World Journal of Applied Economics (2026), 12(1): 1-19
doi: 10.22440/wjae.12.1.1

econworld
Research Article

Artificial Intelligence and Volatility Connectedness in Energy Markets[a]

Halilibrahim Gökgöz[b]

Received: 16.01.2026; Revised: 11.04.2026; Accepted: 13.04.2026

This study analyses the role of artificial intelligence (AI) indices as sources of volatility transmission between clean energy and fossil fuel markets within a time–frequency framework. Using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) frequency connectedness approach, inter-market dynamics are decomposed into short- and medium-to-long-term horizons. The results indicate a high degree of connectedness across the markets under consideration, driven predominantly by short-term components. Directional connectedness findings show that AI indices generally act as net transmitters of volatility relative to clean energy and fossil fuel markets. The analysis further reveals that connectedness varies over time and intensifies markedly during periods of global uncertainty. Overall, the findings indicate that AI indices extend beyond a technological dimension and are meaningfully associated with risk dynamics in energy markets, with implications for financial stability and investment decision-making.

JEL codes: C32, G15, O33, Q35, Q42

Keywords: Artificial intelligence; Clean energy; Fossil fuels; Volatility connectedness; Time frequency analysis

1 Introduction

Global energy systems, particularly in recent years, have undergone a transformation increasingly shaped by digitalisation, financialization, the rise of green finance, and the climate crisis. Pressures related to the fight against climate change and sustainability are driving the transition from fossil fuels to renewable energy, transforming not only the physical infrastructure but also capital allocation mechanisms (Castrejon-Campos et al., 2020; Kyriakarakos, 2025). As sustainability pressures leading to a reorientation of capital flows intensify, the dynamic relationships among clean energy, fossil fuel, and AI-based financial assets are emerging as a new field of research. The rise of AI in energy and financial markets suggests that technology influences not only productivity but also key elements of financial stability, including market volatility, investment behaviour, and risk interconnectedness. By examining the time-frequency-based connectedness between AI indices and clean energy indices, Zeng et al. (2024) find that AI acts as a strong volatility transmitter in the short

[a] I thank the editor and two anonymous referees for their valuable comments and suggestions.
[b] Afyon Kocatepe University, Faculty of Economics and Administrative Sciences, Afyonkarahisar, Türkiye. email: hgokgoz@aku.edu.tr 0000-0001-8000-9993

term and as a determinant of systemic risk in the long term. Similarly, Raggad & Bouri (2025) shows that AI generates asymmetric risk transmission between dirty and clean energy indices and that AI markets are net transmitters of volatility during crisis periods. These results suggest that AI is not a passive element in the financial dynamics of energy markets, but rather an active source of volatility.

The impact of AI on the financial system is also significant for green finance and sustainable investment decisions. Ma et al. (2025), analysing the relationship among fintech, AI, and sustainable finance markets with a Time-Varying Parameter Stochastic Volatility Vector Autoregressive (TVP-SV-VAR) model, states that the long-term connectedness between AI indices and green bond markets has been gradually strengthening, while it leads to negative shock transmission in the short term. Qi et al. (2025) also demonstrates that frequency-based interactions between AI and energy markets influence green finance channels through carbon pricing. These findings reveal that, during the energy transition, the financial system serves not only as an intermediary but also as a channel for the transmission of risk and expectations. This relationship becomes more pronounced when financial stability conflicts with sustainability targets. In their empirical analysis of 119 countries, Wang et al. (2026) demonstrates that the effect of AI on renewable energy intensifies in countries where financial development exceeds a specific threshold. Similarly, Xu (2025) shows that AI enhances energy resilience in economies integrated with green finance policies, and that this effect is linked to financial sustainability. AI-based technological innovations increase the resilience of energy systems (Nepal et al., 2025), and AI improves firms' environmental performance by supporting green innovation processes at the corporate level (Lin et al., 2025). These results demonstrate that financial infrastructure is a critical determinant of AI's effectiveness in the energy transition.

Zhao et al. (2024) illustrates that AI may initially reduce the share of renewable energy in the short and medium terms but ultimately accelerate the energy transition in the long term. Coşkun et al. (2023) states that volatility transmission between clean energy and fossil fuel markets increases during periods of financial stress. Similarly, Zheng et al. (2023) emphasises that frequency-based interactions between the geopolitical risk index and crude oil intensify in crisis periods. The findings of Li et al. (2025) suggest that the relationships between AI and clean energy and fossil fuel markets are sensitive to global events and that this sensitivity evolves over time and across different frequencies. However, the results of Çağlar et al. (2025) indicate that AI does not affect environmental sustainability, suggesting that the relationship between AI and sustainability remains controversial in the literature. Zeng et al. (2024) reveals that NASDAQ OMX Geothermal Index tends to be the highest net transmitter of long- and short-term shocks in the system during extreme upside market conditions, whereas the S&P Global Clean Energy Index seems to be the highest net shock sender in downturn conditions.[1] They also report that market connectedness across markets is stronger under extreme market conditions. Xu (2025) shows that using AI helps to shift the perspective of energy strategy and enhances energy resilience in energy systems. Wang et al. (2024) reports that AI indirectly increases the High-quality Energy Development (HED) index by enhancing green innovation and research and development (R&D) intensity. The empirical findings display that the level of digital economy development affects the effects

[1] These indices are clean energy market benchmarks used in the related literature. The details of indices used in this study are provided in Table 1.

of AI on HED. The empirical results of Raggad & Bouri (2025) analyzing the return and volatility connectedness among AI stock ETF and each segment of the energy markets (dirty energy, clean energy and WTI oil) indicate that the degree of connectedness for the Clean-AI pair tends to be more pronounced than that of the other pairs (AI-WTI and AI-dirty), and clean energy is a receiver of return connectedness from AI stock ETF. Zhang et al. (2025) shows that AI initially increases carbon emissions but reduces them as AI technology develops, indicating a stage-dependent relationship. Such an inverted U-shaped pattern is driven by applied rather than foundational AI, with turning points indicating that reducing total carbon emissions is more difficult than reducing carbon emissions intensity. Qi et al. (2025) explores connectedness within the Carbon-Energy-Green Finance system using time-frequency spillover methods and finds limited short-term connectedness. Wang et al. (2026) examines the impact of AI on the renewable energy transition and shows that AI development substantially accelerates the transition.

Although recent studies have advanced the understanding of the relationship between AI and energy markets, several important limitations remain, as they predominantly focus on either the interaction between AI and clean energy markets or on pairwise relationships between AI and selected energy segments. For instance, Zeng et al. (2024) examines the time frequency linkages between AI and multiple clean energy indices, while Raggad & Bouri (2025) analyzes the pairwise connectedness between AI and clean, dirty, and oil markets using a quantile-based framework. In contrast, our study adopts a unified multivariate connectedness framework that jointly considers AI and energy markets, allowing us to analyze the simultaneous interactions among these markets and to compare their roles within the same system. Furthermore, by decomposing connectedness into short- and medium-to-long-term components, the study provides additional insights into the horizon-dependent nature of volatility transmission. In this sense, the paper extends the existing literature by offering a more integrated approach to the dynamic interactions between AI and energy markets. More specifically, we analyse dynamic volatility spillovers among AI indices, clean energy indices, and fossil fuel markets in the time–frequency domain using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) frequency-connectedness approach of Chatziantoniou et al. (2023). By examining the role of AI in the transmission of financial volatility in energy markets on a frequency basis, the study dynamically measures the relationship between risk transmission and risk reception, reveals the asymmetric and crisis-sensitive connectedness structure among AI, clean energy, and fossil fuels, and provides findings that offer time horizon based risk management strategies for investors and insights for policymakers to guide AI supported energy transition in a balanced manner.

The remainder of the paper is organised as follows. Section 2 presents the literature review, and Section 3 describes the methodology and provides descriptive statistics for the data used. The empirical results are reported in Section 4, and, finally, Section 5 concludes.

2 Literature Review

The linkages between AI indices and clean energy, as well as fossil fuel markets, have become increasingly important alongside the growing role of AI technologies in energy systems and the digitalisation of financial markets (Li et al., 2025). The literature in this field has followed an evolutionary trajectory: while early studies primarily focused on the relationship between clean energy markets and traditional assets such as oil and gold, more recent research has shifted its attention towards the influence of AI and digital assets on energy markets.

The first strand of the literature comprises studies examining the relationship between clean energy indices and traditional energy sources, as well as safe-haven assets. In this context, the empirical results of Elie et al. (2019) reveal that both gold and crude oil, as safe havens against extreme downside movements in clean energy stocks, seem to be no more than weak safe-haven assets for clean energy indices. Dawar et al. (2021) explores the dependence structure among clean energy stock indices, including the S&P Global Clean Energy Index, the MAC Global Solar Energy Index, and the Wilderhill Energy Index, and shows that clean energy stock returns exhibit decreasing dependence on crude oil returns. They also report that the lagged effect of WTI oil returns on clean energy stock returns is substantial, indicating that clean stock returns respond differently to new information about oil returns across market conditions. Kuang (2021) examines whether diversifying into clean energy stocks or green bonds can reduce portfolio downside risk for investors holding dirty energy stocks or international equity indices, and finds that both clean energy stocks and dirty energy stocks offer risk diversification advantages for investors relative to dirty energy stocks. Nevertheless, green bonds reduce risk, whereas clean energy stocks generally increase the risk of the international equity index portfolio. Gustafsson et al. (2022) studies the linkages among clean stock indices and energy metals, which are sensitive to the growth in demand for clean energy solutions, and reveal the nonlinear relationships between markets: except for cobalt, all energy metals are positively related to clean energy stock indices, but none of the energy metals acts as a hedge for clean energy stock markets. The common denominator of these studies is that they demonstrate the sensitivity of clean energy markets to external shocks and fluctuations in commodity prices.

The second branch of the literature focuses on inter-market volatility spillovers, crisis periods, and methodological linkages. Chatziantoniou et al. (2022) explores time-varying integration and return transmission among environmental financial indices (MSCI Global Environment, Dow Jones Sustainability World Index, S&P Green Bond Index, and S&P Global Clean Energy). The empirical results find that the S&P Global Clean Energy and S&P Green Bond indices are both short-term and long-term net receivers of shocks. However, the MSCI Global Environment and Dow Jones Sustainability World Index appear to be both short-term and long-term senders of shocks. The total connectedness indices are heterogeneous over time and economic event dependent. Dias et al. (2023) shows the existence of negative autocorrelation among the Clean Energy Fuels Index, the crude oil market, the Global Clean Energy Index, the natural gas market, and the gold market. Memon et al. (2023) shows multifractal behavior with a substantial effect on the efficiency and increased existence of multifractality during the health crisis in six clean energy markets. Their study also displays that the existence of multifractality and herding behavior symmetry increases during the crisis period. Zeng et al. (2023) reports that most clean energy indices are positively impacted by the health crisis. Their study also shows that the NASDAQ OMX Geothermal Index and NASDAQ OMX Bio/Clean Fuels tend to be senders of spillovers to all grain commodities, whereas the WilderHill Clean Energy Index and NASDAQ OMX Wind Energy Index are the highest recipients of spillovers from other markets. The OMX Geothermal Energy and OMX Bio/Clean Fuels indices dominate the spillover shocks to grain commodity markets. Coşkun et al. (2023) presents the dynamic nature of volatility connectedness across clean energy, oil price risk, gold equity, and commodity markets and further reveals that volatility interlinkage across these markets increases during turbulent periods, such as the COVID-19 pandemic.

The third and most recent strand of the literature concentrates on the transformative impact of AI and digital assets on energy markets. The analysis by Zeng et al. (2024) of time-frequency interdependence and volatility connectedness reveals positive comovements between the clean energy and AI indices, particularly over long investment horizons. They also indicate that the NASDAQ OMX Geothermal Index appears to be the highest net transmitter of short- and long-run shocks in the system under extreme upside market conditions, and the S&P Global Clean Energy Index is the strongest net shock sender in downturn conditions. Yousaf et al. (2024) shows moderate connectedness at median and mean quantiles of AI tokens, AI ETFs and other asset classes, such that AI ETFs (AI tokens) act as high (weak) net transmitters (receivers) of return spillovers. They also display that AI tokens and ETFs do not diversify the risk of other assets during extreme market conditions. Zhang et al. (2024) analyzes the asymmetric effects of negative and positive variations in the AI index and various oil shocks on clean energy stock sub-sectors. They highlight that the effects of oil shocks and AI on clean energy stocks change largely among energy stocks. The health crisis has reinforced the cointegration relationship and reduced short- and long-term asymmetry between the clean energy stocks and the AI index. Zhao et al. (2024) attempts to identify the effect of different AI quantiles on energy structure quantiles in various periods using the wavelet-based quantile-on-quantile method. The empirical findings show that the upper quantile of AI strengthens the share of renewable energy in total energy in the long term, indicating that AI can accelerate the transition to renewable energy. Nepal et al. (2025) reports that AI technology innovation could effectively boost energy resilience. Ma et al. (2025) reveals that the spillover effect of sustainable finance on fintech is more pronounced than that of the AI industry. Additionally, AI has the lowest shock response on the clean energy index, and the short-term impacts of the green bond market remain negative. These findings suggest that AI has evolved into a dynamic and influential source of financial risk in energy markets, rather than remaining a passive technological element.

3 Methodology and Data

3.1 Methodology

This study employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) Frequency Connectedness model. Chatziantoniou et al. (2023) integrates the approaches of Baruník & Křehlík (2018) and Antonakakis et al. (2020) within the TVP-VAR Frequency Connectedness model. Antonakakis et al. (2020) develops their model by combining the connectedness approaches of Diebold & Yılmaz (2012, 2014) with the standard Kalman filter and extends with forgetting factors of Koop & Korobilis (2014). The TVP-VAR model addresses specific limitations of the VAR model, such as arbitrarily chosen rolling windows, data loss, and outliers. It effectively reveals dynamic connectedness among series and is particularly useful for examining risk spillovers, even with low-frequency and limited time-series data (Chatziantoniou et al., 2023; Zheng et al., 2023). Furthermore, the TVP-VAR Frequency Connectedness model enables analysis of volatility spillovers across frequency domains. The TVP-VAR model of order R is calculated as given in Eq. (1).

$$s_t = \Psi_{1t} s_{t-1} + \Psi_{2t} s_{t-2} + \ldots + \Psi_{rt} s_{t-r} + u_t, \quad u_t \ (0, \textstyle\sum_t) \tag{1}$$

where s_t and s_{t-r} are vectors of dimension $Lx1$ denoting the variables at time t and $t-r$, respectively, and u_t denotes the L×1 vector of innovations. The matrices $\sum_t$ and Ψ_{1t} are of dimension LxL, where $x = 1, \ldots, r$. In this study, the model is simplified using the LxL matrix lag-polynomial $\Psi(N) = [K_L - \Psi_1 N - \ldots - \Psi_{rt} N^R]$, where L_K is the identity matrix. The model can be expressed $\Psi(N)_{st} = u_t$. The TVP-VAR process is assumed to be stationary and can be represented as a TVP-Vector Moving Average (TVP-MVA) through the Wold moving average representation ($s_t = \phi(N)u_t$), where $\phi(N)$ is a matrix containing infinite lags and is derived from $\Psi(N) = [\phi(N)]^{-1}$. The matrix $\phi(N)$ is approximately calculated with ϕ_c at horizons $c = 1, \ldots, C$ (Zheng et al., 2023). The Generalized Variance Decomposition Function (GVEFD) is used to measure the impact of changes in each series on the other series:

$$\sigma_{xyt}(C) \ = \ \frac{(\sum_t)_{yy}^{-1} \ \sum_{c=0}^{C} \ ((\phi_c \sum_t)_{xyt})^2}{\sum_{c=0}^{C} \ (\phi_c \sum_t \ \phi_c^{'})_{xx}} \tag{2}$$

$$\tilde{\sigma}_{xyt}(C) \ = \ \frac{\sigma_{xyt}(C)}{\sum_{z=1}^{L} \ \sigma_{xzt}(C)} \tag{3}$$

Eqs. (2) and (3) illustrate the contribution of series y to the forecast error variance of series x at horizon t. To ensure that the sum of the contributions, denoted as $\tilde{\sigma}_{xyt}(C)$, affecting each series equals 1, the $\tilde{\sigma}_{xyt}(C)$ must be normalized as follows:

$$\textstyle\sum_{x=1}^{L} \ \bar{\sigma}_{xyt}(C) \ = \ 1 \tag{4}$$

$$\textstyle\sum_{y=1}^{L} \ \sum_{y=1}^{L} \bar{\sigma}_{xyt}(C) \ = \ L \tag{5}$$

Using the normalized contributions values given in Eqs. (4) and (5), we can calculate the connectedness among the series. We compute the volatility spillovers received by a series from all other series ($from$), the volatility spillovers transmitted by a series to all other series (to), and the net volatility spillovers (net):

$$from_{xt}(C) \ = \ \textstyle\sum_{x=1, x\neq y}^{L} \ \tilde{\sigma}_{xyt}(C) \tag{6}$$

$$to_{xt}(C) \ = \ \textstyle\sum_{x=1, x\neq y}^{L} \ \tilde{\sigma}_{yxt}(C) \tag{7}$$

$$net_{xt}(C) = \ to_{xt}(C) \ - \ from_{xt}(C) \tag{8}$$

Eqs. (6) and (7) represent the total volatility spillover received and transmitted by series x from all other series y, respectively, and Eq. (8) shows the net volatility spillover for each series x, as a difference between the transmitted and received volatilities. A positive net volatility spillover indicates that, on average, series x is a net transmitter of volatility, whereas a negative net volatility spillover indicates that, on average, series x is a net receiver of volatility.

$$TCI_t(C) = \ L^{-1} \ \textstyle\sum_{x=1}^{L} \ to_{xt}(C) \ = \ \sum_{x=1}^{L} \ from_{xt}(C) \tag{9}$$

Eq. (9) represents the Total Connectedness Index (TCI), which indicates the overall volatility spillover. The connectedness formulas illustrate the connectedness in the time domain. In this study, we examine the connectedness among series in the overall time domain and from short- and medium-to-long-term perspectives. To achieve this, we utilize the frequency-based impulse response function proposed by Chatziantoniou et al. (2023).

$$\phi(q^{-nw}) = \sum_{f=0}^{\infty} q^{-iwc} \phi_c \tag{10}$$

where w denotes the frequency, and i represents the square root of -1. The Fourier transform of the infinite-order TVP Vector Moving Average (TVP-VMA) conceptualizes the spectral density of s_t at frequency w (Dammak et al., 2025).

$$F_s(w) = \sum_{c=-\infty}^{\infty} q(s_t \, s_{t-c}^{'}) \, q^{-iwc} = \phi(q^{-iwc}) \sum_t \phi^{'}(q^{iw}) \tag{11}$$

After calculating the TVP-VMA, the Generalized Forecast Error Variance Decomposition (GFEVD), which needs to be normalized using the following formulas, is computed.

$$\sigma_{xyt}(w) = \frac{(\sum_t)_{yy}^{-1} \, |\sum_{c=0}^{\infty} (\phi(w^{-iw}) \sum_t)_{xyt})^2|}{\sum_{c=0}^{\infty} (\phi(q^{-iwc}) \sum_t \sigma(iwc))_{xx}} \tag{12}$$

$$\tilde{\sigma}_{xyt}(w) = \frac{\sigma_{xyt}(w)}{\sum_{z=1}^{L} \sigma_{xzt}(w)} \tag{13}$$

where $\tilde{\sigma}_{xyt}(w)$ explains the portion of changes in series x that originate from series y at frequency w. To analyse connectedness over frequency bands rather than at a single frequency, we define the frequency band $d = (a, b)$, where $a, b \in (-\pi, \pi)$ and $a < b$, as follows:

$$\tilde{\sigma}_{xyt}(d) = \int_a^b \tilde{\sigma}_{xyt}(w) dw \tag{14}$$

The following equations are the connectedness measures over a given frequency band d.

$$from_{xt}(d) = \sum_{x=1, x\neq y}^{L} \tilde{\sigma}_{xyt}(d) \tag{15}$$

$$to_{xt}(d) = \sum_{x=1, x\neq y}^{L} \tilde{\sigma}_{yxt}(d) \tag{16}$$

$$net_{xt}(d) = to_{xt}(d) - from_{xt}(d) \tag{17}$$

$$TCI_t(d) = L^{-1} \sum_{x=1}^{L} to_{xt}(d) = \sum_{x=1}^{L} from_{xt}(d) \tag{18}$$

In this study, the short-term band corresponds to one to five days, while the medium-to-long-term band corresponds to frequencies beyond five days. The sum of connectedness across different frequencies provides the total connectedness in the time domain (overall connectedness).

3.2 Data

This paper investigates the time-frequency connectedness between clean energy, fossil fuel indices, and AI indices. In encompassing all sub-sectors for green energy indices, we utilize the Nasdaq OMX green energy indices, by following Khoury et al. (2024) and Zeng et al. (2024), which comprise four main indices: NASDAQ OMX Renewable Energy Generation, NASDAQ OMX Energy Efficiency, NASDAQ OMX Advanced Materials, and NASDAQ OMX Bio/Clean Fuels. We employ the West Texas Intermediate Crude Oil, Natural Gas Index, and Newcastle Coal Index for fossil fuels. To broadly address the sub-sectors of

AI indices, we focus on the S&P Kensho AI indices, which comprise 10 indices. However, some of these indices overlap in their firm coverage; thus, to ensure coverage of all AI sectors without redundancy, we use the S&P Kensho Advanced Manufacturing Index, the S&P Kensho AI Enablers & Adopters Index, and the S&P Kensho New Economy RAIC Index. The selected S&P Kensho AI indices are chosen to capture distinct segments of the AI ecosystem while limiting overlap among constituent firms. This selection provides a broader, more balanced representation of AI-related activities without introducing excessive duplication across indices. Table 1 provides descriptions of the variables used.

Table 1: Definition of indices

Index	Abbr.	Definition
NASDAQ OMX Renewable Energy Generation	GRNREG	It measures the performance of companies producing energy from renewable resources such as wind, geothermal, solar, biomass, and hydroelectric power.
NASDAQ OMX Energy Efficiency	GRNENEF	It measures the performance of companies providing products and services that enhance energy efficiency, including energy management, smart grids, green IT, and energy storage.
NASDAQ OMX Advanced Materials	GRNAM	Measures the performance of companies that develop and produce advanced materials used in clean energy technologies, including materials for solar panels, wind turbines, and batteries.
NASDAQ OMX Bio/-Clean Fuels	GRNBIO	It measures the performance of companies producing and distributing clean fuels, such as biofuels, hydrogen, and natural gas, which serve as alternatives to petroleum-based fuels.
West Texas Intermediate Crude Oil	WTI	It represents the benchmark price for crude oil.
Natural Gas Index	GAS	It represents the futures prices for natural gas traded on the NYMEX.
Newcastle Coal Index	COAL	It represents the futures price of coal shipped from the Port of Newcastle.
S&P Kensho Advanced Manufacturing Index	KMAKEP	It measures the performance of companies producing technologies that enable next-generation manufacturing activities. The AI indices cover the S&P Kensho Smart Factories Index, S&P Kensho 3D Printing Index, S&P Kensho Robotics Index, and S&P Kensho Virtual Reality Index.
S&P Kensho Artificial Intelligence Enablers & Adopters Index	KAIEATP	It measures the performance of companies that develop and enable AI technology, as well as companies poised to benefit from the adoption of AI technology.
S&P Kensho New Economy RAIC Index	KRAICP	It measures the performance of companies involved in the robotics, AI, and cloud (RAIC) industries. The index covers the S&P Kensho New Economy Index Series 9 subsector, which includes Autonomous Vehicles, Robotics, Cyber Security, Future Payments, Genetic Engineering, Smart Grids, Space, Nanotechnology, and Cleantech.

Source: Nasdaq OMX QGreen (2025); S&P Kensho AI (2025); Khoury et al. (2024); Zeng et al. (2024)

We employ daily data on Clean Energy, Fossil Fuels, and AI indices from June 15, 2018, to January 19, 2024. The S&P Kensho AI Enablers & Adopters Index, which began calculation on June 15, 2018, marks the start of our sample period. Prior to the analysis, we transform these variables into daily return series.

The descriptive statistics presented in Table 2 indicate that the mean of all series, except for WTI, is positive. The standard deviations of the Fossil Fuels indices are higher than those of the Clean Energy and AI indices. The high standard deviation of fossil fuels can

Table 2: Descriptive statistics

	GRNREG	GRNENEF	GRNAM	GRNBIO	WTI	GAS	COAL	KMAKEP	KAIEATP	KRAICP
Mean	0.00034	0.00043	0.00000	0.00036	-0.00201	0.00065	0.00048	0.00056	0.00071	0.00041
Median	0.00049	0.00077	0.00000	0.00034	0.00218	0	0	0.00080	0.00129	0.0001
Maximum	0.09342	0.10716	0.08002	0.14331	0.37662	0.21894	0.40575	0.11358	0.10570	0.10705
Minimum	-0.14151	-0.11445	-0.11397	-0.16636	-3.05966	-0.19687	-0.35109	-0.10440	-0.13557	-0.12780
Std. Dev.	0.01365	0.01451	0.01644	0.02302	0.09431	0.04138	0.02797	0.01933	0.01679	0.01773
Skewness	-0.60760	-0.16731	-0.42855	-0.60869	-25.85128	0.07709	0.12232	-0.07492	-0.33457	-0.43220
Kurtosis	15.69440	11.05461	7.97846	10.10940	808.61500	5.41336	65.12996	6.76693	9.39713	8.41596
JB	9,547***	3,815***	1,498***	3,054***	3,8259,554***	343***	226,625***	834***	2,428***	1,765***
ERS	-11.298***	-15.411***	-7.540***	-8.879***	-14.565***	-9.889***	-13.28***	-16.552***	-16.269***	-16.644***

be attributed to the observation period covering events with significant global economic impact, such as the COVID-19 pandemic (declared a global pandemic in March 2020), the Ukraine-Russia Conflict (which began in February 2022), the collapse of Silicon Valley Bank (SVB, in March 2023), and the Israel-Palestine War (which started in October 2023). These events have caused energy price shocks, primarily due to uncertainties in energy supply and demand. For example, during the onset of COVID-19, oil prices dropped to $42 on April 20, 2020, the lowest price since 2015 (Gökgöz & Kandemir, 2023). Additionally, the Ukraine-Russia conflict and the discourse around Russia potentially cutting off gas supplies have caused uncertainties in the energy market, leading to rising energy prices. This period has also highlighted the importance of countries meeting their own energy needs and the significance of renewable energy sources. The Israel-Palestine war can also be cited as another event causing uncertainties in energy supply, given its geographical location near the Gulf countries, which are significant in oil production. The findings reveal that the Clean Energy and AI indices exhibit patterns that diverge from those of Fossil Fuels. Except for GAS and COAL, the skewness values are negative, and the kurtosis values for all series indicate leptokurtic traits. The Jarque-Bera (JB) values indicate that none of the series follows a normal distribution. The Elliott, Rothenberg, and Stock (ERS) shows that all series are stationary at level (I_0).

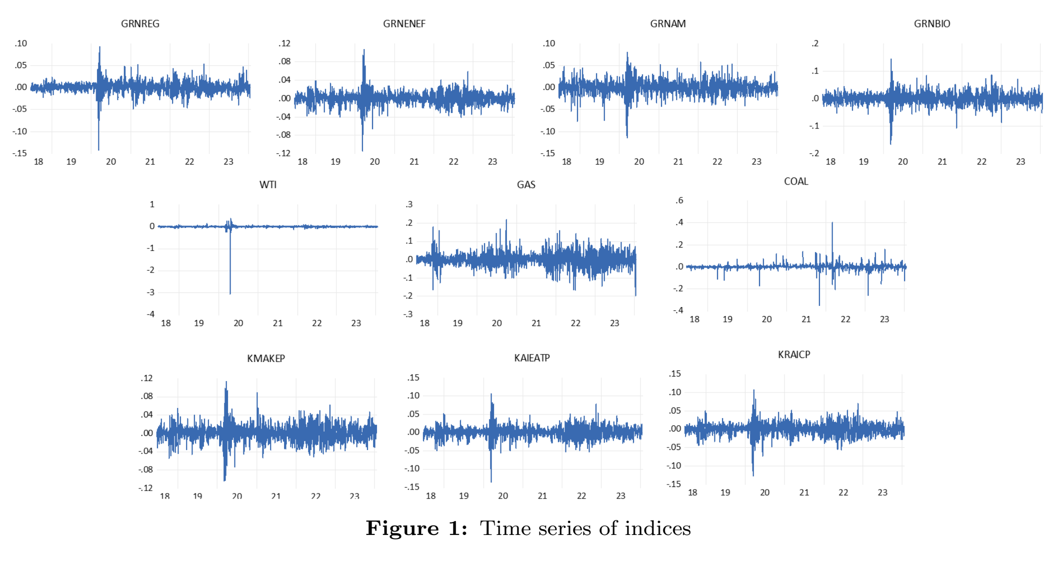


Figure 1: Time series of indices

The time series of each variable depicted in Figure 1 illustrates that the volatility of all indices varies over time and is influenced by the abovementioned events, and the impact of COVID-19 is more pronounced than the others. The most significant deviations in all series, except for COAL, occur during the initial period of COVID-19. For COAL, the most significant deviation is observed during the onset of the Ukraine-Russia conflict. This indicates that the indices for clean energy, fossil fuels, and AI are sensitive to global events.

4 Empirical Results & Interpretation

We analyze the dynamic interactions across different time-frequency domains between clean energy indices, fossil fuels, and AI indices using the TVP-VAR frequency connectedness approach by Chatziantoniou et al. (2023). The time-frequency domains include total time, distinguished between short-term (one to five lags) and medium-to-long-term (beyond five lags). Our analysis primarily presents the average connectedness between clean energy indices, fossil fuels, and AI indices. These average connectedness values provide insights into interactions across different time domains, thereby enabling an assessment of whether connectedness varies with time frequency. Subsequently, the analysis will dynamically reveal the total connectedness and pairwise net connectedness across different time-frequency domains to assess time-dependent changes in these relationships.

The findings provided in Table 3 indicate that the average total connectedness among the series is 62.44% (Panel A), with 51.4% (Panel B) attributable to short-term and 11.04% to medium-to-long-term connectedness. The predominance of short-term connectedness between clean energy indices and fossil fuels with AI indices suggests that the relationships among these series are more instantaneous, implying that shocks in one series are quickly reflected in the others. Across all frequency domains, AI indices (except GRENEF) generally act as net transmitters of volatility compared to clean energy indices and fossil fuels. However, on average, GRENEF acts as a net volatility transmitter across all series, indicating the impact of AI and innovative technologies on clean energy and fossil fuels.[2] Given that GRENEF measures the performance of companies aiming to enhance energy efficiency through AI and computing technologies, it can also be considered a type of AI and innovative technology index alongside a clean energy index. This could explain the AI indices' role as volatility transmitters relative to clean energy indices and fossil fuels.

The finding that AI indices are net transmitters of volatility in relation to clean energy indices aligns with Maleki et al. (2022), who found that AI facilitates the development of infrastructure for clean energy efficiently and cost-effectively; Wang et al. (2019), who demonstrated AI's role in developing smart grids and efficiently transferring energy and renewable resources; and Adedeji et al. (2020), who highlighted AI's contribution to the security, efficiency, and sustainability of clean energy. Fossil fuels are primary sources of energy, including electricity production. These applications provide an economic rationale for linking AI-related developments to volatility dynamics in fossil fuel markets. The role of AI indices as net transmitters of volatility on fossil fuels is consistent with findings of Hwang et al. (2020) and Mustafa et al. (2022), who emphasizes AI's significant role in analyzing the environmental effects of fossil fuels. Additionally, clean energy indices act as net trans-

[2] The index includes firms that rely on advanced technologies and digital solutions. Therefore, although it is classified as a clean energy index, its behaviour may also reflect broader technological dynamics.

Table 3: Connectedness in time and frequency domains

Panel A: Avarage connectedness in time domain											
	GRNREG	GRNENEF	GRNAM	GRNBIO	WTI	GAS	COAL	KMAKEP	KAIEATP	KRAICP	FROM
GRNREG	29.87	11.62	7.9	7.5	2.18	1.81	1.1	12.35	10.56	15.11	70.13
GRNENEF	9.7	23.42	12.84	6.31	0.95	1.07	0.46	16.42	13.78	15.05	76.58
GRNAM	8.53	16.59	29.2	6.6	0.99	1.06	0.8	13.53	10.14	12.57	70.8
GRNBIO	9.29	8.63	7.25	36.53	2.59	1.19	1.46	10.75	8.93	13.38	63.47
WTI	3.51	2.08	1.51	3.84	77.6	2.56	2.05	2.07	2.11	2.72	22.45
GAS	2.54	1.28	1	1.33	2.59	84.4	1.9	1.1	1.91	1.91	15.56
COAL	1.56	0.91	0.62	0.7	1.39	2.52	89.11	1.03	1.07	1.1	10.89
KMAKEP	9.6	15.27	9.84	7.17	0.79	0.94	0.39	21.88	15.5	18.63	78.12
KAIEATP	9.12	14.27	8.18	6.62	0.77	1.04	0.44	17.41	24.45	17.7	75.55
KRAICP	11.06	13.81	8.78	8.36	0.92	1.16	0.29	18.43	15.54	21.65	78.35
TO	64.91	84.47	57.92	48.43	13.2	13.3	8.9	93.08	79.55	98.18	561.92
Inc.Own	94.78	107.89	87.12	84.96	90.7	97.8	98	114.95	104	119.82	TCI
Net	-5.22	7.89	-12.88	-15.04	-9.29	-2.23	-2	14.95	4	19.82	62.44
Panel B: Avarage connectedness in frequency domain											
Short-term horizon, for one to five days											
	GRNREG	GRNENEF	GRNAM	GRNBIO	WTI	GAS	COAL	KMAKEP	KAIEATP	KRAICP	FROM
GRNREG	24.26	9.57	6.6	6.07	1.42	0.96	0.51	10.06	8.52	12.14	55.86
GRNENEF	8.14	19.96	10.9	5.26	0.74	0.81	0.28	13.86	11.6	12.68	64.27
GRNAM	7.15	14.02	25.24	5.48	0.77	0.89	0.54	11.33	8.45	10.49	59.12
GRNBIO	7.45	7.25	6.19	31.81	1.89	0.67	0.9	9.03	7.44	11.17	51.97
WTI	2.33	1.58	1.21	3.03	66	1.38	1.23	1.59	1.57	2	15.91
GAS	1.72	0.99	0.83	1.06	1.79	72.6	1.21	0.87	1.43	1.44	11.35
COAL	0.97	0.67	0.48	0.55	0.91	1.37	74.54	0.8	0.75	0.81	7.32
KMAKEP	8.04	13.11	8.42	6.06	0.59	0.65	0.24	18.82	13.29	15.95	66.37
KAIEATP	7.64	12.22	6.97	5.59	0.57	0.77	0.3	14.9	21.09	15.12	64.07
KRAICP	9.21	11.8	7.54	7.08	0.67	0.8	0.21	15.76	13.28	18.49	66.34
TO	52.65	71.22	49.14	40.2	9.35	8.3	5.41	78.21	66.34	81.79	462.59
Inc.Own	76.9	91.17	74.37	72.02	75.4	80.9	79.95	97.03	87.43	100.29	TCI
Net	-3.21	6.94	-9.99	-11.77	-6.56	-3.05	-1.91	11.84	2.26	15.45	51.4
Medium-to-long-term horizon, for five days and beyond											
	GRNREG	GRNENEF	GRNAM	GRNBIO	WTI	GAS	COAL	KMAKEP	KAIEATP	KRAICP	FROM
GRNREG	5.61	2.05	1.3	1.43	0.75	0.85	0.59	2.29	2.04	2.97	14.27
GRNENEF	1.57	3.46	1.94	1.04	0.22	0.26	0.18	2.55	2.18	2.38	12.31
GRNAM	1.38	2.57	3.96	1.12	0.21	0.16	0.26	2.2	1.69	2.08	11.68
GRNBIO	1.85	1.39	1.06	4.71	0.71	0.51	0.56	1.72	1.49	2.21	11.5
WTI	1.18	0.5	0.29	0.81	11.6	1.18	0.83	0.48	0.54	0.72	6.54
GAS	0.82	0.29	0.17	0.26	0.8	11.9	0.69	0.22	0.48	0.47	4.22
COAL	0.58	0.24	0.14	0.15	0.48	1.15	14.57	0.23	0.32	0.29	3.57
KMAKEP	1.55	2.16	1.42	1.11	0.19	0.28	0.15	3.06	2.21	2.68	11.76
KAIEATP	1.48	2.05	1.21	1.03	0.2	0.27	0.15	2.51	3.36	2.58	11.47
KRAICP	1.85	2.01	1.25	1.28	0.24	0.36	0.08	2.67	2.26	3.15	12.01
TO	12.26	13.26	8.78	8.23	3.81	5.03	3.49	14.87	13.21	16.38	99.33
Inc.Own	17.87	16.71	12.74	12.94	15.4	16.9	18.06	17.93	16.57	19.54	TCI
Net	-2.01	0.94	-2.9	-3.27	-2.73	0.82	-0.08	3.11	1.74	4.37	11.04

Note: Each row indicates the percentage of a series' variability attributable to the corresponding series in the columns. *From* represents the average volatility a series has experienced, while *To* indicates the average volatility it transmitted to other series over time, and *Net* denotes the difference between these two. *Inc.Own* reflects the total average volatility. The connectedness values increase from light yellow to dark green. The total connectedness network represents the overall average net pairwise connectedness over the time domain; the short-term connectedness network spans one to five days, and the medium-to-long-term connectedness network spans five days to infinity.

mitters of volatility concerning fossil fuels. The widespread adoption and increased production and use of renewable energy sources are expected to reduce reliance on fossil fuels. The interconnectedness of clean energy indices with fossil fuels, as shown in the findings, is consistent with studies such as those by Tang et al. (2023), which find similar connectedness, and with Sanyel & Wuables (2022), who argues that clean energy reduces fossil fuel use and thereby decreases air pollution. Figure 2 summarizes Table 3 and presents the average connectedness between series across different time frequencies. While most connectedness among the series arises from short-term interactions, the overall role in net connectedness remains consistent. AI indices and the clean energy index GRNENEF act as net transmitters of volatility, whereas the remaining clean energy indices and fossil fuels are in a net receiver position. However, the fossil fuel index GAS is a net receiver in both total and short-term, but becomes a net transmitter of volatility in the medium-to-long-term. This shift to a net-transmitter position for GAS could be explained by its more pronounced role as a net transmitter relative to WTI and COAL in the medium and long term, which is consistent with Adi's (2022) findings that gas prices influence oil and coal prices. This finding indicates that natural gas shocks may play a more persistent role in medium- and long-term dynamics of fossil fuel markets.

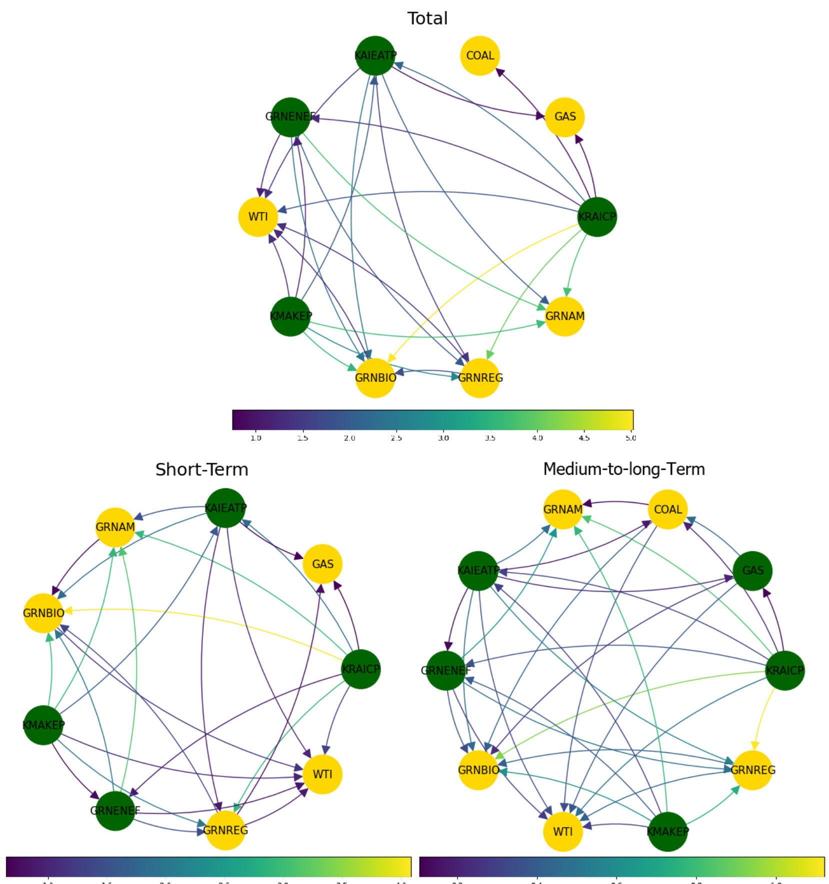


Figure 2: Avarage pairwise connectedness network

Notes: The plots illustrate the net volatility transmissions between series. The direction of the arrow indicates the flow from the net transmitter to its receiver. The thickness of the arrow represents the intensity of the net volatility transmission. Green-coloured series are, on average, net transmitters of volatility, while yellow-coloured series are typically net receivers.

Average connectedness values (Table 3 and Figure 2) represent the mean total connectedness across the series over the observation period. Therefore, these averages do not reveal changes in total connectedness over time. Given the sensitivity of the relationships among clean energy indices, fossil fuels, and AI indices to global events, dynamic analysis of these relationships is crucial.

Figure 3 illustrates the temporal changes in total connectedness among the series. The findings demonstrate that the overall connectedness among the series fluctuates over time and is generally high. Moreover, short-term connectedness predominates throughout the period, indicating that changes in the series are sensitive to one another and manifest their effects in the short term. Total connectedness across all frequency domains mainly increased during the initial phase of COVID-19. This may be because the pandemic generated a broader and more synchronised shock across financial markets, economic activity, and energy demand, whereas the Russia-Ukraine conflict and the Israel-Palestine war, although highly influential, were more concentrated in specific channels, particularly energy supply and geopolitical uncertainty. The lockdowns associated with COVID-19 reduced industrial production, creating uncertainties about energy demand and causing global uncertainty. These uncertainties affected energy prices, leading to price shocks that, in turn, affected the connectedness among clean energy indices, fossil fuels, and AI indices. During this period, the accuracy of energy consumption forecasts and the role of AI in forecasting became critically important for determining energy prices accurately. Wang et al. (2020) suggests that using AI for forecasting energy consumption can contribute to energy stability and accurate policy formation during global uncertainties such as COVID-19. The finding that connectedness between clean energy and fossil fuels indices with AI indices peaked during COVID-19 aligns with Tiwari et al. (2021) and Zeng et al. (2024), highlighting the series' dynamic and responsive nature to global crises.

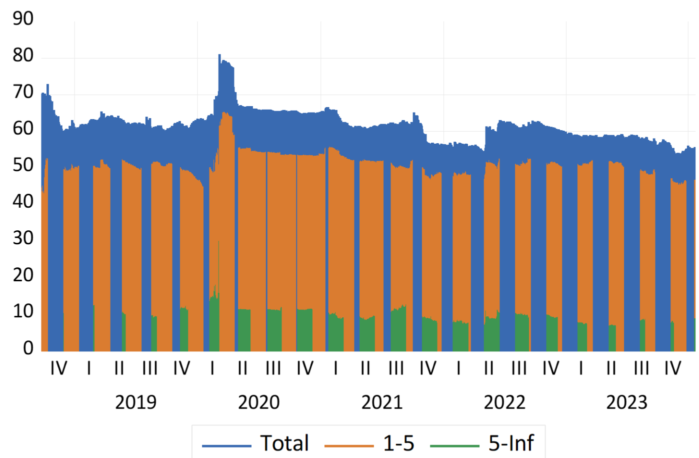
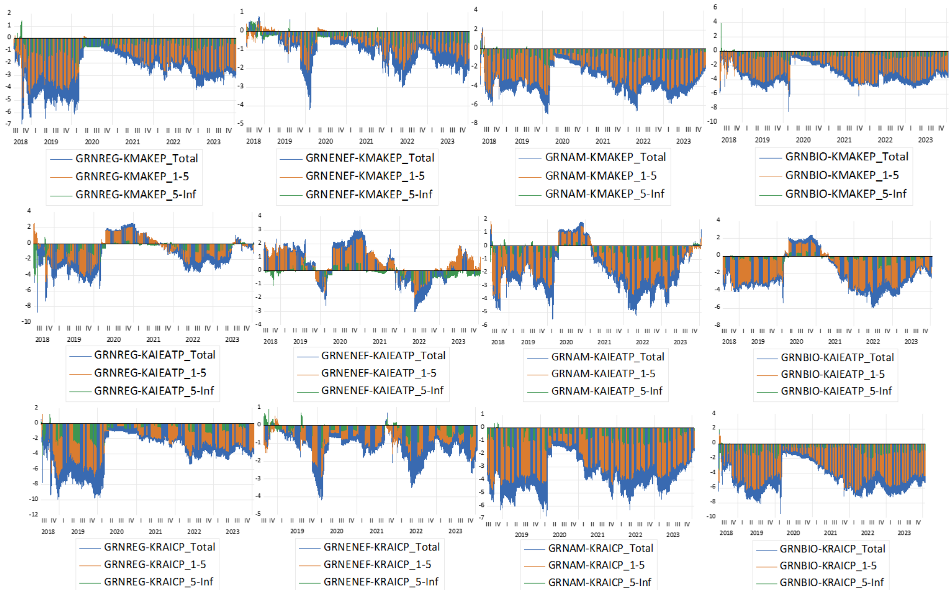


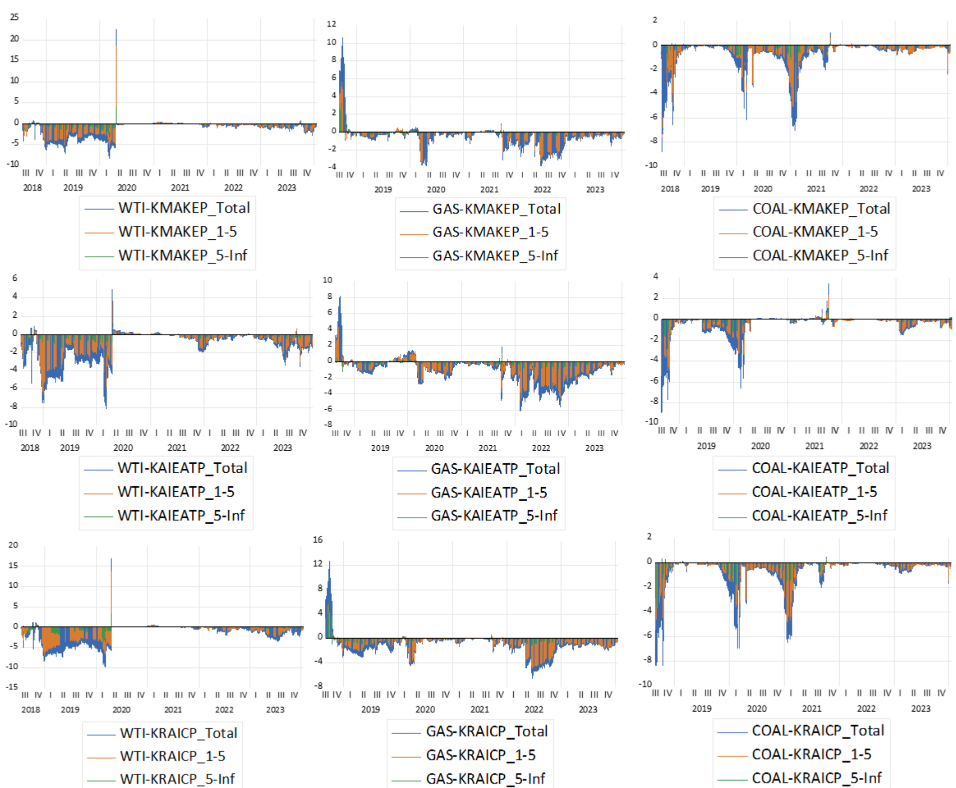
Figure 3: Total Connectedness Index (TCI)

The Total Connectedness Index (TCI) depicted in Figure 3 illustrates the overall interlinkages among the indices over time. However, the pairwise connectedness among these indices may be influenced differently by global events, leading to distinct patterns across index groups. Accordingly, using pairwise connectedness graphs, we report on the connectedness between each pair of indices: clean energy and AI in Figure 4a and fossil fuels and AI in Figure 4b. Overall, pairwise connectedness indicates that AI indices serve as the net transmitters of volatility relative to clean energy indices and fossil fuels throughout the period. However, the net volatility transmissions vary by series and over time.

The impact of global events such as COVID-19, the Ukraine-Russia conflict, the collapse of SVB, and the Israel-Palestine War is evident in this pairwise connectedness. Each global event affects the series differently, and the impact of different global events varies even within



(a) Green Finance and AI Indices



(b) Fossil Fuels and AI Indices

Figure 4: Net Pairwise Directional Connectedness

Notes: Positive values indicate that clean energy indices/fossil fuels are net volatility transmitters, whereas negative values indicate that AI indices are net volatility transmitters in the pairwise connectedness.

the same series. During COVID-19, the net pairwise connectedness between clean energy indices and AI indices decreased. In some cases, AI indices shifted from being net transmitters to net receivers of volatility against clean energy indices. This shift could be attributed to an increase in mutual volatility transmissions, as depicted in Figure 3, leading to a decrease in the intensity of net connectedness.

A similar pattern is observed with the pairwise connectedness findings for fossil fuels and AI indices, as depicted in Figure 4b. At the onset of COVID-19, some pairings show a decrease in net connectedness, whereas others exhibit a significant increase. Notably, the net connectedness of WTI with all AI indices reversed direction at the start of COVID-19; previously, it was a net receiver of volatility against AI indices, but it became a net transmitter during the pandemic. Conversely, the net pairwise connectedness of GAS with AI indices decreased at the start of COVID-19, while that of COAL increased. These differing outcomes are also observed in the effects of other global events. The finding that AI indices are net volatility transmitters relative to clean energy indices aligns with the findings of Zeng et al. (2024) and Zhao et al. (2024), who demonstrated AI's influence on the transition to renewable energy. Similarly, the finding that AI indices are net transmitters of volatility to fossil fuels is consistent with Tiwari et al. (2021), who showed that AI affects carbon pricing. Moreover, the sensitivity of pairwise connectedness to global events can be linked to Wang et al. (2020)'s assessments that AI contributed to the development of renewable energy systems amid COVID-19.

5 Conclusion

This study investigates dynamic connectedness between artificial intelligence (AI) indices and clean energy and fossil fuel markets within a time-frequency framework using the TVP-VAR frequency-connectedness approach. The findings indicate that the overall level of connectedness among these markets is high and is largely driven by short-term components, suggesting that shocks arising between AI and energy markets are transmitted rapidly throughout the financial system. The empirical results indicate that AI indices tend to act as net transmitters of volatility compared to clean energy indices and fossil fuels. This finding suggests that AI extends beyond a purely technological component and is closely associated with risk dynamics in energy markets. Accordingly, price dynamics and volatility interactions in energy markets appear to be increasingly linked to technology-driven financial developments. The dynamic results further reveal that connectedness varies substantially over time and intensifies markedly during periods of global uncertainty, such as the COVID-19 pandemic. Additionally, net pairwise connectedness suggests that the direction of risk transmission between markets can shift during crisis periods. This evidence highlights that the roles of energy and technology-oriented assets within the financial system are not static but are highly sensitive to prevailing market conditions.

The findings suggest several implications for financial regulators, policymakers, and investors. The rapid transmission of AI-related financial risks to energy markets underscores the need to explicitly consider AI- and technology-oriented financial assets in systemic risk assessments. In particular, the predominance of short-term connectedness indicates that macroprudential policies aimed at preserving market stability during periods of stress should be broadened to account for technology-based risk channels. More specifically, the findings suggest that green finance policies may benefit not only from considering environmental objectives but also from the volatility transmission channels associated with AI-related financial assets. In this respect, regulatory frameworks for digital and AI-based infrastructure in energy markets may need to consider their potential role in amplifying cross-market risk transmission during periods of stress. From an investor's perspective, the results further suggest that portfolio diversification and risk management strategies involving energy assets should incorporate AI-driven market dynamics, especially during times of heightened uncertainty.

References

Adedeji, P., Akinlabi, S., Madushele, N., & Olatunji, O. (2020). Potential Roles of Artificial Intelligence in the LCI of Renewable Energy Systems. In S. S. Emamian, M. Awang, & F. Yusof (Eds.), *Advances in Manufacturing Engineering. Lecture Notes in Mechanical Engineering* (p. 275-285). Springer, Singapore. doi:10.1007/978-981-15-5753-8_26

Adi, T. W. (2022). The International Gas and Crude Oil Price Variability Effect on Indonesian Coal Mining Companies Listed at IDX. *International Journal of Energy Economics and Policy*, *12*(5), 1-10. doi:10.32479/ijeep.13263

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), 84. doi:10.3390/jrfm13040084

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271-296. doi:10.1093/jjfinec/nby001

Çağlar, A. E., Rej, S., & Mert, M. (2025). Zero-emission vision: The roles of artificial intelligence and clean energy in environmental sustainability improvement. *Journal of Environmental Management*, *3950*, 127880. doi:10.1016/j.jenvman.2025.127880

Castrejon-Campos, O., Aye, L., & Hui, F. K. P. (2020). Making policy mixes more robust: An integrative and interdisciplinary approach for clean energy transitions. *Energy Research & Social Science*, *64*, 101425. doi:10.1016/j.erss.2020.101425

Chatziantoniou, I., Abakah, E. J. A., Gabauer, D., & Tiwari, A. K. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production*, *361*, 132088. doi:10.1016/j.jclepro.2022.132088

Chatziantoniou, I., Gabauer, D., & Gupta, R. (2023). Integration and risk transmission in the market for crude oil: new evidence from a time-varying parameter frequency connectedness approach. *Resources Policy*, 103729. doi:10.1016/j.resourpol.2023.103729

Coşkun, M., Khan, N., Saleem, A., & Hammoudeh, S. (2023). Spillover connectedness nexus geopolitical oil price risk, clean energy stocks, global stock, and commodity markets. *Journal of Cleaner Production*, *429*, 139583. doi:10.1016/j.jclepro.2023.139583

Dammak, W., Gökgöz, H., & Jeribi, A. (2025). Time-Frequency Connectedness in Global Banking: Volatility and Return Dynamics of BRICS and G7 Banks. *Global Economy Journal*, *25*(01n02), 2550004. doi:10.1142/S2194565925500046

Dawar, I., Dutta, A., Bouri, E., & Saeed, T. (2021). Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression. *Renewable Energy*, *163*, 288-299. doi:10.1016/j.renene.2020.08.162

Dias, R., Teixeira, N., Alexandre, P., & Chambino, M. (2023). Exploring the connection between clean and dirty energy: Implications for the transition to a carbon-resilient economy. *Energies*, *16*(13), 4982. doi:10.3390/en16134982

Diebold, F. X., & Yılmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. doi:10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. doi:10.1016/j.jeconom.2014.04.012

Elie, B., Naji, J., Dutta, A., & Uddin, G. S. (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. *Energy*, *178*, 544-553. doi:10.1016/j.energy.2019.04.155

Gustafsson, R., Dutta, A., & Bouri, E. (2022). Are energy metals hedges or safe havens for clean energy stock returns? *Energy*, *244*, 122708. doi:10.1016/j.energy.2021.122708

Gökgöz, H., & Kandemir, T. (2023). *Trampadan Kripto Paraya*. Nobel, Ankara.

Hwang, Y. S., Um, J.-S., & Schlüter, S. (2020). Evaluating the Mutual Relationship between IPAT/Kaya Identity Index and ODIAC-Based GOSAT Fossil-Fuel CO2 Flux: Potential and Constraints in Utilizing Decomposed Variables. *International Journal of Environmental Research and Public Health*, *17*(6), 5976. doi:10.3390/ijerph17165976

Khoury, R. E., Alshater, M. M., Li, Y., & Xiong, X. (2024). Quantile time-frequency connectedness among G7 stock markets and clean energy markets. *The Quarterly Review of Economics and Finance*, *93*, 71-90. doi:10.1016/j.qref.2023.11.004

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101–116. doi:10.1016/j.euroecorev.2014.07.002

Kuang, W. (2021). Are clean energy assets a safe haven for international equity markets? *Journal of Cleaner Production*, *302*, 127006. doi:10.1016/j.jclepro.2021.127006

Kyriakarakos, G. (2025). Artificial Intelligence and the Energy Transition. *Sustainability*, *17*(3), 1140. doi:10.3390/su17031140

Li, Z., Xing, Y., Shao, X., Zhong, Y., & Su, Y. H. (2025). Transitioning the energy landscape: AI's role in shifting from fossil fuels to renewable energy. *Energy Economics*, 108729. doi:10.1016/j.eneco.2025.108729

Lin, N., Sun, Z., Li, Z., & Qin, C. (2025). The path to green Innovation: The impact of artificial intelligence applications on corporate continuous green innovation. *Journal of Environmental Management*, *395*, 127724. doi:10.1016/j.jenvman.2025.127724

Ma, C. Q., Liu, X., Klein, T., & Ren, Y. S. (2025). Decoding the nexus: How fintech and AI stocks drive the future of sustainable finance. *International Review of Economics & Finance*, *98*, 103877. doi:10.1016/j.iref.2025.103877

Maleki, R., Asadnia, M., & Razmjou, A. (2022). Artificial Intelligence-Based Material Discovery for Clean Energy Future. *Advanced Intelligent Systems*, *4*(10), 2200073. doi:10.1002/aisy.202200073

Memon, B. A., Aslam, F., Asadova, S., & Ferreira, P. (2023). Are clean energy markets efficient? A multifractal scaling and herding behavior analysis of clean and renewable energy markets before and during the COVID19 pandemic. *Heliyon*, *9*(12), e22694. doi:10.1016/j.heliyon.2023.e22694

Mustafa, A., Tariq, Z., Mahmoud, M., & Abdulraheem, A. (2022). Artificial Intelligence Approach for Predicting the Shale Brittleness Index - A Middle East Basin Case Study. In *The SPE EuropEC - Europe Energy Conference featured at the 83rd EAGE Annual Conference & Exhibition, Madrid, Spain.* doi:10.2118/209707-MS

Nasdaq OMX QGreen. (2025). https://indexes.nasdaqomx.com/Index/Overview/QGREEN.

Nepal, R., Zhao, X., Dong, K., Wang, J., & Sharif, A. (2025). Can artificial intelligence technology innovation boost energy resilience? The role of green finance. *Energy Economics*, *142*, 108159. doi:10.1016/j.eneco.2024.108159

Qi, S., Pang, L., Li, X., & Huang, L. (2025). The dynamic connectedness in the "carbon-energy-green finance" system: The role of climate policy uncertainty and artificial intelligence. *Energy Economics*, *143*, 108241. doi:10.1016/j.eneco.2025.108241

Raggad, B., & Bouri, E. (2025). Artificial intelligence and clean/dirty energy markets: tail-based pairwise connectedness and portfolio implications. *Future Business Journal*, *11*(1), 1-24. doi:10.1186/s43093-025-00451-8

Sanyel, S., & Wuables, D. J. (2022). The potential impact of a clean energy society on air quality. *Earth's Future*, *10*, e2021EF002558. doi:10.1029/2021EF002558

S&P Kensho AI. (2025). https://www.spglobal.com/spdji/en/index-family/thematics/innovative-technology/ai-robotics-automation/#indices.

Tang, C., Aruga, K., & Hu, Y. (2023). The Dynamic Correlation and Volatility Spillover among Green Bonds, Clean Energy Stock, and Fossil Fuel Market. *Sustainability*, *15*(8), 6586. doi:10.3390/su15086586

Tiwari, A. K., Abakah, E. J. A., Le, T.-L., & Hiz, D. I. L. (2021). Markov-switching dependence between artificial intelligence and carbon price: The role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. *Technological Forecasting and Social Change*, *163*, 120434. doi:10.1016/j.techfore.2020.120434

Wang, B., Wang, J., Dong, K., & Nepal, R. (2024). How does artificial intelligence affect high-quality energy development? Achieving a clean energy transition society. *Energy Policy*, *186*, 114010. doi:10.1016/j.enpol.2024.114010

Wang, B., Yang, Z., Xuan, J., & Jiao, K. (2020). Crises and opportunities in terms of energy and AI technologies during the COVID-19 pandemic. *Energy and AI*, *1*, 100013. doi:10.1016/j.egyai.2020.100013

Wang, Q., Zhang, S., & Li, R. (2026). Artificial intelligence in the renewable energy transition: The critical role of financial development. *Renewable and Sustainable Energy Reviews*, *226*, 116280. doi:10.1016/j.rser.2025.116280

Wang, W., Zhou, Z., & Liu, C. (2019). Index systems for analysis and evaluation of clean energy development based on AHP. In *IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2), Changsha, China* (p. 1353-1356). doi:10.1109/EI247390.2019.9061794

Xu, B. (2025). Inclusive green finance approach to assess energy resilience: Integrating artificial intelligence (AI) utilization in energy strategy perspective. *Energy Strategy Reviews*, *59*, 101696. doi:10.1016/j.esr.2025.101696

Yousaf, I., Youssef, M., & Goodell, J. W. (2024). Tail connectedness between artificial intelligence tokens, artificial intelligence ETFs, and traditional asset classes. *Journal of International Financial Markets, Institutions and Money*, *91*, 101929. doi:10.1016/j.intfin.2023.101929

Zeng, H., Abedin, M. Z., Zhou, X., & Lu, R. (2024). Measuring the extreme linkages and time-frequency co-movements among artificial intelligence and clean energy indices. *International Review of Financial Analysis*, *92*, 103073. doi:10.1016/j.irfa.2024.103073

Zeng, H., Lu, R., & Ahmed, A. D. (2023). Return connectedness and multiscale spillovers across clean energy indices and grain commodity markets around COVID-19 crisis. *Journal of Environmental Management*, *340*, 117912. doi:10.1016/j.jenvman.2023.117912

Zhang, F., Wang, Q., & Li, R. (2025). How does clean energy reshape the nonlinear relationship between artificial intelligence and carbon emissions? Evidence from renewable and nuclear energy. *Energy Economics*, *149*, 108785. doi:10.1016/j.eneco.2025.108785

Zhang, H., Fang, B., He, P., & Gao, W. (2024). The asymmetric impacts of artificial intelligence and oil shocks on clean energy industries by considering COVID-19. *Energy*, *291*, 130197. doi:10.1016/j.energy.2023.130197

Zhao, Q., Wang, L., Stan, S.-E., & Mirza, N. (2024). Can artificial intelligence help accelerate the transition to renewable energy? *Energy Economics*, *134*, 107584. doi:10.1016/j.eneco.2024.107584

Zheng, J., Wen, B., Jiang, Y., Wang, X., & Shen, Y. (2023). Risk spillovers across geopolitical risk and global financial markets. *Energy Economics*, *127*, 107051. doi:10.1016/j.eneco.2023.107051