 'To' contributes differently to the SPGTCED, as well as the DJUSNF and ARCA. The SPGTCED also has a larger impact on ARCA (22.04%), but the impact of ARCA on SPGTCED is only about 23.58%.

The ECO acts as the main transmitter of volatility with 3.08%, followed by the ARCA with 1.43%. The DJUSNF has a negative net volatility connectedness of 4.5%, so as a recipient. The SPGTCED performs as the largest volatility recipient with a net connectedness of 1.6%. The DJUSNF is also a recipient with a negative net connectedness of 0.9%. The ARCA performs as a transmitter of volatility with 1.43% and 2.5%, as shown in Tables 5 and 6, respectively.

From the directional connectedness analysis, we provide deeper insights into the transmission of shocks across markets. The results indicate that the Clean Energy Index acts as a net transmitter of volatility, while the technological innovation index is the primary receiver of shocks. This asymmetry can be explained by the central role of clean energy markets in reflecting changes in global energy policies, environmental regulations, and investor sentiment toward sustainable assets. As a result, shocks originating in the clean energy sector tend to propagate to related markets, including technological innovation.

Conversely, the technological innovation index appears to absorb shocks from other sectors, which may reflect its diversified nature and its exposure to multiple industries. Non-ferrous metals, on the other hand, exhibit relatively weaker spillover effects, suggesting that their dynamics are influenced by a broader set of macroeconomic and industrial factors, rather than being primarily driven by developments in clean energy markets.

The overall conclusion for the whole period is that the dependence structure between the Clean Energy Index and the two indices under study is symmetrical and can be suitably fitted by Student's t-copula construction. Moreover, the dependence is time-varying for all the considered pairs. In terms of the strength of the dependence, the findings indicate that along most of the considered period, the dependence between the renewable energy index and the innovation technology index is much higher than that with the non-ferrous metal index.

Regarding the connectedness measures, the findings show a moderate total connectedness between the studied indices, revealing that exogenous shocks have a limited effect on the renewable energy, the non-ferrous metal, and the innovation technology indices. More interestingly, the renewable energy index (ECO) is the largest volatility transmitter, while the innovation technology index is the major receiver of shocks.

Having described the patterns of dependence and the connectedness between the Clean Energy Index and the non-ferrous metals and innovation technology indices in normal market conditions, we next check whether the relationship patterns of the assets considered have been affected by the COVID-19 pandemic.

4.4. The Impact of the COVID-19 Pandemic on the Dependence and Connectedness Patterns

4.4.1. Testing the Change in Dependence and Spillovers

Table 7 reports Student's T-statistics and their corresponding *p*-values obtained from the test of equality of the average dependence and connectedness in the periods before and during the COVID-19 pandemic. The findings clearly show that the null hypothesis of the equality between the average of dependence and connectedness must be rejected. Therefore, there is a difference in the average of dependence and in the average of connectedness before and during the pandemic. Accordingly, the COVID-19 pandemic has significantly affected the connection between clean energy and the other considered indices. Moreover, the patterns of connectedness between the indices have changed due to the COVID-19 pandemic crisis.

Table 7. Tests of equality between the average dependence and connectedness levels.

	Panel A. Dependence		**Panel B. Connectedness**	
	T-Stat	***p*-Value**	**T-Stat**	***p*-Value**
ECO-DJUSNF	−7.467 ***	0.000	−4.563 ***	0.000
ECO-ARCA	−3.700 ***	0.000	−11.197 ***	0.000
SPGTCED-DJUSNF	−13.867 ***	0.000	−11.325 ***	0.000
SPGTCED-ARCA	−10.236 ***	0.000	−10.909 ***	0.000

Note: The test is performed on data covering two months for each period. *** Significant at level 1%.

From an economic standpoint, this result reflects the presence of a global systemic shock that simultaneously affected multiple sectors. The pandemic disrupted supply chains, reduced industrial production, and generated unprecedented levels of uncertainty in financial markets. These factors contributed to a stronger synchronization of market movements, thereby increasing both dependence and connectedness across sectors.

4.4.2. The Impact of COVID-19 on the Dependence Patterns

Table 8 presents the pairwise dependence among the renewable energy indices as well as the non-ferrous metals and innovation technology indices. We found that renewable energy shows significantly higher dependence on the other indices under study during the COVID-19 period compared to the pre-pandemic period. The upsurge of the dependence between the renewable energy indices and the non-ferrous metal index is quite similar to the variation in the dependence between the renewable energy indices and the innovation technology index (25% vs. 26%). The increase in the dependence between the Clean Energy Index and the non-ferrous metals and innovation technology indices is confirmed for both clean energy indices used in the copula estimation (ECO and SPGTCED).

Figure 4 also shows that the pairwise dependence increased significantly through the considered period of the COVID-19 pandemic. More interestingly, the graphical presentation shows that the change in dependence is not observed only on average, but there is a significant change in the time paths of the dependence levels across the clean energy indices, as well as the non-ferrous metals and innovation technology indices. Hence, the greatest volatilities of the dependence between the indices under study are seen in the

COVID-19 period. Extreme dependence is also detected in this period, reaching values of 0.998 for the pairs (ECO, DJUSNF) and (ECO, ARCA).

Table 8. Summary of the time-varying dependencies before and during the COVID-19 periods.

	Before COVID-19				During COVID-19			
	ECO		SPGTCED		ECO		SPGTCED	
	DJUSNF	ARCA	DJUSNF	ARCA	DJUSNF	ARCA	DJUSNF	ARCA
Mean	0.332	0.502	0.425	0.310	0.582	0.679	0.581	0.554
Std. Dev.	0.241	0.218	0.074	0.280	0.288	0.258	0.102	0.314
Skewness	−0.471	0.186	0.354	0.313	−0.321	−0.832	0.442	−0.403
Kurtosis	3.089	3.083	1.954	2.714	2.568	3.953	2.377	2.575
Minimum	−0.306	−0.117	0.309	−0.234	−0.348	−0.330	0.420	−0.455
Maximum	0.823	0.981	0.568	0.957	0.998	0.998	0.817	0.996

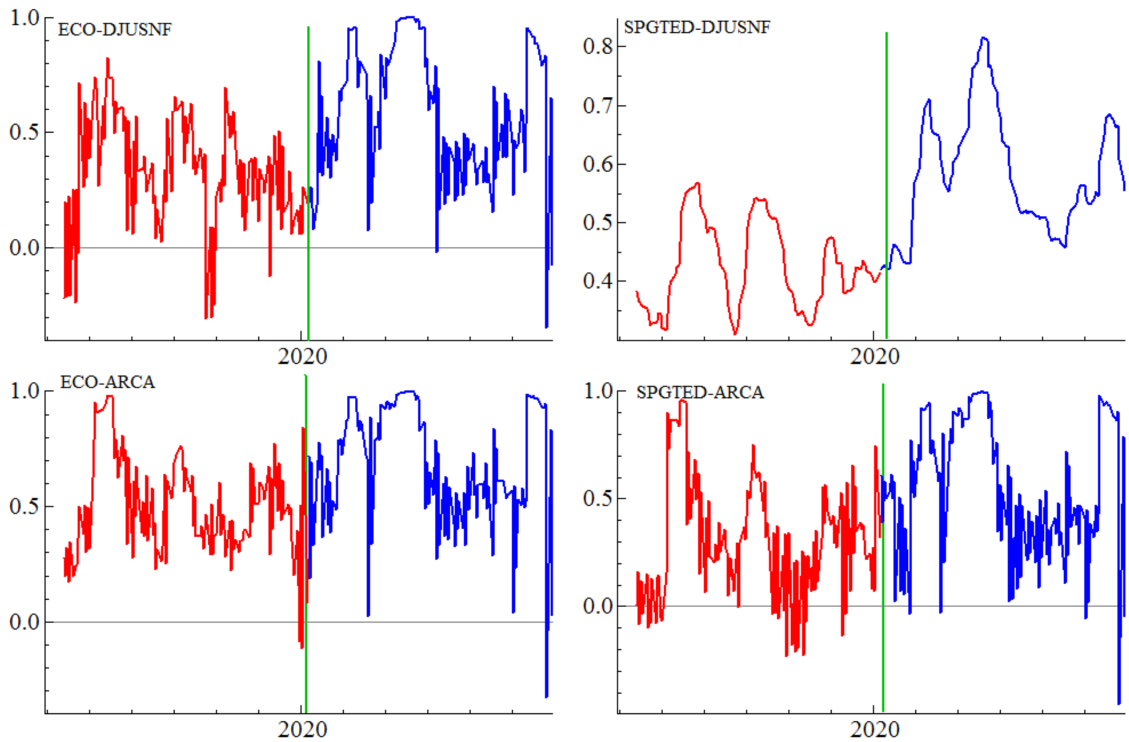

Figure 4. Time-varying dependence before and during the COVID-19 pandemic period. Note: red indicates the period before the official announcement of the COVID-19 pandemic, green indicates the announcement date (18 January 2020), and blue indicates the period after the announcement of the pandemic.

This result, revealing the strengthening of dependence between the Clean Energy Index and the non-ferrous metals and innovation technology indices, supports the 'shift-contagion' theory. According to this theory, cross-market correlations mostly occur during the life span of a crisis. The shift contagion to clean energy, non-ferrous metals, and innovation technology market can be driven by large common shocks in oil prices during the COVID-19 period. However, testing for shift-contagion is highly recommended, but it remains a challenging task for researchers (see, for instance, ref. [39,40]).

4.4.3. The Impact of COVID-19 on Connectedness Patterns

After having analyzed the connectedness between the various indices over the entire period from 31 December 2004 to 31 July 2020, which covers the main financial crises, and examining the dependence patterns, we now discuss the impact of the COVID-19 pandemic on the connectedness behavior across the clean energy indices, as well as DJUSNF and ARCA.

Two groups of connectedness systems are discussed; the first concerns connectedness between ECO, DJUSNF, and ARCA, and the second focuses on connectedness between SPGTCED, DJUSNF, and ARCA. The results of both connectedness systems are stated in Table 9. The results of the first connectedness system show that the own connectedness of indices is the largest individual element of the table, exciding 60% in the pre-COVID-19 period. Their own connectedness decreased significantly during the COVID-19 period. For instance, the own connectedness of the renewable energy index dropped from 60.7% before the COVID-19 outbreak to 38.69% during the pandemic. The significant decrease in one's own connectedness suggests an increase in the sensitivity of the considered index to the exogenous shock.

Table 9. Connectedness measures of both connectedness systems.

	Connectedness System 1				Connectedness System 2			
To (*i*)	**ECO**	**DJUSNF**	**ARCA**	**From**	**SPGTCED**	**DJUSNF**	**ARCA**	**From**
ECO/SPGTCED	60.730	14.236	25.034	39.270	76.168	4.993	18.839	23.832
DJUSNF	15.581	69.122	15.297	30.878	5.311	77.264	17.425	22.736
ARCA	24.302	15.135	60.564	39.436	16.170	16.840	66.990	33.010
To others	39.883	29.371	40.331	109.585	21.481	21.833	36.264	79.578
All	100.613	98.493	100.894	TCI = 36.52	97.649	99.097	103.254	TCI = 26.52
Net	0.613	−1.507	0.894	-	−2.351	−0.903	3.254	-
Conclusion	Net-transmitter	Net-recipient	Net-transmitter	-	Net-recipient	Net-recipient	Net-transmitter	-
ECO/SPGTCED	38.693	29.127	32.180	61.307	41.609	27.619	30.771	58.391
DJUSNF	31.381	40.465	28.154	59.535	29.947	40.986	29.067	59.014
ARCA	31.256	24.142	44.602	55.398	30.897	24.546	44.557	55.443
To others	62.637	53.268	60.335	176.240	60.844	52.165	59.838	172.847
All	101.330	93.733	104.937	TCI = 58.74	102.454	93.151	104.396	TCI = 57.61
Net	1.330	−6.267	4.937	-	2.454	−6.849	4.396	-
Conclusion	Net-transmitter	Net-recipient	Net-transmitter	-	Net-transmitter	Net-recipient	Net-transmitter	-

Regarding the net-pairwise directional spillovers, Table 9 shows that the renewable energy (ECO) and the innovation technology indices are net-transmitters of shocks in the pre- and pandemic periods, whereas the non-ferrous metal index acts as a net-receiver of shocks.

More interestingly, Table 9 shows that the total connectedness increased significantly from 36.52% in the pre-pandemic period to 58.74% during the COVID-19 period, suggesting that the indices under study have become more connected due to the pandemic.

Similar conclusions can be drawn by considering the SPGTCED with the DJUSNF and the ARCA ones, as reported in Table 9 (connectedness system two). In fact, the results show that their own connectedness decreased sharply during the COVID-19 pandemic, while the total net connectedness became significantly higher (26.52% vs. 57.61%).

Overall, the results show that our findings are robust, since the two groups of connectedness systems provide similar conclusions in terms of own, net, and total connectedness.

To apprehend the true patterns of the connectedness between the clean energy indices (ECO and SPGTCED), as well as the non-ferrous metal and the innovation technology indices, before and during the pandemic, we plot in Figures 5 and 6 the dynamic total connectedness and the net connectedness indices, respectively.

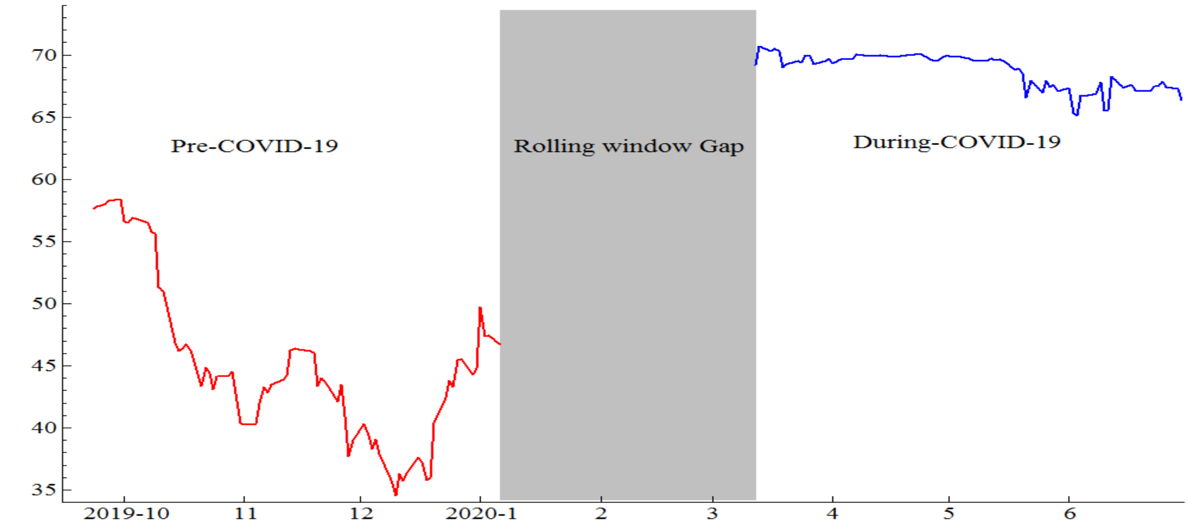

Figure 5. The total connectedness between indices before and during the COVID-19 pandemic period.

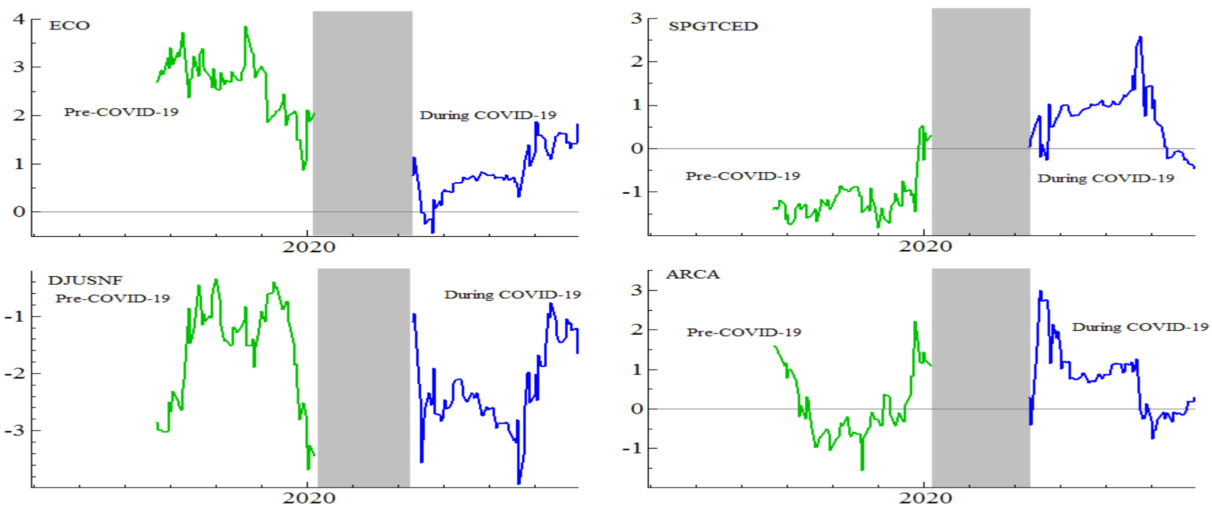

Figure 6. The net connectedness between indices before and during the COVID-19 pandemic period.

Figure 5 shows that before the pandemic period, the total connectedness index (TCI) spanned between 35% and 58%. In this period, the TCI was strongly volatile; it peaked in October 2019 and reached its lowest point at the end of 2019. During the pandemic period, the TCI rested between 70% and 75%, indicating a significant increase in the connectedness among the considered indices. This result confirms the findings reported in the dynamic connectedness tables. In addition, the TCI seems to be more stable compared to that in the pre-COVID-19 period.

The increase in connectedness during the COVID-19 period is also found in other financial markets. For instance, ref. [41] shows that the total degree of volatility spillover between developed and emerging stock markets is extremely high during the pandemic. Ref. [42] found that the return transmissions between the crude oil, S&P 500, and gold markets have become clearer during the COVID-19 crisis. It is shown that co-movements between energy companies during the outbreak of the COVID-19 pandemic increased significantly [43]. Using high-frequency five-min trading data of the most actively traded U.S. ETFs before and during the COVID-19 outbreak, ref. [44] highlight radical changes in the structure and time-varying patterns of volatility connectedness between equities and main commodities. They also show an intensified volatility during the COVID-19 pandemic.

Figure 6 indicates that the patterns of the net connectedness have also changed during the pandemic. The figure shows that the net connectedness of the renewable energy index has remained a shock transmitter to all the other indices. Yet, the net connectedness of this index has become lower in the pandemic period than during the pre-COVID-19 period. In addition, the SPGTCED has become a net-transmitter in the COVID-19 period after being a net-receiver before the pandemic period. In contrast, the DJUSNF has remained the largest receiver of shocks.

This change may reflect the increased importance of digital technologies and innovation-driven sectors during the pandemic, particularly in supporting economic activity and facilitating the transition to more resilient systems.

Overall, the increase in connectedness during the COVID-19 period highlights the vulnerability of interconnected markets to systemic shocks and underscores the importance of considering dynamic linkages in both investment and policy decisions.

5. Policy Implications

The findings of this study provide several important implications for policymakers, regulators, and market participants involved in the global transition toward sustainable energy systems. By pointing out the significance of the dynamic linkage among clean energy, non-ferrous metals, and technological innovation, the results stress the need for coordinated strategies that account for the systemic nature of these markets.

First, the findings revealing a significant upsurge in dependence and connectedness during the COVID-19 period suggest that clean energy markets are highly sensitive to global shocks. This implies that policymakers should boost the resilience of the clean energy sector by promoting diversification within energy sources. In addition, policymakers should improve this resilience across supply chains. Importantly, ensuring stable access to critical non-ferrous metals, such as copper, aluminum, and nickel, is vital to reducing vulnerabilities that can be caused by supply disruptions. Indeed, strategic stockpiling policies, investment in recycling technologies, and the development of alternative materials may help mitigate these risks.

Second, the results highlight the central role of technological innovation in influencing the dynamics of clean energy markets. Given the strong linkages between clean energy and technology indices, policies that support research and development, digital infrastructure, and innovation ecosystems can improve the efficiency and stability of the energy transition. In this context, governments may consider increasing incentives for clean technology innovation, such as subsidies, tax credits, and public–private partnerships.

Third, the evidence of increased connectedness and reduced diversification benefits during crisis periods has important implications for financial regulation and market stability. Regulators should recognize that shocks in one segment of the clean energy ecosystem can rapidly propagate to others, potentially amplifying systemic risk. Accordingly, it is essential to improve monitoring actions of cross-market linkages and the integration of climate-related financial risks into macroprudential frameworks. In addition, stress-testing scenarios that incorporate interconnected markets may also help identify vulnerabilities in advance.

Finally, the findings of the study emphasize the importance of adopting a holistic policy approach that simultaneously addresses energy, resources, and technological dimensions. The transition toward a low-carbon economy helps to secure the supply of critical materials and foster innovation. Coordinated policies that align these objectives can contribute to a more resilient and sustainable energy system.

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6. Conclusions

In this paper, we investigated the linkage patterns among clean energy, non-ferrous metal, and technology innovation indices, with a particular emphasis on the impact of the COVID-19 pandemic. By combining copula-based modeling with a dynamic connectedness framework, the study provides a comprehensive analysis of both nonlinear dependence structures and volatility spillover dynamics across these interrelated markets.

The empirical results reveal that the dependence structure between the clean energy and the other sectors is symmetrical and can be suitably fitted by a Student's *t* copula construction. In addition, the dependence is time-varying for all the considered pairs. In terms of strength of dependence, the findings indicate that for most of the considered period, the dependence between the renewable energy index and the innovation technology is much higher than the non-ferrous metal index.

Essentially, the total connectedness index changes from 36.52% (pre-COVID-19) to 58.74% (during COVID-19), and from 26.52% (pre-COVID-19) to 57.61% (during COVID-19), respectively, for connectedness system one (ECO with DJUSNF and ARCA) and connectedness system two (when considering SPGCTCED rather than ECO). These results show the great impact of the COVID-19 pandemic on clean energy sectors. Moreover, we show how the SPGTCED transformed from a risk receiver (before the outbreak of the pandemic) to a volatility transmitter after the beginning of the pandemic. The findings show that the COVID-19 pandemic increased volatility spillovers, supporting the financial contagion effects.

Regarding the connectedness measures, the findings show a moderate total connectedness between the studied indices, revealing that exogenous shocks have limited effects on the renewable energy, the non-ferrous metal, and the innovation technology indices. Moreover, the renewable energy index (ECO) is the largest volatility transmitter, while the innovation technology index is the largest receiver of shocks.

In addition, the investigation of the impact of the COVID-19 pandemic shows that both dependence and connectedness significantly increased during the pandemic, suggesting that the indices under study became more connected due to the pandemic. This result shows the upsurge of linkages and co-movements between markets during the health crisis, much like the impact of the global financial crisis (2007–2008) on several financial assets.

From an economic and financial perspective, these findings have important implications. For investors, the increase in dependence and connectedness during turbulent periods highlights the need to account for tail risks and dynamic correlations when constructing diversified portfolios involving clean energy and related assets. For policymakers, the strong interdependence between clean energy, critical materials, and technological innovation underscores the importance of ensuring resilient supply chains and stable financial environments to support the ongoing energy transition. In particular, the results suggest that disruptions affecting one segment of this system may propagate rapidly to others, potentially amplifying systemic risk.

Despite the significant contributions of the current study, several limitations should be acknowledged. First, the analysis is based on a limited set of indices representing broad market segments, which may not fully capture the heterogeneity within clean energy technologies, specific non-ferrous metals, or different areas of technological innovation. Second, the sample period ends in July 2020 and therefore primarily reflects the initial phase of the COVID-19 pandemic, without capturing longer-term adjustments and recovery dynamics. Finally, while the empirical framework effectively identifies patterns of dependence and connectedness, it does not explicitly incorporate macroeconomic, geopolitical, or policy-related variables that may influence these relationships.

These limitations provide several avenues for future research. Extending the analysis to include a longer post-pandemic period would allow for an assessment of the persistence of the observed effects and the long-term evolution of market interdependencies. Future studies could also consider a more disaggregated approach by examining specific clean energy subsectors or individual critical minerals, such as lithium or cobalt, which play a key role in renewable energy technologies. Finally, incorporating macroeconomic indicators, uncertainty measures, or policy variables could help explain the drivers of dependence and spillover dynamics.

Overall, by interpreting the COVID-19 pandemic as a global stress event, this study provides new evidence on the structure and evolution of linkages between clean energy, non-ferrous metals, and technological innovation. The findings contribute to a better understanding of how these interconnected markets behave under both normal and extreme conditions and offer valuable insights for enhancing the resilience and sustainability of the global energy transition.

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Abbreviations

The following abbreviations are used in this manuscript:

IEA	International Energy Agency
ECO	WilderHill Clean Energy Index
SPGTCED	S&P Global Clean Energy Index
ARCA	NYSE Arca Tech 100 Index
DJUSNF	Dow Jones U.S. Non-ferrous Metals Index
ESDC	European Sovereign Debt Crisis
DY	Diebold and Yilmaz Model

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